

MORTALITY IMPROVEMENT RATE MODELLING AND PROJECTING

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AGENDA

- Motivation
- History
- Model Construction
- Case Study: Modelling Mortality Rates
Modelling Mortality Improvement Rates
- Conclusions

MODELLING & PROJECTING MORTALITY

IMPROVEMENT RATES: HISTORY

MR- mortality rates

Lee & Carter (1992) Brouhns, Denuit, Vermunt (2002) Renshaw & Haberman (2006)	Cairns, Blake, Dowd et al. (2008) Plat (2009) Haberman & Renshaw (2011)
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MR- mortality improvement rates

Willets (2004) Richards, Kirkby, Currie (2005) Renshaw & Haberman (2006) CMI

DATA

$(d_{xt}, e_{xt}, \omega_{xt})$: age x , period t

$y_{xt} = \hat{m}_{x,t} = \frac{d_{xt}}{e_{xt}}$ - empirical mortality rate

$z_{xt} = 2 \frac{(1 - \hat{m}_{x,t} / \hat{m}_{x,t-1})}{(1 + \hat{m}_{x,t} / \hat{m}_{x,t-1})}$ - mortality improvement rate

improving mortality (over time) $\Rightarrow z_{xt} > 0$

deteriorating mortality (over time) $\Rightarrow z_{xt} < 0$

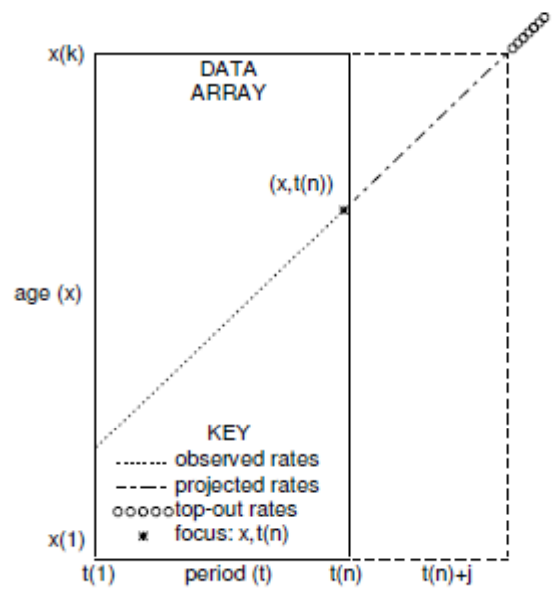
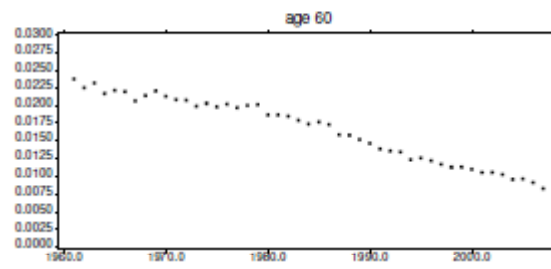
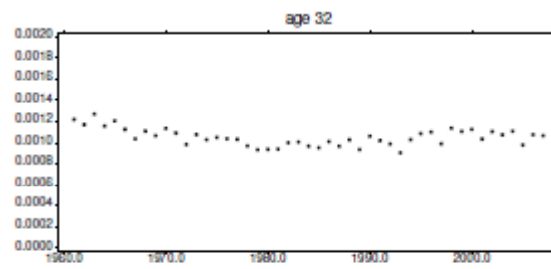


Fig 2. Schematic diagram depicting a rectangular age-period data array with cohort trajectory, focus at age x , in peripheral year $t(n)$, partitioned in three: comprising observed, projected and top-out mortality rates.



E&W 1961-2007 male mortality.
MR vs period, fixed ages: 32 or 60

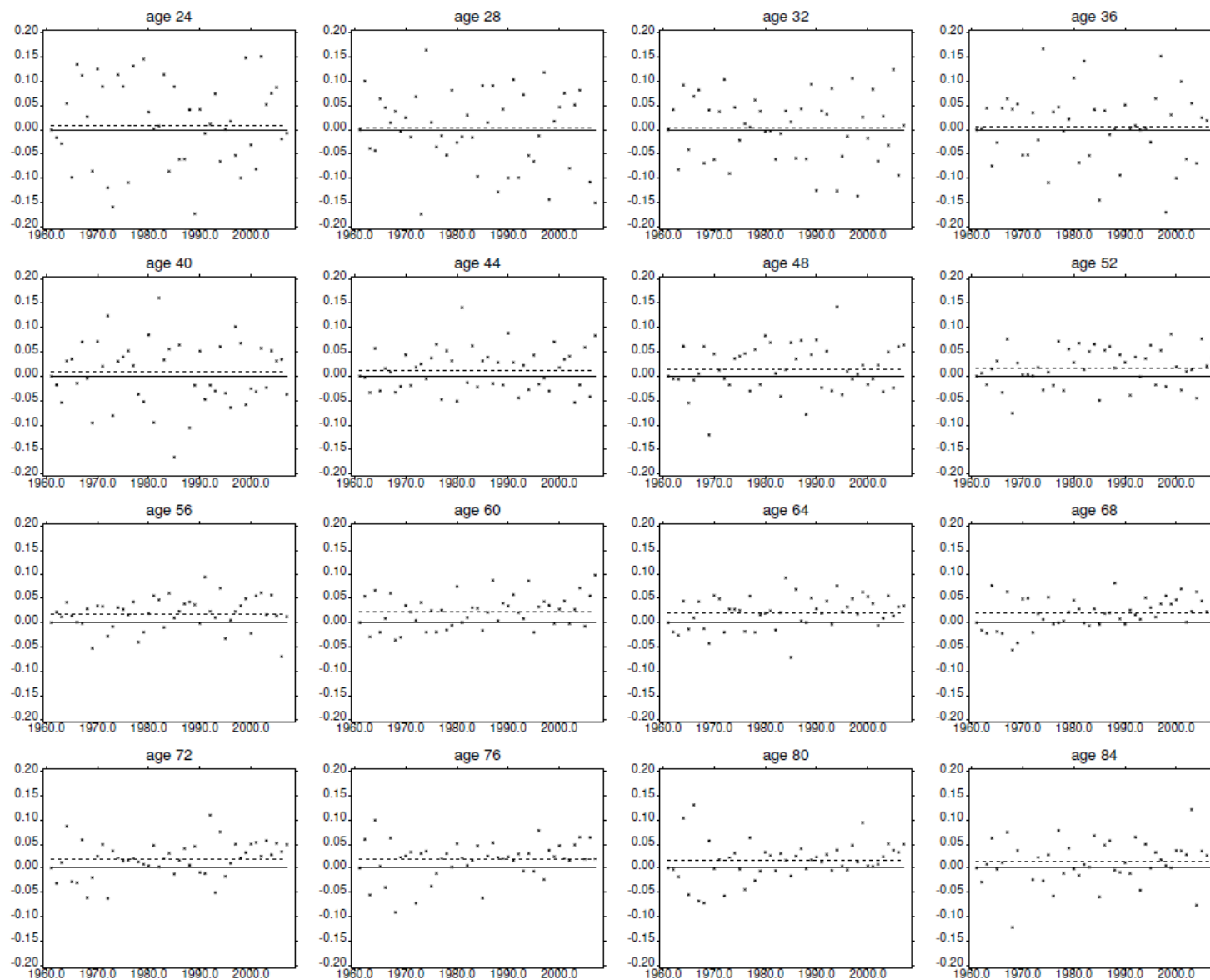


Fig 3a. England & Wales 1961-2007 male mortality experience. Mortality improvement rates (MIR) and their average over time (dotted line), plotted against calendar year for various fixed ages.

