

# Forecasting Socio-Economic Differences in the Mortality of Danish Males

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Actuarial  
Research Centre

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## Modelling, Measurement and Management of Longevity and Morbidity Risk

- New/improved models for modelling longevity
- Management of longevity risk
- Underlying drivers of mortality
- Modelling morbidity risk for critical illness insurance



# Outline

- Introduction and motivation for multi-population modelling
- Constructing a new dataset
- Modelling Danish sub-population mortality
- Forecast correlations and basis risk
- Applications

# 1. Motivation: Stochastic Mortality

$n$  lives, probability  $p$  of survival,  $N$  survivors

- Unsystematic mortality risk:

$$\Rightarrow N|p \sim \text{Binomial}(n, p)$$

$\Rightarrow$  risk is diversifiable,  $N/n \rightarrow p$  as  $n \rightarrow \infty$

- Systematic mortality risk:

$\Rightarrow p$  is uncertain

$\Rightarrow$  risk associated with  $p$  is not diversifiable



## Motivation: Longevity Risk

Interested in *longevity risk*:

The risk that **in aggregate** people live longer **than anticipated**.

⇒ pension plan has insufficient cash to pay promised pensions



# Multi-Population Challenges

- Data availability
- Data quality and depth
- Model complexity
  - single population models can be complex
  - 2-population versions are more complex
  - multi-pop .....
- Multi-population modelling requires
  - (fairly) simple single-population models
  - simple dependencies between populations



## 2. A New Case Study and a New Model

- Sub-populations differ from national population
  - socio-economic factors
  - other factors
- Denmark
  - High quality data on ALL residents
  - 1981-2012 available
  - Can subdivide population using covariates on the database



- *What can we learn from Danish data that will inform us about other populations?*
- Key covariates (amongst others):
  - Wealth
  - Income





# Problem

- High income  $\Rightarrow$  “affluent” *and low mortality*  
BUT
- Low income  $\nRightarrow$  not affluent, high mortality
- High wealth  $\Rightarrow$  “affluent” *and low mortality*  
BUT
- Low wealth  $\nRightarrow$  not affluent, high mortality

Empirical solution: use a combination

- Affluence,  $A = \text{wealth} + K \times \text{income}$
- $K = 15$  seems to work well *statistically* as a predictor
- Low affluence,  $A$ , predicts poor mortality



## Subdividing Data (after much experimentation!)

- Males resident in Denmark for the previous 12 months
- Divide population in year  $t$ 
  - into 10 equal sized Groups (approx)
  - using *affluence, A*
- Individuals can change groups up to age 67
- Group allocations are locked down at age 67  
(better than not locking down at age 67)

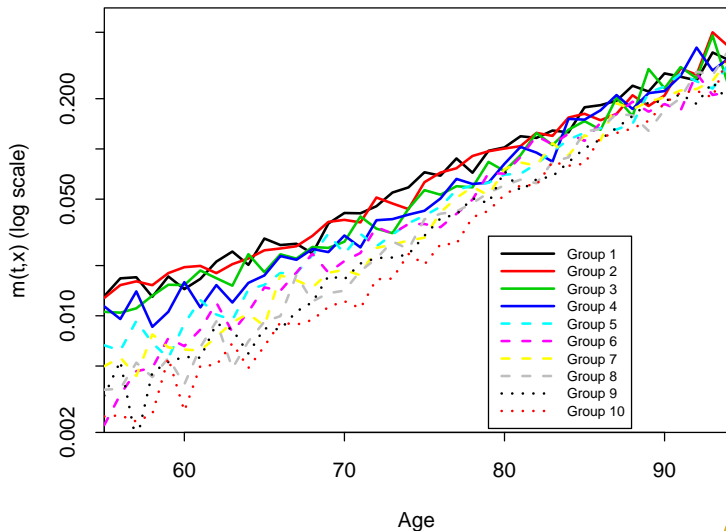


## Subdivided Data

- Ages 55-94; Years 1985-2012
- Exposures  $E^{(i)}(t, x)$  for groups  $i = 1, \dots, 10$   
range from over 4250 down to 13
- Deaths  $D^{(i)}(t, x)$   
range from 151 down to 4
- Crude death rates  
 $\hat{m}^{(i)}(t, x) = D^{(i)}(t, x) / E^{(i)}(t, x)$
- Small groups  $\Rightarrow$  Poisson risk is important



