Demographic Forecasting: Incorporating Qualitative Insight in Quantitative Modeling

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Harvard University

Joint work with Federico Girosi (RAND)
with contributions from Kevin Quinn and Gregory Wawro

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- Approach: Formalizing qualitative insights in quantitative models

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  - Goal: include as much information as possible from any source

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- New ways of creating Bayesian priors
- Produces forecasts and farcasts using considerably more information

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  - Resolves analogous issues in predicting mortality by age, sex, and cause

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	Over Best Previous	to Best Conceivable
Cardiovascular	22	49
Lung Cancer	24	47
Transportation	16	31
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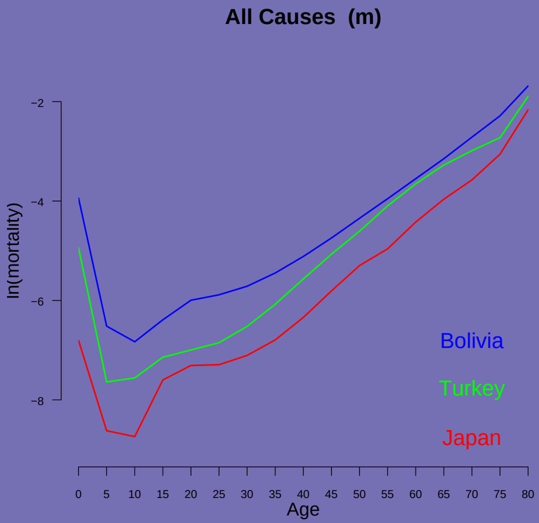
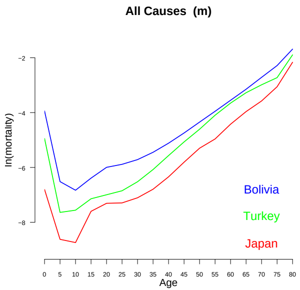
- Does *considerably* better with more informative covariates

All-Cause Mortality Age Profile Patterns



Existing Method 1: Parameterize the Age Profile



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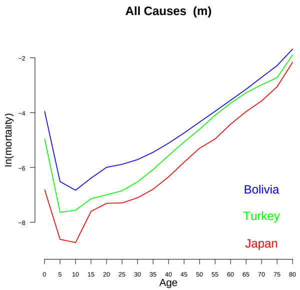

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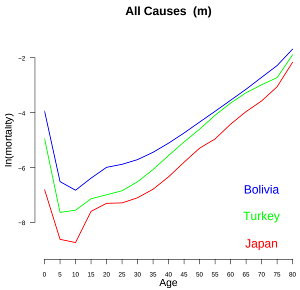

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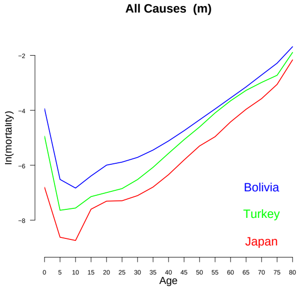

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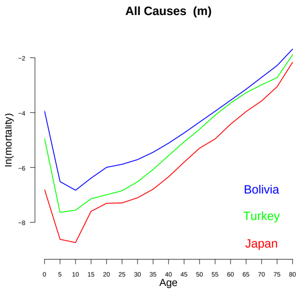

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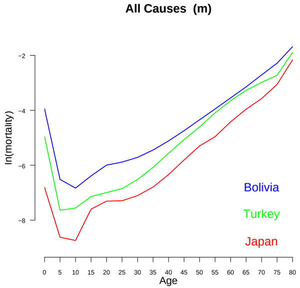

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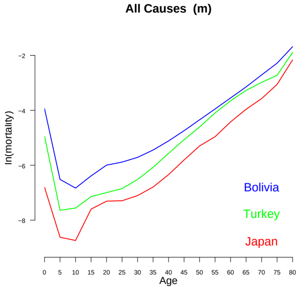

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- But does it fit anything else?

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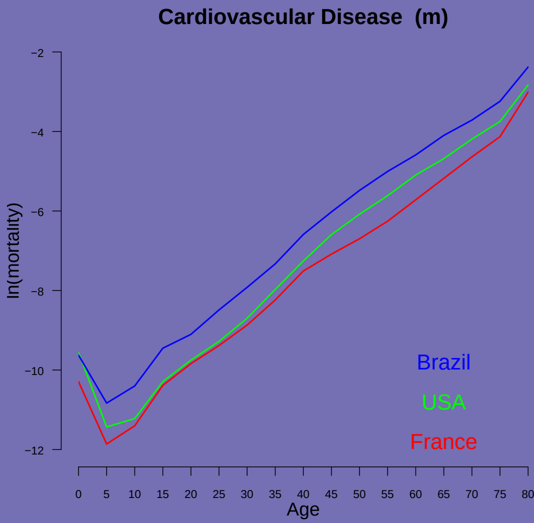

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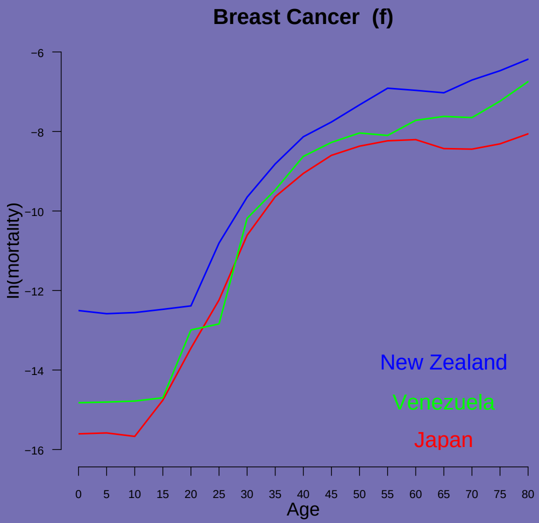

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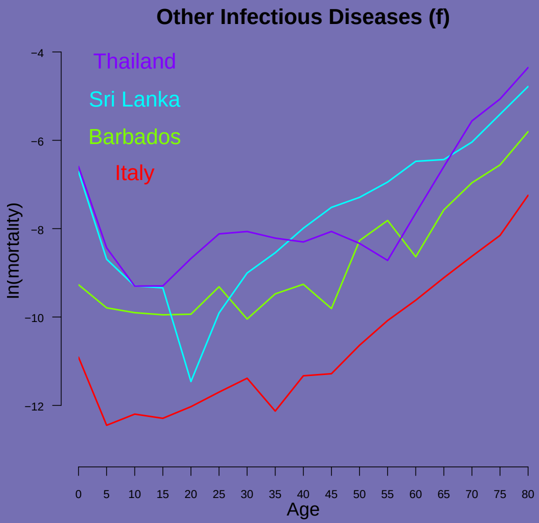

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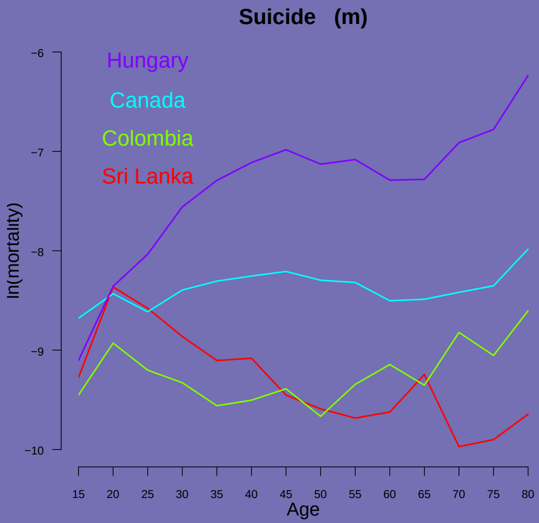

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Deterministic Projections

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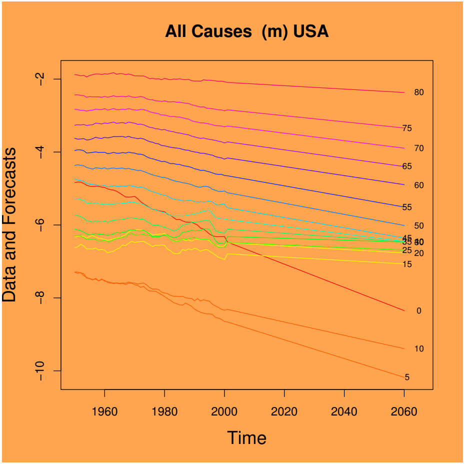

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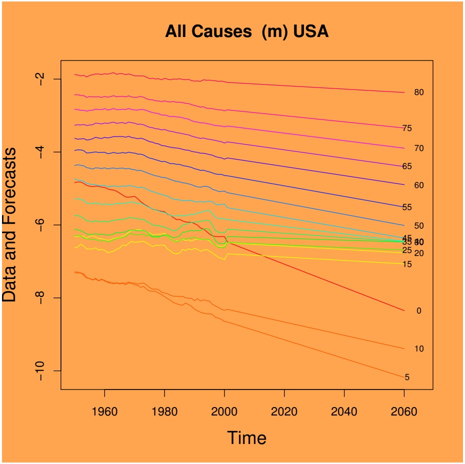
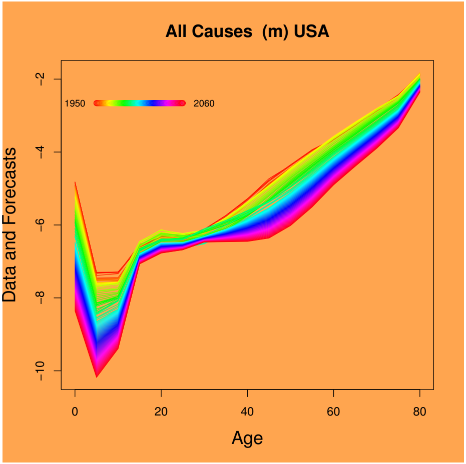
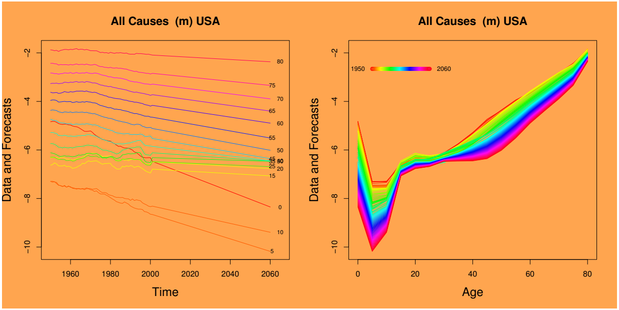




Existing Method 2: Deterministic Projections



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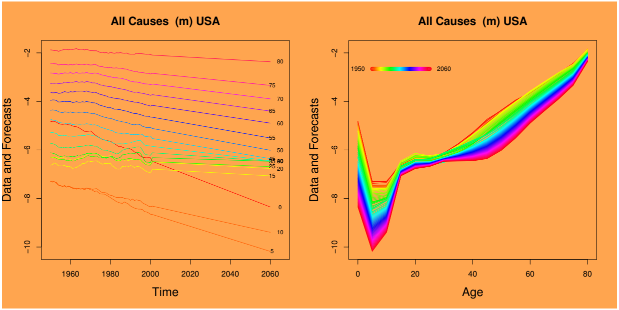