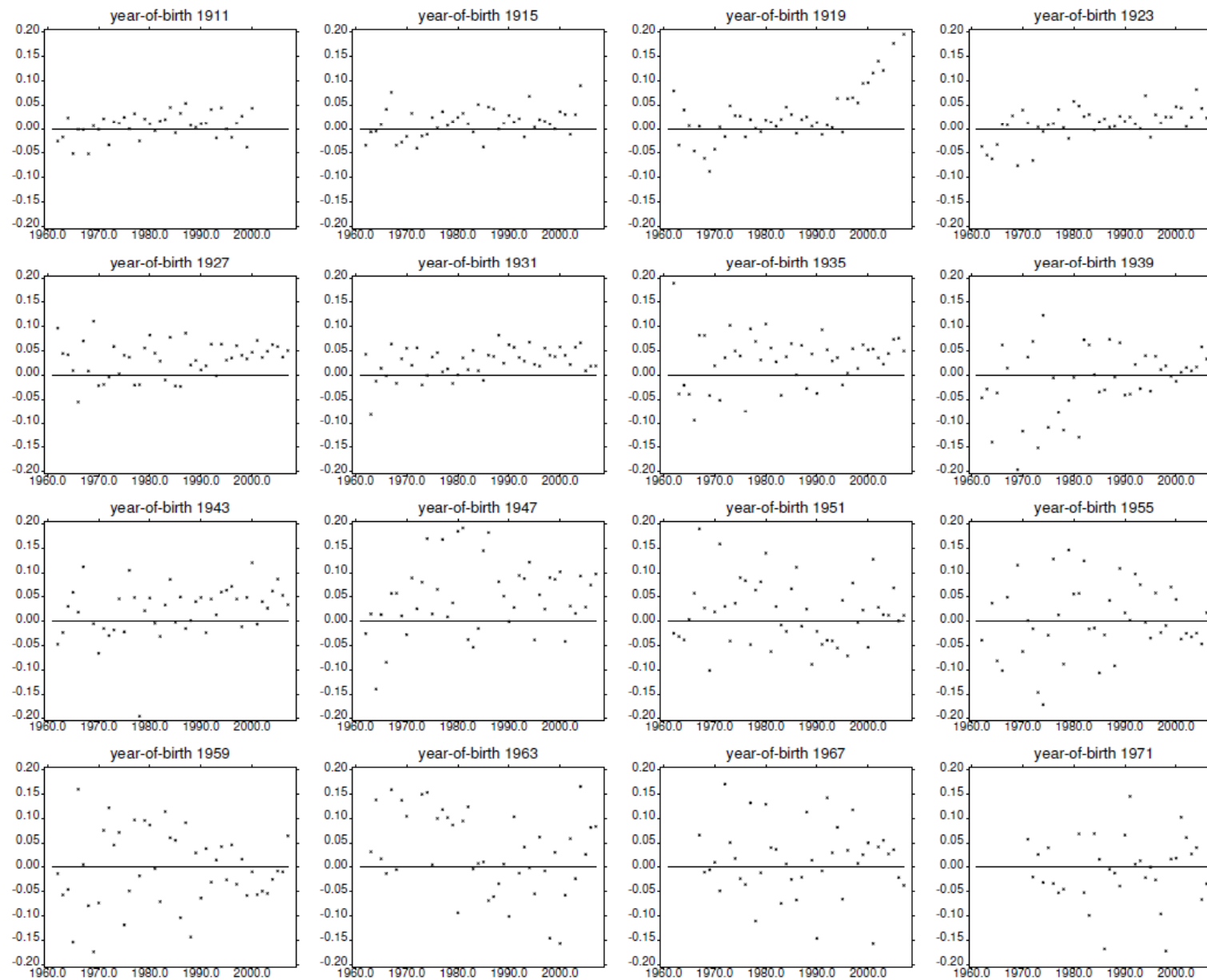
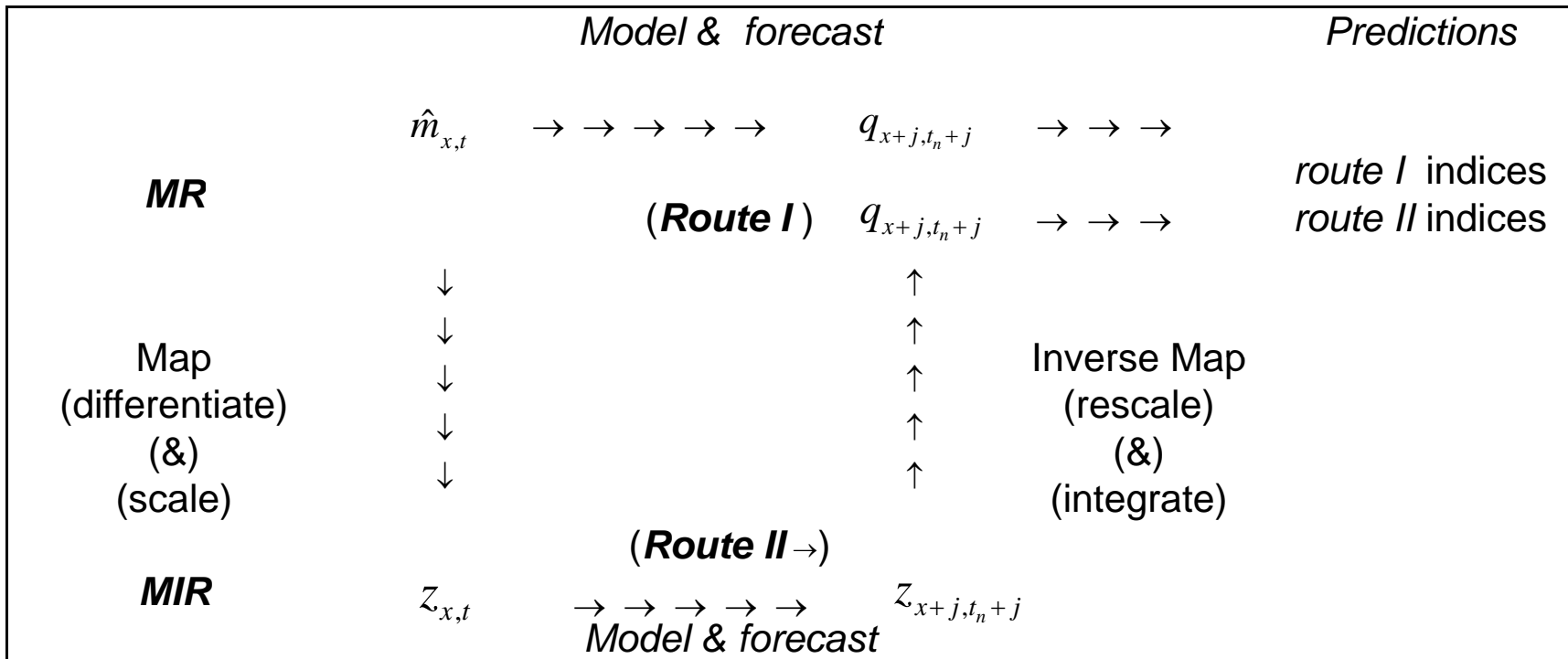


Fig 3b. England & Wales 1961-2007 male mortality experience. Mortality improvement rates (MIR) plotted against year of observation for various fixed years-of-birth (cohorts).