## Males Crude $m(t,x)$ ; 2012



## Modelling the underlying death rates, $m^{(k)}(t, x)$

$m^{(k)}(t, x)$  = pop.  $k$  death rate in year  $t$  at age  $x$

Population  $k$ , year  $t$ , age  $x$

$$\log m^{(k)}(t, x) = \beta^{(k)}(x) + \kappa_1^{(k)}(t) + \kappa_2^{(k)}(t)(x - \bar{x})$$

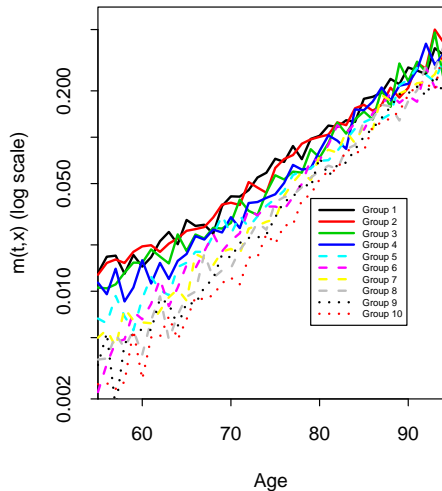
(Extended CBD with a non-parametric base table,  $\beta^{(k)}(x)$ )

- 10 groups,  $k = 1, \dots, 10$  (low to high affluence)
- 28 years,  $t = 1985, \dots, 2012$
- 40 ages,  $x = 55, \dots, 94$

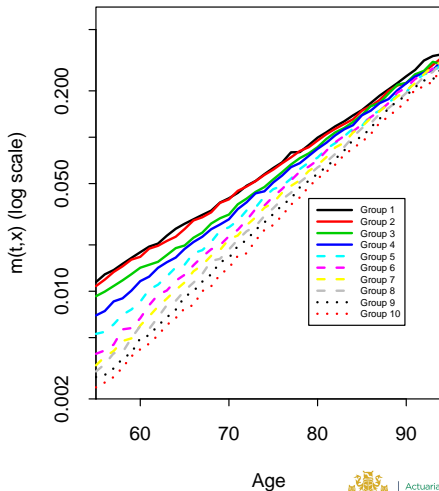


# Model-Inferred Underlying Death Rates 2012

## Males Crude $m(t,x)$ ; 2012



## Males CBD-X Fitted $m(t,x)$ ; 2012 Point Estimates



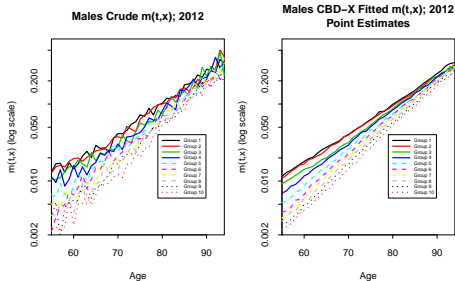
## Modelling the death rates, $m_k(t, x)$

$$\log m^{(k)}(t, x) = \beta^{(k)}(x) + \kappa_1^{(k)}(t) + \kappa_2^{(k)}(t)(x - \bar{x})$$

- Model fits the 10 groups well without a cohort effect
- Non-parametric  $\beta^{(k)}(x)$  is essential to preserve group rankings
  - Rankings are evident in crude data
  - *“Bio-demographical reasonableness”*:  
more affluent  $\Rightarrow$  healthier



# Model-Inferred Underlying Death Rates 2012



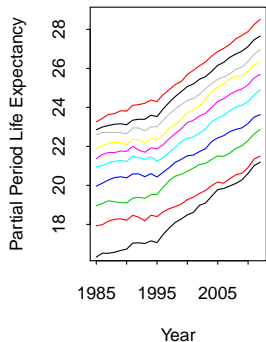
- Gap reduces from over  $5\times$  to  $1.3\times$
- Or **+14 years** difference for Group 1 $\rightarrow$ 10, age 55; **+9** at 67.
- Convergence  $\Rightarrow$  way ahead for modelling very high ages???