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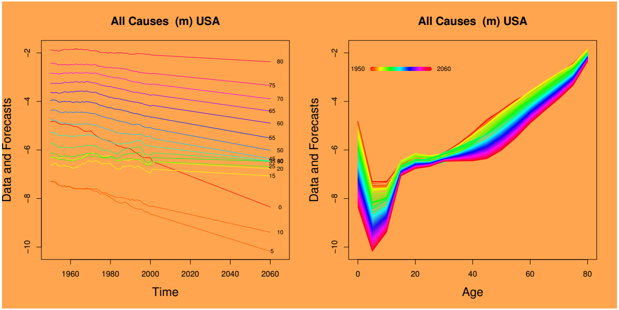

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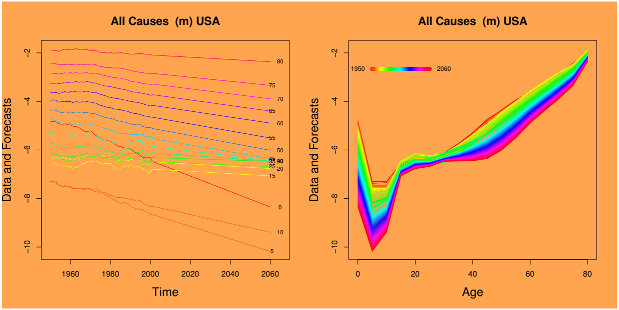

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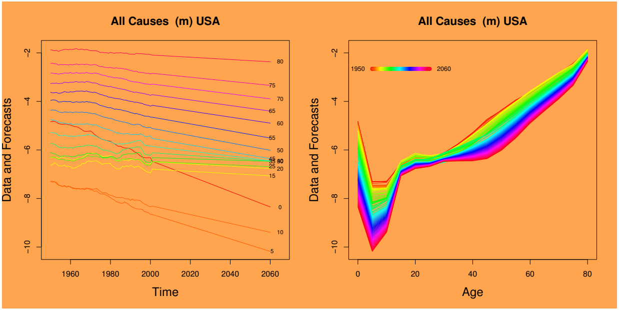

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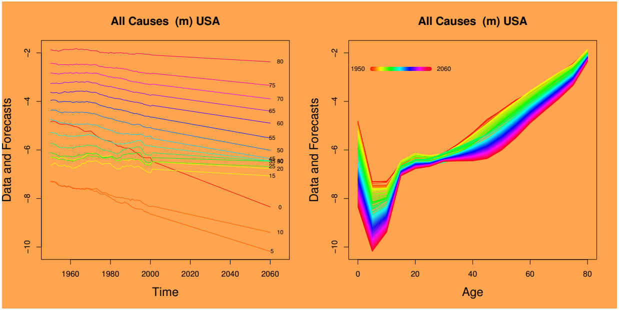

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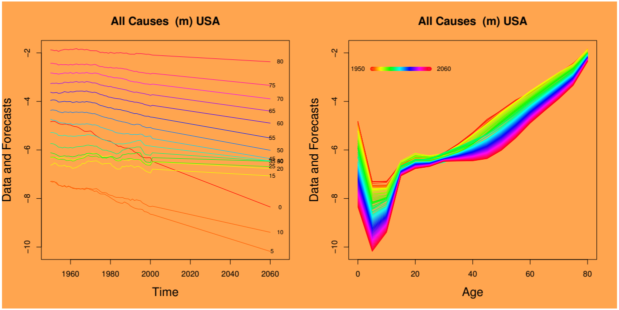

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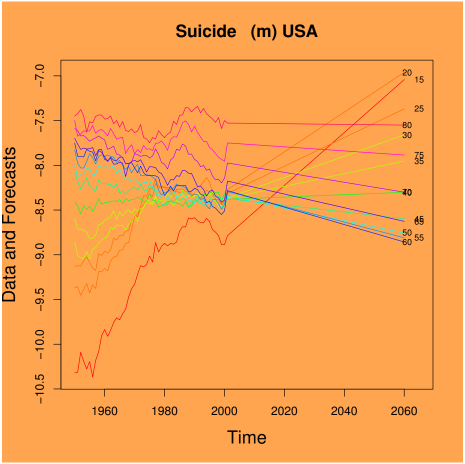

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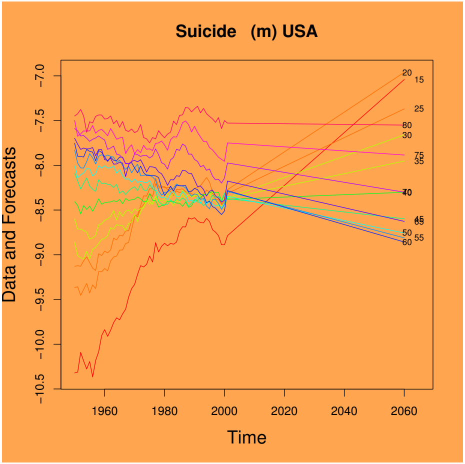

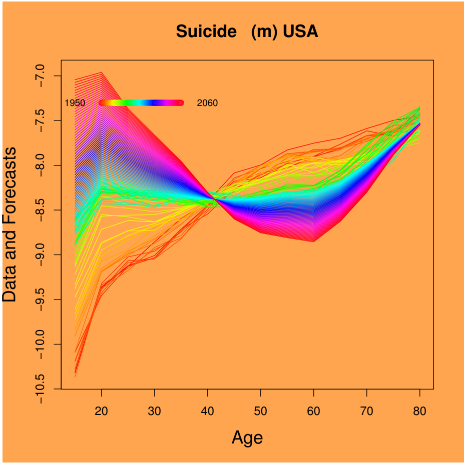

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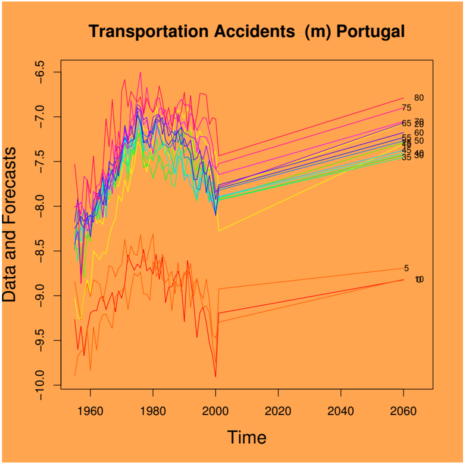

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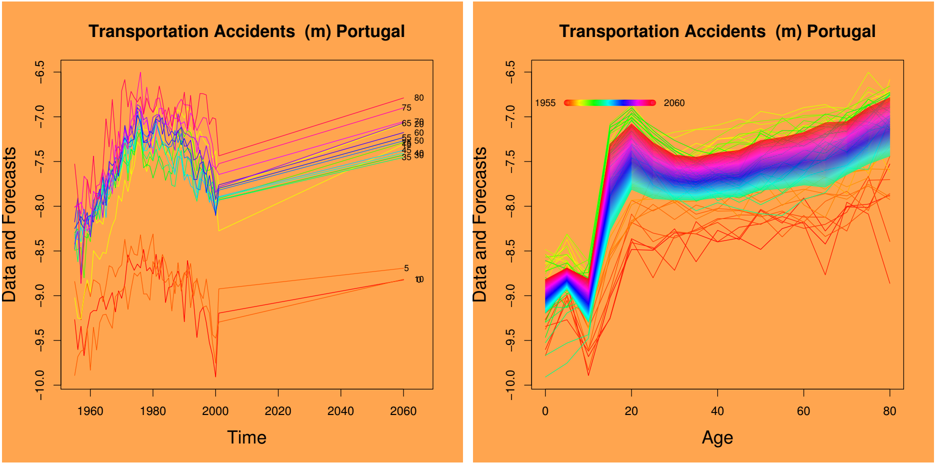

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  - Allow variables to change meaning in different countries (such as GDP) or time periods (ICD changes)

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- Qualitative knowledge: patterns are similar, not identical.

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$$\mathrm{P}(y_i|\eta_i) = \left\{\prod_{s=1}^{S}\prod_{k=1}^{K_s}\left[F(\tau_{is}^{k}|\mu_i,1) - F(\tau_{is}^{k-1}|\mu_i,1)\right]^{\mathbf{I}(y_{is}=k)}\right\}\frac{\sqrt{\mathfrak{B}}P_{10}P_{11}}{\sqrt{\mathfrak{B}}P_{10}+P_{11}},$$

$$L_s(\beta,\omega^2,\gamma|y) \propto \prod_{i=1}^{n}\int_{-\infty}^{\infty}\prod_{s=1}^{S}\prod_{k=1}^{K_s}\left[F(\tau_{is}^{k}|X_i\beta+\eta_i,\,1)\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\phi\right.$$

$$\mathrm{RD}_\gamma = \sqrt{\mathfrak{B}}/(1+\sqrt{\mathfrak{B}}) - 1/(1+\sqrt{\mathfrak{B}}) - \left. F(\tau_{is}^{k-1}|X_i\beta+\eta_i,\,1)\right]^{\mathbf{I}(y_{is}=k)} N(\eta_i|0,$$

$\Theta_{ab} = \Pr(X_a|Y=b)$, $\mathfrak{B} = (\Theta_{11}\Theta_{00})/(\Theta_{01}\Theta_{10})$. $\phi = (\mathfrak{B}\zeta01^2/\zeta11^2)^{1/2}$
$= \sqrt{\mathfrak{B}}\zeta01/\zeta11$, and $\gamma = \sqrt{\mathfrak{B}}/(\sqrt{\mathfrak{B}}+\eta_{11}/\eta_{10})$. Then, RD_γ

$$\eta_{11}\gamma = \frac{\sqrt{\mathfrak{B}}\eta_{10}\Lambda_{11}}{\sqrt{\mathfrak{B}}\Lambda_{10}+\Lambda_{11}}, \qquad \Lambda_{01}\gamma = \frac{\sqrt{\mathfrak{B}}\Lambda_{01}\Gamma_{10}}{\sqrt{\mathfrak{B}}\Gamma_{10}+\Gamma_{11}}, \zeta\Gamma GK \boxtimes \Phi\phi$$

$$\Gamma_{10}(1-\gamma) = \frac{\Gamma_{10}\Gamma_{11}}{\sqrt{\mathfrak{B}}\Gamma_{10}+P_{11}}, \qquad P_{00}(1-\gamma) = \frac{P_{11}P_{00}}{\sqrt{\mathfrak{B}}P_{10}+P_{11}}.$$

$$\mathrm{rd} \in \left[\min[\mathrm{rd}(\underline{\tau}_j), \mathrm{rd}(\bar{\tau}_j)], \max[\mathrm{rd}(\underline{\tau}_j), \mathrm{rd}(\bar{\tau}_j)]\right]$$

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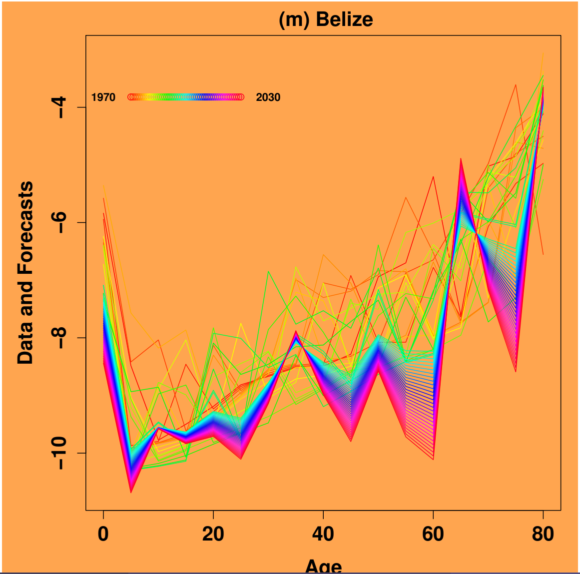
- Added a wide array of ways to combine cross-sections