$m_{x,t}$ - Central mortality rate (MR); $z_{x,t}$ - mortality improvement rate (MIR)
 q_{x+j,t_n+j} - predicted probability of death **MR** predictions- **route I**; **MIR** predictions- **route II**

MORTALITY RATES (Route I)

APPROACH

TARGET:

m_{xt} - central rate of mortality

PARAMETRIC PREDICTOR STRUCTURES:

$$LC : \eta_{xt} = \alpha_x + \beta_x \kappa_t$$

$$H_1 : \eta_{xt} = \alpha_x + \beta_x \kappa_t + \iota_{t-x}$$

$$H_0 : \eta_{xt} = \alpha_x + \kappa_t + \iota_{t-x}$$

$$M5 : \eta_{xt} = \alpha_x + \kappa_t^{(1)} + (x - \bar{x}) \kappa_t^{(2)}$$

$$M6 : \eta_{xt} = \alpha_x + \kappa_t^{(1)} + (x - \bar{x}) \kappa_t^{(2)} + \iota_{t-x}$$

$$M7 : \eta_{xt} = \alpha_x + \kappa_t^{(1)} + (x - \bar{x}) \kappa_t^{(2)} + b(x) \kappa_t^{(3)} + \iota_{t-x}$$

MORTALITY RATES (Route I)

APPROACH

$$b(x) = \left\{ (x - \bar{x})^2 - \frac{1}{k} \sum_{i=x_1}^{x_k} (i - \bar{x})^2 \right\}, \quad \bar{x} = \frac{1}{k} \sum_{i=x_1}^{x_k} i$$

MODEL FITTING:

Let $D_{xt} \sim P(e_{xt} m_{xt})$ i.i.d., with constant dispersion

$$Y_{xt} = \frac{D_{xt}}{e_{xt}}, \quad E(Y_{xt}) = m_{xt}, \quad \text{Var}(Y_{xt}) = \phi \frac{m_{xt}}{\omega_{xt} e_{xt}}$$

log link $\log m_{xt} = \eta_{xt}$, parametric predictor η_{xt} , weights $\omega_{xt} e_{xt}$,

scale parameter ϕ , variance function $V(u) = u$

To fit: minimise the model deviance.

MORTALITY IMPROVEMENT RATES (Route II) APPROACH

MOTIVATION:

$$\log m_{xt} = \eta_{xt} \Rightarrow \frac{1}{m_{xt}} \frac{\partial m_{xt}}{\partial t} = \frac{\partial \eta_{xt}}{\partial t}$$

Notational convention: re-define symbols appropriately

TARGET:

η_{xt} - mortality improvement rate

MORTALITY IMPROVEMENT RATES (Route II) APPROACH

DUAL PARAMETRIC PREDICTOR STRUCTURES:

$$LC : \eta_{xt} = \beta_x \kappa_t$$

$$H_1 : \eta_{xt} = \beta_x \kappa_t + \iota_{t-x}$$

$$H_0 : \eta_{xt} = \kappa_t + \iota_{t-x}$$

$$M5 : \eta_{xt} = \kappa_t^{(1)} + (x - \bar{x}) \kappa_t^{(2)}$$

$$M6 : \eta_{xt} = \kappa_t^{(1)} + (x - \bar{x}) \kappa_t^{(2)} + \iota_{t-x}$$

$$M7 : \eta_{xt} = \kappa_t^{(1)} + (x - \bar{x}) \kappa_t^{(2)} + b(x) \kappa_t^{(3)} + \iota_{t-x} \quad \text{LINK FUNCTION: IDENTITY}$$

MORTALITY IMPROVEMENT RATES (Route II) APPROACH

MODEL FITTING (Single stage):

Assume $Z_{xt} \sim N(\eta_{xt}, \sigma^2)$ i.i.d., constant dispersion

$$E(Z_{xt}) = \eta_{xt}, \quad \text{Var}(Z_{xt}) = \sigma^2 \frac{1}{\omega_{xt}}$$

identity link, parametric predictor η_{xt} , weights ω_{xt}

scale parameter σ^2 , variance function $V(u) = 1$.

To fit: minimise the model deviance.

MORTALITY IMPROVEMENT RATES (Route II) APPROACH

MODEL FITTING (Joint Modelling with 2 stages):

Stage 1:

Assume $Z_{xt} \sim N(\eta_{xt}, \phi_{xt} \sigma^2)$ i.i.d., variable dispersion

$$E(Z_{xt}) = \eta_{xt}, \text{Var}(Z_{xt}) = \sigma^2 \frac{\phi_{xt}}{\omega_{xt}}$$

identity link, parametric predictor η_{xt} , weights ω_{xt} / ϕ_{xt}

scale parameter σ^2 , variance function $V(u) = 1$

Yields: residuals $r_{xt} = z_{xt} - \hat{\eta}_{xt}$ to form Stage 2 responses.

MORTALITY IMPROVEMENT RATES (Route II) APPROACH

Stage 2:

Model squared residuals R_{xt}^2 as follows

$$E(R_{xt}^2) = \phi_{xt}, \quad \text{Var}(R_{xt}^2) = \rho \frac{\phi_{xt}^2}{\omega_{xt}}$$

log link $\log(\phi_{xt}) = \zeta_x$, predictor ζ_x , weights ω_{xt}

scale parameter ρ , variance function $V(u) = u^2$

Yields: fitted values $\hat{\phi}_{xt}$ which are then used as Stage 1 weights

To fit: minimise the model deviances.

FITTING THE MODELS

- Use England and Wales male mortality experience for 1961-2007 ages 20-89
- Fit Route I, Route II models (single stage and joint stages)

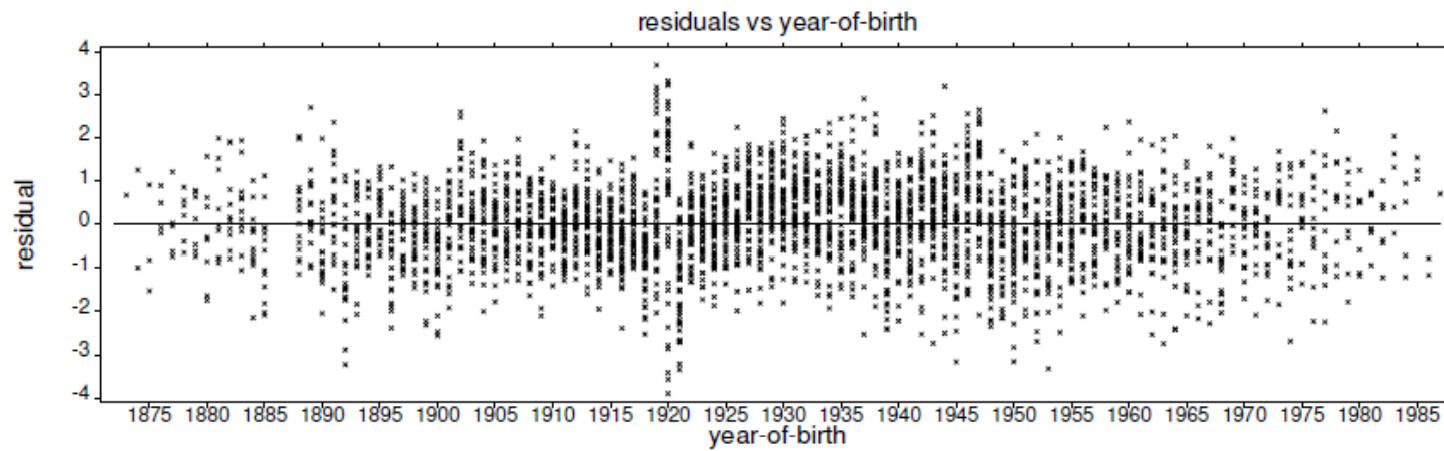
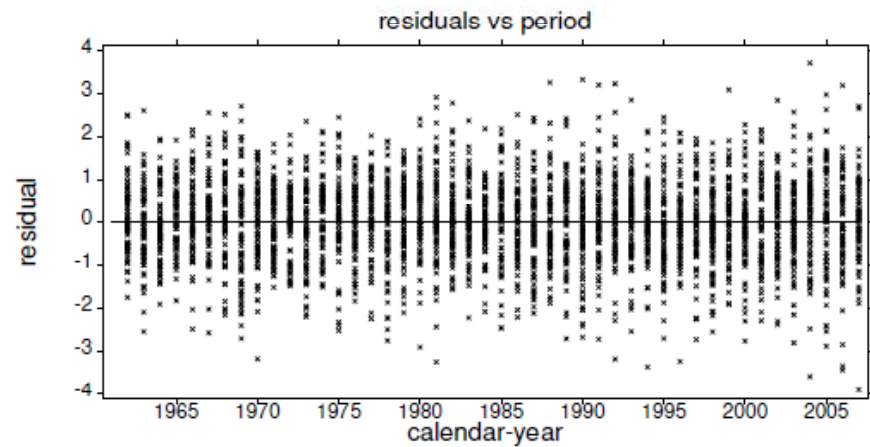
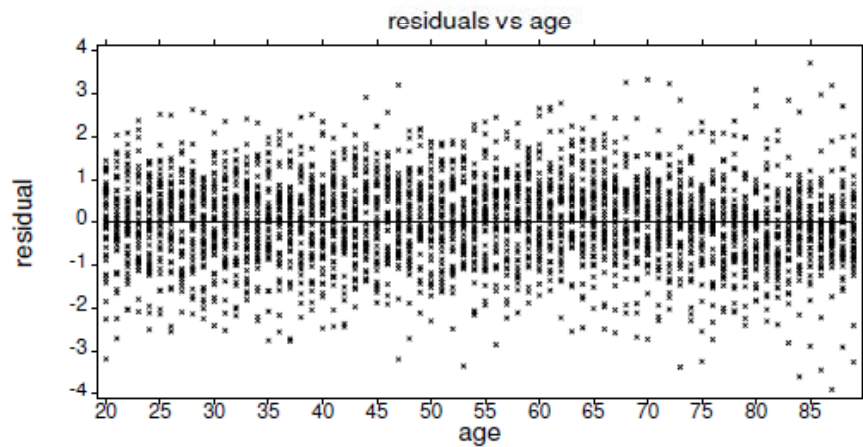