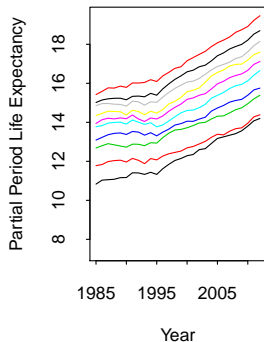


# Partial Period Life Expectancy for Groups 1-10

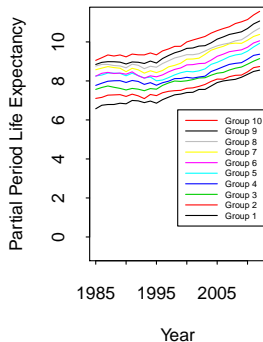
**Males Period EL:  
Age 55**



**Males Period EL:  
Age 65**



**Males Period EL:  
Age 75**



- $t \rightarrow t + 1$ : Allow for correlation
  - between  $\kappa_1^{(k)}(t + 1)$  and  $\kappa_2^{(k)}(t + 1)$
  - between groups  $k = 1, \dots, 10$
  
- Medium/long term,  $t \rightarrow t + T$ :  
*group specific period effects gravitate towards the national trend (coherence)*  
 $\Rightarrow$  Bio-demographical reasonableness:  
groups should not diverge



## A specific model

$$\begin{aligned}\kappa_1^{(i)}(t) &= \kappa_1^{(i)}(t-1) + \mu_1 + Z_{1i}(t) && \text{(random walk)} \\ &\quad - \psi \left( \kappa_1^{(i)}(t-1) - \bar{\kappa}_1(t-1) \right) && \text{(gravity between groups)} \\ \kappa_2^{(i)}(t) &= \kappa_2^{(i)}(t-1) + \mu_2 + Z_{2i}(t) \\ &\quad - \psi \left( \kappa_2^{(i)}(t-1) - \bar{\kappa}_2(t-1) \right)\end{aligned}$$

where

$$\bar{\kappa}_1(t) = \frac{1}{n} \sum_{i=1}^n \kappa_1^{(i)}(t) \quad \text{and} \quad \bar{\kappa}_2(t) = \frac{1}{n} \sum_{i=1}^n \kappa_2^{(i)}(t)$$



## A specific model

$$\kappa_1^{(i)}(t) = \kappa_1^{(i)}(t-1) + \mu_1 + Z_{1i}(t) - \psi \left( \kappa_1^{(i)}(t-1) - \bar{\kappa}_1(t-1) \right)$$

$$\kappa_2^{(i)}(t) = \kappa_2^{(i)}(t-1) + \mu_2 + Z_{2i}(t) - \psi \left( \kappa_2^{(i)}(t-1) - \bar{\kappa}_2(t-1) \right)$$

Model structure  $\Rightarrow$

- $(\bar{\kappa}_1(t), \bar{\kappa}_2(t)) \sim$  bivariate random walk
- Each  $\kappa_1^{(i)}(t) - \bar{\kappa}_1(t) \sim AR(1)$  reverting to 0
- Each  $\kappa_2^{(i)}(t) - \bar{\kappa}_2(t) \sim AR(1)$  reverting to 0
- $\beta^{(i)}(x)$  vs  $\beta^{(j)}(x) \Rightarrow$  intrinsic group differences



## Non-trivial correlation structure: between different ages and groups

$$\begin{aligned}\kappa_1^{(i)}(t) &= \kappa_1^{(i)}(t-1) + \mu_1 + Z_{1i}(t) - \psi \left( \kappa_1^{(i)}(t-1) - \bar{\kappa}_1(t-1) \right) \\ \kappa_2^{(i)}(t) &= \kappa_2^{(i)}(t-1) + \mu_2 + Z_{2i}(t) - \psi \left( \kappa_2^{(i)}(t-1) - \bar{\kappa}_2(t-1) \right)\end{aligned}$$

The  $Z_{ki}$  are multivariate normal, mean 0 and

$$\text{Cov}(Z_{ki}, Z_{lj}) = \begin{cases} v_{kl} & \text{for } i = j \\ \rho v_{kl} & \text{for } i \neq j \end{cases}$$

$\rho$  = cond. correlation between  $\kappa_1^{(i)}(t)$  and  $\kappa_1^{(j)}(t)$  etc.