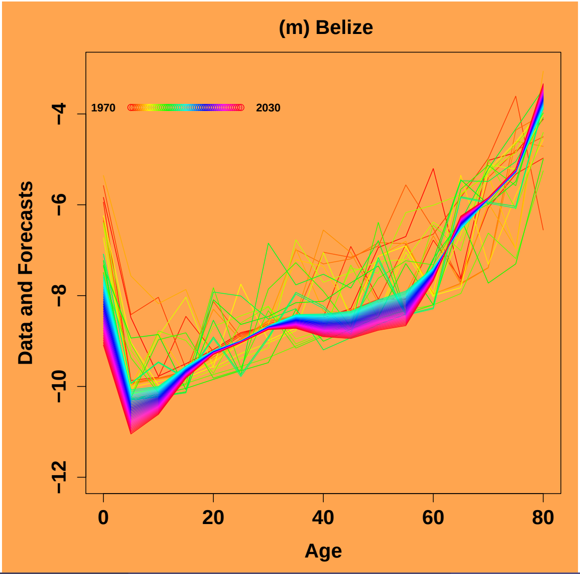
Mortality from Respiratory Infections, Males

Least Squares



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

Smoothing over Age Groups



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

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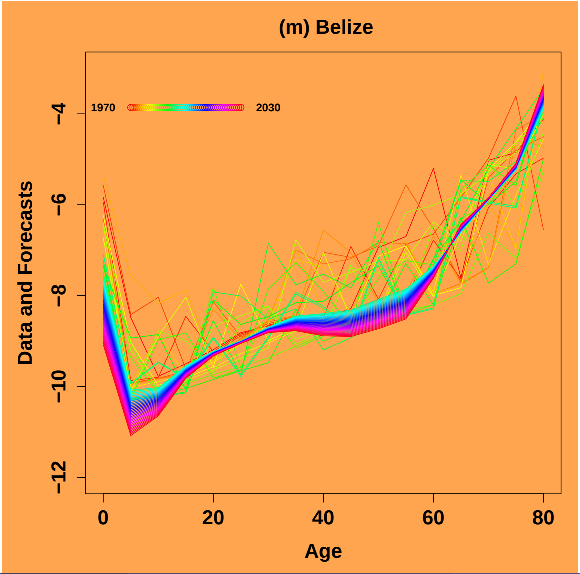

Mortality from Respiratory Infections, males, $\sigma = 1.15$

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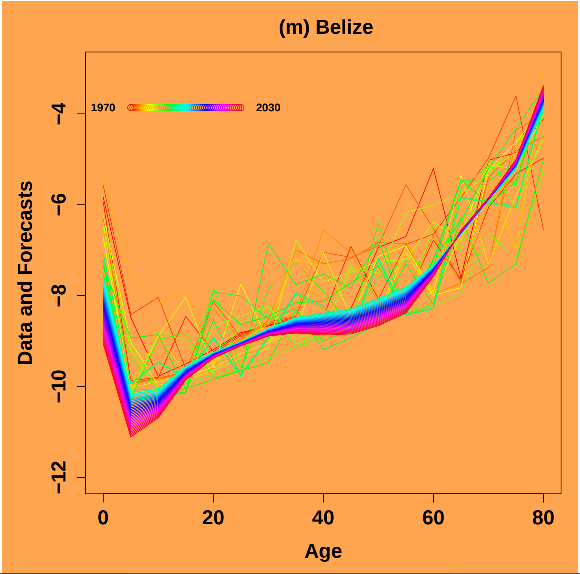

Mortality from Respiratory Infections, males, $\sigma = 0.87$

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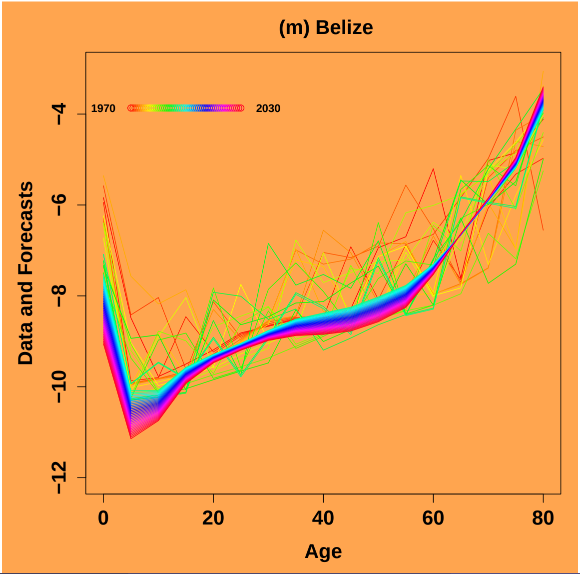

Mortality from Respiratory Infections, males, $\sigma = 0.66$

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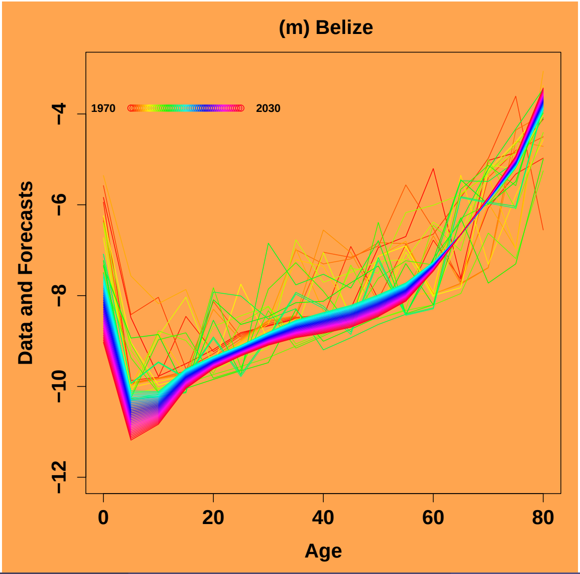
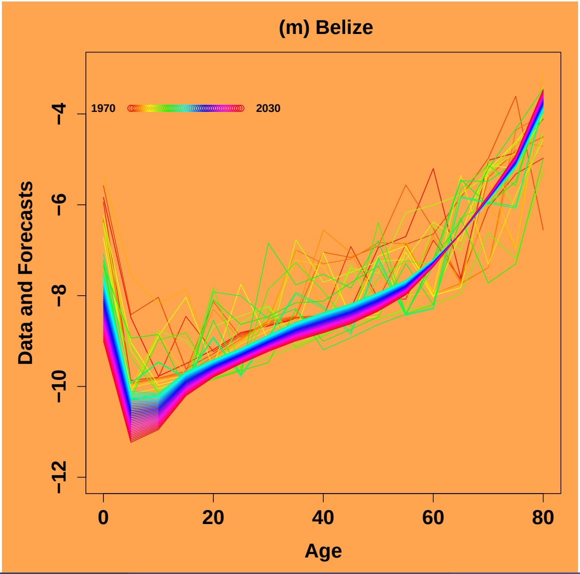


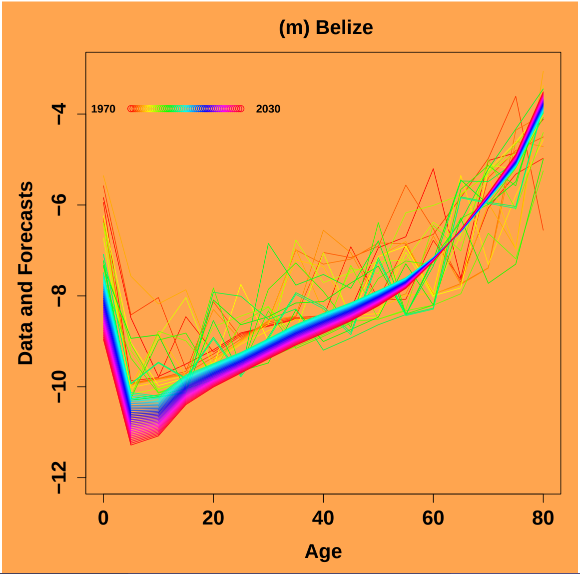
Mortality from Respiratory Infections, males, $\sigma = 0.50$

Smoothing over Age Groups



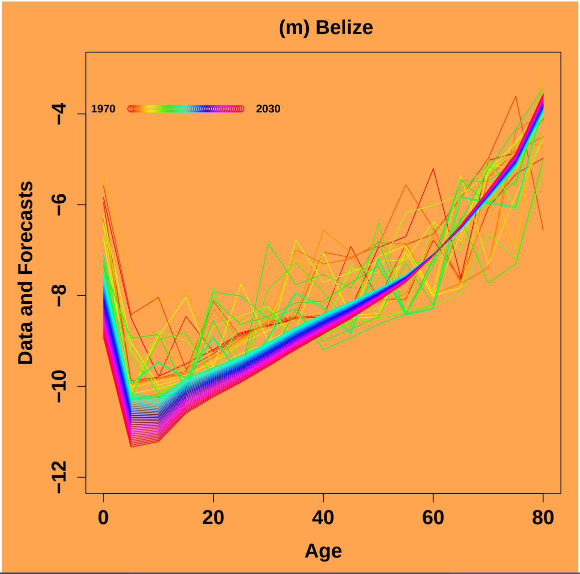
Mortality from Respiratory Infections, males, $\sigma = 0.38$

Smoothing over Age Groups



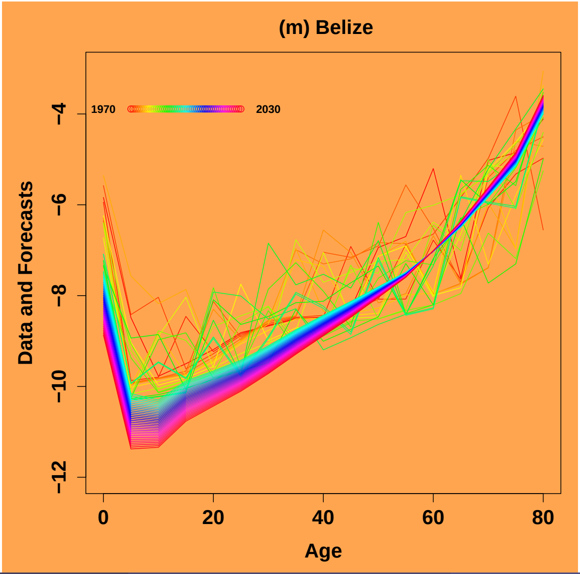
Mortality from Respiratory Infections, males, $\sigma = 0.28$