Fig 4b. England & Wales 1961-2007 male mortality experience, ages 20-89. MIR JLC modelling: standardised residual plots.

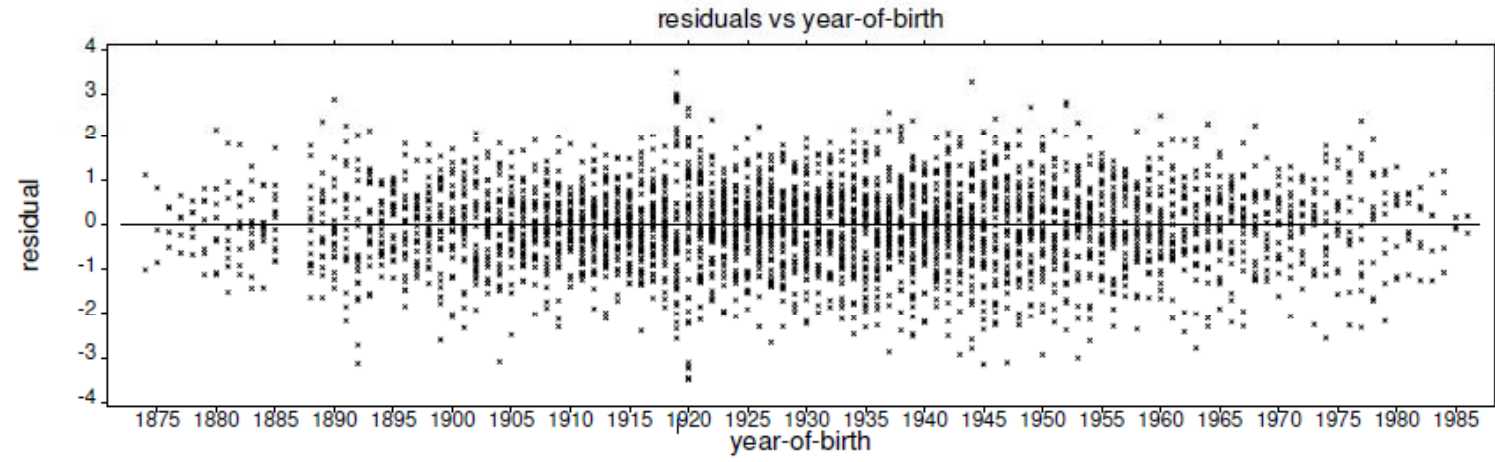
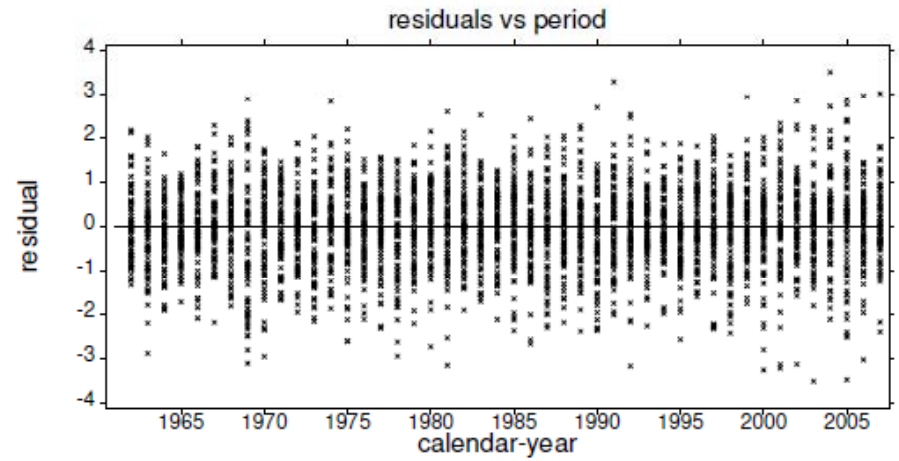
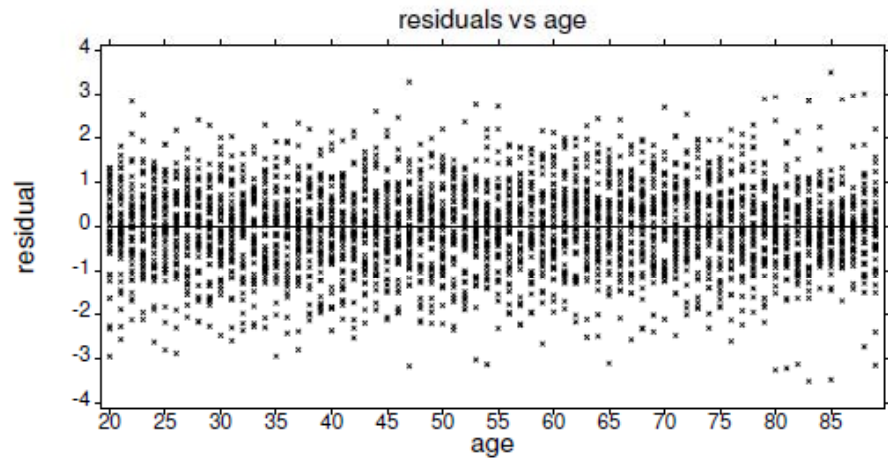
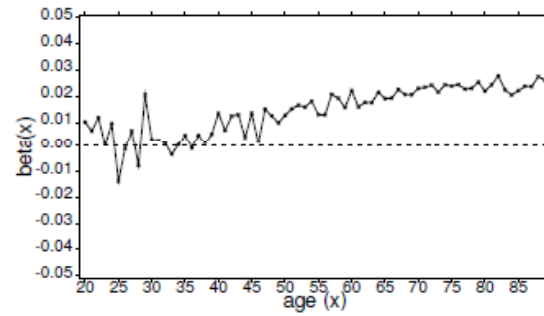
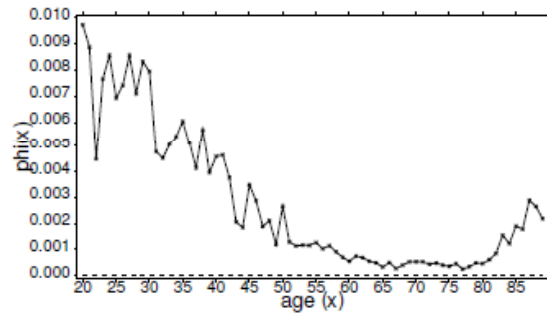
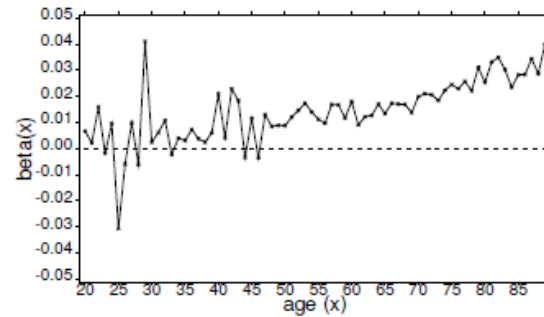


