

Background and Rationale

- Uncertainty is immanent in all forecasts. In demography, the most difficult variable to predict is migration - a very complex process.
- In population forecasts, the main sources of uncertainty include:
 - Problems with data quality and availability
 - **Selection of the forecasting model [1]** ← **Current study**
 - Judgemental model assumptions
- How is uncertainty usually dealt with in migration forecasting?
 - Ignored (judgemental deterministic models)
 - Acknowledged, but not quantified (variant projections)
 - **Acknowledged and quantified (stochastic forecasts)** ←

Aims and Scope

- **Aim 1:** To contribute to the advancement of migration forecasting methodology using standard tools of Bayesian statistics
- **Aim 2:** To prepare forecasts of long-term migration between Germany and three European countries (Italy, Poland and Switzerland) for 2005-2010
- **Data:** yearly migration rates (MR)
 $MR = \text{Migrants} / \text{Population} \times 1,000$
 Economic variables: GDP per capita in PPP (Y), unemployment rates (U)



Sources: Eurostat, World Bank, UN ECE, NSIs (1985-2004, Poland: 1991-2004)

Option 1: Bayesian Model Selection and Averaging (Non-Nested Models)

Methodology [2]

Given data vector \mathbf{x} , forecast vector \mathbf{x}^F , and model space $\mathbf{M}=\{M_i\}$, such that $\bigcup_{i \in \mathbf{M}} M_i = \mathbf{M}$ and $i \neq j \Rightarrow M_i \cap M_j = \emptyset$, one can obtain:

- (1) Bayesian model selection criteria, based on the comparison of posterior probabilities of models:
$$p(M_i | \mathbf{x}) = \frac{p(M_i) \cdot p(\mathbf{x} | M_i)}{\sum_{k: M_k \in \mathbf{M}} p(M_k) \cdot p(\mathbf{x} | M_k)}$$
- (2) Averaged forecasts:
$$\bar{p}(\mathbf{x}^F | \mathbf{x}) = \sum_{k: M_k \in \mathbf{M}} p(M_k | \mathbf{x}) \cdot p(\mathbf{x}^F | \mathbf{x}, M_k)$$

Assumptions

Let \mathbf{M} be the ARMA[1,1] model class with constraints, $e_t \sim \text{iid } N(0, \sigma^2)$:

- M_1 : $\ln(MR_t) = c + e_t$ (oscillations),
- M_2 : $\ln(MR_t) = c + \ln(MR_{t-1}) + e_t$ (random walk with drift),
- M_3 : $\ln(MR_t) = c + \phi \ln(MR_{t-1}) + e_t$, $\phi \neq 0$, $\phi \neq 1$ [AR(1)],
- M_4 : $\ln(MR_t) = c - \theta e_{t-1} + e_t$, $\theta \neq 0$ [MA(1)],
- M_5 : $\ln(MR_t) = c + \phi \ln(MR_{t-1}) - \theta e_{t-1} + e_t$, $\phi \neq 0$, $\theta \neq 0$ [ARMA(1,1)].

Prior probabilities for models: (a) $p(M_i) = 0.2$ for all i [flat prior], and (b) $p(M_i) \propto 2^{-i}$ [Occam's razor favouring M_i with less parameters i].

Prior distributions for parameters: $c \sim N(0, 100^2)$ [hardly informative], $\phi, \theta \sim N(0.5, 1^2)$ [likely stationary], $\tau = 1/\sigma^2 \sim \Gamma(0.5, 0.5)$ [low precision].

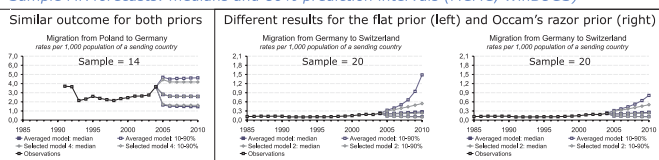
Selected Results

- Model choice is sensitive on prior probabilities $p(M_i)$, but often yields random walks
- Median forecasts for (a) and (b) are plausible and similar; prediction intervals can differ
- Weak fit (small samples): role of prior information

Estimated model posterior probabilities

Model (M_i)	M_1	M_2	M_3	M_4	M_5
Flat prior	0.200	0.200	0.200	0.200	0.200
Occam's razor prior	0.200	0.200	0.154	0.154	0.277
Migration from Italy to Germany, $m_{i,c}$	0.000	0.347	0.205	0.007	0.441
$p(M_i)$ prior (a)	0.000	0.616	0.181	0.007	0.196
Migration from Germany to Italy, $m_{c,i}$	0.000	0.249	0.367	0.018	0.366
$p(M_i)$ prior (b)	0.000	0.456	0.250	0.018	0.174
Migration from Poland to Germany, $m_{i,c}$	0.155	0.092	0.198	0.313	0.241
$p(M_i)$ prior (a)	0.272	0.168	0.175	0.275	0.111
Migration from Germany to Poland, $m_{c,i}$	0.079	0.207	0.291	0.171	0.252
$p(M_i)$ prior (b)	0.135	0.361	0.240	0.147	0.108
Migration from Switzerland to Germany, $m_{i,c}$	0.119	0.283	0.224	0.166	0.208
$p(M_i)$ prior (a)	0.187	0.431	0.173	0.128	0.081
Migration from Germany to Switzerland, $m_{c,i}$	0.000	0.469	0.311	0.003	0.217
$p(M_i)$ prior (b)	0.000	0.456	0.232	0.002	0.081