Smoothing over Age Groups



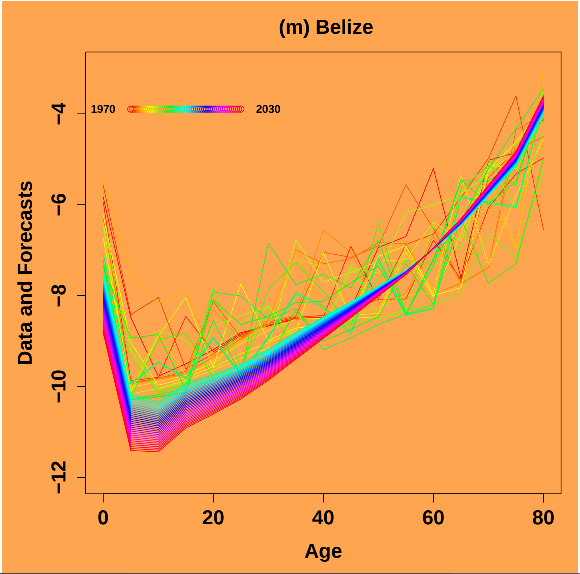
Mortality from Respiratory Infections, males, $\sigma = 0.21$

Smoothing over Age Groups



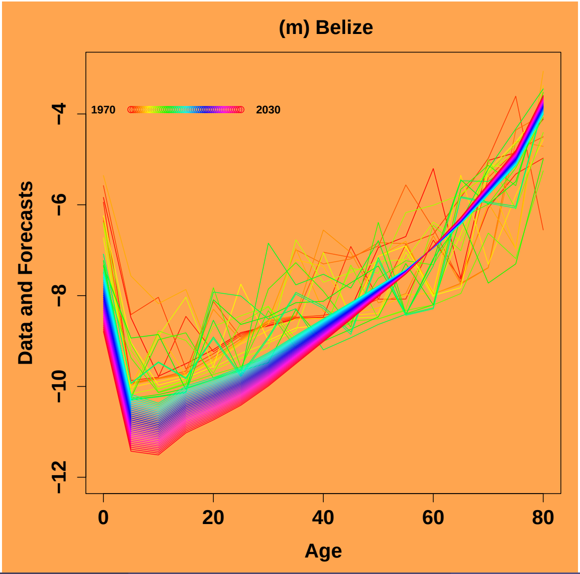
Mortality from Respiratory Infections, males, $\sigma = 0.16$

Smoothing over Age Groups



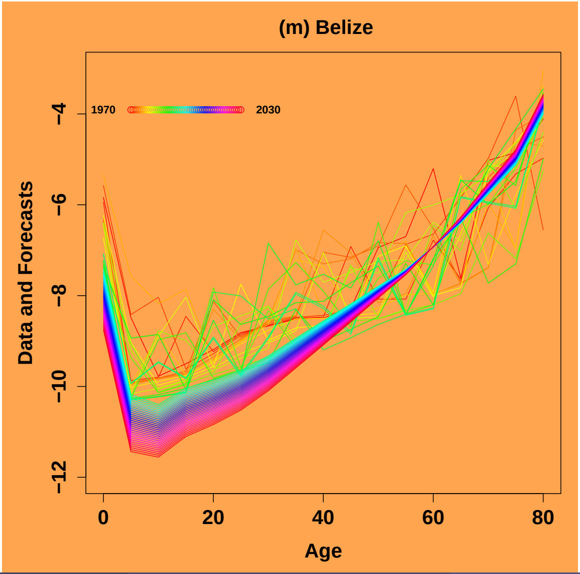
Mortality from Respiratory Infections, males, $\sigma = 0.12$

Smoothing over Age Groups



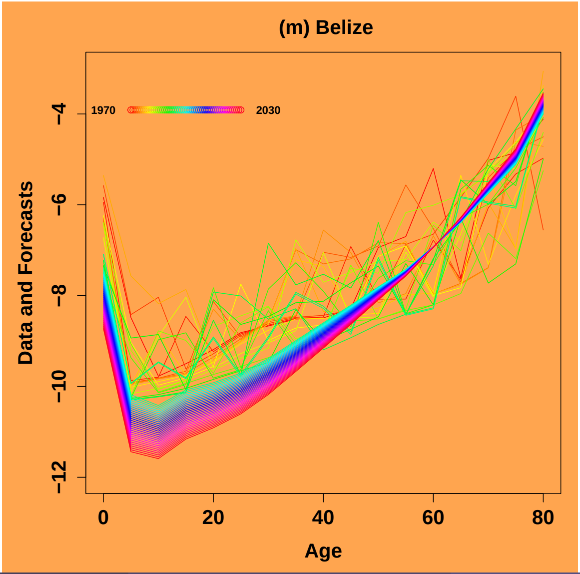
Mortality from Respiratory Infections, males, $\sigma = 0.09$

Smoothing over Age Groups



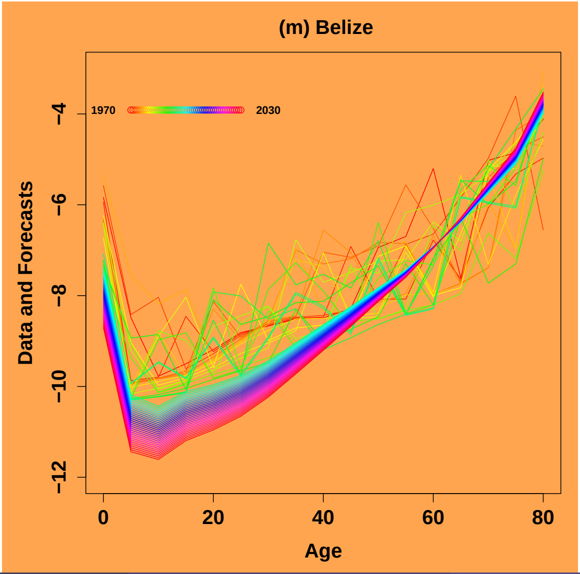
Mortality from Respiratory Infections, males, $\sigma = 0.07$

Smoothing over Age Groups



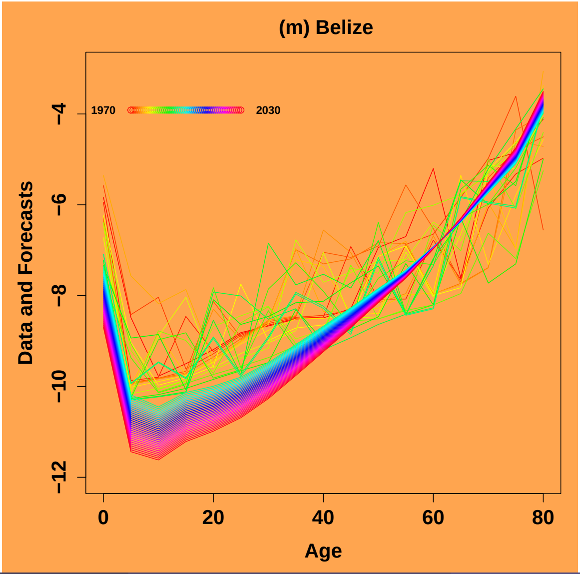
Mortality from Respiratory Infections, males, $\sigma = 0.05$

Smoothing over Age Groups



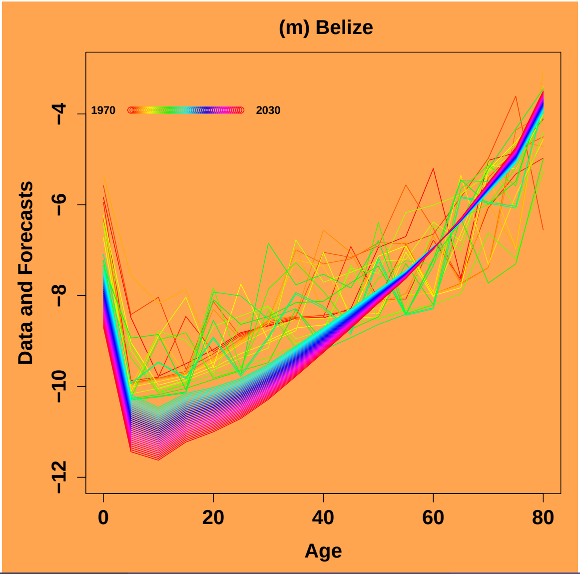
Mortality from Respiratory Infections, males, $\sigma = 0.04$

Smoothing over Age Groups



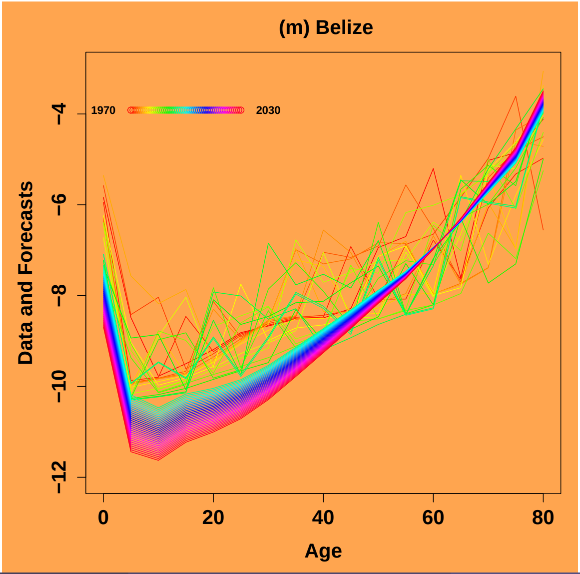
Mortality from Respiratory Infections, males, $\sigma = 0.03$

Smoothing over Age Groups



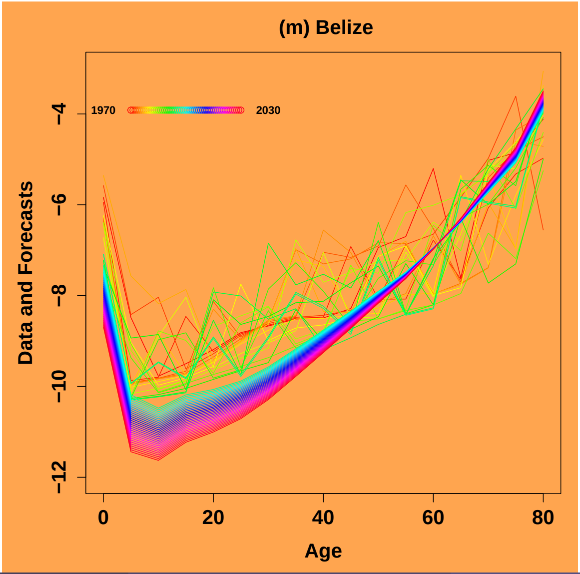
Mortality from Respiratory Infections, males, $\sigma = 0.02$

Smoothing over Age Groups



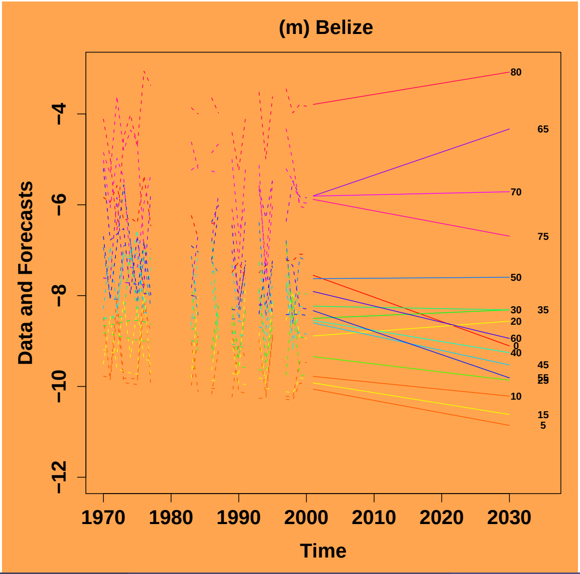
Mortality from Respiratory Infections, males, $\sigma = 0.01$

