

Mortality and Deprivation

Torsten Kleinow
joint work with Jie Wen and Andrew J.G. Cairns

Heriot-Watt University, Edinburgh

Actuarial Research Centre, IFoA

ARC workshop - Edinburgh - April 2018



Actuarial
Research Centre
Institute and Faculty
of Actuaries

Index of Multiple Deprivation

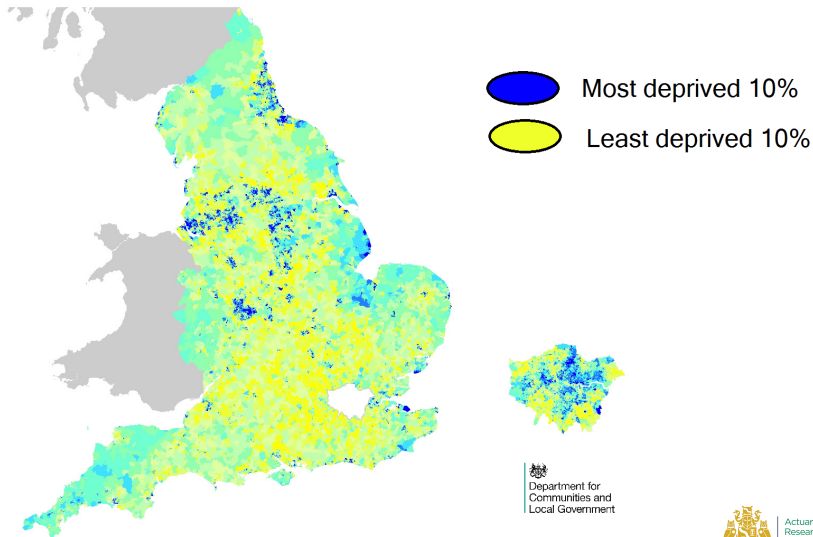
The IMD is a weighted combination of seven indices of deprivation:

- Income (22.5%)
- Employment (22.5%)
- Education (13.5%)
- Health (13.5%)
- Crime (9.3%)
- Barriers to Housing and Services (9.3%)
- Living environment (9.3%)

source: GOV.UK



Index of Multiple Deprivation (IMD) areas



- We consider mortality rates for males in England for the ten IMD deciles (2015).
- ages: 40-89, years: 2001-2015
- source: Office for National Statistics



Model for the Number of Death in Different Groups

$$D_{xti} \sim \text{Poisson}(m_{xti}E_{xti})$$

For each period (calendar year) t , age x and socio-economic group i we have

D_{xti} : Number of deaths,

E_{xti} : Central exposure-to-risk

m_{xti} : force of mortality



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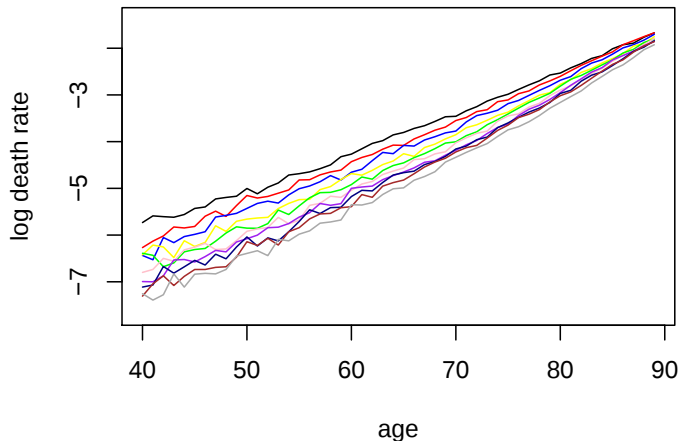
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We define socio-economic groups with reference to the Index of Multiple Deprivation for England.



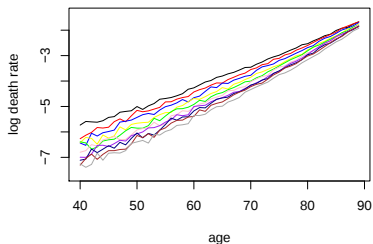
Death rates by IMD decile

male mortality in year 2015

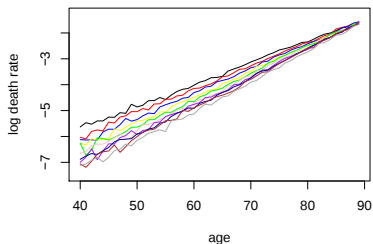


Death rates by IMD decile

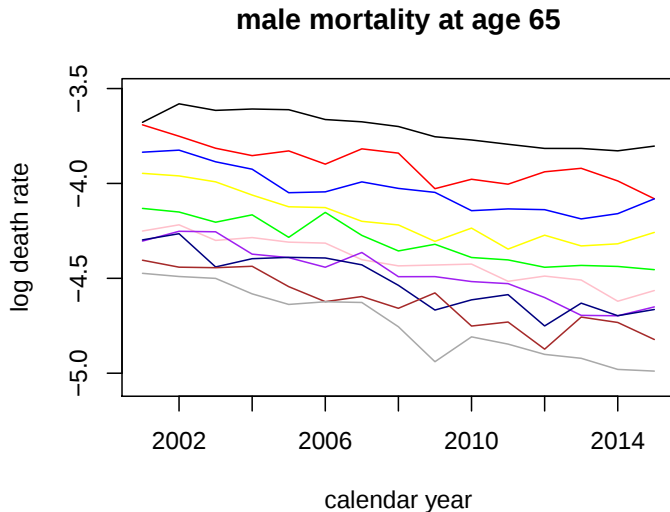
male mortality in year 2015



male mortality in year 2001



Death rates by IMD decile



All considered models are variants of group specific Lee-Carter type models with the extension to a second age-period effect by Renshaw & Haberman (2003):

$$\log m_{xti} = \alpha_{xi} + \beta_{xi}^1 \kappa_{ti}^1 + \beta_{xi}^2 \kappa_{ti}^2 + \gamma_{ci}$$

where $c = t - x$ is the cohort (year of birth).



