

A forecast reconciliation approach to cause-of-death mortality modeling

Han Li, Hong Li, Yang Lu and **Anastasios Panagiotelis**

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Interesting questions

- Forecast mortality rate for both total and individual causes.
 - Input to bond pricing models.
 - Capital reserving implications.
- Cause Elimination
 - What happens if we cure cancer?

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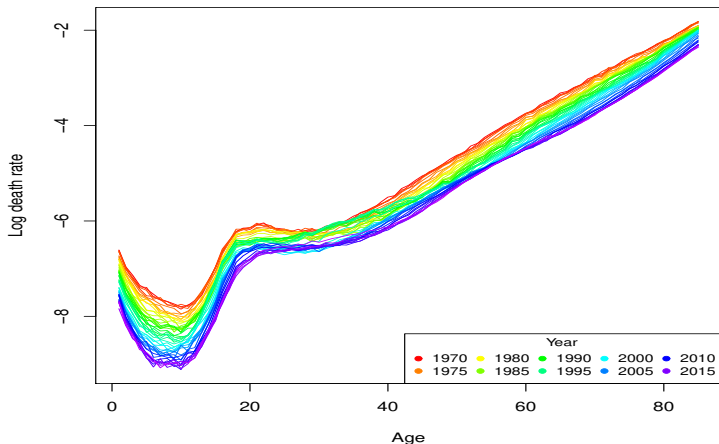
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$$m_t(x) = \frac{d_t(x)}{E_t(x)}.$$

Here, $d_t(x)$ is the number of deaths and $E_t(x)$ is the exposure for age x in year t .

What does this look like?

U.S.A.: male death rates (1970–2015)



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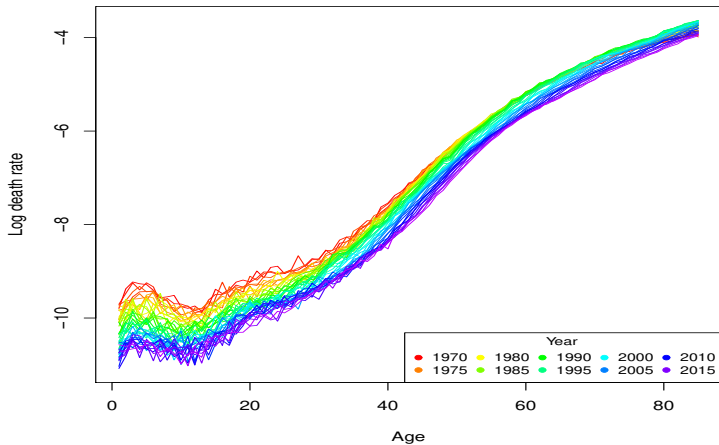
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- We considered 8 causes: Cancer, Diabetes, External, Influenza, Mental, Nephritis, Vascular and Other.
- What do the data look like for different causes?