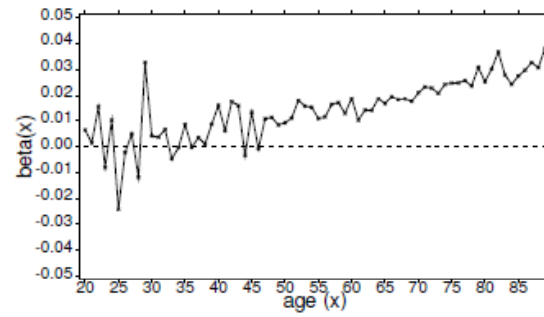
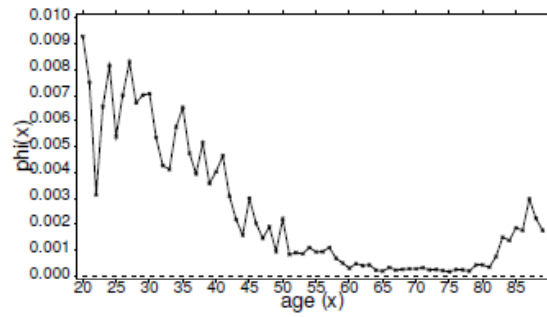
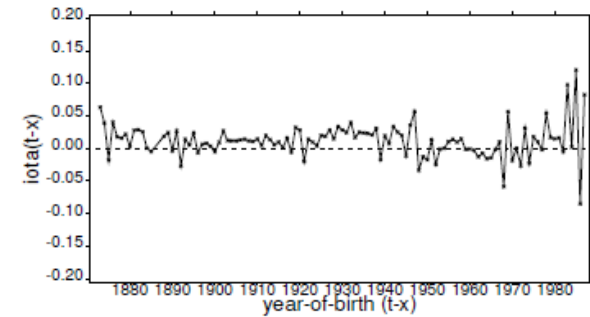
Fig 4d. England & Wales 1961-2007 male mortality experience, ages 20-89. MIR JH1 modelling: standardised residual plots.



MIR JLC modelling



MIR H1 modelling



MIR JH1 modelling

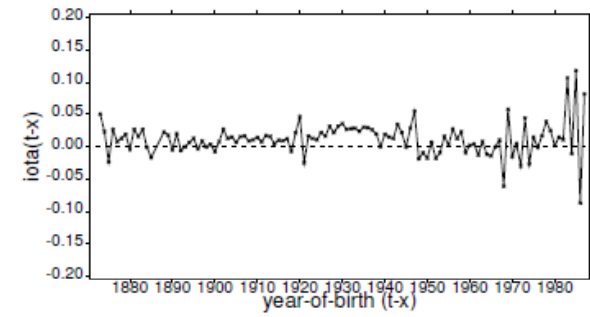


Fig 6. E&W males, ages 20-89. MIR models (rows), fitted parameters
 left panels:- $\phi(x)$; centre panels:- $\beta(x)$; right panels:- $\iota(t-x)$.

MODEL DYNAMICS

Recall for dual modelling

$$MR : \kappa_t \mapsto MIR : \frac{\partial \kappa_t}{\partial t}$$

Consequently

$$MR : ARIMA(p, 1, q) \mapsto MIR : ARMA(p, q)$$

UNIVARIATE CASE AR(1):

$$\kappa_t - \mu = \varphi(\kappa_{t-1} - \mu) + \varepsilon_t; \varepsilon_t \sim N(0, \tau^2) \text{ i.i.d.}$$

Forecasts

$$\kappa_{t_n+j} = \mu + \varphi^j(t_n - \mu); j = 1, 2, 3, \dots$$

MAPPING *MIR* PREDICTIONS TO *MR* PREDICTIONS

Compute *MIR* predictions z_{x,t_n+j} and

convert to *MR* predictions using -

$$m_{x,t_n+j} = m_{x,t_n+j-1} \frac{(2 - z_{x,t_n+j})}{(2 + z_{x,t_n+j})}; j = 1, 2, 3, \dots$$

Need starter values m_{x,t_n}

Once converted, compute

$$q_{x,t_n+j} \approx 1 - \exp(-m_{x,t_n+j})$$

TOPPING OUT BY AGE

Extrapolate model projections

$$q_{x+j, t_n+j} : j = 1, 2, \dots, x_k - x; (x < x_k)$$

using

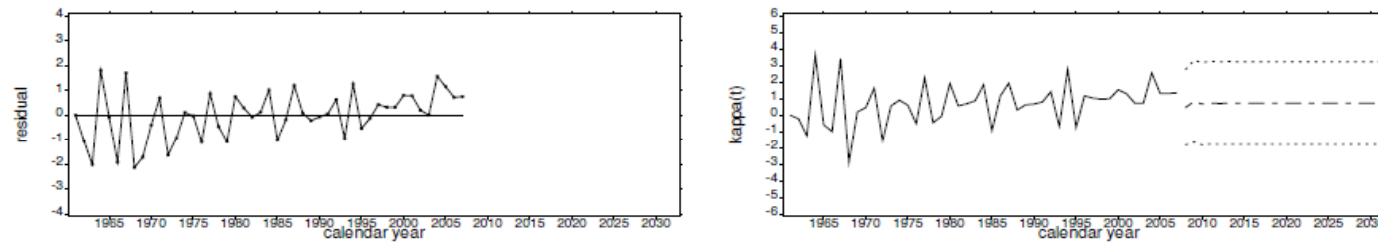
$$\log(q_{x+j, t_n+j}) = a + b \{j - (x_k - x - 1)\} \\ + c \{j - (x_k - x - 1)\} \{j - (x_k - x)\};$$

$$j = x_k - x - 1, x_k - x, x_k - x + 1, \omega - x$$

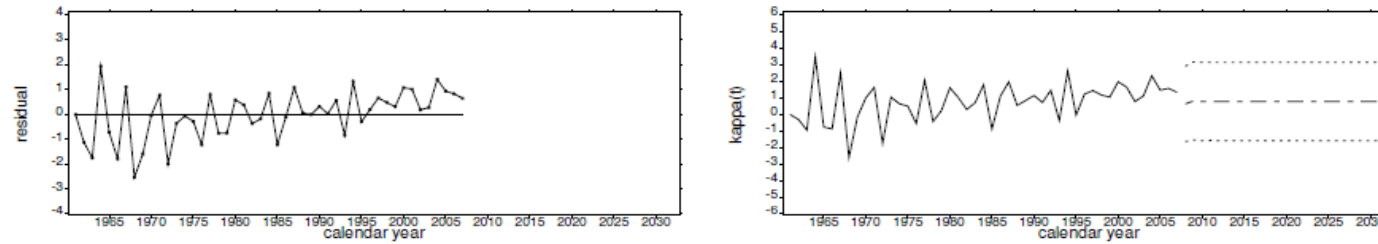
requiring

$$q_{x_k-1, t_n+x_k-x-1}, q_{x_k, t_n+x_k-x}, q_{\omega, t_n+x_k-x}$$

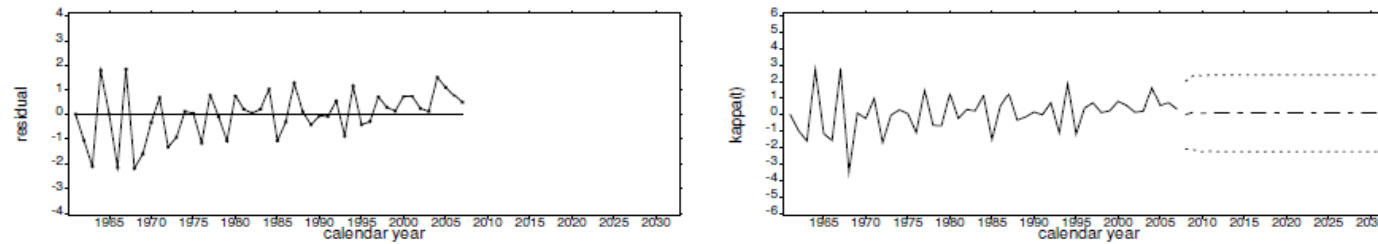
to determine a, b, c .