- Model is very simple
  - One gravity parameter,  $0 < \psi < 1$
  - One between-group correlation parameter,  $0 < \rho < 1$
- Many generalisations are possible
- But more parameters + more complex computing
- This simple model seems to fit quite well.
- Nevertheless  $\Rightarrow$  potential for further work



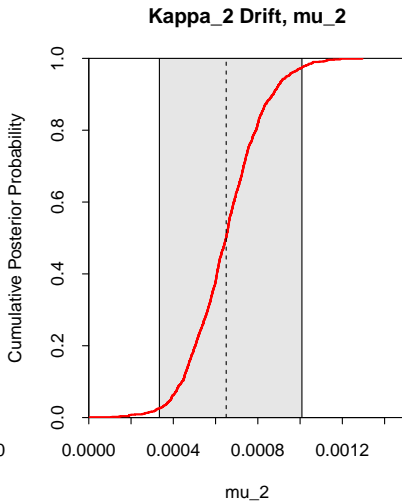
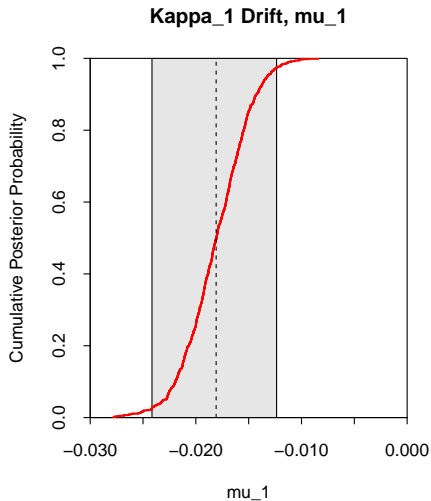
## Prior distributions

- As uninformative as possible
- $\mu_1, \mu_2 \sim$  improper uniform prior
- $\{v_{ij}\} \sim$  Inverse Wishart
- $\rho \sim \text{Beta}(2, 2)$
- $\psi \sim \text{Beta}(2, 2)$

State variables and process parameters estimated using MCMC (Gibbs + Metropolis-Hastings)

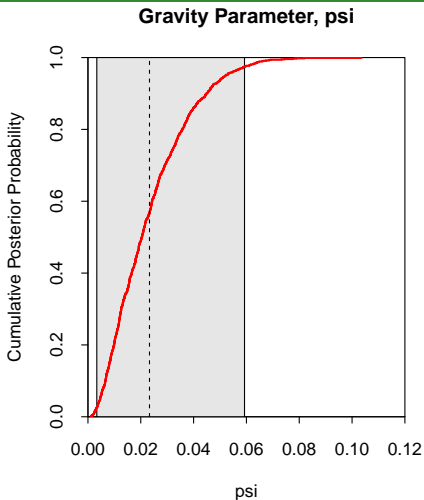
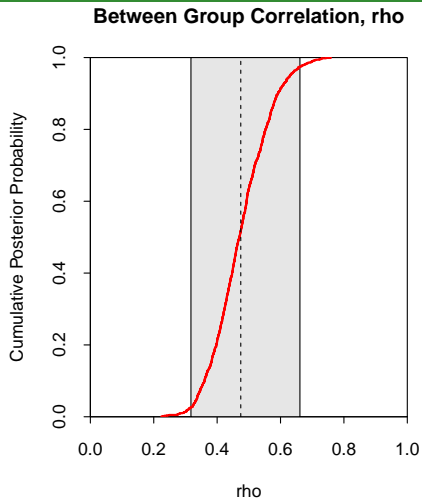


