International Mortality and Longevity Webinar

Longevity trend risk over limited time horizons

Stephen J. Richards

4th June 2019

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Overview

1. Theory v. practice

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2. About Longevitas

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3. The longevity-risk problem

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6. VaR v. CTE

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3. The longevity-risk problem
4. Multi-year view
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6. VaR v. CTE
7. Managing longevity risk

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3. The longevity-risk problem
4. Multi-year view
5. Deferred annuities
6. VaR v. CTE
7. Managing longevity risk
8. Conclusions

1 Theory v. practice

Theory v. practice

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"practice suggests problems essentially new for science and thus challenges one to seek quite new methods. And if theory gains much when new applications or new developments of old methods occur, the gain is still greater when new methods are discovered"

Chebyshev [1856]

2 About Longevitas

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- Research partnership with Heriot-Watt University.

2 Services for actuaries

- Experience analysis and mis-estimation:

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- Stochastic mortality projections and capital:

PROJECTIONS TOOLKIT

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PROJECTIONS TOOLKIT

- Rating pension schemes:

mortalityrating.com

3 The longevity-risk problem

3 Trend v. one-year view

"Whereas a catastrophe can occur in an instant, longevity risk takes decades to unfold"

The Economist [2012]

3 Trend v. one-year view

- Longevity trends emerge slowly over many years. . .

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  …but insurance regulations view risks as single-year catastrophes.

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  ….but insurance regulations view risks as single-year catastrophes.
- How do you reconcile the two?
- How do you fit a long-term risk into a short-term view?

3 Trend v. one-year view

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3 Trend v. one-year view

Time for some Chebyshevian new methods:

- Create new models just for this specific task, e.g Plat [2011] and Börger [2010], or

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- Create new models just for this specific task, e.g Plat [2011] and Börger [2010], or
- Create a framework for existing projection models like Lee and Carter [1992], Cairns et al. [2006].

Solution from Richards et al. [2014]:

3 Trend v. one-year view

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Solution from Richards et al. [2014]:

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2. Use model to simulate next year's experience data.

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Solution from Richards et al. [2014]:

1. Pick a model and fit it to real data.
2. Use model to simulate next year's experience data.
3. Refit the model using real and simulated data.

3 Sensitivity of forecast

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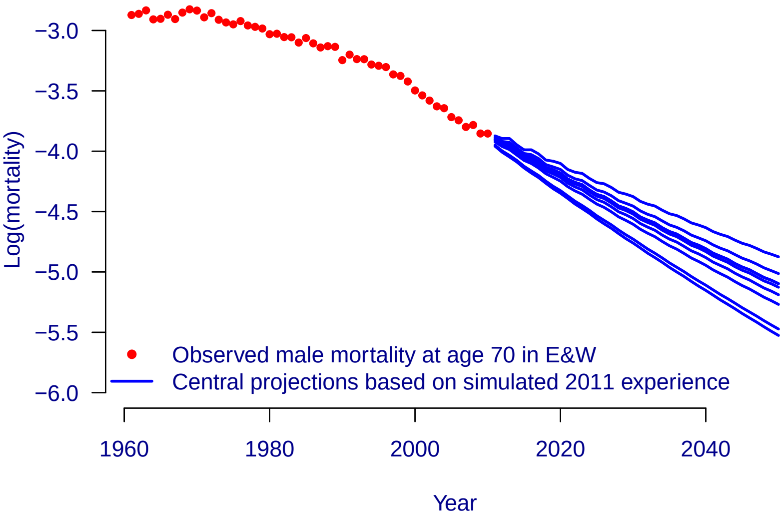

Source: Lee-Carter example from Richards et al. [2014].

3 Trend v. one-year view

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6. Repeat (2)–(5) a few thousand times.

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Sample of liability values $\{x_1, x_2, \ldots, x_m\}$.

3 Liability values

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- VaR-style solvency capital:

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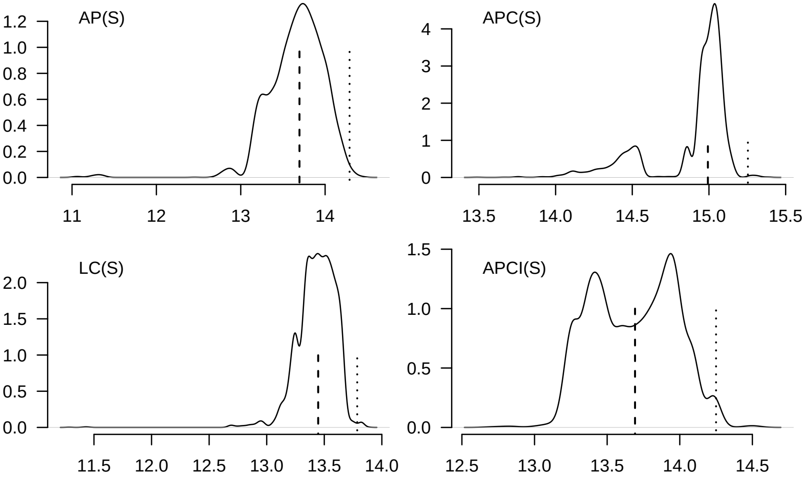
3 Simulated liability values