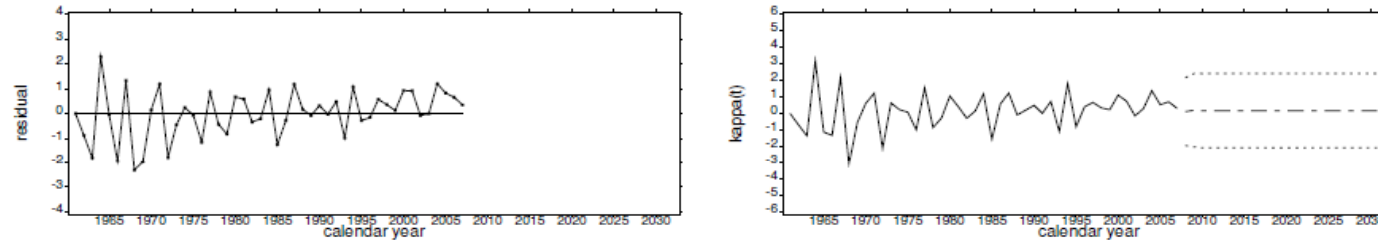
MIR LC modelling



MIR JLC modelling



MIR H1 modelling



MIR JH1 modelling

Fig 5. E&W 1961-2007 males, ages 20-89. AR(1) period index processes with forecasts (RH panels), residuals (LH panels): MIR- models (rows).

INDICES OF INTEREST

Life expectancy predictions-

$$e_x(t_n) = \frac{\sum_{j \geq 1} l_{x+j}(t_n + j) \left\{ 1 - \frac{1}{2} q_{x+j, t_n+j} \right\}}{l_x(t_n)}$$

Fixed rate annuity value predictions-

$$a_x(t_n) = \frac{\sum_{j \geq 0} l_{x+j}(t_n + j) v^j}{l_x(t_n)}$$

ESTIMATING PREDICTION INTERVALS BY SIMULATION: MIR

Generate predictions and prediction intervals.

Period index modelled as an $AR(1)$ process.

($VAR(1)$ process if multivariate).

ESTIMATING PREDICTION INTERVALS BY SIMULATION: MIR

ALGORITHM

For simulation $k = 1, 2, \dots, K$

For $j = 1, 2, \dots, J$

1. sample $\xi_k^{*(j)}$ from $N(0, 1)$
2. compute $\kappa_{t_n+j|k}^* = \kappa_{t_n+j} + \sqrt{mse_{t_n+j}} \xi_k^{*(j)}$
3. compute $z_{x+j, t_n+j|k}^*$
4. compute $m_{x+j, t_n+j|k}^*$
5. compute $q_{x+j, t_n+j|k}^*$
6. apply topping-out
7. compute indices of interest.

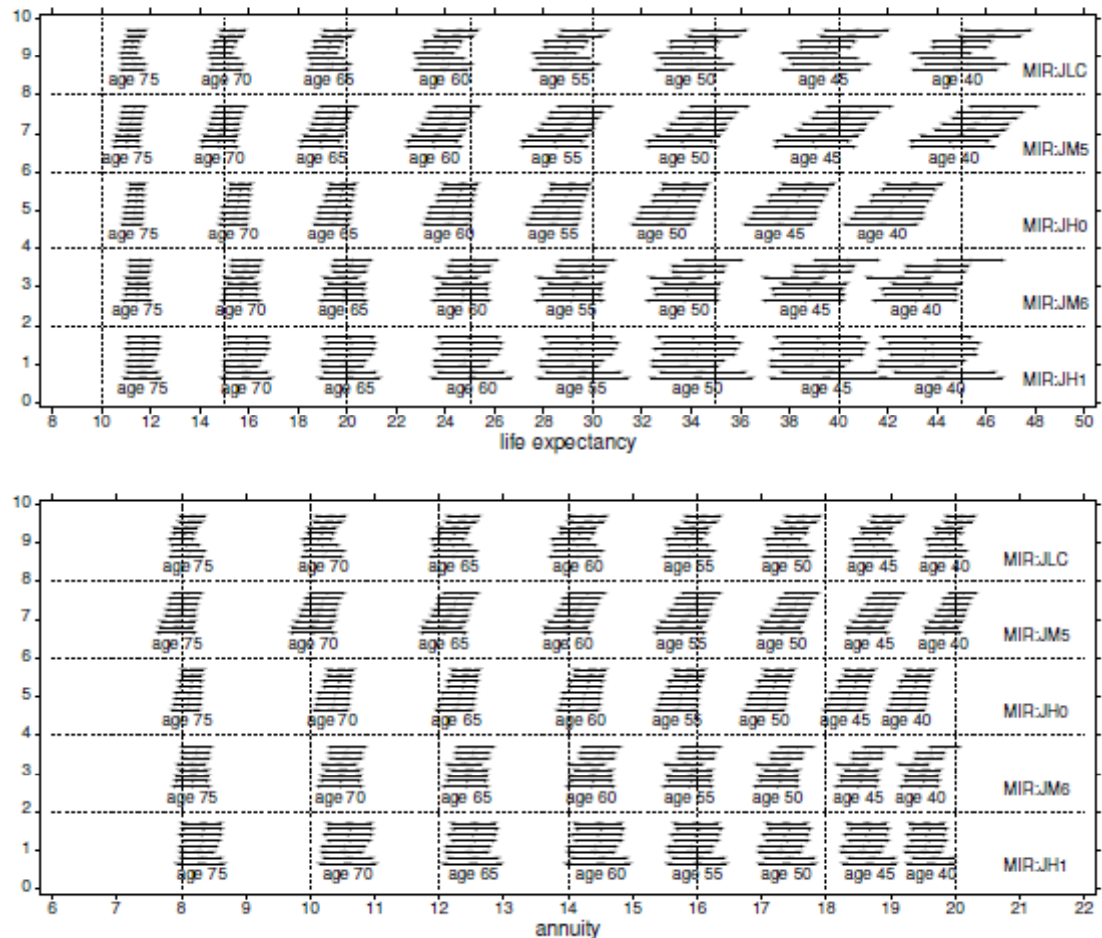


Fig 7a. E&W 1961-2007 males, ages 20-89. Year 2007 life expectancy and 4% annuity simulated 10%,50%,90% quantile predictions, subject to biennial front-end data deletions 1961(02)75 in ascending sequence, ages 40(05)75. MIR Route II approach. Structures- LC, M5, H0, M6, H1 fitted by joint modelling. Topping-out: $q(109)=1$