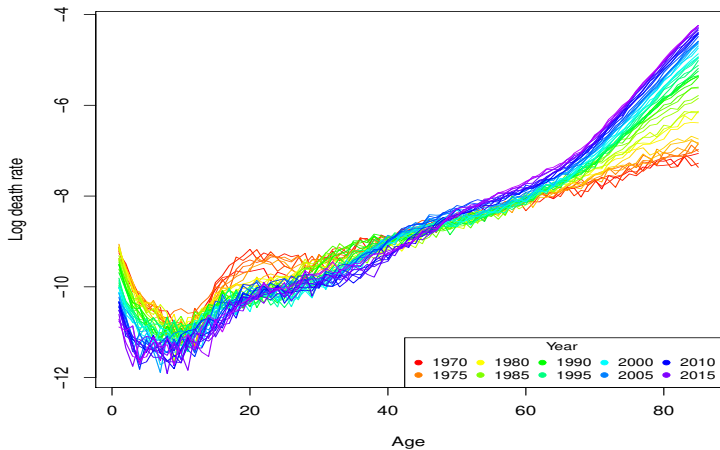
Cancer

Cancer male mortality rates



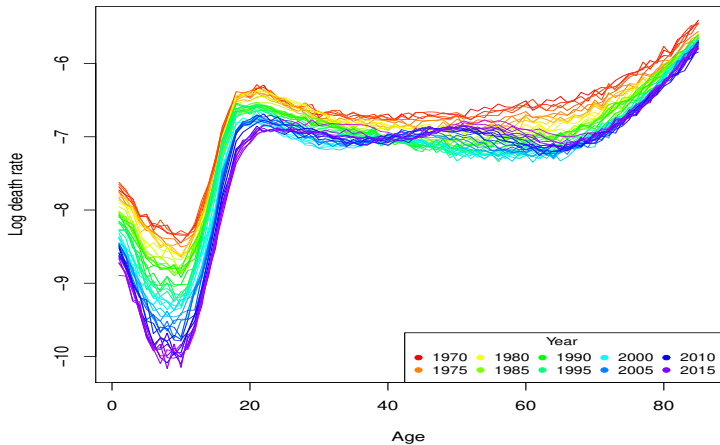
Mental

Mental male mortality rates



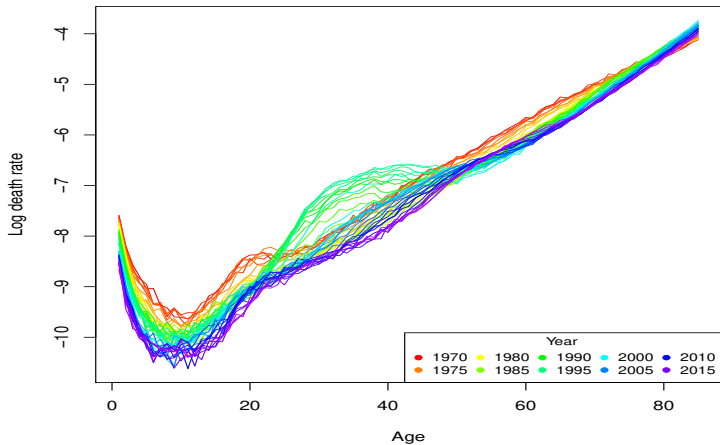
External

External male mortality rates



Other

Other male mortality rates



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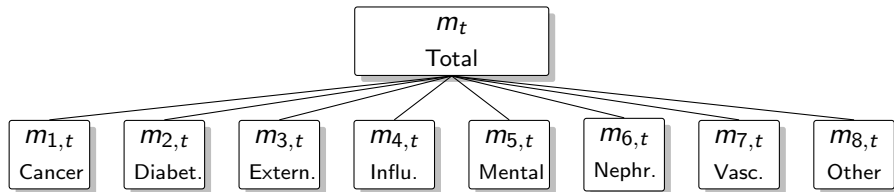
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- Therefore, for a given age, the total mortality rate must be the sum of the mortality rates by each cause.
- These are a *hierarchical time series*.

Hierarchy



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- **Bottom up:** Forecast cause specific mortality then add up.
 - Bottom level series are noisy.
- Why not forecast the total AND the cause specific mortality rates?

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- Can lead to decisions that are not aligned.
- We know that the target of the forecast *will* adhere to constraints
- We should not waste this information.

Why not incorporate in modeling?

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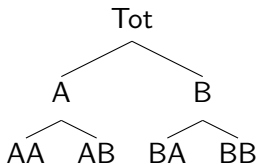
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Forecast Reconciliation!!!

A simple hierarchy

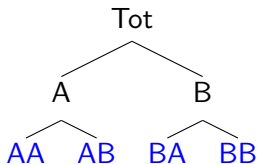
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- Let n be the number of series, \mathbf{y}_t be an n -vector of all series.
- Let q be the number of bottom level series and \mathbf{b}_t be an q -vector of the bottom level series.

