



## Actuarial Research Centre

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# Actuarial Research Centre (ARC)

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# Modelling Mortality: the Effect of Small Population Size on Parameter Estimation

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- Background and Motivation
- Mortality Model
- Data
- Method of Simulation
- Testing Systematic Parameter Difference
- Common Cohort Effect Testing
- Conclusions

## Background

- Many mortality models, e.g. Lee-Carter model (1992) and CBD (2006), have been introduced to provide a good fitness for large sized populations
- Actuaries are interested in modelling relatively much smaller populations, e.g. Pension scheme
- Historical data has shown that smaller population has significant variability on its pattern compared with larger population
- Booth (2006) showed poorness of fit of Lee-Carter model to smaller populations

## Motivation

- Investigate to what extent information contained in larger population can be adopted

Death count  $D(t, x)$  and corresponding exposure  $E(t, x)$  of

- Males and Females in England and Wales (EW)
- Males only in Scotland
- Year range: 1961-2011
- Age range: 50-89, last birthday

Note: The limited size of dataset inevitably results in extra uncertainty to the parameter estimates

- Mortality model, M7:

$$\text{logit}q(t, x) = \kappa_t^{(1)} + \kappa_t^{(2)}(x - \bar{x}) + \kappa_t^{(3)}((x - \bar{x}) - \hat{\sigma}_x^2) + \gamma_{t-x}^{(4)}$$

- $\kappa_t^{(i)}$ , period effect;  $\gamma_{t-x}^{(4)}$ , cohort effect

- Let  $\theta = (\kappa_t^{(1)}, \kappa_t^{(2)}, \kappa_t^{(3)}, \gamma_{t-x}^{(4)})$

- 

$$q(t, x) = 1 - \exp[-m(\theta, t, x)]$$

- Assume

$$D(t, x) \sim Po(m(\theta; t, x)E(t, x))$$

- Sampling variation in  $D(t, x)$  leads to noise in  $\kappa_t^{(i)}$  and  $\gamma_c^{(4)}$  estimates

- $E_0(t, x)$ ,  $D_0(t, x)$ : the benchmark exposure and corresponding deaths, respectively.
- $\hat{\theta}_0$ : the benchmark parameter estimates for  $D_0(t, x)$ .
- Simulation model

$$D_w(t, x) | \hat{\theta}_0 \sim Po(m(\hat{\theta}_0, t, x) w E_0(t, x))$$

where  $w = 1, 0.1, 0.01$

- Simulate  $D_w(t, x) \rightarrow \hat{\theta}_w$
- $D_w(t, x)^j, \hat{\theta}_w^j$ , where  $j = 1, \dots, K$
- Let the exposure of England and Wales,  $E_{EW}(t, x)$  be the bench mark, i.e.  
 $E_0(t, x) = E_{EW}(t, x)$

- Recall for random variables  $X_1, \dots, X_n$  with pdf or pmf  $f(x|\theta)$ , the asymptotic distribution of MLE  $\hat{\theta}$  is

$$\hat{\theta} \asymp N(\theta_0, \frac{1}{I(\theta_0)})$$

where  $I$  is the Fisher information

- In our case,

$$\hat{\theta}_w \asymp N(\hat{\theta}^{EW}, \frac{1}{I(\hat{\theta}^{EW})})$$

where

$$I(\hat{\theta}^{EW}) = w \sum_{t,x} \frac{E_{t,x}^{EW}}{m(t, x, \hat{\theta}^{EW})} \left( \frac{\partial m(t, x, \theta_w)}{\partial \theta_w} \right)^2$$

- Thus the variation of  $\hat{\theta}_w$  is inversely proportional to the population size

(E.g. Kendall, 1991, Volume 2)

- Define likelihood function:  $L(x|\theta) = \prod_{i=1}^n f(x_i|\theta)$ , where  $\theta = (\theta_r, \theta_s)$ ,  $r + s = k$ .
- Null hypothesis and alternative:

$$H_0 : \theta_r = \theta_{r0}; \quad H_1 : \theta_r \neq \theta_{r0}.$$

- Unconditional maximum of  $L(x|\theta)$ ,

$$L(x | \hat{\theta}_r, \hat{\theta}_s)$$

where  $(\hat{\theta}_r, \hat{\theta}_s)$  is MLEs of  $(\theta_r, \theta_s)$

- Conditional maximum

$$L(x | \theta_{r0}, \tilde{\theta}_s(\theta_{r0})).$$

where  $\tilde{\theta}_s(\theta_{r0})$  is the MLEs of  $\theta_s$ , given  $H_0$  holds

- Log-scaled test statistic

$$\Gamma = -2\log \frac{L(x | \theta_{r0}, \tilde{\theta}_s)}{L(x | \hat{\theta}_r, \hat{\theta}_s)}$$

Set  $s = 0$

- The null hypothesis and alternative:

$$H_0 : \theta_r^w = \theta_{r0}; \quad H_1 : \theta_r^w \neq \theta_{r0}.$$

where  $\theta_r^w$  is the parameters for population  $w$ .