# Posterior Distributions and 95% Credibility Intervals

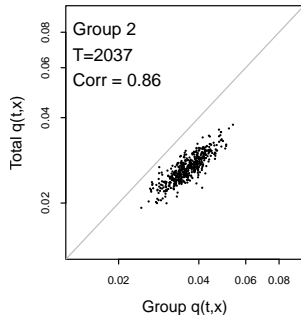
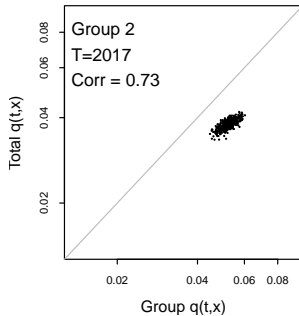
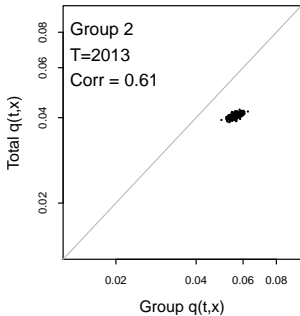




# Posterior Distributions and 95% Credibility Intervals



# Simulated Group versus Population Mortality, $q(t, x)$



As  $T$  increases: +1 year; +5 years; +25years

- Scatterplots become more dispersed
- Shift down and to the left
- Correlation increases



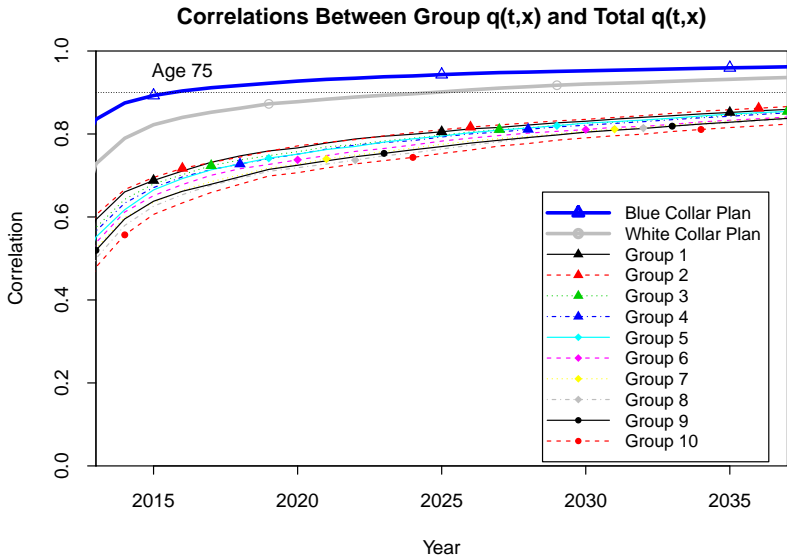
Deciles are quite narrow subgroups

More diversified e.g.

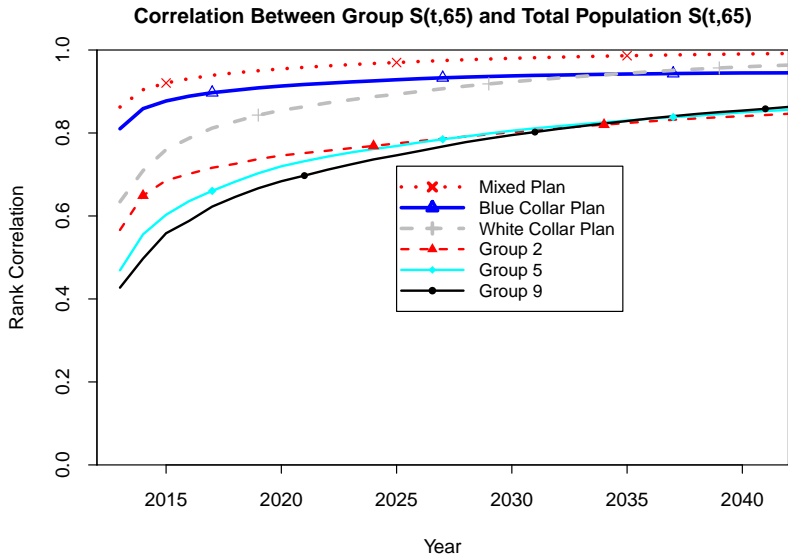
- **Blue collar pension plan**  
⇒ equal proportions of groups 2, 3, 4
- **White collar pension plan**  
⇒ equal proportions of groups 8, 9, 10
- **Mixed plan**  
⇒ proportions  $(0, 0, 1, 2, \dots, 7, 8)/36$  (e.g. amounts)