- We don't know the distribution of $X \ldots$

  $\ldots$ but we do have a sample $\{x_1, x_2, \ldots, x_m\}$.
- Estimate $\mathbb{E}[X]$ from mean of sample.
- Estimate Q_α from sample using Harrell and Davis [1982].

3 One-year liability densities



Annuities payable to male aged 70. Means marked with dashed line and $Q_{99.5\%}$ marked with dotted line.
Source: Richards et al. [2017, Table 4].

3 Value-at-risk

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  ... and exercise *actuarial judgement*.

4 Multi-year view

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- Richards et al. [2014] was for one-year insurer solvency.

4 Multi-year view

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- The same methodology has other applications. . .

4 Multi-year view

Medium-term business planning:

- 3–5 years for insurer ORSA.

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Medium-term business planning:

- 3–5 years for insurer ORSA.
- Ten-year "glide path" to buy-out for pension schemes.

4 Multi-year view

- Take one-year framework from Richards et al. [2014].

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- Extend time horizon to 3–5 years.

4 Multi-year view

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- Take one-year framework from Richards et al. [2014].
- Extend time horizon to 3–5 years.
- Reduce p-value to, say, 95%. . .

4 Females, Lee-Carter model

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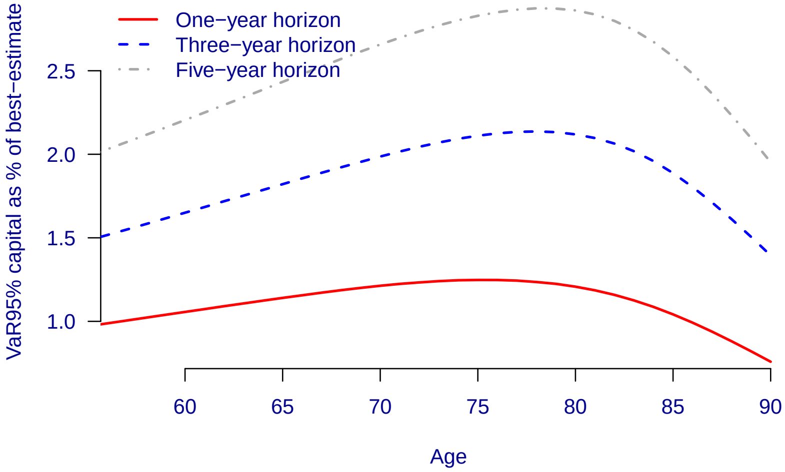
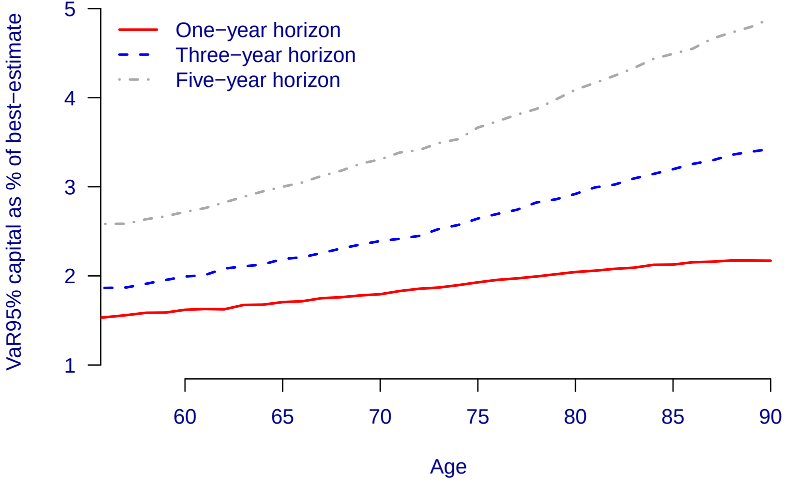