- Log-scaled test statistic is

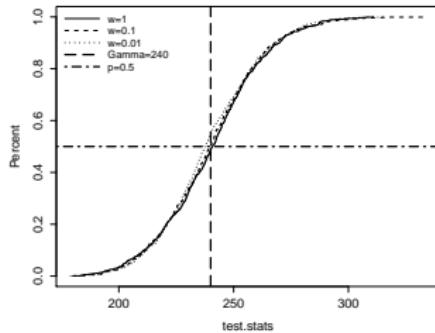
$$\Gamma^w = -2(I(x_w | \theta_{r0}) - I(x_w | \hat{\theta}_r))$$

- Under  $H_0$ ,  $\Gamma^w$  has asymptotic  $\chi_r^2$  distribution with  $r$  degree of freedom.

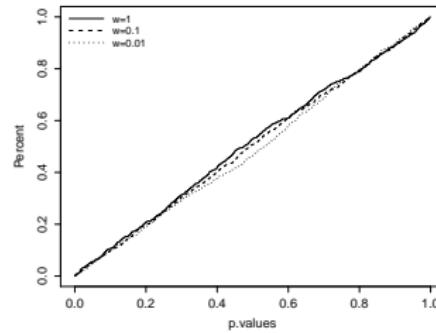
Let

$$\theta_{r0} = \hat{\theta}^{EW}; \quad \hat{\theta}_r = \hat{\theta}_w$$

(a) Test Statistics,  $\Gamma^w$



(b) P-values,  $P_w$



# Testing Systematic Parameter Difference

Power of the LR test

Power of hypothesis test:

$$\text{Prob}(\text{Reject } H_0 \mid H_1 \text{ is True}) = 1 - \text{type II error rate}$$

Define  $\hat{\theta}^{(i)}$ :

- $\hat{\theta}^{(1)} = (\hat{\kappa}_t^{EW,(1)} + \lambda, \hat{\kappa}_t^{EW,(2)}, \hat{\kappa}_t^{EW,(3)}, \hat{\gamma}_c^{EW,(4)})$
- $\hat{\theta}^{(2)} = (\hat{\kappa}_t^{EW,(1)}, \hat{\kappa}_t^{EW,(2)} + \lambda, \hat{\kappa}_t^{EW,(3)}, \hat{\gamma}_c^{EW,(4)})$
- $\hat{\theta}^{(3)} = (\hat{\kappa}_t^{EW,(1)}, \hat{\kappa}_t^{EW,(2)}, \hat{\kappa}_t^{EW,(3)} + \lambda, \hat{\gamma}_c^{EW,(4)})$
- $\hat{\theta}^{(4)} = (\hat{\kappa}_t^{EW,(1)}, \hat{\kappa}_t^{EW,(2)}, \hat{\kappa}_t^{EW,(3)}, \hat{\gamma}_c^{EW,(4)} + \lambda)$

# Testing Systematic Parameter Difference

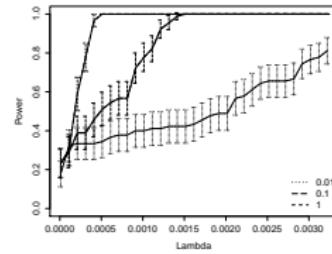
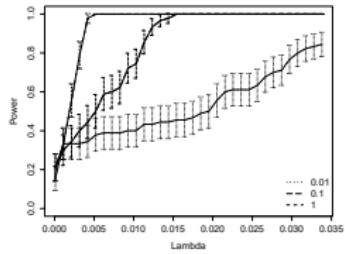
Power of the LR test, Ctd

- Simulate

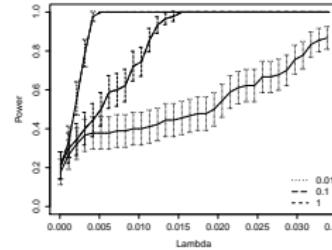
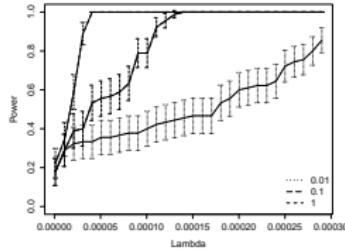
$$D_{t,x}^{w,(i)} \mid \hat{\theta}^{(i)} \sim Po(m(\hat{\theta}^{(i)}, t, x) w E_{t,x}^{EW}), i = 1, 2, 3, 4$$

- $\hat{\theta}_{r,w}^{(i)}$ , the MLEs of  $D_{t,x}^{w,(i)} \mid \hat{\theta}^{(i)}$
- Propose LR test by setting  $\theta_{r0} = \hat{\theta}^{(i)}$ ;  $\hat{\theta}_r = \hat{\theta}_{r,w}^{(i)}$

(a) The Power of LR test when  $\kappa^{(1)}$  shifted (b) The Power of LR test when  $\kappa^{(2)}$  shifted