The \mathbf{S} matrix

Coherence holds when

$$\mathbf{y}_t = \mathbf{S}\mathbf{b}_t$$

The $n \times q$ matrix \mathbf{S} defines the aggregation constraints, e.g.

$$\mathbf{S} = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ \mathbf{I}_{4 \times 4} \end{pmatrix}$$

As a regression model

- Cast the problem as a regression model with base forecasts $\hat{\mathbf{y}}_{T+h}$ as the “dependent variable” and \mathbf{S} as the “design matrix”.

$$\hat{\mathbf{y}}_{T+h} = \mathbf{S}\boldsymbol{\beta}_{T+h} + \mathbf{e}_{T+h}$$

- Initial approach (Athanasopoulos et al, 2009; Hyndman et al, 2011) was to fit by OLS yielding reconciled forecasts:

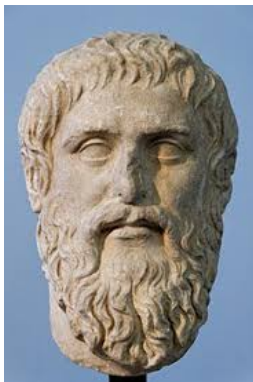
$$\tilde{\mathbf{y}}_{T+h} = \mathbf{S}(\mathbf{S}'\mathbf{S})^{-1}\mathbf{S}'\hat{\mathbf{y}}_{T+h}$$

Generalisation

- Wherever we can use OLS we can use GLS

$$\tilde{\mathbf{y}}_{T+h} = \mathbf{S}(\mathbf{S}'\mathbf{W}^{-1}\mathbf{S})^{-1}\mathbf{S}'\mathbf{W}^{-1}\hat{\mathbf{y}}_{T+h}$$

- Diagonal \mathbf{W} considered by Athanasopoulos et al (2017)
- MinT approach (Wickremasuriya et al, 2019) use a \mathbf{W} that is an estimate of the *in-sample* forecast error covariance matrix.



ΑΓΕΩΜΕΤΡΗΤΟΣ ΜΗΔΕΙΣ ΕΙΣΙΤΩ

Those without knowledge of geometry may not enter.

Coherent Subspace

Definition

The **coherent subspace** is the q -dimensional linear subspace of \mathbb{R}^n spanned by the columns of \mathbf{S} , i.e. $\mathfrak{s} = \text{sp}(\mathbf{S})$

Instead of using bottom-level series the top and $q - 1$ bottom level could be used.

Although \mathbf{S} would be different \mathfrak{s} would be the same.

Coherent Point Forecast

Definition

A **coherent point forecast** is any forecast lying in the linear subspace \mathfrak{s}

Reconciled Point Forecast

Let $\hat{\mathbf{y}} \in \mathbb{R}^n$ be an incoherent forecast and $\psi(\cdot)$ be a function $\psi : \mathbb{R}^n \rightarrow \mathfrak{s}$.

Definition

A **point forecast** $\tilde{\mathbf{y}}$ is reconciled with respect to $\psi(\cdot)$ iff

$$\tilde{\mathbf{y}} = \psi(\hat{\mathbf{y}})$$

Projections

- While this definition is quite general, the special case where ψ is a projection has some interesting properties.

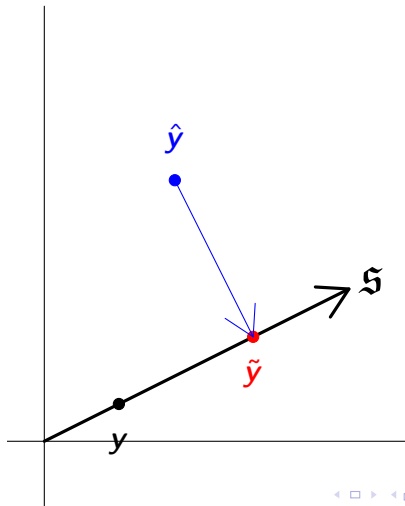
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- For instance, if base forecasts are unbiased then reconciliation using a projection preserves unbiasedness.
- Also reconciliation via a projection is guaranteed to reduce the distance between the forecast and the target.

Geometry



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Why reconciliation works

- The realised observation always lies on \mathfrak{s} .
- Orthogonal projections always get us 'closer' to all points in \mathfrak{s} including the actual realisation.
- Ergo reconciliation reduces the error and not just in expectation.
- What about the MinT approach?