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common period effects : $\kappa_{ti}^k = \kappa_t^k$ (Li and Lee, 2005)



Models

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common period effects : $\kappa_{ti}^k = \kappa_t^k$ (Li and Lee, 2005)

group specific trends in common period effects : $\kappa_{ti}^k = \kappa_t^k + \eta_i(t - \bar{t})$

and variations with and without cohort effects.



Models

$$\text{m1: } \log m_{xti} = \alpha_{xi} + \kappa_{ti}^1 + (x - \bar{x})\kappa_{ti}^2 \quad (\text{Plat, 2009})$$

$$\text{m2: } \log m_{xti} = \alpha_{xi} + \beta_x^1 \kappa_{ti}^1 + \beta_x^2 \kappa_{ti}^2 \quad (\text{Kleinow, 2015})$$

⋮

$$\text{m6: } \log m_{xti} = \alpha_x + \kappa_{ti}^1 + (x - \bar{x})\kappa_{ti}^2 \quad \text{m1} + \text{common } \alpha$$

⋮

$$\begin{aligned} \text{m9: } \log m_{xti} = & \alpha_x + \eta_i(x - \bar{x}) + \kappa_t^1 \\ & + d_i^0 + d_i^1(t - \bar{t}) \\ & + (x - \bar{x})(\kappa_t^2 + d_i^2(t - \bar{t})) \end{aligned}$$

⋮

$$\text{m12: } \log m_{xti} = \alpha_{xi} + \beta_{xi}^1 \kappa_{ti}^1 + \beta_{xi}^2 \kappa_{ti}^2 \quad (\text{Renshaw\&Haberman, 2003})$$

⋮

$$\text{m14: } \log m_{xti} = \alpha_x + \beta_x^1 \kappa_{ti}^1 + \beta_x^2 \kappa_{ti}^2 \quad \text{m2} + \text{common } \alpha$$

$$\text{m15: } \log m_{xti} = \alpha_{xi} + \beta_x^1 \kappa_t^1 + \beta_{xi}^2 \kappa_{ti}^2 \quad (\text{Li\&Lee, 2005})$$

+ variants with common or group-specific cohort effect, γ_c or γ_{ci} .



Estimation and Identifiability

- Maximum Likelihood estimation based on $D_{x,t,i} \sim \text{Poisson}(\mu_{x,t,i} E_{x,t,i}^c)$ is applied to obtain estimated parameter values.
- All suggested models have some identifiability issues, that is, different parameter values lead to the same fitted mortality rates m_{xti} , and, therefore to the same value of the likelihood function.
- To obtain unique parameter values we apply model-specific constraints.



Questions for this talk

$$\log m_{xti} = \alpha_{xi} + \beta_{xi}^1 \kappa_{ti}^1 + \beta_{xi}^2 \kappa_{ti}^2 + \gamma_{ci}$$

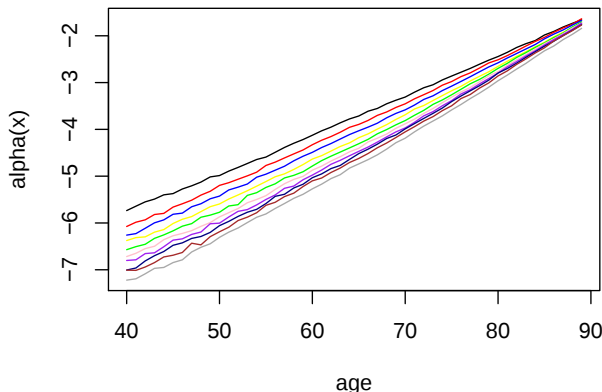
- What parameters should be chosen to be group specific and which parameters are common?
- Should age-effects be estimated?
- Should we include cohort effects (common or group specific)?
- What parameters show the greatest differences between IMD groups?
- Are the groups clustered?



Parameter estimates - m12 - the most general model

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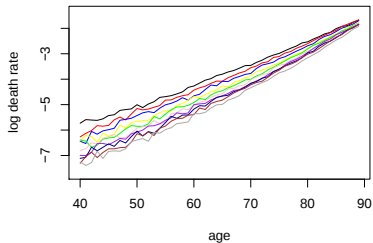
MLE estimated $\alpha(x)$ – m12



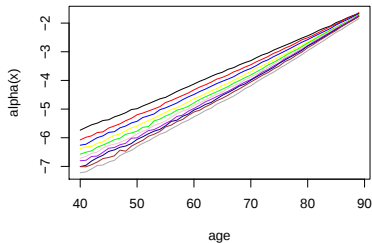
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male mortality in year 2015



