

Statistical Modelling of Population Processes

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Recent advances in the analysis of categorical and count data
LSE, December 2013

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- Increasing need for population estimates and forecasts to include uncertainty

Rationale for Bayesian methods

- Increasing need for population estimates and forecasts to include uncertainty
- Methods for integrating uncertainty are underdeveloped in these areas

Rationale for Bayesian methods

- Increasing need for population estimates and forecasts to include uncertainty
- Methods for integrating uncertainty are underdeveloped in these areas
- The Bayesian approach offers a natural, flexible and probabilistic framework to integrate:
 - variability in data
 - uncertainty in model parameters
 - uncertainty in model choice
 - expert judgements, including their uncertainty

Rationale for Bayesian Methods

Example 1: Cohort Component Population Projections

Example 2: Integrated Modelling of European Migration
Conclusions

Example 1: Cohort component population projections

- **Objective:** To explore the consequences of choosing different specifications of age-specific fertility and mortality forecasting models in a closed cohort projection model

Example 1: Cohort component population projections

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- **Acknowledgements**
Research undertaken by the Centre for Population Change (CPC) funded by the Economic and Social Research Council (ESRC)

Thanks to other members of the CPC Modelling Team: Jakub Bijak, Jon Forster, Xiaoling Ou, James Raymer and Arkadiusz Wiśniowski

Forecasting age-specific mortality

- Model M1: Poisson-log-normal extension of the Lee-Carter model

$$D_{x,t} \sim Po(E_{x,t}m_{x,t})$$

$$\log(m_{x,t}) = \alpha_x + \beta_x k_t + \xi_{x,t}$$

$$k_t = p_1 + p_2 k_{t-1} + \xi_t^k$$

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- Model M2: Poisson-log-normal extension of the Lee-Carter model with cohort component (Haberman and Renshaw, 2006)

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$$\log(m_{x,t}) = \alpha_x + \beta_x k_t + \gamma_x c_{t-x} + \xi_{x,t}$$

$$k_t = p_1 + p_2 k_{t-1} + \xi_t^k$$

$$c_t = p_3 + p_4 c_{t-1} + \xi_t^c$$

Logarithm of female $m_{x,t}$ in the UK, 1974 to 2007

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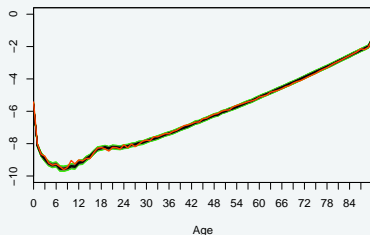
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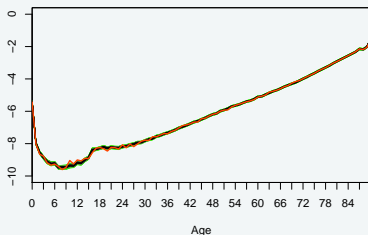
Female population projection model

Model fit, 1990 and 2007

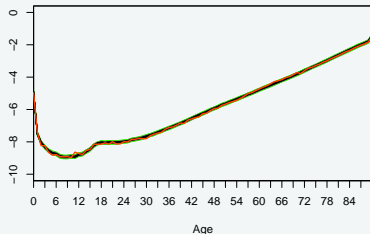
1990, Model M1



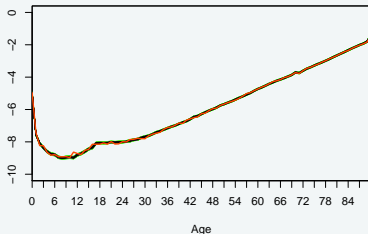
1990, Model M2



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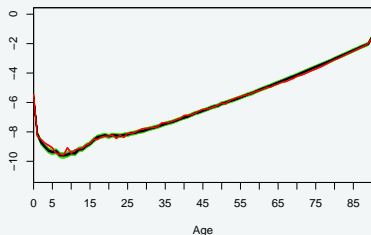
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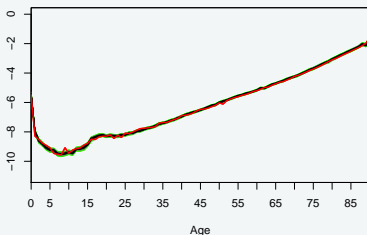
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Forecasted female mortality, 2008 and 2022