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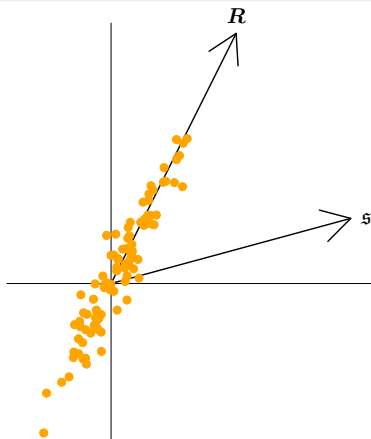
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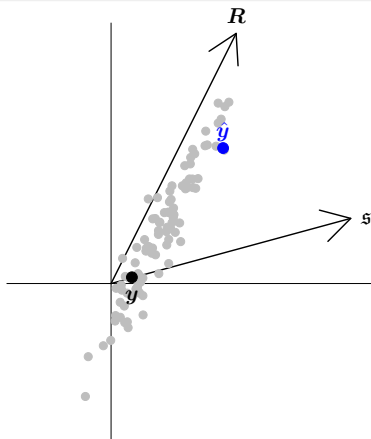
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- Projecting along this direction is more likely to result in a reconciled forecast that is closer to the target.

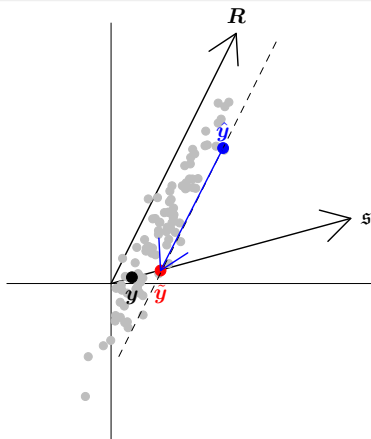
In-Sample errors



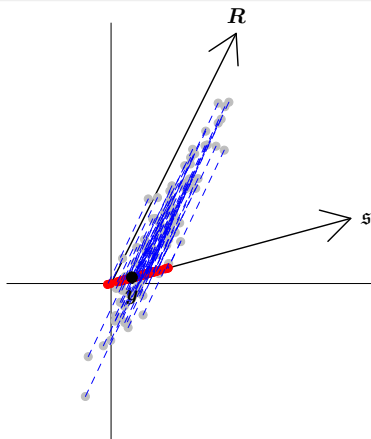
Base Forecast



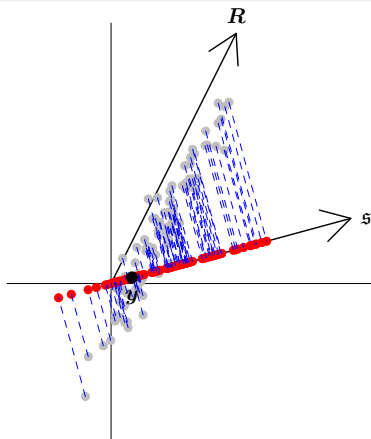
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Geometry: Orthogonal Projection



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- What happens if we *artificially* construct a middle level?
- We did this by clustering causes of death.
- This idea is novel in the forecast reconciliation literature.

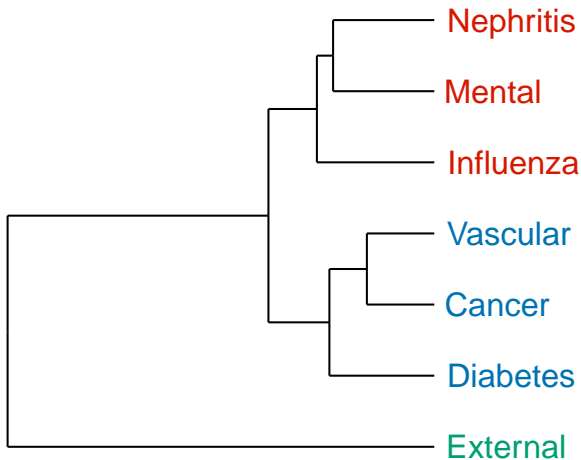
Cause clustering

- Consider a matrix $\mathbf{M}_j := \{m_{j,t}(x)\}_{x=1,\dots,85,t=1970,\dots,2015}$
- The distance between cause k and cause j is