Immediate annuities under Lee-Carter model. UK data ages 50–104, 1971–2016

4 Females, APC model



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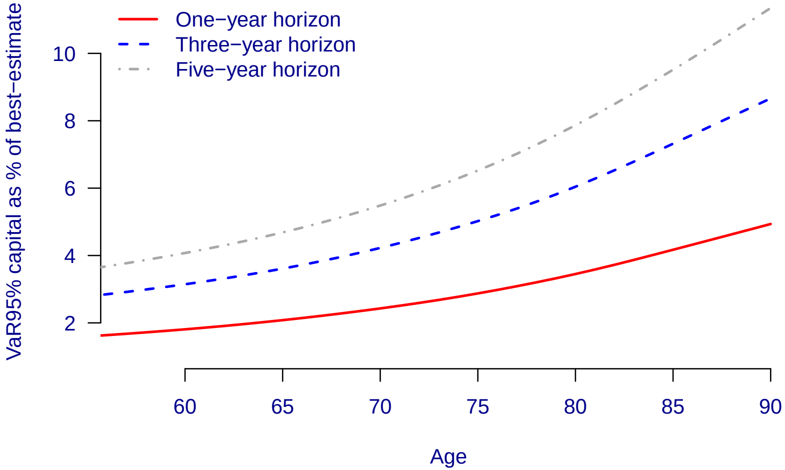

Immediate annuities under M5(S) model. UK data ages 50–104, 1971–2016

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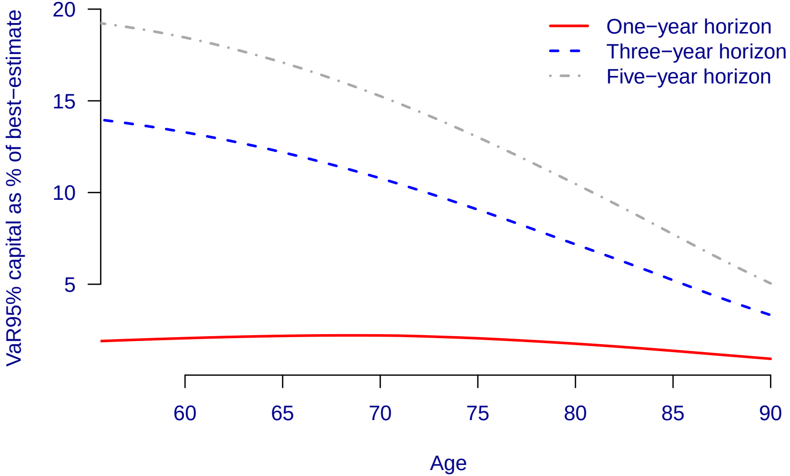

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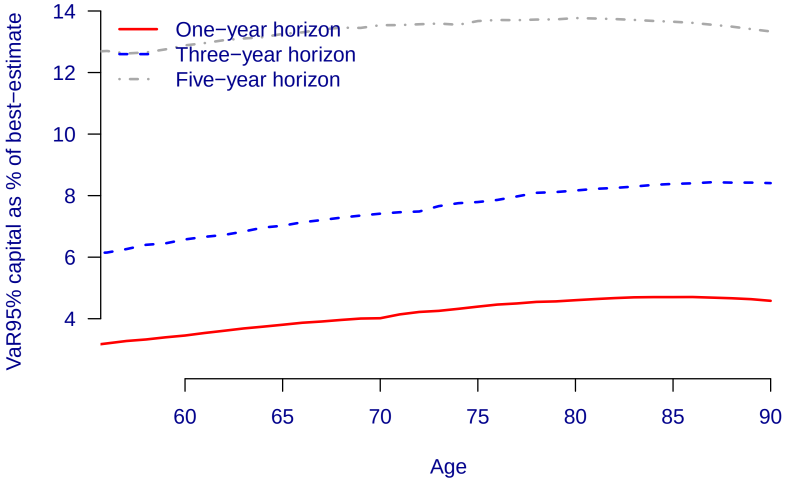

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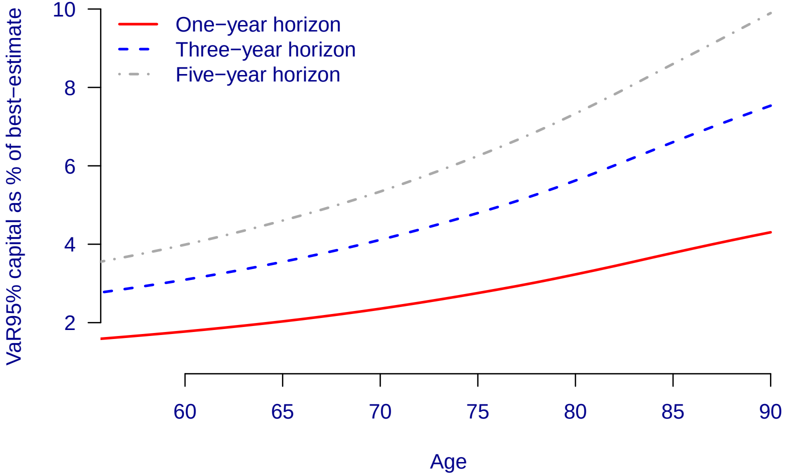

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  … and exercise actuarial judgement (*again!*).