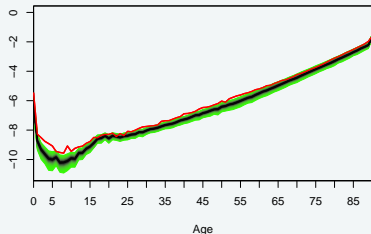
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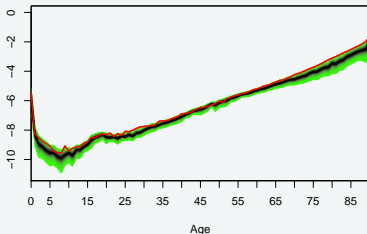
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- Model F2: Lee-Carter model with cohort component

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Fertility $f_{x,t}$ in the UK, 1974 to 2007

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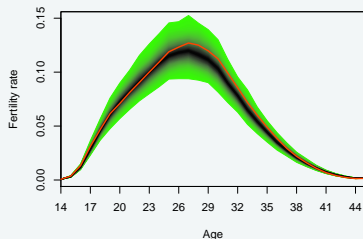
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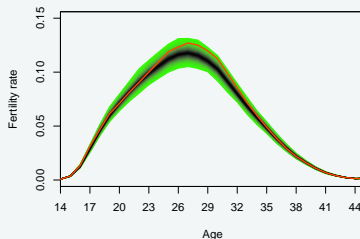
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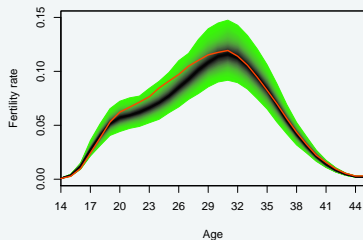
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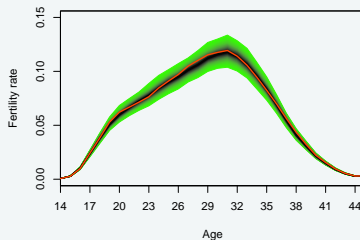
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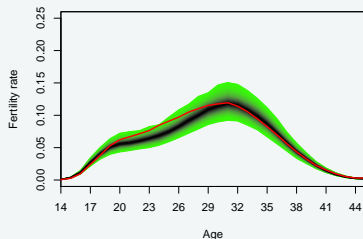
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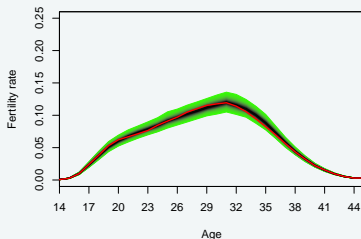
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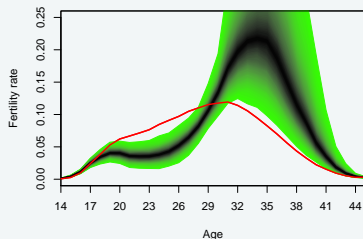
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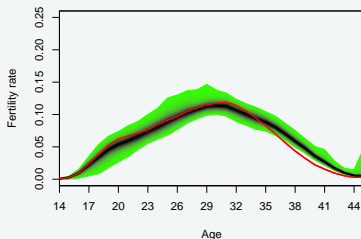
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Female population projection model

$$\begin{bmatrix} P_{0,t+1} \\ P_{1,t+1} \\ \vdots \\ P_{89,t+1} \\ P_{90+,t+1} \end{bmatrix} = \begin{bmatrix} 0 & \dots & b_{14,t} & \dots & b_{45,t} & \dots & 0 \\ s_{0,t} & 0 & 0 & & \dots & & 0 \\ 0 & s_{1,t} & 0 & & \dots & & 0 \\ \vdots & & \ddots & & & & \vdots \\ \vdots & & & \ddots & & & \vdots \\ 0 & 0 & \dots & & s_{88,t} & 0 & 0 \\ 0 & 0 & \dots & & 0 & s_{89,t} & s_{90+,t} \end{bmatrix} \begin{bmatrix} P_{0,t} \\ P_{1,t} \\ \vdots \\ P_{89,t} \\ P_{90+,t} \end{bmatrix}$$

where life table birth rates come from the fertility model:

$$b_{x,t} = g(f_{x,t})$$

and survivorship rates come from the mortality model:

$$s_{x,t} = g(m_{x,t})$$

Forecasted female population by age, M1+F1

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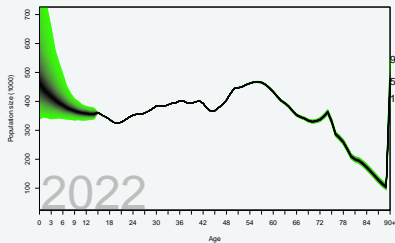
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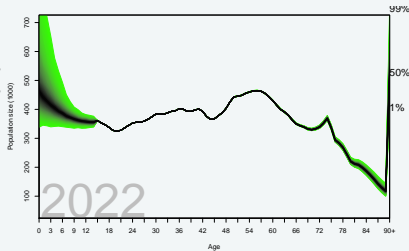
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Forecasted female population by age, 2022

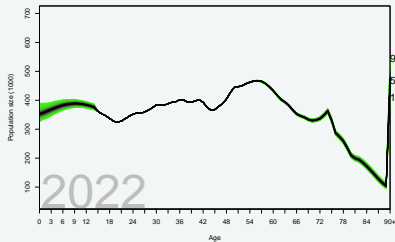
Model M1+F1



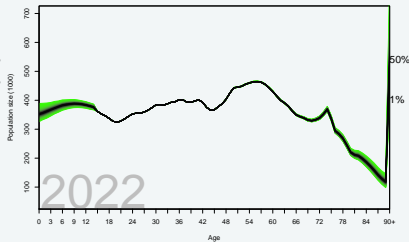
Model M2+F1



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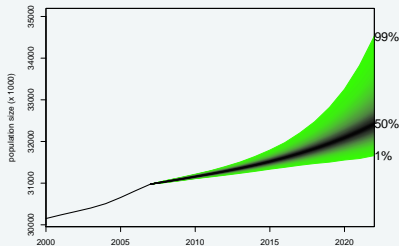
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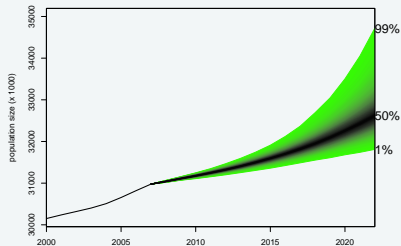
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Forecasted female population totals

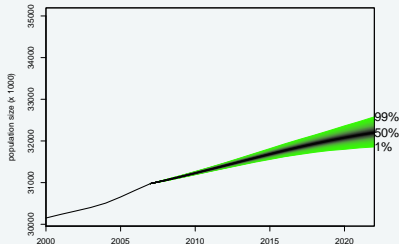
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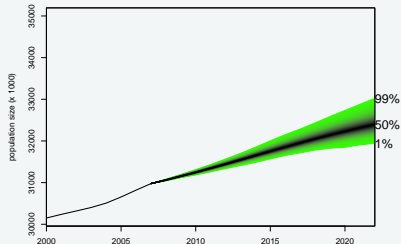
Model M2+F1



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- University of Oslo
 - Nico Keilman and Solveig Christiansen

- To provide a general framework for modelling migration flows between countries in the world in the context of inconsistent, inadequate and missing data

Objectives

- To provide a general framework for modelling migration flows between countries in the world in the context of inconsistent, inadequate and missing data
- Focus is on recent international migration flows between European Union and European Free Trade Association (EFTA) countries, using primarily publicly available sources, as well as qualitative information from experts

Double-entry matrix for selected countries, 2003

Origin		Destination									
		BE	CZ	DK	DE	EE	GR	ES	FR	IE	IT
BE	I		80	587	4291	3037	1959
	E	
CZ	I	...		232	9258	388	915
	E	78		47	950	2	66	70	283	31	197
DK	I	...	65		2693	764	281
	E	511	180		2540	133	229	1720	1333	264	782
DE	I	...	1228	3221		13746	12902
	E	4623	8909	2712		597	18106	16236	19060	2415	33802
EE	I	...	4	169	947		...	60	103
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ES	I	...	103	1665	14647	2051
	E	647	34	130	2109	4	38		2474	487	801
FR	I	...	462	1488	18133	8847		...	4647
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IT	I	...	274	895	23702	5796	
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I = receiving country's reported flow; E = sending country's reported flow;
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- The methodology is integrated and provides a synthetic data base with **measures of uncertainty** for international migration flows and other model parameters
- There are two key design aspects of the methodology:
 - The development of the underlying **statistical model**
 - The specification and **elicitation** of relevant **expert prior information**