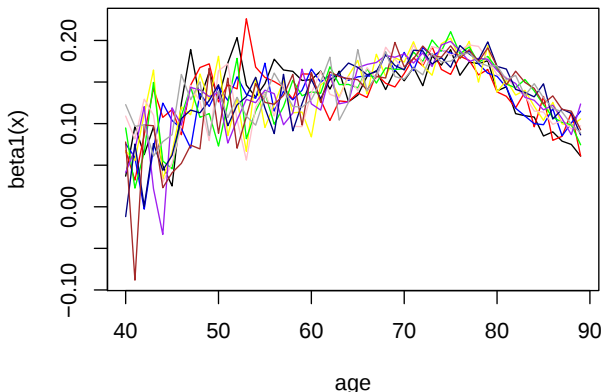
MLE estimated alpha(x) - m12



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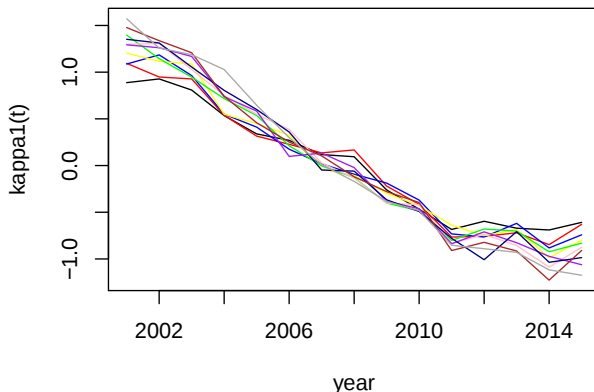
MLE estimated beta1(x) – m12



Parameter estimates - m12 - the most general model

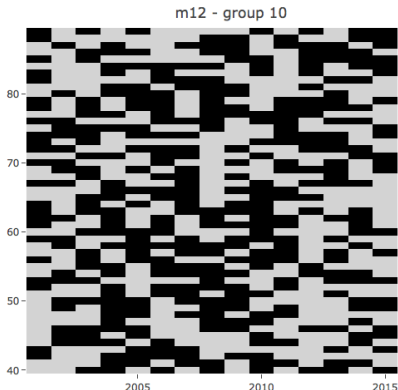
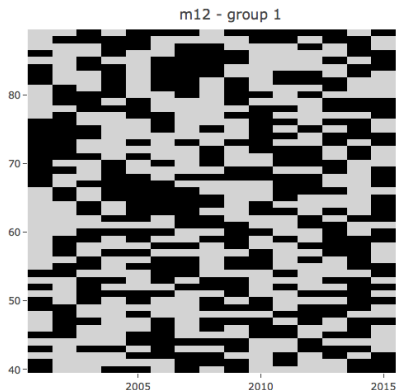
$$\log m_{xti} = \alpha_{xi} + \beta_{xi}^1 \kappa_{ti}^1 + \beta_{xi}^2 \kappa_{ti}^2 \text{ (Renshaw\&Haberman, 2003)}$$

MLE estimated kappa1(t) – m12



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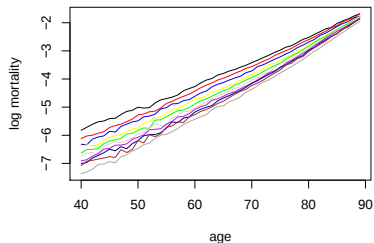
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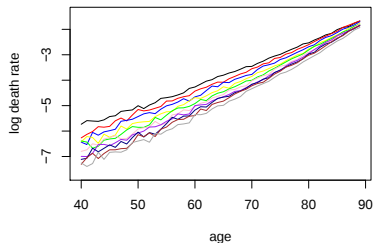
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Fitted mortality in 2015 – m12



male mortality in year 2015



Parameter estimates - m12 - the most general model

Bayesian Information Criterion: $k \log n - 2 \log(L)$

	Log-likelihood	parameters	constraints	d.o.f.	BIC
m12	-30,131.47	1800	40	1760	75,966.82



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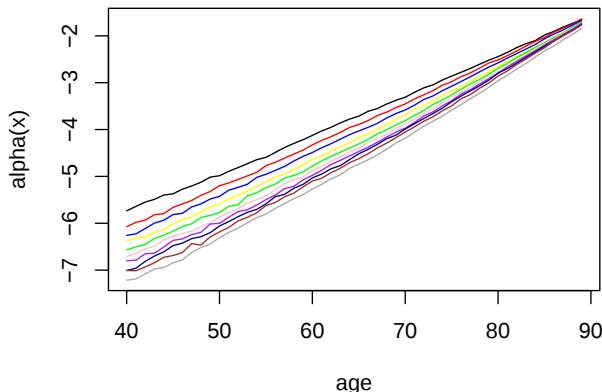
- good fit
- very large number of parameters



Parameter estimates - m2 - common beta

$$\log m_{xti} = \alpha_{xi} + \beta_x^1 \kappa_{ti}^1 + \beta_x^2 \kappa_{ti}^2 \text{ (Kleinow, 2015)}$$