Smoothing over Age Groups



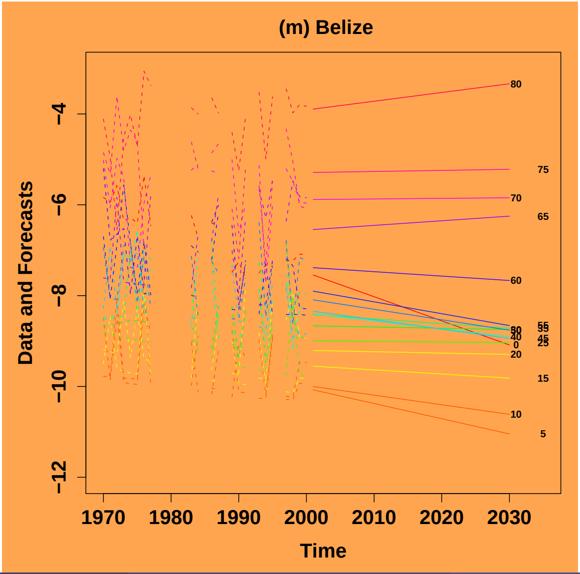
Mortality from Respiratory Infections, males

Least Squares



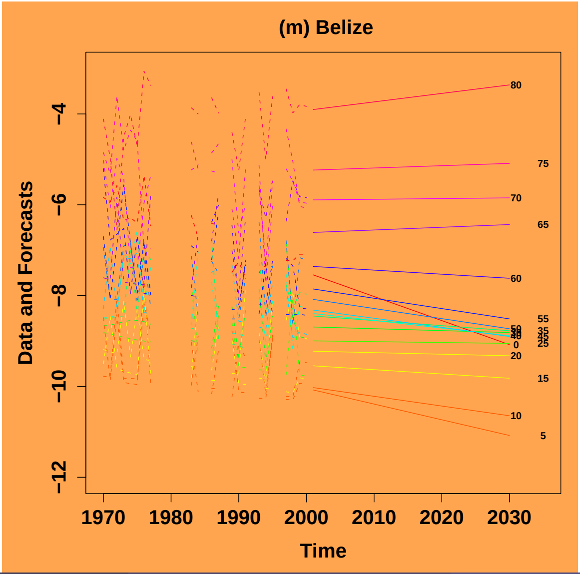
Mortality from Respiratory Infections, males, $\sigma = 2.00$

Smoothing over Age Groups



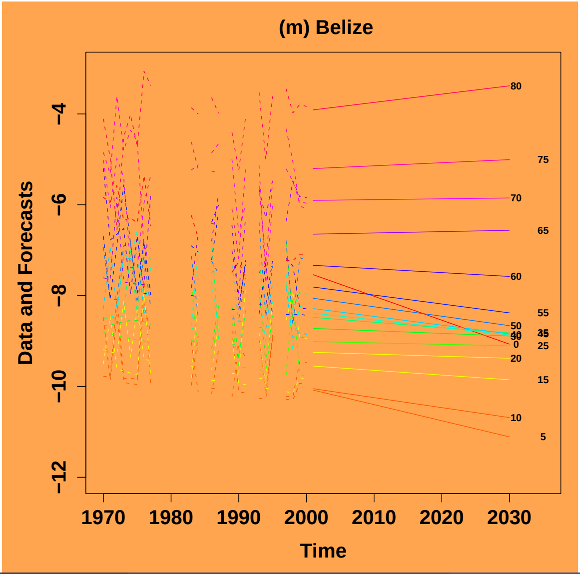
Mortality from Respiratory Infections, males, $\sigma = 1.51$

Smoothing over Age Groups



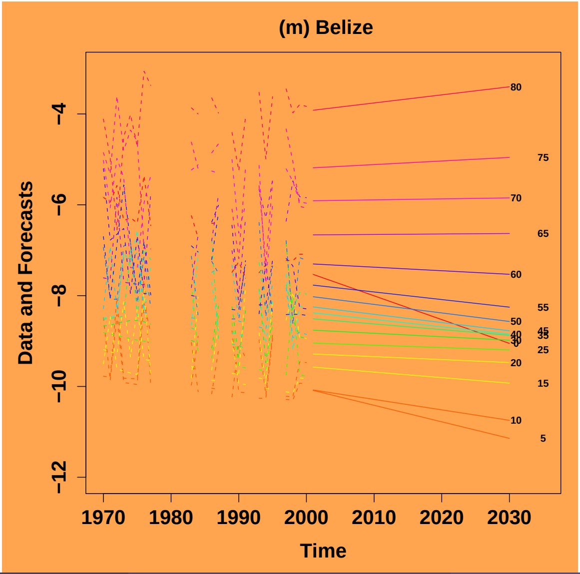
Mortality from Respiratory Infections, males, $\sigma = 1.15$

Smoothing over Age Groups



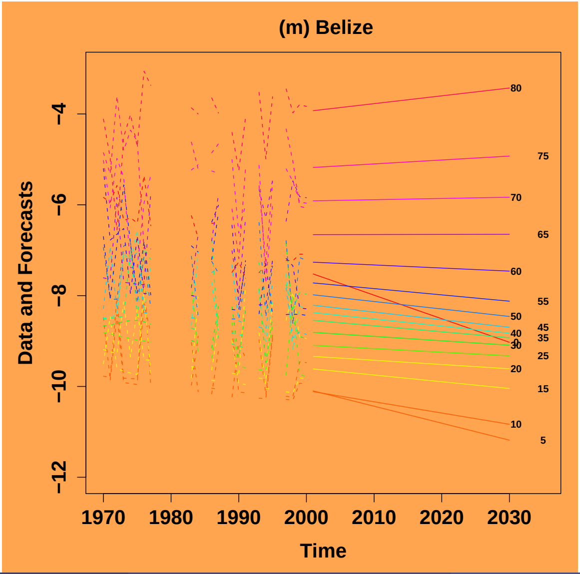
Mortality from Respiratory Infections, males, $\sigma = 0.87$

Smoothing over Age Groups



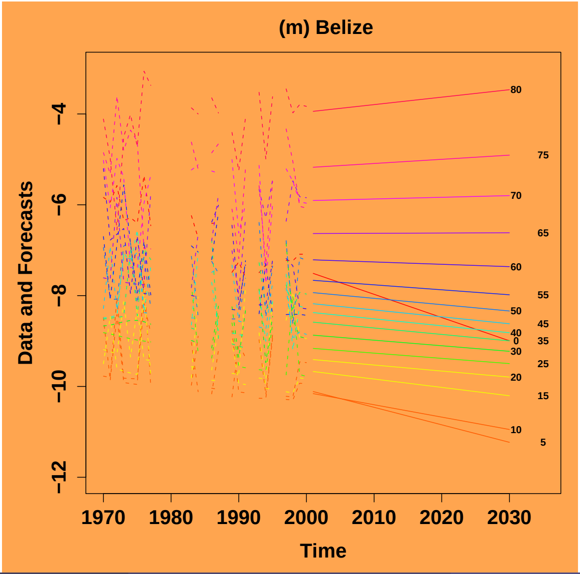
Mortality from Respiratory Infections, males, $\sigma = 0.66$

Smoothing over Age Groups



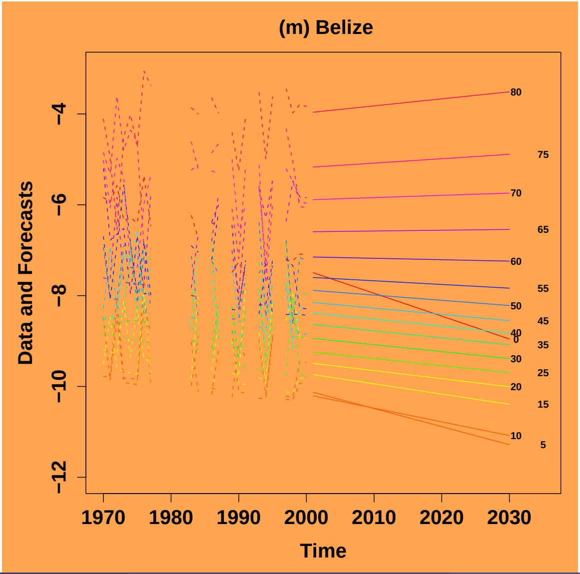
Mortality from Respiratory Infections, males, $\sigma = 0.50$

Smoothing over Age Groups



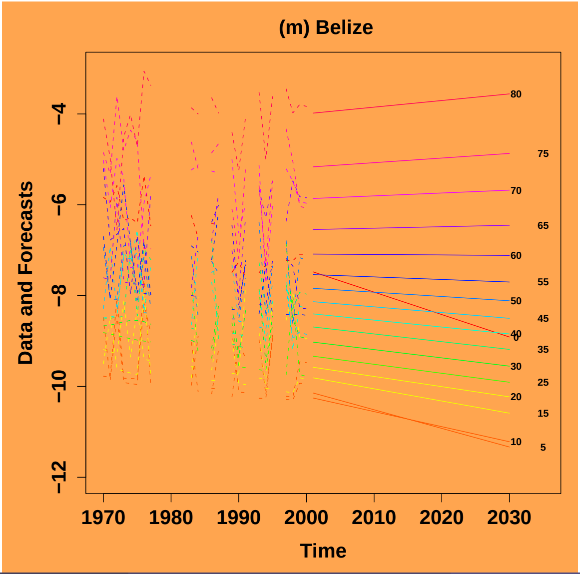
Mortality from Respiratory Infections, males, $\sigma = 0.38$

Smoothing over Age Groups



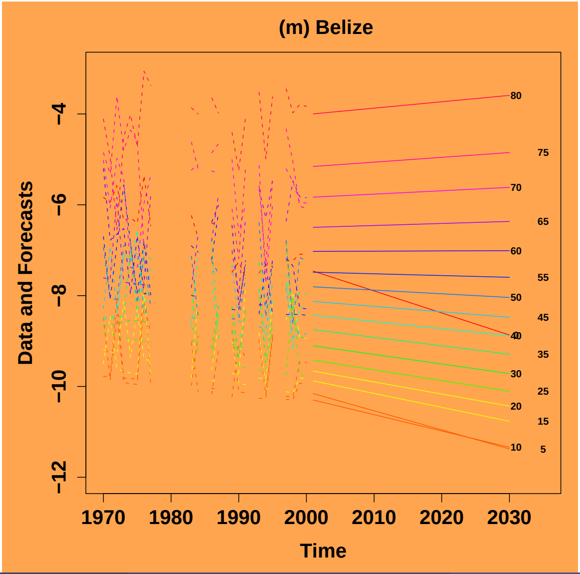
Mortality from Respiratory Infections, males, $\sigma = 0.28$

Smoothing over Age Groups



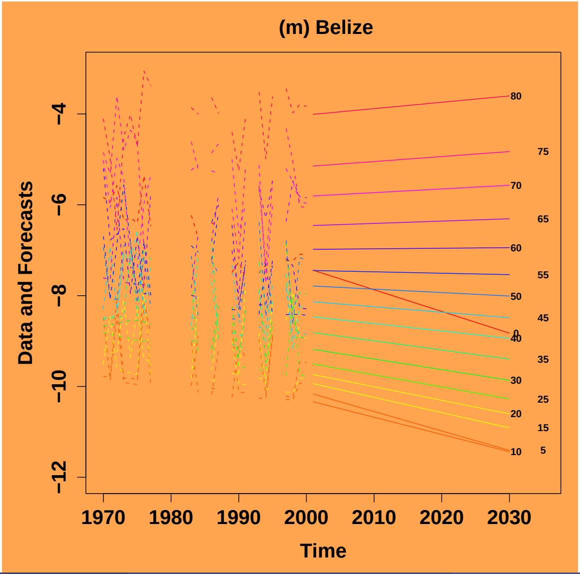
Mortality from Respiratory Infections, males, $\sigma = 0.21$