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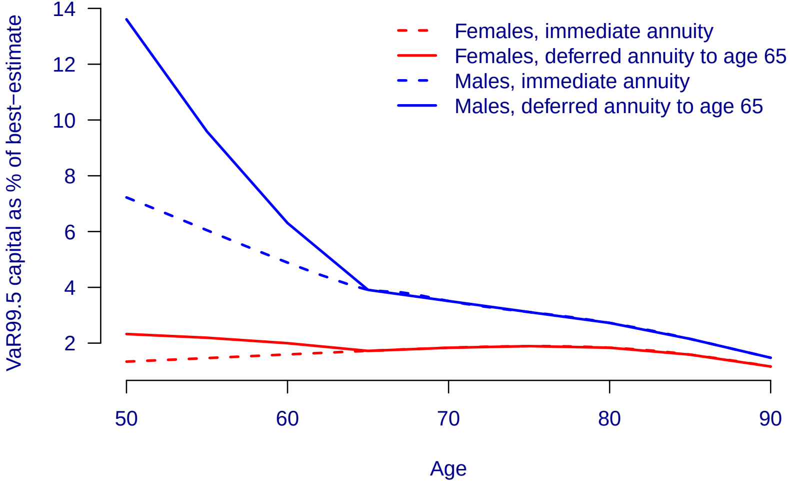
- What about deferred annuities and pensions?
- Assume payment from age 65.
- Compare VaR99.5% solvency capital for immediate and deferred annuities.

5 Solvency capital, Lee-Carter



Deferred and immediate annuities under Lee-Carter model. UK data ages 50–104, 1971–2016

5 Solvency capital, APC model

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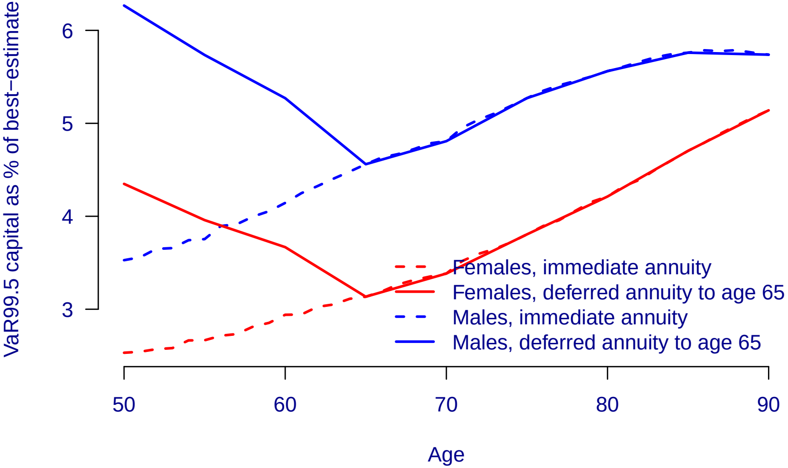

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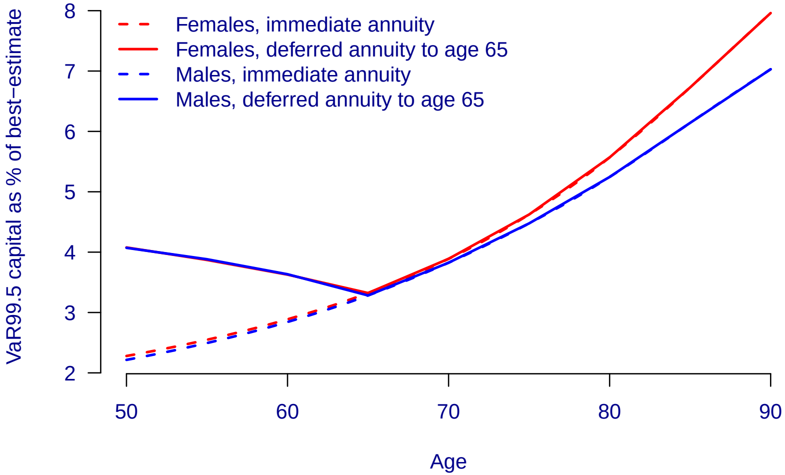

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5 Deferred annuities

- Depending on age, solvency capital for deferred annuities can be double that of annuities in payment.