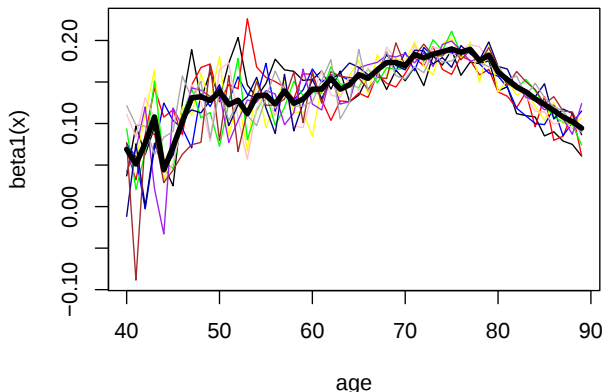
MLE estimated $\alpha(x)$ – m2



Parameter estimates - m2 - common beta

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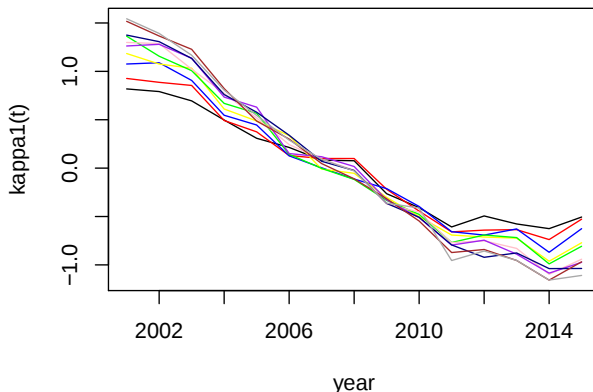
MLE estimated beta1(x) – m2 vs m12



Parameter estimates - m2 - common beta

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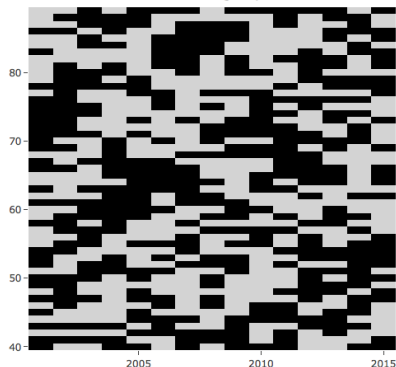
MLE estimated kappa1(t) – m2



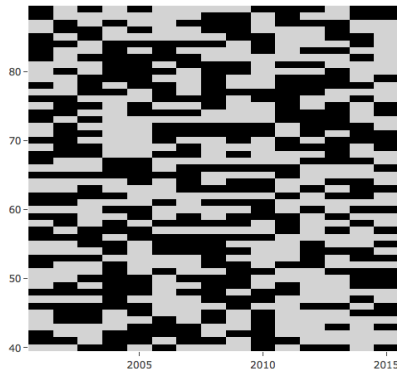
Parameter estimates - m2 - common beta

$$\log m_{xti} = \alpha_{xi} + \beta_x^1 \kappa_{ti}^1 + \beta_x^2 \kappa_{ti}^2 \text{ (Kleinow, 2015)}$$

m2 - group 1



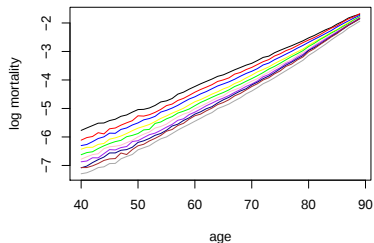
m2 - group10



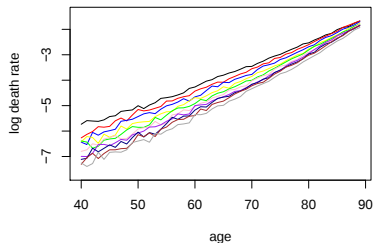
Parameter estimates - m2 - common beta

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Fitted mortality in 2015 – m2



male mortality in year 2015



Parameter estimates - m2 - common beta

Bayesian Information Criterion: $k \log n - 2 \log(L)$

	Log-likelihood	parameters	constraints	d.o.f.	BIC
m2	-30,591.20	900	22	878	69,016.49
m12	-30,131.47	1800	40	1760	75,966.82



Parameter estimates - m2 - common beta

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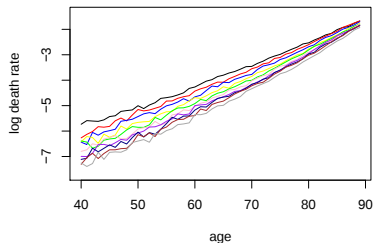
- reasonable fit
- smaller number of parameters than m12
- BIC improved



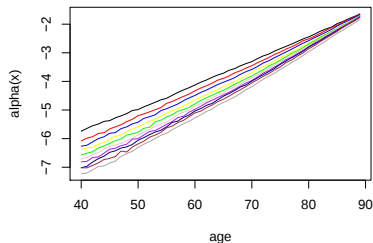
Parameter estimates - m1

$$\log m_{xti} = \alpha_{xi} + \kappa_{ti}^1 + (x - \bar{x})\kappa_{ti}^2 \text{ (Plat, 2009)}$$

male mortality in year 2015



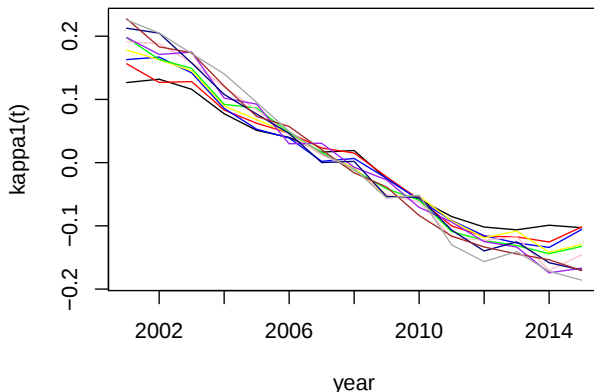
MLE estimated alpha(x) - m1



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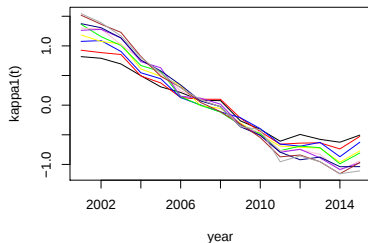
MLE estimated kappa1(t) – m1