Smoothing over Age Groups



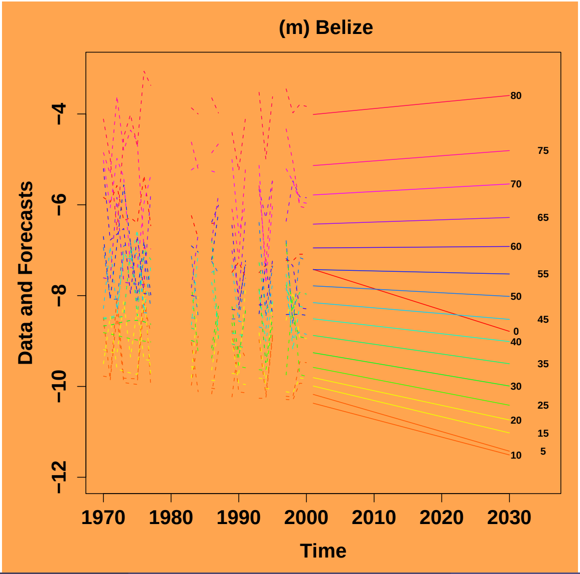
Mortality from Respiratory Infections, males, $\sigma = 0.16$

Smoothing over Age Groups



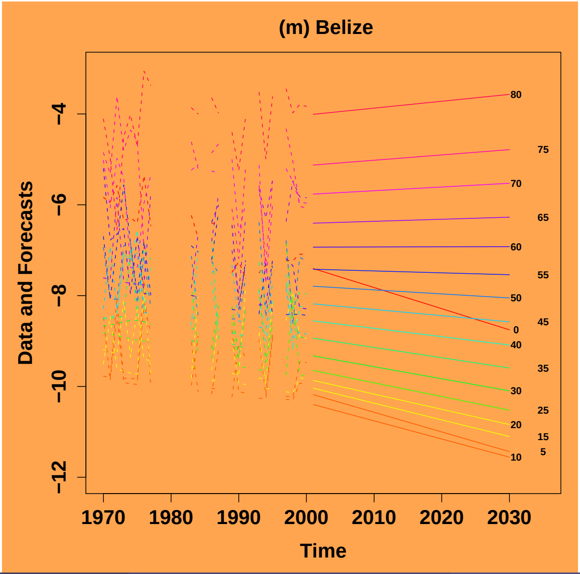
Mortality from Respiratory Infections, males, $\sigma = 0.12$

Smoothing over Age Groups



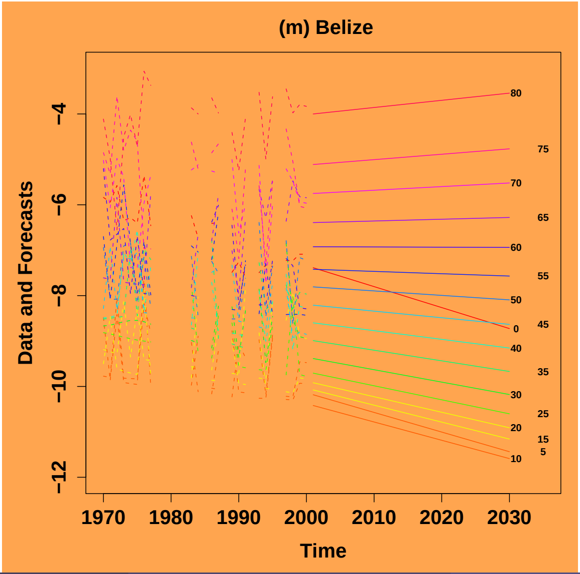
Mortality from Respiratory Infections, males, $\sigma = 0.09$

Smoothing over Age Groups



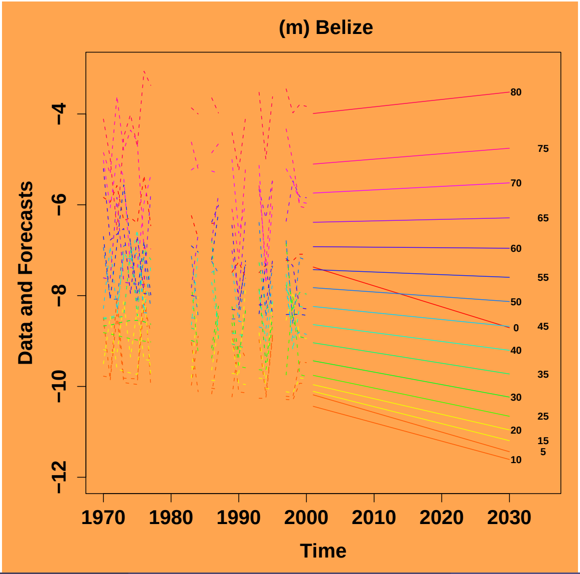
Mortality from Respiratory Infections, males, $\sigma = 0.07$

Smoothing over Age Groups



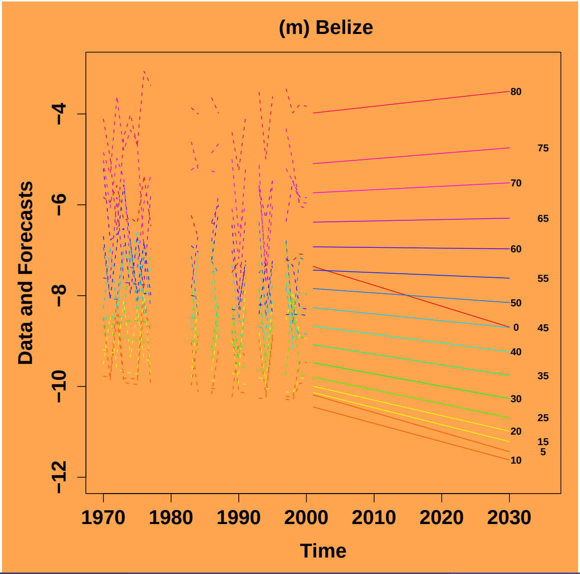
Mortality from Respiratory Infections, males, $\sigma = 0.05$

Smoothing over Age Groups



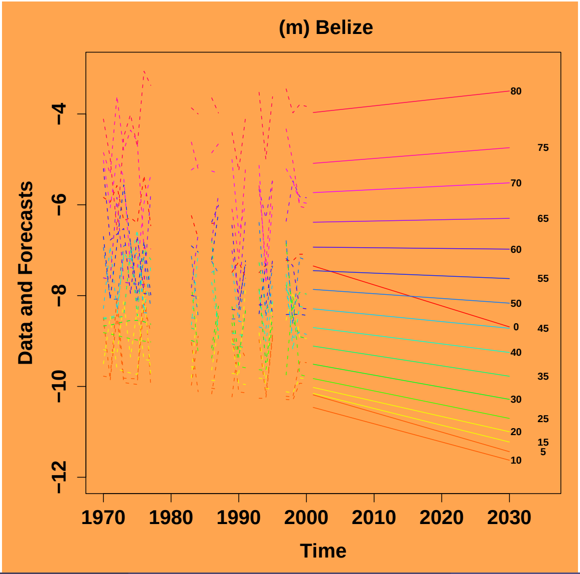
Mortality from Respiratory Infections, males, $\sigma = 0.04$

Smoothing over Age Groups



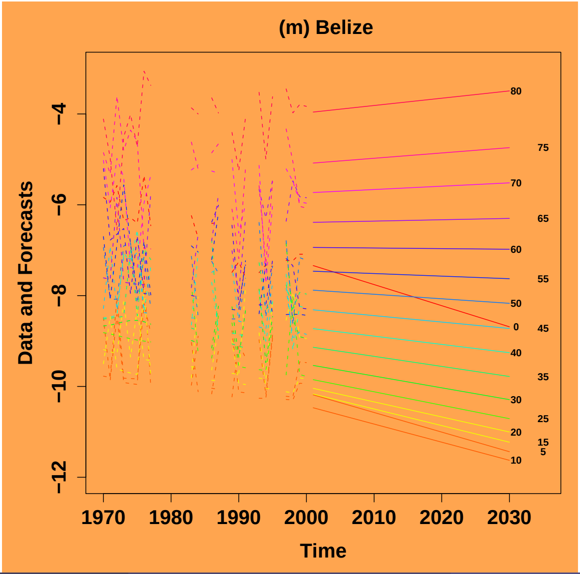
Mortality from Respiratory Infections, males, $\sigma = 0.03$

Smoothing over Age Groups



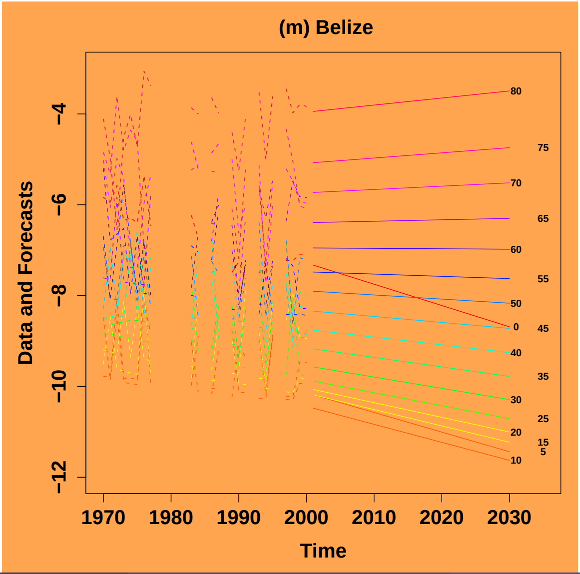
Mortality from Respiratory Infections, males, $\sigma = 0.02$

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

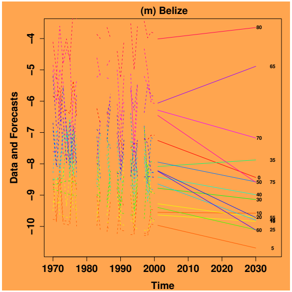
Log-mortality in Belize males from respiratory infections