5 Deferred annuities

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- Depending on age, solvency capital for deferred annuities can be double that of annuities in payment.
- Sharp differences in solvency capital by gender.

6 VaR v. CTE

6 VaR

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- Our unknown liability is X (say).
- VaR-style solvency capital:

$$\left(\frac{Q_\alpha}{\mathbb{E}[X]} - 1\right) * 100\%$$

where Q_α is α-quantile of X, i.e. $\Pr(X < Q_\alpha) = \alpha$.

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6 CTE

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- Our unknown liability is X (say).
- CTE-style solvency capital:

$$\left(\frac{\mathbb{E}[X|X \geq Q_\alpha]}{\mathbb{E}[X]} - 1\right) * 100\%$$

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- But how does VaR99.5% compare to CTE99%?

6 VaR v. CTE

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- How does VaR capital compare to CTE capital?
- $\text{CTE}_\alpha > \text{VaR}_\alpha$ (obviously!)
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- Can calculate both from same sample...

6 UK, Lee-Carter model

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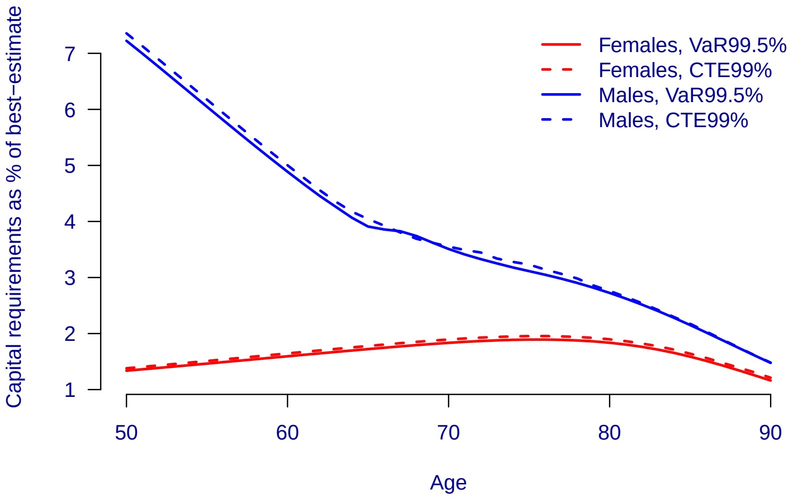

Annuities in payment under Lee-Carter model. UK data ages 50–104, 1971–2016

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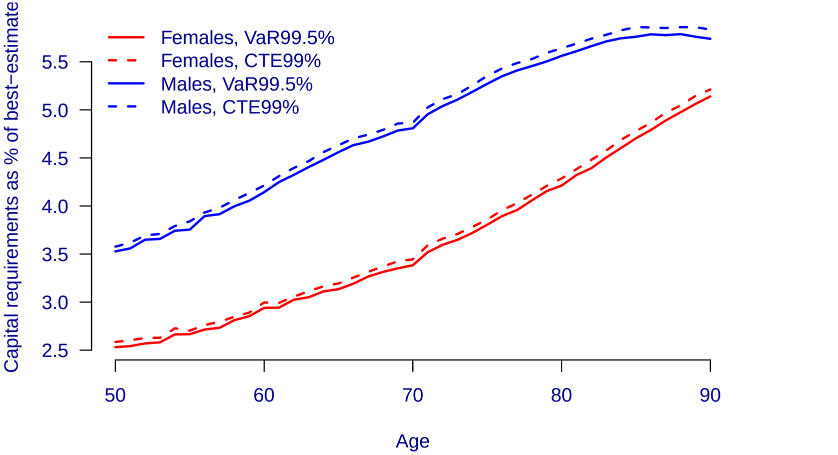