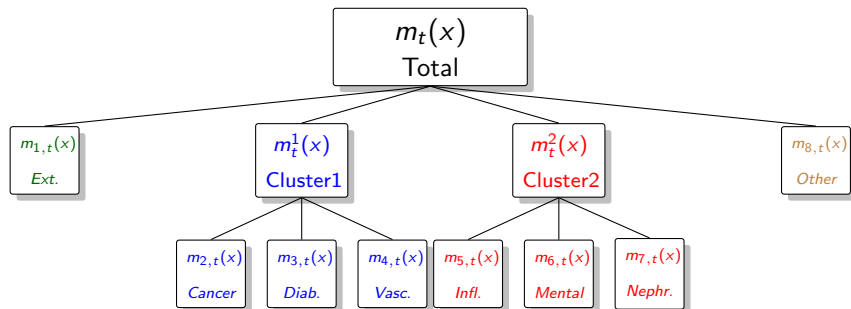
$$\delta_{j,k} = \|(1/s_j)\mathbf{M}_j - (1/s_k)\mathbf{M}_k\|_F$$

- The s_j is a scale factor and $\|\cdot\|_F$ is the Frobenius norm.
- Ward's method was used for clustering.
- Results were robust to different choices of scale, matrix norm and clustering method.

Dendrogram



Three-level Hierarchy



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- We would expect mortality from other causes to be higher.
- With a subtle adjustment to forecast reconciliation this can be achieved.

Cause Elimination

Simply remove the column of \mathbf{S} corresponding to cause. For 2-level hierarchy and first cause

$$\mathbf{S} = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ & & & & \mathbf{I}_{8 \times 8} & & & \end{pmatrix}$$

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$$\mathbf{S}_{-1} = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ & & & \mathbf{I}_{7 \times 7} & & & \end{pmatrix}$$

Forecast Evaluation

- Use 1970-2000 as a training sample.
- Consider $h = 1$ through to $h = 15$ step ahead forecasts and compare to test sample 2001-2015.
- Evaluate forecasts using mean absolute percentage error (MAPE) averaged over 85 age groups.
- Consider 2-level and 3-level hierarchy.

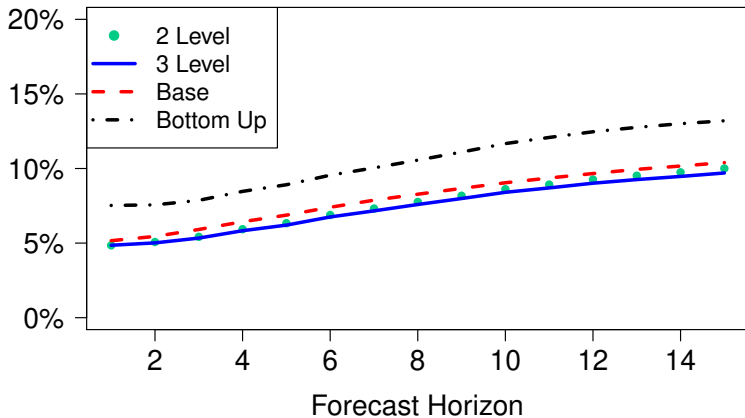
Results ($h=15$)

	2-level MinT	3-level MinT	Base	Bottom-up
Total	10.00%	9.70%	10.40%	13.20%
Cancer	17.98%	16.96%	20.06%	-
Diabetes	23.51%	21.78%	25.48%	-
External	19.11%	19.07%	20.62%	-
Influenza	37.17%	35.62%	38.36%	-
Mental	19.65%	20.02%	19.96%	-
Nephritis	59.60%	59.31%	61.31%	-
Vascular	16.37%	16.70%	17.37%	-
Other	26.64%	25.22%	34.46%	-