Least Squares

Smoothing Trends over Age Groups

Log-mortality in Belize males from respiratory infections

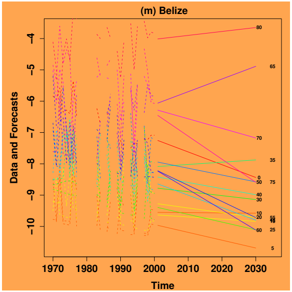
Least Squares

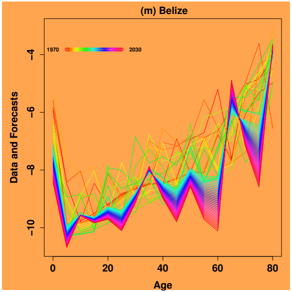


Smoothing Trends over Age Groups

Log-mortality in Belize males from respiratory infections

Least Squares

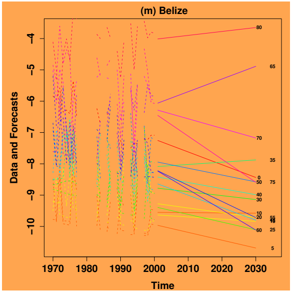


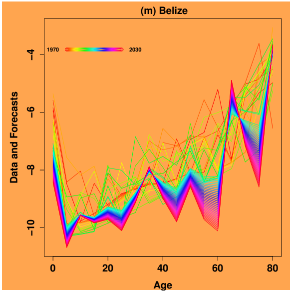


Smoothing Trends over Age Groups

Log-mortality in Belize males from respiratory infections

Least Squares



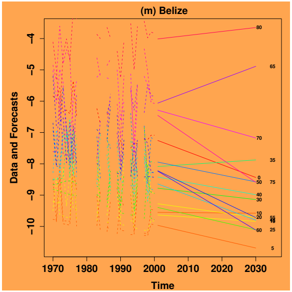


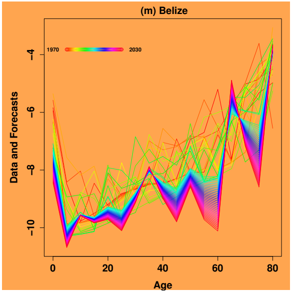
Smoothing
Age Groups

Smoothing Trends over Age Groups

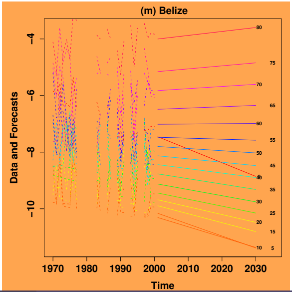
Log-mortality in Belize males from respiratory infections

Least Squares





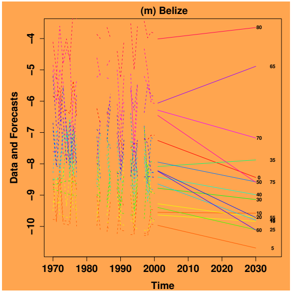
Smoothing
Age Groups

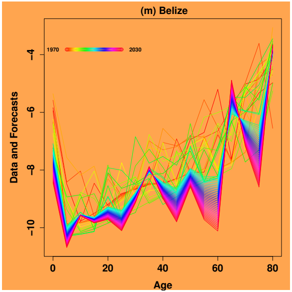


Smoothing Trends over Age Groups

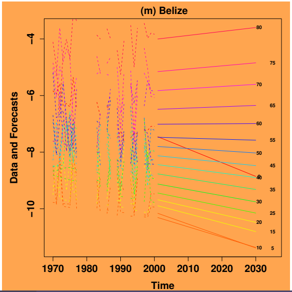
Log-mortality in Belize males from respiratory infections

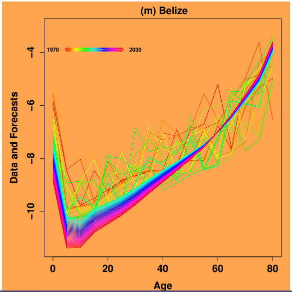
Least Squares





Smoothing Age Groups





Smoothing Trends over Age Groups and Time

Smoothing Trends over Age Groups and Time

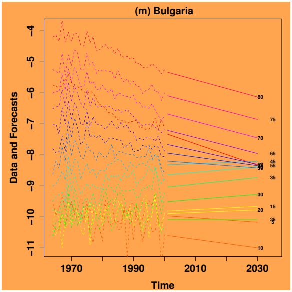
Log-Mortality in Bulgarian males from respiratory infections

Least Squares

Smoothing Trends over Age Groups and Time

Log-Mortality in Bulgarian males from respiratory infections

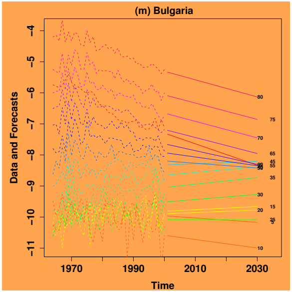
Least Squares

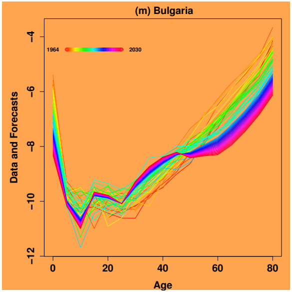


Smoothing Trends over Age Groups and Time

Log-Mortality in Bulgarian males from respiratory infections

Least Squares





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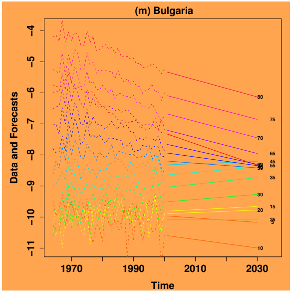
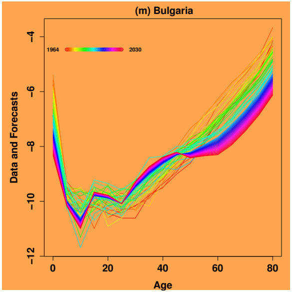


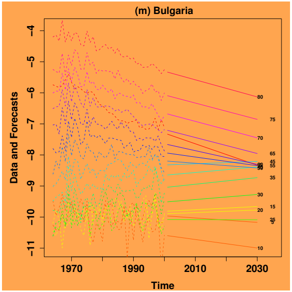


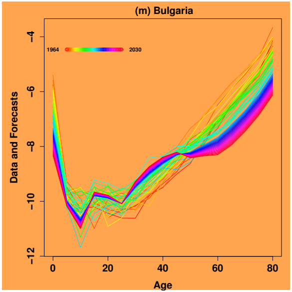
Smoothing
Age and Time

Smoothing Trends over Age Groups and Time

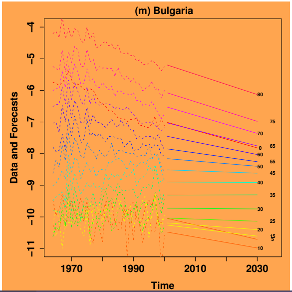
Log-Mortality in Bulgarian males from respiratory infections

Least Squares





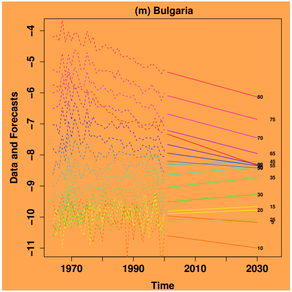
Smoothing
Age and Time

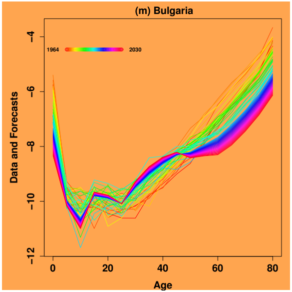


Smoothing Trends over Age Groups and Time

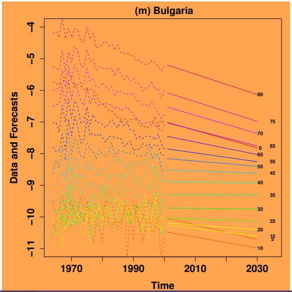
Log-Mortality in Bulgarian males from respiratory infections

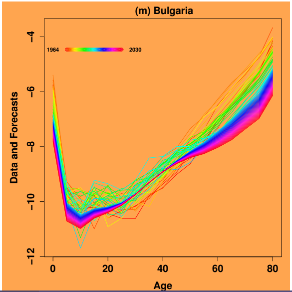
Least Squares





Smoothing
Age and Time





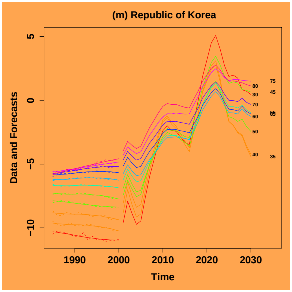
Using Covariates (GDP, tobacco, trend, log trend)

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

Lung cancer in Korean Males

Least Squares

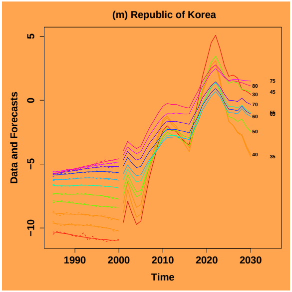
Least Squares

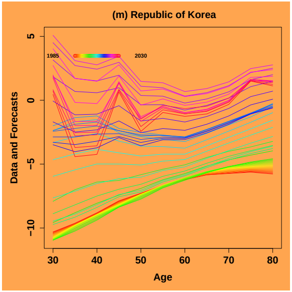


Using Covariates (GDP, tobacco, trend, log trend)

Lung cancer in Korean Males

Least Squares

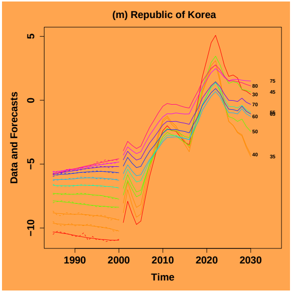


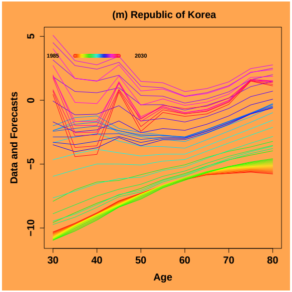


Using Covariates (GDP, tobacco, trend, log trend)

Lung cancer in Korean Males

Least Squares



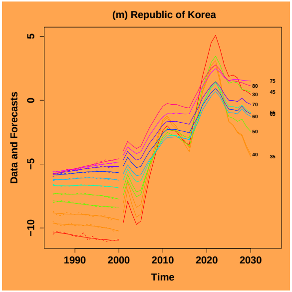


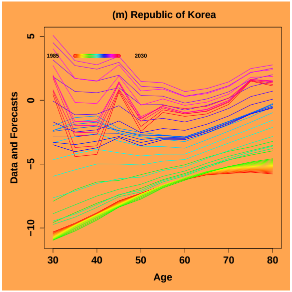
Smooth over age, time, age/time

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

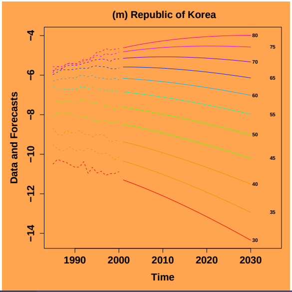
Lung cancer in Korean Males

Least Squares





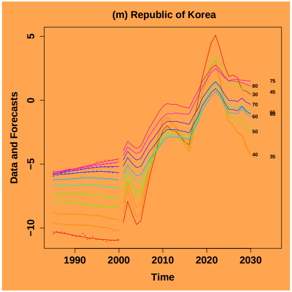
Smooth over age, time, age/time

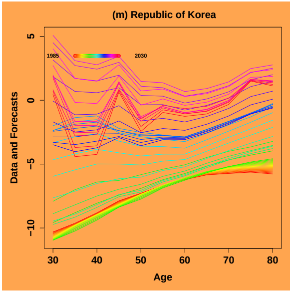


Using Covariates (GDP, tobacco, trend, log trend)

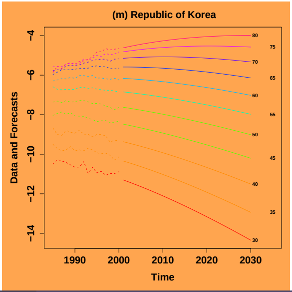
Lung cancer in Korean Males

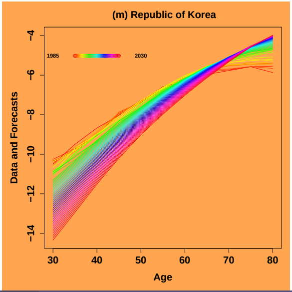
Least Squares





Smooth over age, time, age/time





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

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Lung cancer in Males, Singapore