- Scope: flows between 31 EU and EFTA countries, 2002-2008

Modelling framework

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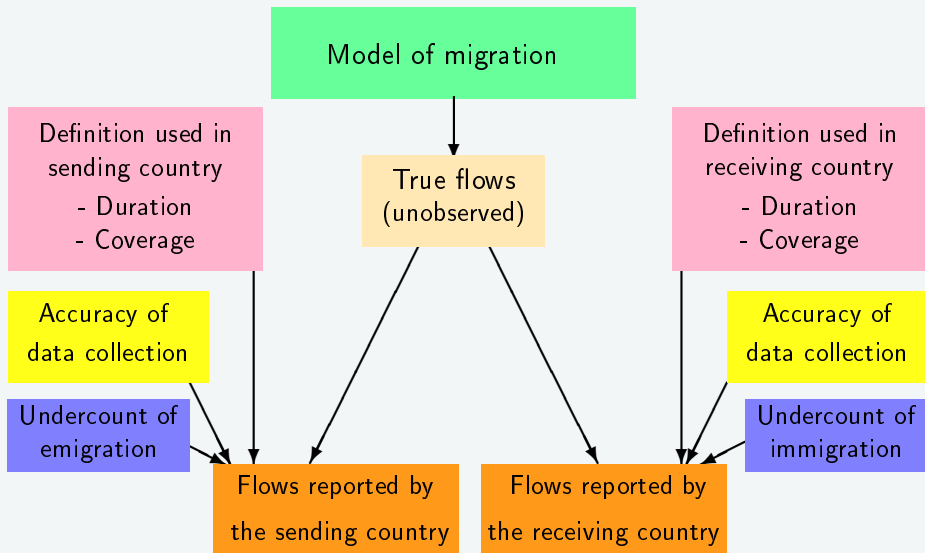
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Duration of stay criterion
Coverage of subpopulations
Undercount of emigrants and immigrants
Accuracy of data collecting systems

} \Rightarrow **Measurement error model**

Modelling framework ...



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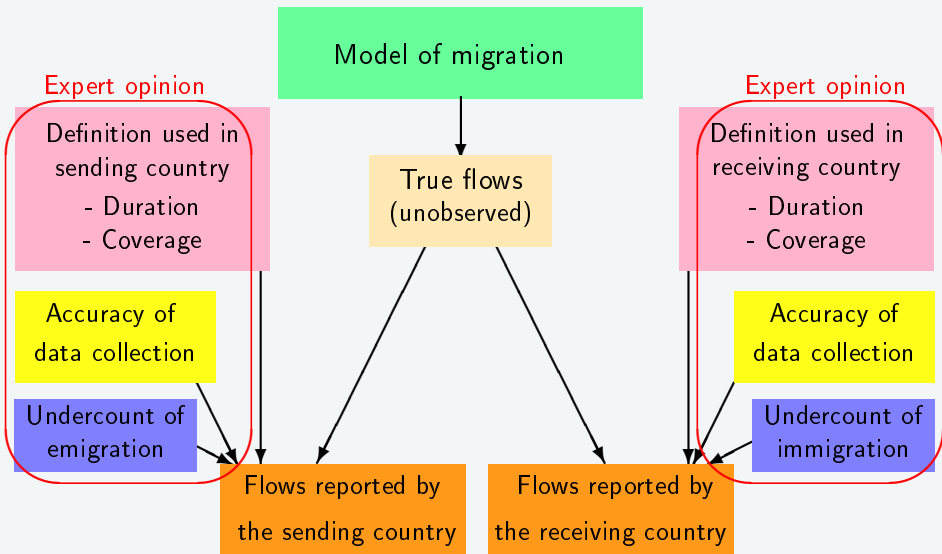
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Modelling framework - model equations