(c) The Power of LR test when  $\kappa^{(3)}$  shifted (d) The Power of LR test when  $\gamma^{(2)}$  shifted



Question: does population A share the same cohort effect, given  $\gamma_B^{(4)}$  already estimated

- $\theta_r = \gamma_A^{(4)}; \theta_s = (\kappa_t^{(1)}, \kappa_t^{(2)}, \kappa_t^{(3)})$
- Test statistic

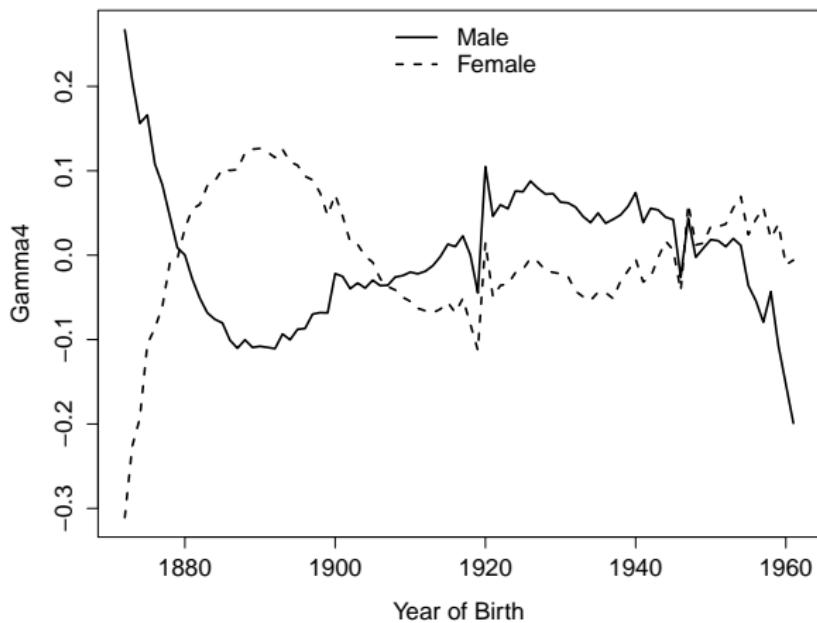
$$\Gamma = -2\log \frac{L(x | \theta_{r0}, \tilde{\theta}_s)}{L(x | \hat{\theta}_r, \hat{\theta}_s)}$$

Let

- B: EW males
- A1: EW females,  $\Gamma_{A1} = 6311 \rightarrow p \simeq 0$
- A2: Scotland males,  $\Gamma_{A2} = 193 \rightarrow p \simeq 0$
- However, we see great improvement on the test statistic from A1 to A2.

# LR Test for Common Cohort Effect in Two Populations

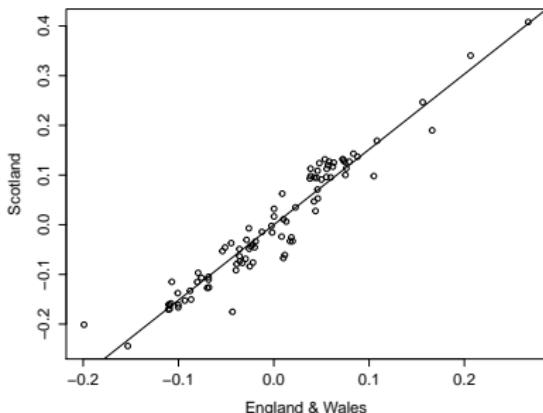
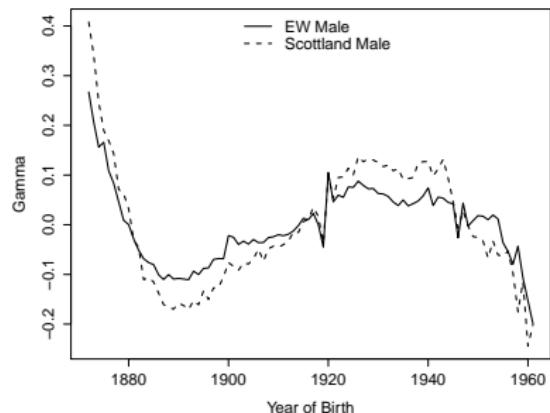
Testing Common Cohort Effect between Males and Females in England & Wales



# LR Test for Common Cohort Effect in Two Populations

Application of LR Test to Empirical Datasets

Let A, B be males in Scotland and England & Wales respectively



- Both populations have similar pattern.
- Strong linear relationship between cohort effect estimates of Scotland and England & Wales.

- The variation of parameter estimates can be significantly and proportionally increased by reducing the population size.
- For the given dataset,  $\chi^2$  provides a good asymptotic approximation for the LR test statistic under null hypothesis.
- The power of LR test is approximately proportional to the population size. We can significantly improve the power by increasing the population size.
- Males and Females in England & Wales; males in England & Wales and Scotland do not have the same cohort effect.