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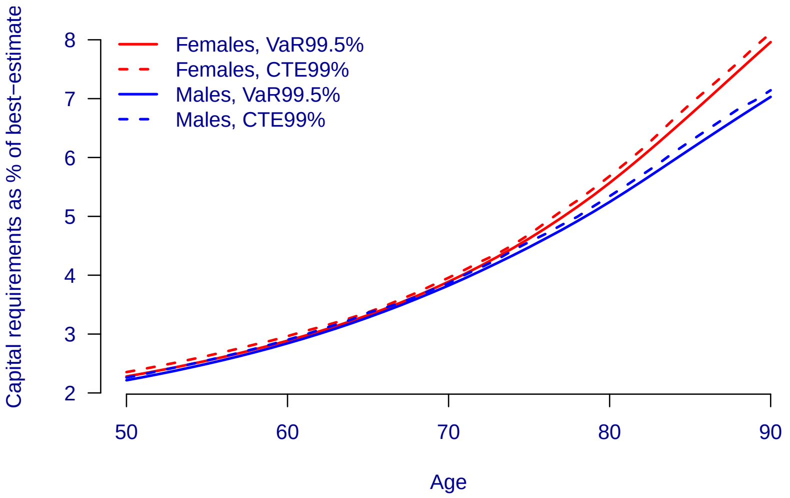
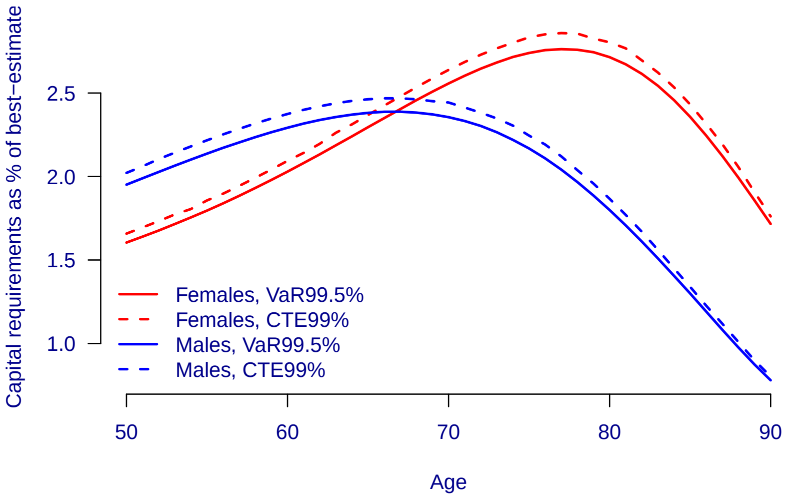


Annuities in payment under M5(S) model. UK data ages 50–104, 1971–2016

6 Netherlands, Lee-Carter



Annuities in payment under LC(S) model. Netherlands data ages 50–104, 1971–2016

6 Netherlands, APC model

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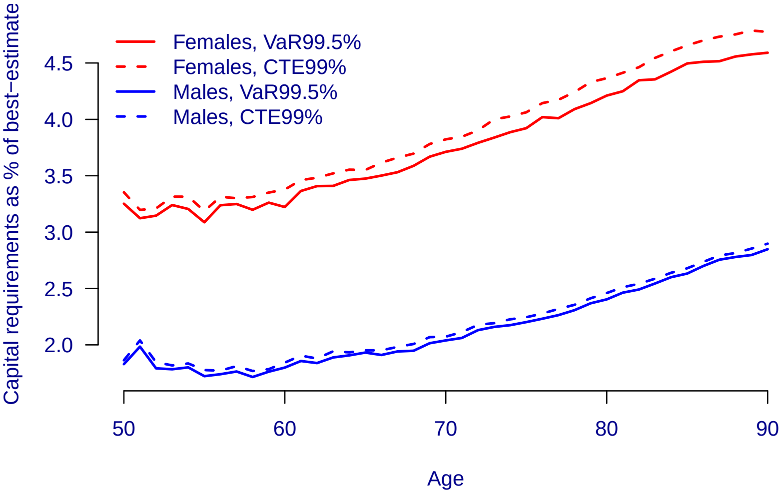

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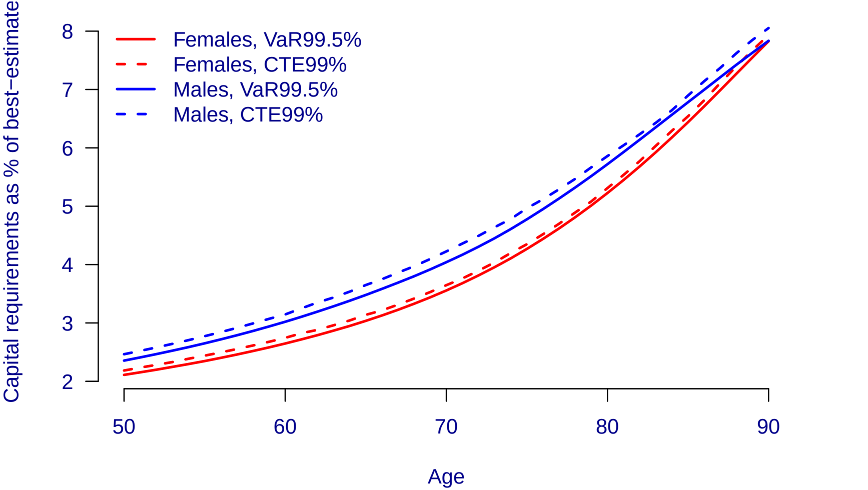