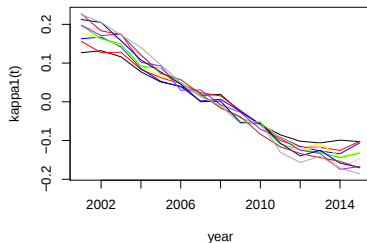
Parameter estimates - m1

$$\log m_{xti} = \alpha_{xi} + \kappa_{ti}^1 + (x - \bar{x})\kappa_{ti}^2 \text{ (Plat, 2009)}$$

MLE estimated kappa1(t) - m2

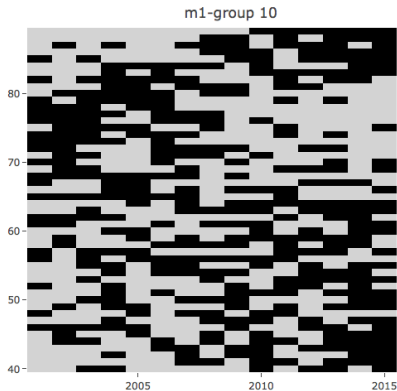
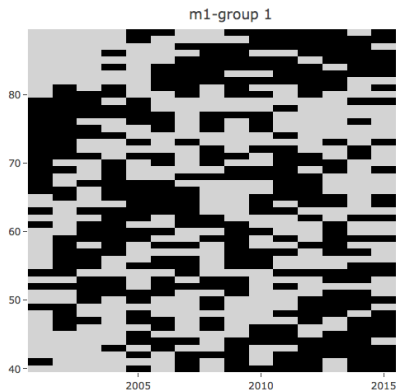


MLE estimated kappa1(t) - m1



Parameter estimates - m1

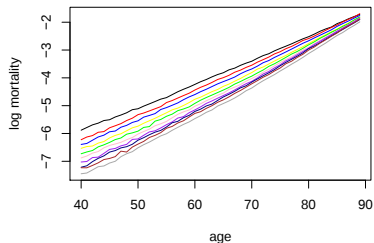
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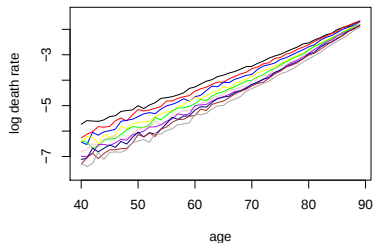
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Fitted mortality in 2015 - m1



male mortality in year 2015



Parameter estimates - m1

Bayesian Information Criterion: $k \log n - 2 \log(L)$

	Log-likelihood	parameters	constraints	d.o.f.	BIC
m1	-31,403.22	800	20	780	69,766.10
m2	-30,591.20	900	22	878	69,016.49
m12	-30,131.47	1800	40	1760	75,966.82



Parameter estimates - m1

Bayesian Information Criterion: $k \log n - 2 \log(L)$

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- model does not fit as well as m2 and m12 (lower likelihood)
- number of parameters reduced further
- but BIC does not improve



Next steps

$$\begin{aligned} \text{m1:} \quad \log m_{xti} &= \alpha_{xi} + \kappa_{ti}^1 + (x - \bar{x})\kappa_{ti}^2 && (\text{Plat, 2009}) \\ \text{m2:} \quad \log m_{xti} &= \alpha_{xi} + \beta_x^1 \kappa_{ti}^1 + \beta_x^2 \kappa_{ti}^2 && (\text{Kleinow, 2015}) \\ \text{m12:} \quad \log m_{xti} &= \alpha_{xi} + \beta_{xi}^1 \kappa_{ti}^1 + \beta_{xi}^2 \kappa_{ti}^2 && (\text{Renshaw\&Haberman, 2003}) \end{aligned}$$



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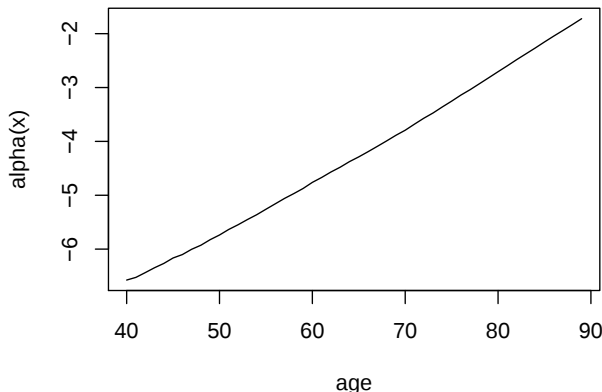
Try a common alpha for m1 and m2.