# Forecast Correlations: Mortality Rates at Age 75

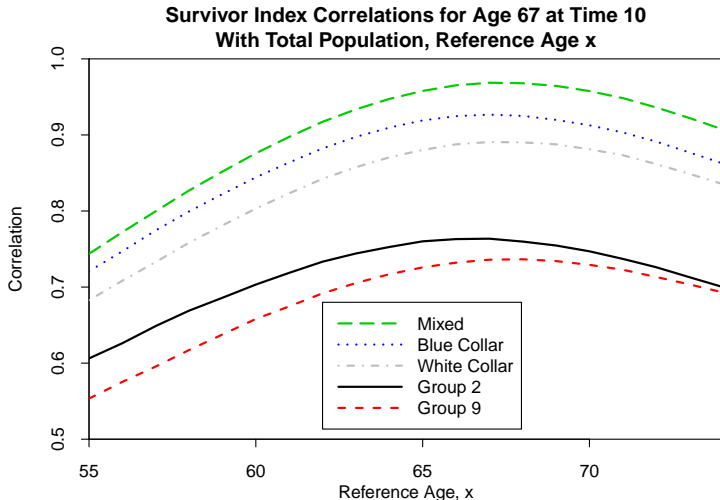


# Forecast Correlations: Cohort Survivorship from 65



# Forecast Correlations: Cohort Survivorship

Different reference ages:  $cor(S_X(10, 67), S_{TOT}(10, x))$



# Modelling Conclusions

- Development of a new multi-population dataset for Denmark
  - strong bio-demographically reasonable group rankings based on a new measure of affluence*
- Unlike multi-country data
  - a priori* ranking of affluence-related groups
- Proposal for a simple new multi-population model
- Mortality rates converge at high ages
- Strong correlations over medium to long term even allowing for parameter uncertainty
- Correlations depend strongly on diversity of sub-population



### 3. Postscript: Education as an Alternative Covariate

- **Level of Highest Education** also known to be a good predictor
  - Various US studies
  - Mackenbach et al. (2003) including Denmark: Std. Mortality Rates
  - Bronnum-Hansen and Baadsgaard (2012) Denmark:  $LE(x = 30)$
- As close as possible on a *like for like* basis:

Crude death rates; age 30+; matching years.

Affluence  $\Rightarrow$

- Wider spread of SMR's than M. et al. (2003)
  - Wider spread of  $LE(30)$  than BHB (2012)
- 
- More to be done.





## 4. Hedging and Economic Capital

### Choices

- No hedging
- Hedge using own experience
- Hedge using standardised instrument: national mortality

### Basis Risk

Two sources of basis risk considered here

- Population basis risk
- Sub-optimal choice of hedging instrument  
tradeoff: price vs basis risk



# Economic capital relief using longevity options

- Population 1: national population; reference for hedge  
notional portfolio of males aged 65:  $A_1 = \text{P.V. pension payments}$
- Population 2: hedger's own population  
portfolio of males aged 65:  $A_2 = \text{P.V. pension payments}$