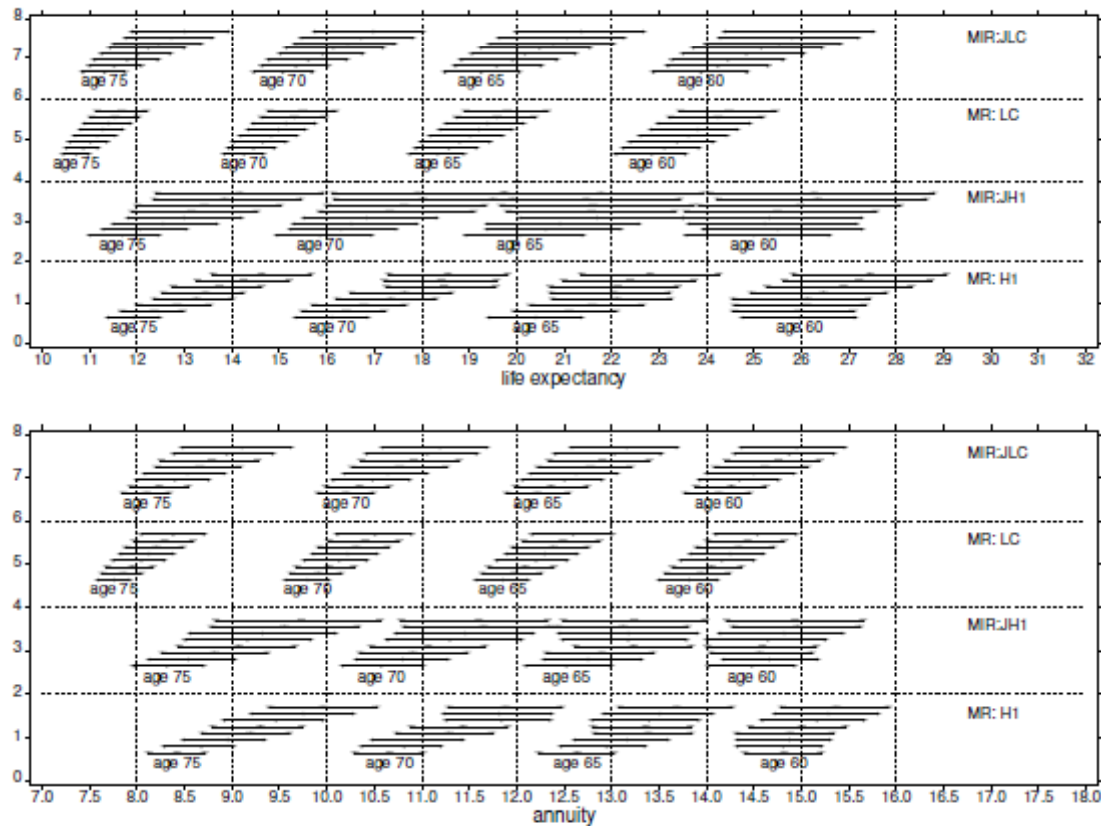
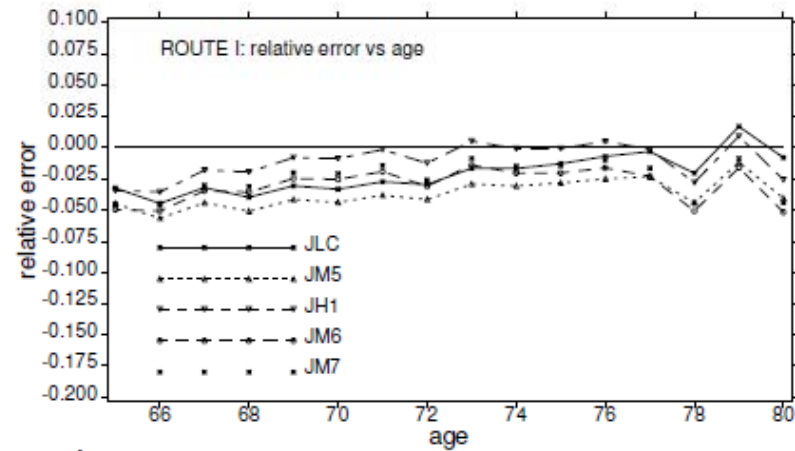
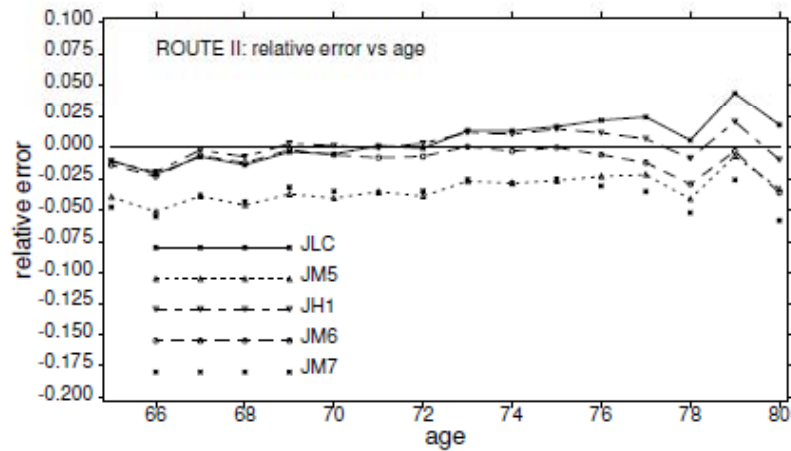


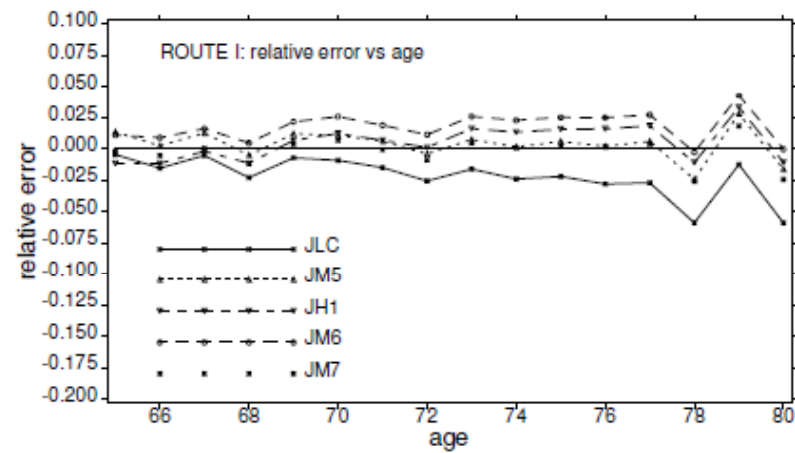
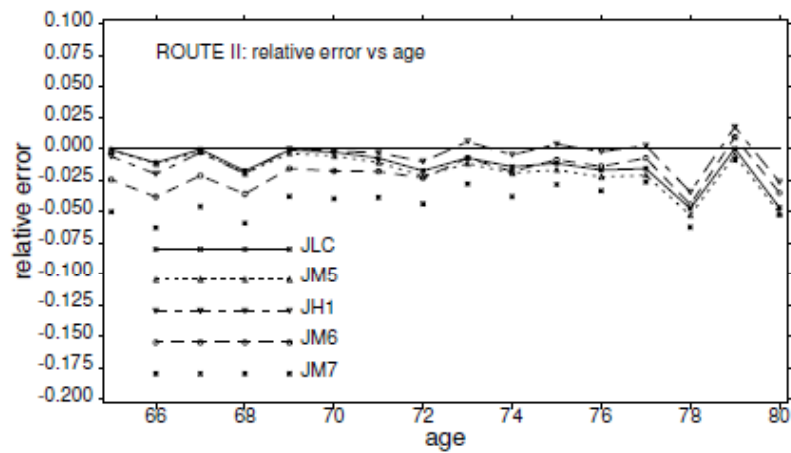
Fig 15. E&W 1961-2007 males, ages 20-89. Evolving biennial 2007(02)21 life expectancy and 4% annuity simulated 10%,50%,90% quantile predictions in ascending sequence, ages 60(05)75. Adjacent Route II and Route I approaches comparing MIR:JLC / MR:LC and MIR:JH1 / MR:H1 case structures. Topping-out: $q(109)=1$

FORECASTING

- Use England and Wales male experience for 1961-1982, ages 55-89 to fit models and then calculate life expectancies (and annuity values) for age x in 1982 by cohort method where $x = 65, 66, \dots, 80$
- Compare values for same indices calculated using raw mortality rates for 1983-2007, by depicting (predicted-actual) values against age.



male experience



female experience

Fig 15a. E&W male and female mortality experiences. Retrospective relative error in 1982 predicted life expectancies.(Route II LH panels; Route I RH panels): ages 65-80.