Parameter estimates - m14 - common alpha and beta

$$\log m_{xti} = \alpha_x + \beta_x^1 \kappa_{ti}^1 + \beta_x^2 \kappa_{ti}^2$$

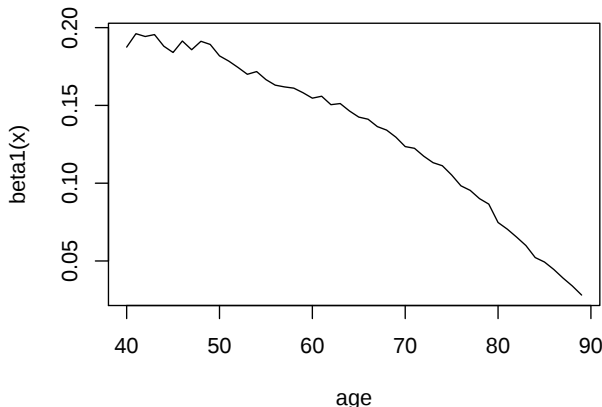
MLE estimated alpha(x) – m14



Parameter estimates - m14 - common alpha and beta

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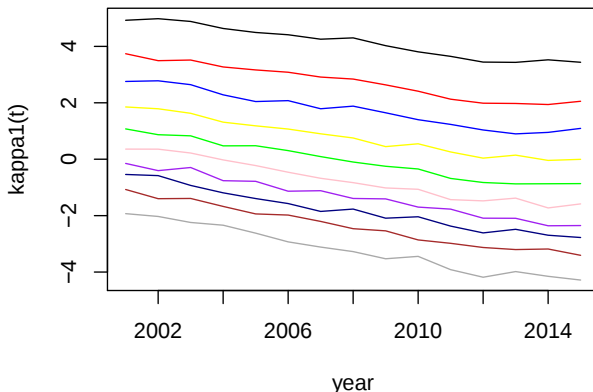
MLE estimated beta1(x) – m14



Parameter estimates - m14 - common alpha and beta

$$\log m_{x_{ti}} = \alpha_x + \beta_x^1 \kappa_{ti}^1 + \beta_x^2 \kappa_{ti}^2$$

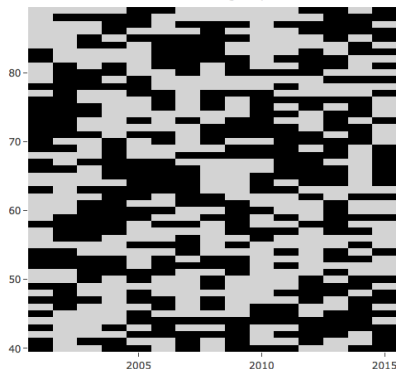
MLE estimated kappa1(t) – m14



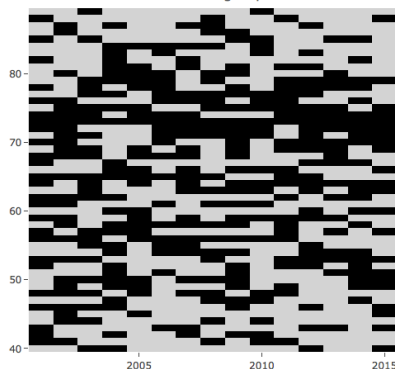
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$$\log m_{xti} = \alpha_x + \beta_x^1 \kappa_{ti}^1 + \beta_x^2 \kappa_{ti}^2$$

m14 - group 1



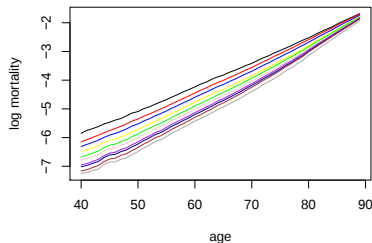
m14 - group 10



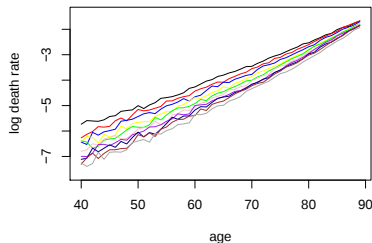
Parameter estimates - m14 - common alpha and beta

$$\log m_{xti} = \alpha_x + \beta_x^1 \kappa_{ti}^1 + \beta_x^2 \kappa_{ti}^2$$

Fitted mortality in 2015 – m14



male mortality in year 2015



Parameter estimates - m14 - common alpha and beta

Bayesian Information Criterion: $k \log n - 2 \log(L)$

	Log-likelihood	parameters	constraints	d.o.f.	BIC
m1	-31,403.22	800	20	780	69,766.10
m2	-30,591.20	900	22	878	69,016.49
m12	-30,131.47	1800	40	1760	75,966.82
m14	-30,852.96	450	4	446	65,685.42



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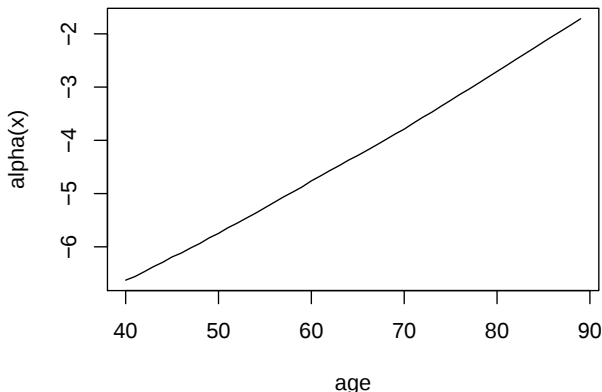
- higher likelihood than m1 with fewer parameters
- best BIC



Parameter estimates - m6 - M1 with common α

$$\log m_{xti} = \alpha_x + \kappa_{ti}^1 + (x - \bar{x})\kappa_{ti}^2$$

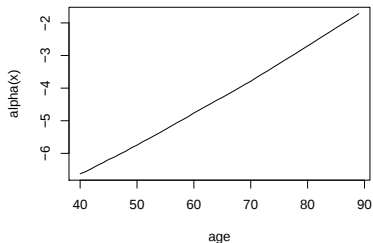
MLE estimated $\alpha(x)$ – m6



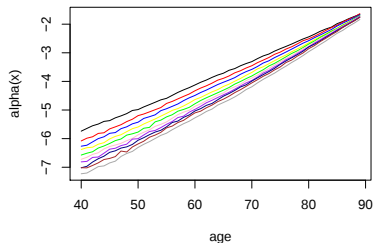
Parameter estimates - m6 - M1 with common alpha