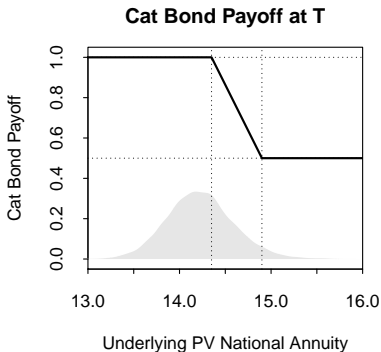
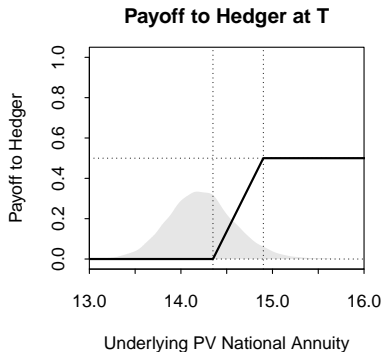


# Economic capital relief using longevity options

- Three choices:
  - No hedging of  $A_2$
  - Hedge  $A_2$  with population 1 longevity swap  $A_1 - \hat{A}_1$
  - Hedge  $A_2$  with out-of-the-money option on  $A_1(T)$   
Payoff at  $T = 20$ ; underlying  $A_1(T)$  includes estimated  $t > T$  cashflows



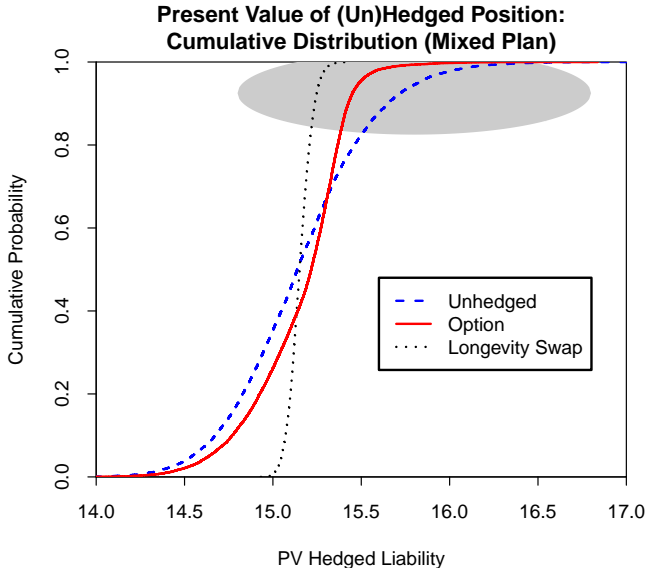
# Index Based Hedge: Payoffs



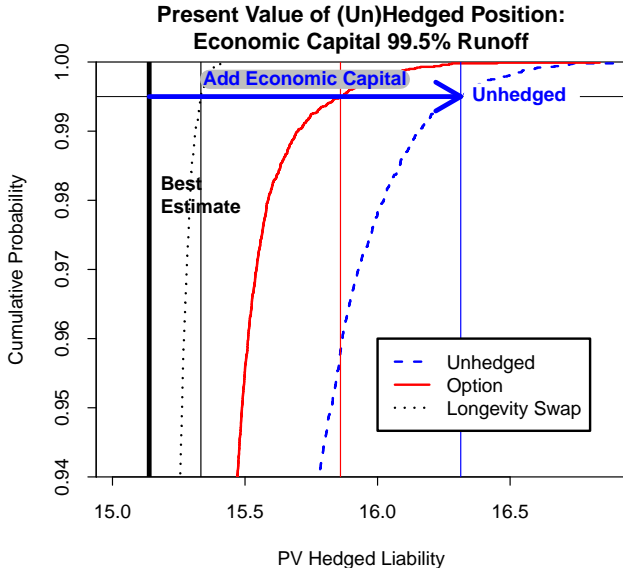
Attachment/Detachment at approx 60% / 95%