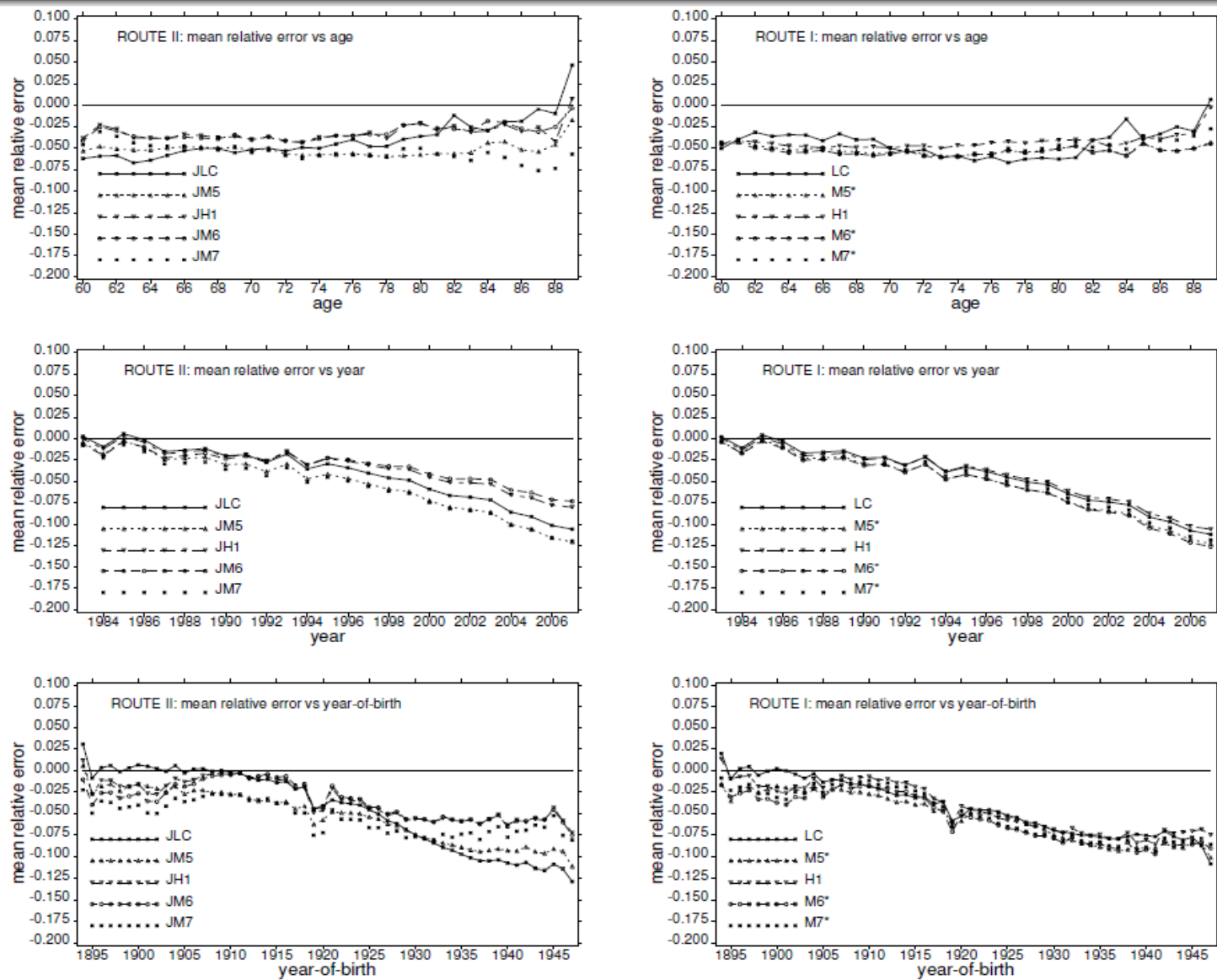


Fig 15b. EW males. Retrospective relative error in 1982 predicted log death rates, averaged over ages, years, cohorts respective. (Route II LH panels; Route I RH panels) based on region bounded by ages 60-89, years 1983-2007.

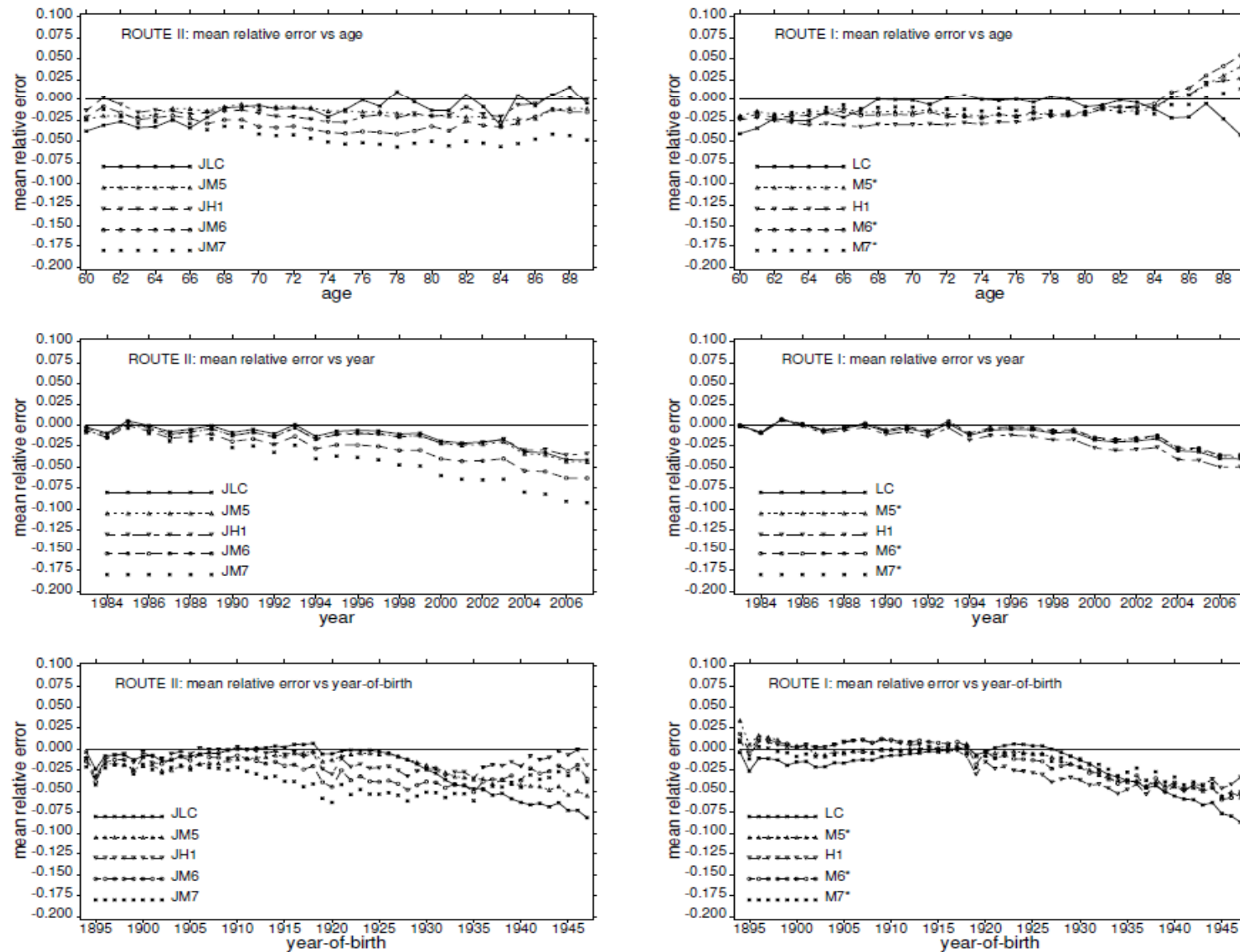


Fig 15c. EW females. Retrospective relative error in 1982 predicted log death rates, averaged over ages, years, cohorts respective. (Route II LH panels; Route I RH panels) based on region bounded by ages 60-89, years 1983-2007.

CONCLUSIONS

- Differencing the mortality rate series can lead to stationarity.
- Mortality improvement rate models have some advantages
 - age span of data is less restricted (for M5, M6, M7)
 - age index, α_x , plays no role
- Forward predictions show regular and desirable properties.
- Cohort-based version of MIR models is being developed.