S - sending, R - receiving country, z - observed flows, y - true flows

Data equations:

$$z_{ijt}^S \sim \text{Po}(\mu_{ijt}^S)$$

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Measurement error model:

$$\log \mu_{ijt}^S = \log y_{ijt} + \delta_{m(i)} + \kappa_i + \lambda_{f(i)} + \varepsilon_{ijt}^S \quad \varepsilon_{ijt}^S \sim N(0, \tau_{c(i)}^S)$$

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Migration model:

$$\begin{aligned} \log y_{ijt} = & \alpha_1 + \alpha_2 \log P_{it} + \alpha_3 \log P_{jt} + \alpha_4 \log(G_{it}/G_{jt}) + \alpha_5 \log T_{ijt} \\ & + \alpha_6 C_{ij} + \alpha_7 A_{it} + \alpha_8 A_{jt} + \alpha_9 A_{ijt} + \alpha_{10} S_{ij} + \alpha_{11} S_{ji} \\ & + \alpha_{12} N_{ij} + \alpha_{13} M_{ijt} + \alpha_{14} F_{ijt} + \beta_t E_t + \nu_{ij} + \xi_{ijt} \end{aligned}$$

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- For high undercount of emigrants countries:
mean obs emigration flow = 38% × true flows

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- For high undercount of emigrants countries:
mean obs emigration flow = 38% × true flows
- For low undercount of immigrants countries:
mean obs immigration flow = 86% × true flows

Results

- Results incorporate expert opinions
- Duration of stay factors: $\text{mean obs flow} = \text{true flow} \times \text{duration}$

no time limit	3 months	6 months	12 months	permanent
188%	159%	137%	100%	44%

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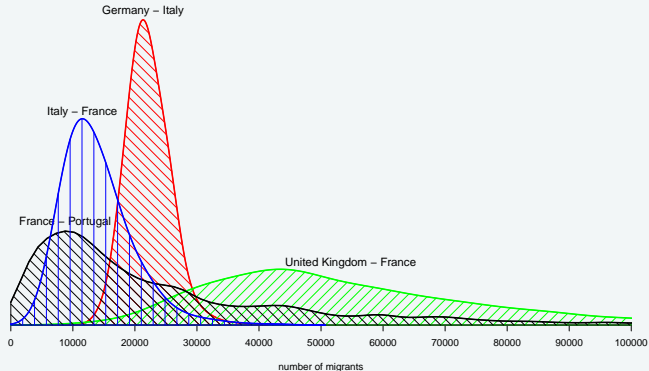
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- Accuracy: immigration data > emigration data
Scandinavian systems most accurate, survey-based least accurate

Posterior densities of true migration flows



Rationale for Bayesian Methods

Example 1: Cohort Component Population Projections

Example 2: Integrated Modelling of European Migration

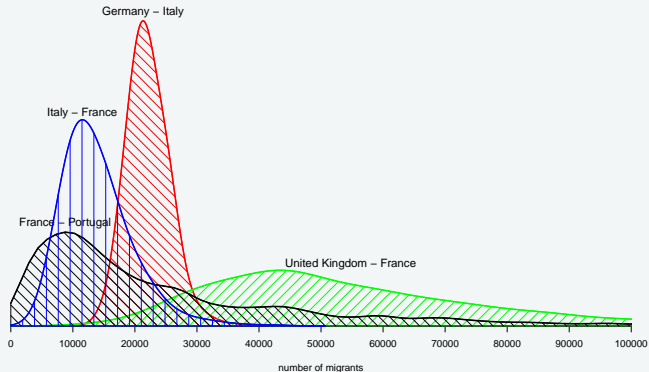
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Posterior densities of true migration flows



flow	mean	std.dev	rel.std.dev	median
FR-PT	29,400	43,100	147%	17,000
IT-FR	14,000	5,600	40%	12,800
DE-IT	22,100	3,300	15%	21,800
UK-FR	55,400	24,900	45%	49,600

Rationale for Bayesian Methods

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 - combine models for different components, such as mortality and fertility
 - combine a measurement model and a structural model
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 - combine a measurement model and a structural model
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 - provide coherent measures of uncertainty
- Bayesian methods can also incorporate model uncertainty
- Further work
 - currently including immigration and emigration in the cohort component projections
 - Bayesian model averaging planned for the cohort component projections
 - have extended the European migration model to estimate flows by age and sex