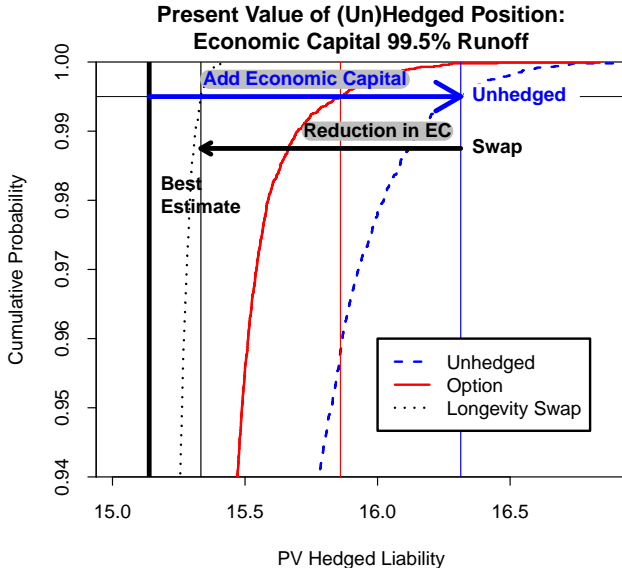
# Impact of Hedging with $T = 20$ Option or Index Swap



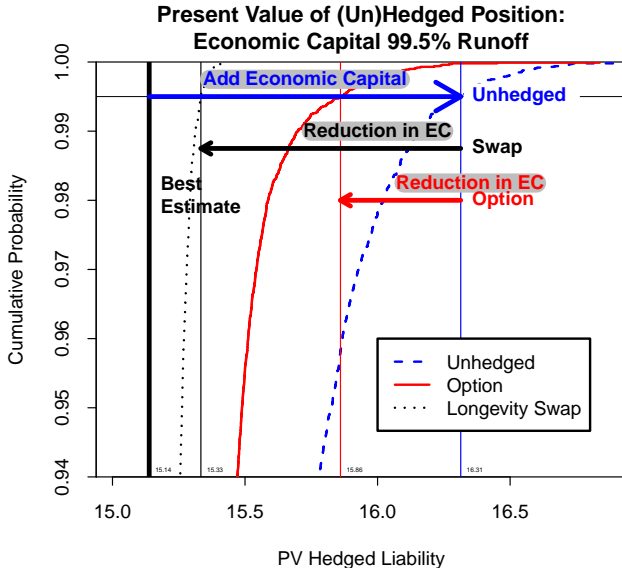
# Impact of Hedging with $T = 20$ Option or Index Swap



# Impact of Hedging with $T = 20$ Option or Index Swap



# Impact of Hedging with $T = 20$ Option or Index Swap





# Challenges 1

- Simulation example assumes swaps and options priced at actuarially fair value
- But swap and option premiums might be more expensive
- Compare premium versus value of reduction in Economic Capital over multiple time periods

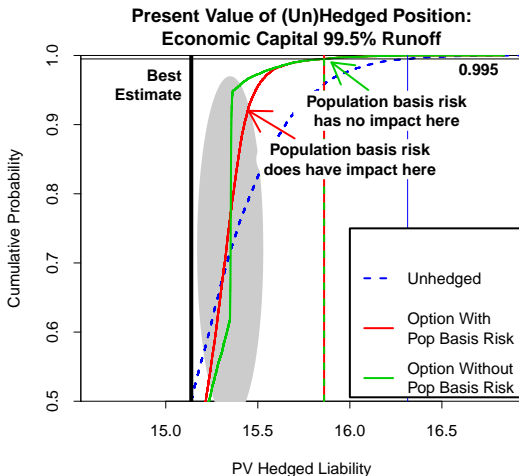


## Challenges 2

- Bull spread option:
  - Choice of attachment/detachment points  
 $K_1, K_2$
  - Maximum cat bond loss
  - Capital markets capacity  $\leftrightarrow$  annuity liabilities
  - Risk premiums
  - Sub-optimal instrument basis risk



# What is the impact of population basis risk?



Conclusion depends on  $K_2 \ll 99.5\%$  quantile.

Basis risk from "sub-optimal" choice of hedging instrument<sup>†</sup>



## 5. Summary

- Danish data allows insight into relative mortality dynamics between socio-economic sub-populations
- Conclusions for other countries likely to be similar
- Economic capital example is one of many potential risk management applications

Working paper available on website.

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# Thank You!

## Questions?

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