Annuities in payment under M5(S) model. Netherlands data ages 50–104, 1971–2016

6 VaR v. CTE

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- Longevity trend-risk capital very comparable between VaR99.5% and CTE99%.
- CTE99% usually slightly more prudent than VaR99.5%.
- Difference usually under 0.1%.

7 Managing longevity risk

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- Keep risk, or

7 Managing longevity risk

- Keep risk, or
- Transfer risk, or

7 Managing longevity risk

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- Keep risk, or
- Transfer risk, or
- Hedge risk.

7 Transferring longevity risk

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- "Indemnity" means the exact portfolio experience is insured.
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  ...although there is a risk that the reinsurer might fail (counterparty risk).

7 Hedging longevity risk

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- The value of a hedging contract is supposed to move in line with the liabiities.
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- How big is this risk?

7 Index-based hedges

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- Define contract using population mortality.

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- Term n years.

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- At end of term, fit Lee-Carter model (say) and it use to value annuity with unknown value X.
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  $\Rightarrow$ This is just another multi-year VaR calculation.

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$$h(X) = \max\left(0, \min\left(\frac{X - AP}{EP - AP}, 1\right)\right)$$

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- Standardise payoff, h, as:

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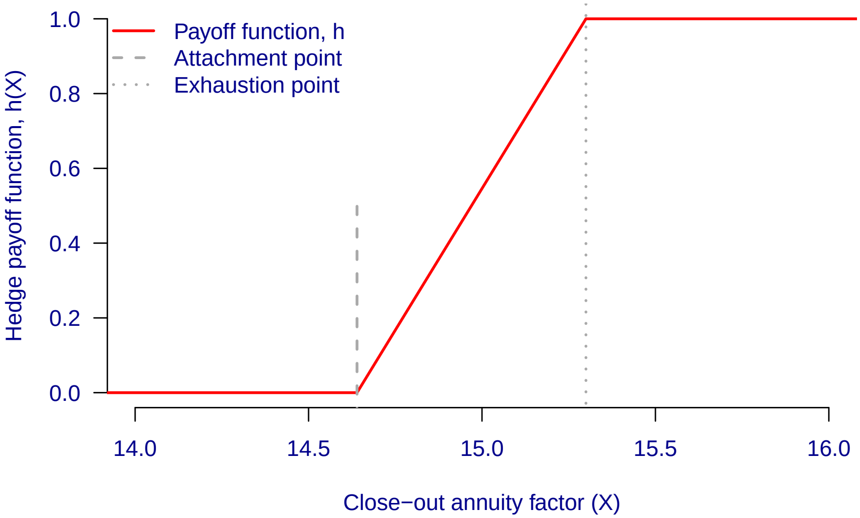
- See Cairns and El Boukfaoui [2017] for detailed discussion.

7 Hedge payoff function



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- Set $AP = Q_{\alpha_1}$ and $EP = Q_{\alpha_2}$ $(\alpha_1 < \alpha_2)$.

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- Q_α set with reference to Lee-Carter sample paths over n years, i.e. an n-year VaR simulation.
- Probability of payoff is $1 - \alpha_1$.
- Mean payoff can be estimated from VaR results.

7 Example hedge contract

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- $n = 15$ years.
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- Follow Cairns and El Boukfaoui [2017] and set $AP = Q_{60\%}$ and $EP = Q_{95\%}$.

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- $n = 15$ years.
- Use Lee-Carter model for close-out calculation.
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- Probability of a payoff is 0.4.

7 Example hedge contract

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- $n = 15$ years.
- Use Lee-Carter model for close-out calculation.
- Follow Cairns and El Boukfaoui [2017] and set $AP = Q_{60\%}$ and $EP = Q_{95\%}$.
- Probability of a payoff is 0.4.
- Average payoff is 0.375 (from 5,000 simulations).

7 Model risk

- Lee-Carter model used for both sample paths over n years **and** for payoff calculation.

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- What happens if the sample paths follow a *different* model?