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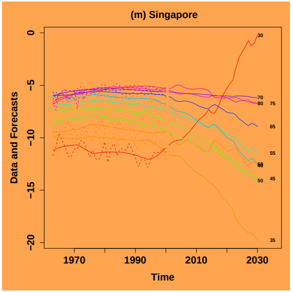

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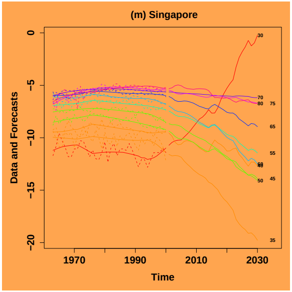

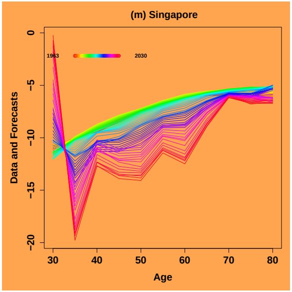

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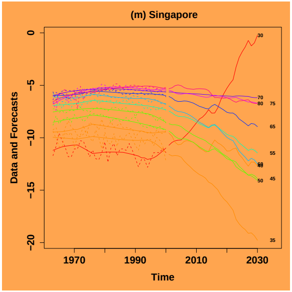

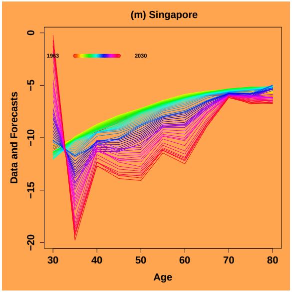

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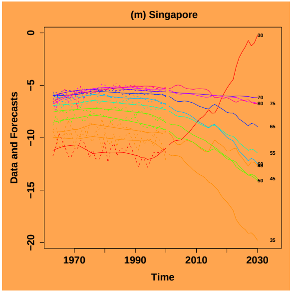

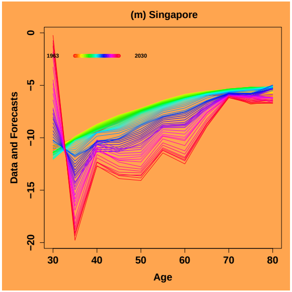

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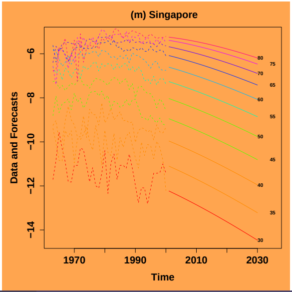

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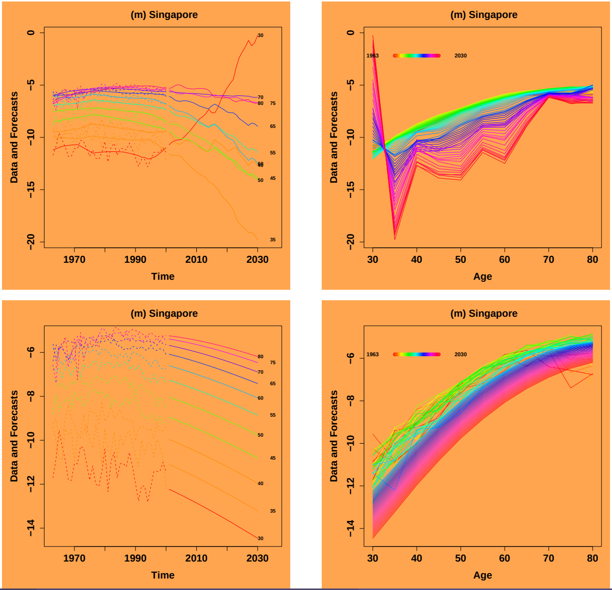
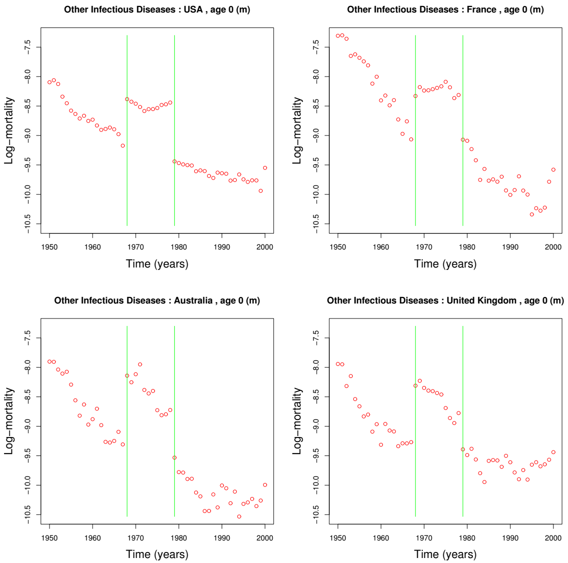
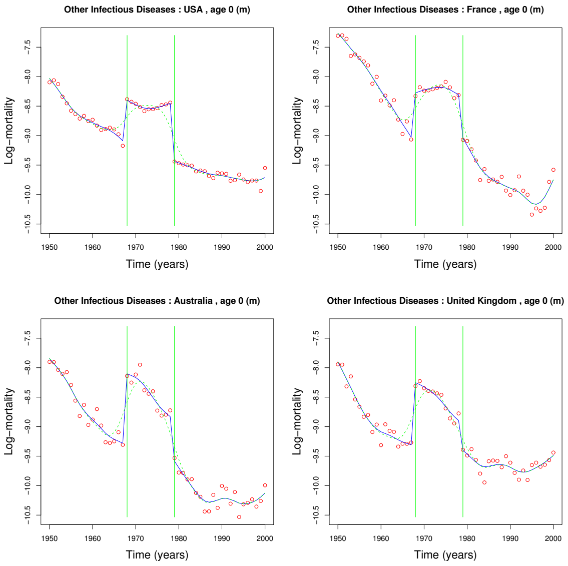


What about ICD Changes?



Fixing ICD Changes



Formalizing (Prior) Indifference

equal color = equal probability

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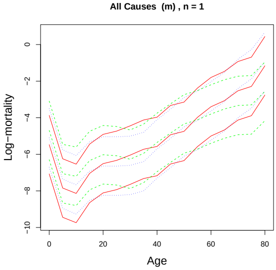

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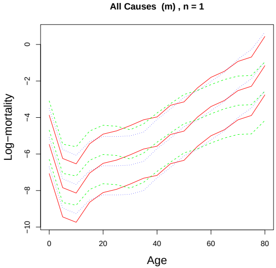
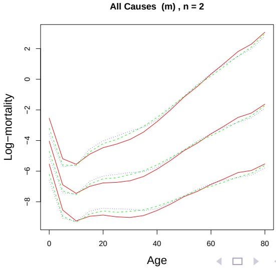


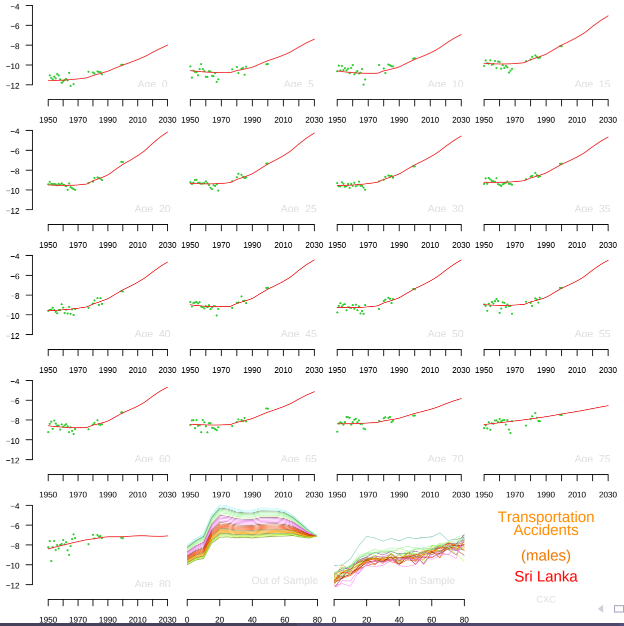
Level and slope indifference



A book manuscript, YourCast software, etc.

http://GKing.Harvard.edu

Without Country Smoothing



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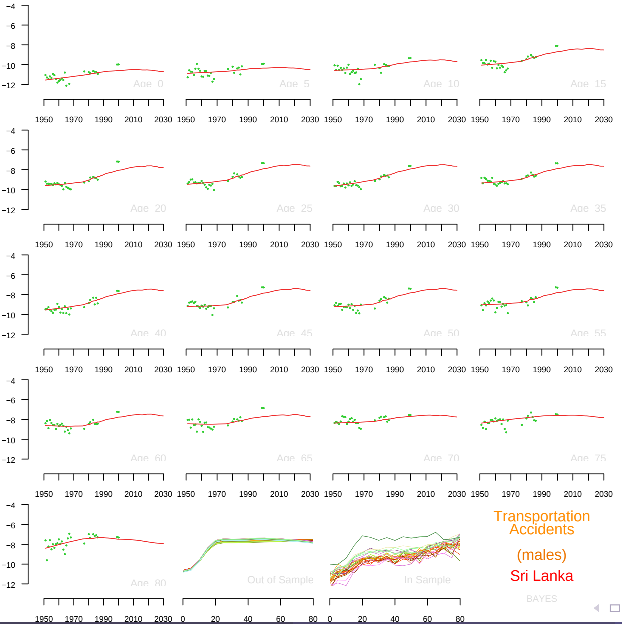

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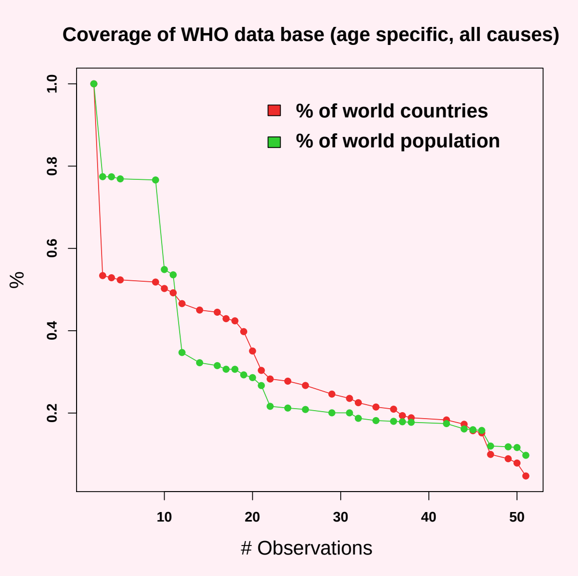
Many Short Time Series



Preview of Results: Out-of-Sample Evaluation

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Mean Absolute Error in Males (over age and country)

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	Mean Absolute Error			% Improvement	
	Best Previous	Our Method	Best Conceivable	Over Best Previous	to Best Conceivable
Cardiovascular	0.34	0.27	0.19	22	49
Lung Cancer	0.36	0.27	0.17	24	47
Transportation	0.37	0.31	0.18	16	31
Respiratory Chronic	0.45	0.39	0.26	13	30
Other Infectious	0.55	0.48	0.32	12	30
Stomach Cancer	0.30	0.27	0.20	8	24
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