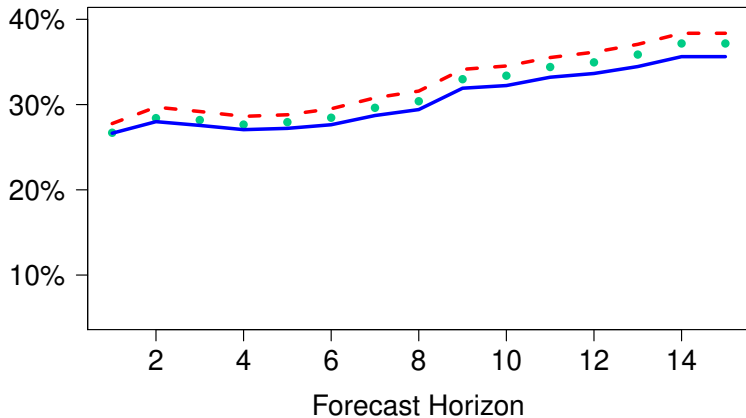
Summary

- The 2-level MinT always better than Base
- With one exception (mental), the 3-level MinT always better than Base.
- With two exceptions (mental and vascular), 3-level MinT better than 2-level MinT
- When reconciliation beats base it is always significant by Diebold Mariano (DM) test.
- Mixed results for DM tests between 2-level and 3-level.

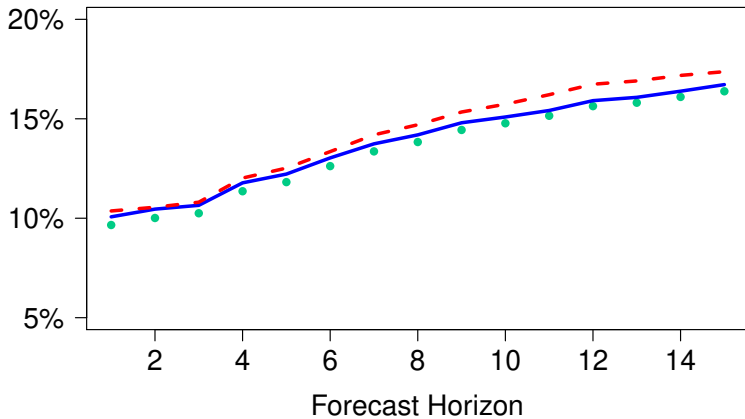
Total mortality MAPE



Influenza MAPE



Vascular MAPE



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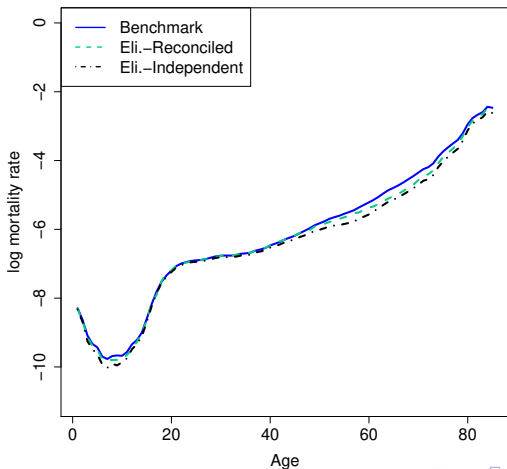
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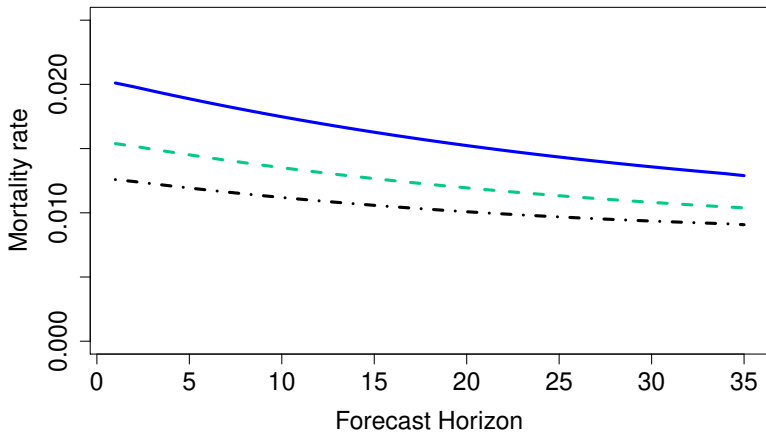
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- Results here are for the 2-level hierarchy.

Total Mortality 2050: Cancer eliminated



Total Mortality age 70: Cancer eliminated



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- Questions?