Impact of different sample-path models on payoff:

Model	Payoff prob.	Mean payoff
LC(S)	0.40	0.375
M5(S)	0.53	0.592
2DAC	0.80	0.434
M6	0.82	0.710

Source: own calculations using population data for males in Netherlands, ages 50–104, 1971–2016. Annuity values discounted at 2% p.a.

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$\Rightarrow$ Actuarial judgement required on both counts.

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- Consider the spread at various ages under CBD model (M5)...

7 M5 sample paths — age 70

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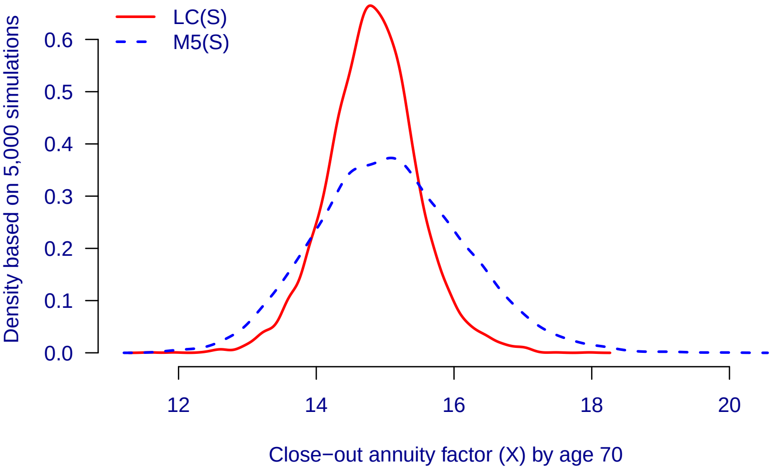
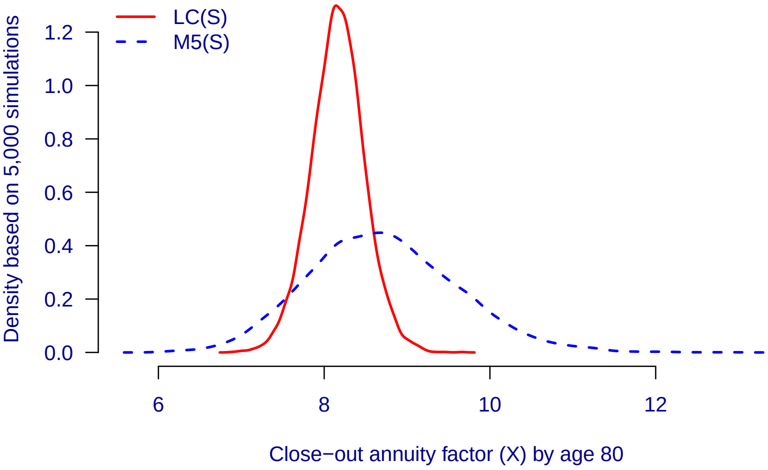


VaR annuity factors valued under Lee-Carter model after 15 years of mortality following the M5(S) model. Netherlands data for males aged 50–104, 1971–2016. Annuity cashflows discounted at 2% p.a.

7 M5 sample paths — age 80



VaR annuity factors valued under Lee-Carter model after 15 years of mortality following the M5(S) model. Netherlands data for males aged 50–104, 1971–2016. Annuity cashflows discounted at 2% p.a.

7 M5 sample paths — age 90

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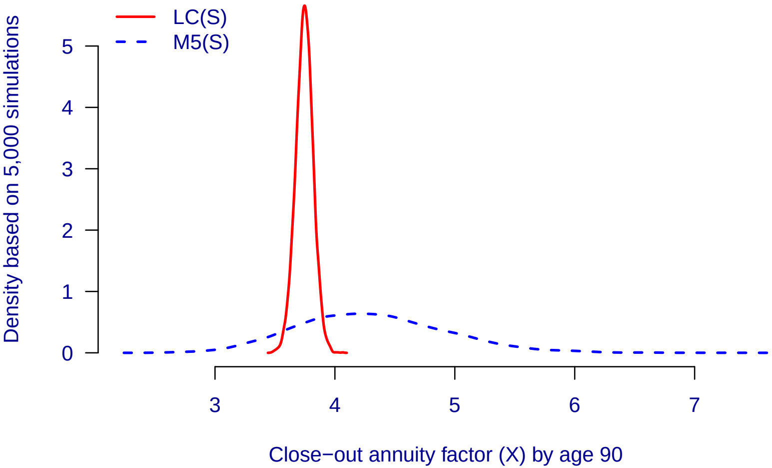

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More on longevity risk at www.longevitas.co.uk

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