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MLE estimated alpha(x) - m6



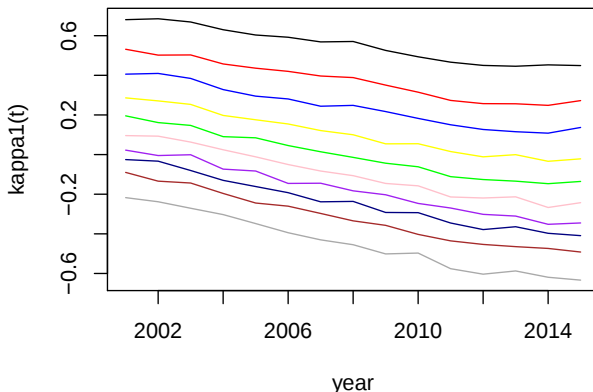
MLE estimated alpha(x) - m1



Parameter estimates - m6 - M1 with common alpha

$$\log m_{xti} = \alpha_x + \kappa_{ti}^1 + (x - \bar{x})\kappa_{ti}^2$$

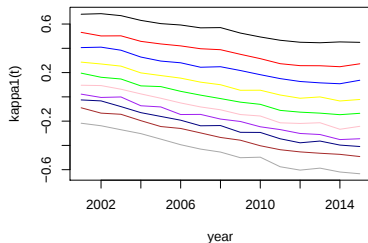
MLE estimated kappa1(t) - m6



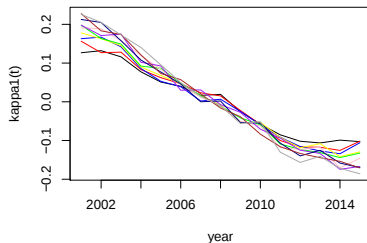
Parameter estimates - m6 - M1 with common alpha

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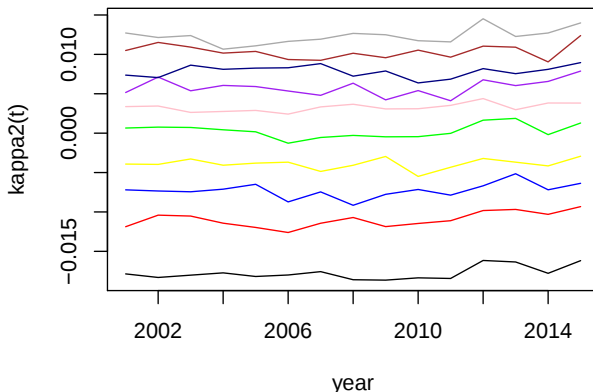
MLE estimated kappa1(t) - m1



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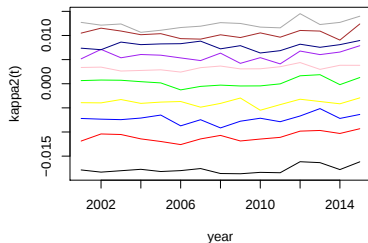
MLE estimated kappa2(t) - m6



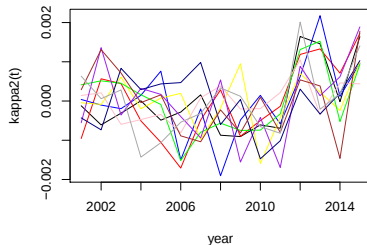
Parameter estimates - m6 - M1 with common alpha

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MLE estimated kappa2(t) - m6

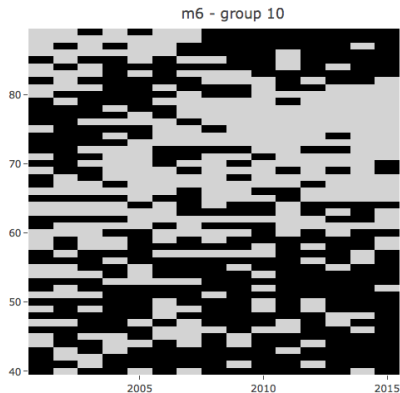
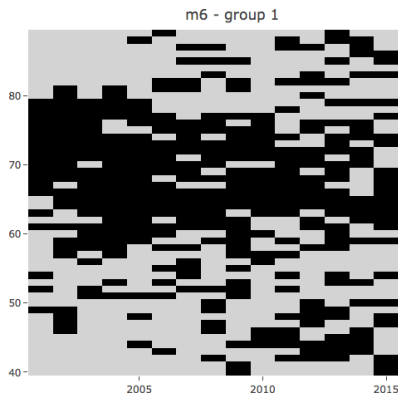


MLE estimated kappa2(t) - m1



Parameter estimates - m6 - M1 with common alpha

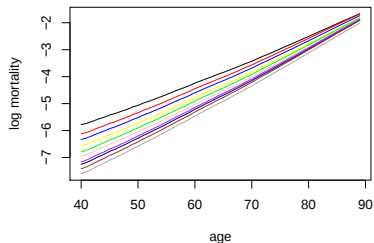
$$\log m_{xti} = \alpha_x + \kappa_{ti}^1 + (x - \bar{x})\kappa_{ti}^2$$



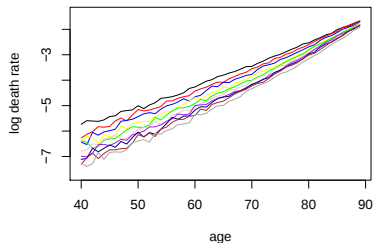
Parameter estimates - m6 - M1 with common alpha

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Fitted mortality in 2015 – m6



male mortality in year 2015



Parameter estimates - m6 - M1 with common alpha

Bayesian Information Criterion: $k \log n - 2 \log(L)$

	Log-likelihood	parameters	constraints	d.o.f.	BIC
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- smallest number of parameters
- second best model in terms of BIC
- better BIC than m1



Ranking the Models - Goodness of Fit - Bayesian Information Criterion: $k \log n - 2 \log(L)$

	Log-likelihood	parameters	constraints	d.o.f.	BIC
m1	-31,403.22	800	20	780	69,766.10
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m3	-31,962.82	530	2	528	68,636.80
m4	-31,700.90	665	11	654	69,237.21
m5	-31,474.15	675	12	663	68,864.03
m6	-32,052.10	350	2	348	67,209.29
m7	-31,467.01	665	11	654	68,769.44
m8	-31,460.51	675	12	663	68,836.75
m9	-32,184.56	120	6	114	65,386.30
m10	-31,536.52	550	4	546	67,944.81
m11	-30,323.70	1350	22	1328	72,496.68
m12	-30,131.47	1800	40	1760	75,966.82
m13	-30,558.20	1150	20	1130	71,199.00
m14	-30,852.96	450	4	446	65,685.42
m15	-30,462.15	1215	22	1193	71,560.04



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Ranking the Models - Goodness of Fit - Bayesian Information Criterion: $k \log n - 2 \log(L)$

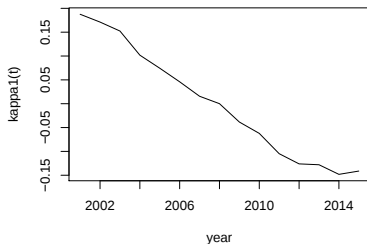
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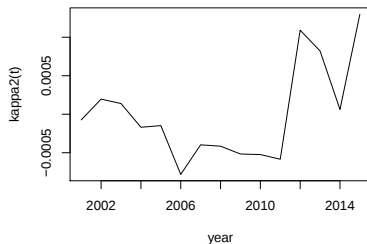
Lowest BIC - M9

$$\log m_{xti} = \alpha_x + \eta_i(x - \bar{x}) + \kappa_t^1 + d_i^0 + d_i^1(t - \bar{t}) + (x - \bar{x})(\kappa_t^2 + d_i^2(t - \bar{t}))$$

MLE estimated kappa1(t) - m9

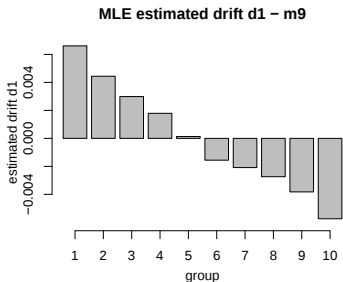
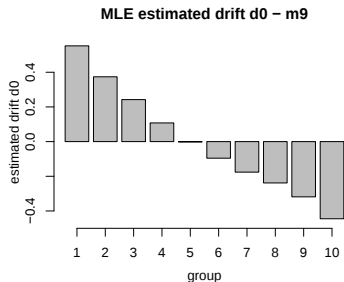


MLE estimated kappa2(t) - m9



Lowest BIC - M9

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- Lowest BIC, few parameters
- introduces constant group specific improvement rates
- for ever increasing mortality differentials



Models

$$\text{m1: } \log m_{xti} = \alpha_{xi} + \kappa_{ti}^1 + (x - \bar{x})\kappa_{ti}^2 \quad (\text{Plat, 2009})$$

$$\text{m2: } \log m_{xti} = \alpha_{xi} + \beta_x^1 \kappa_{ti}^1 + \beta_x^2 \kappa_{ti}^2 \quad (\text{Kleinow, 2015})$$

⋮

$$\text{m6: } \log m_{xti} = \alpha_x + \kappa_{ti}^1 + (x - \bar{x})\kappa_{ti}^2 \quad \text{m1} + \text{common } \alpha$$

⋮

$$\begin{aligned} \text{m9: } \log m_{xti} = & \alpha_x + \eta_i(x - \bar{x}) + \kappa_t^1 \\ & + d_i^0 + d_i^1(t - \bar{t}) \\ & + (x - \bar{x})(\kappa_t^2 + d_i^2(t - \bar{t})) \end{aligned}$$

⋮

$$\text{m12: } \log m_{xti} = \alpha_{xi} + \beta_{xi}^1 \kappa_{ti}^1 + \beta_{xi}^2 \kappa_{ti}^2 \quad (\text{Renshaw\&Haberman, 2003})$$

⋮

$$\text{m14: } \log m_{xti} = \alpha_x + \beta_x^1 \kappa_{ti}^1 + \beta_x^2 \kappa_{ti}^2 \quad \text{m2} + \text{common } \alpha$$

$$\text{m15: } \log m_{xti} = \alpha_{xi} + \beta_x^1 \kappa_t^1 + \beta_{xi}^2 \kappa_{ti}^2 \quad (\text{Li\&Lee, 2005})$$



Conclusions

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- However, for a narrower age range (65-89), models with constant/linear β 's, (Plat (2009) + common α) are better.
- Cohort effect do not improve the fit for those models
- If a cohort effect is included it should be a common cohort effect