Sample MR forecasts: medians and 80% prediction intervals (MCMC, WinBUGS)



Option 2: Hybrid Bayesian-LR Nested VAR Modelling 'General to Specific'

Methodology [3]

Given the k -dimensional VAR(1) model M_0 : $\mathbf{y}_t = \mathbf{c} + \mathbf{A}\mathbf{y}_{t-1} + \mathbf{e}_t$, $\mathbf{A} = [a_{ij}]_{k \times k}$, the significance of the impact of the i -th component of \mathbf{y}_{t-1} ($y_{t-1,i}$) on the remaining $k-1$ components of \mathbf{y}_t is tested by imposing restrictions $a_{ij} = 0$ ($j \neq i$), defining a new model, M_i . Estimation of the parameters is Bayesian, while the selection is based on the log-likelihood ratio test:

$$LR(M_i, M_0) = -2(\ln p(\mathbf{x} | M_i, \theta_0) - \ln p(\mathbf{x} | M_0, \theta_0)) \quad [\theta: \text{model parameters}]$$

Similarly, restrictions on an extended nested model structure $M_0 \supset M_1 \supset M_2 \supset \dots$, and for feedback effects ($a_{ij} = a_{ji} = 0$, $j \neq i$), can be tested.

Assumptions

Let M_0 be such that $\mathbf{y}_t = [\ln(MR_t), \ln(Y_t^R/Y_t^S), \ln(U_t^S)]'$, where R and S indicate respectively the receiving and sending country.

The following models are considered: M_0 , M_{21} , M_{31} , and M_{23} [AR(1)].

Error term is a 3-dimensional Gaussian white noise: $\mathbf{e}_t \sim \text{iid } N(\mathbf{0}, \mathbf{T})$, where \mathbf{T} denotes the precision matrix.

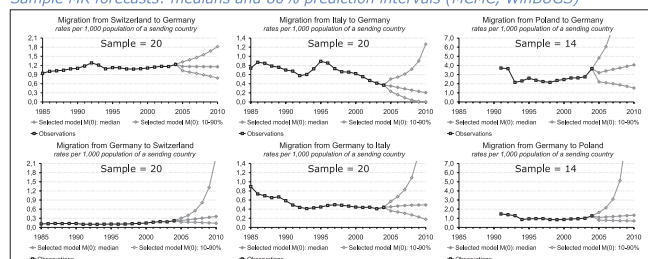
Prior distributions for parameters in M_0 : $c_i \sim N(0, \sqrt{1000^2})$, $a_{ii} \sim N(1, 1^2)$, $a_{12}, a_{13} \sim N(0.5, 1^2)$ [from the migration push-and-pull factors theory], $a_{21} \sim N(0, 0.1^2)$, $a_{31} \sim N(0, \sqrt{0.1^2})$, $a_{23}, a_{32} \sim N(0.1, \sqrt{0.5^2})$ [weak relations], $\mathbf{T} \sim \text{Wishart}(\mathbf{P}, 3)$, $\mathbf{P} = [p_{ij}]_{3 \times 3}$, $p_{ii} = 1$ and $p_{ij} = 0.005$ for $i \neq j$ [low precision].

For M_{21} , M_{31} , and M_{23} , appropriate elements of \mathbf{A} and \mathbf{P} are set to 0.

Selected Results

- The LR tests did not reduce the initial models M_0 despite weak fits
- Median forecasts of MR are plausible, but 80% predictive intervals are mostly too wide and exploding (\mathbf{y}_t close to 3D random walks)

Sample MR forecasts: medians and 80% prediction intervals (MCMC, WinBUGS)



Conclusions

- Both approaches account for the uncertainty of model specification, but in most models the errors of MR forecasts are implausibly high, due to: (1) small samples, (2) a likely random-walk (unpredictable) character of MR , and (3) the uncertainty of Y and U in the VARs
- Bayesian inference is suitable for forecasting migration based on short series, which are the only available data in most of Europe
- Possible paths of further research:
 - Use of fully Bayesian Lindley-type HPD tests for VAR restrictions
 - Wider classes of time series models; other explanatory variables
 - Analysis of robustness against changes in prior distributions

Notes and Acknowledgements

- [1] Ahlburg DA. 1995. *Math. Popul. Stud.* **5**(3), 281-290.
- [2] Hoeting JA, Madigan D, Raftery AE, Volinsky CT. 1999. *Stat. Sci.* **14**(4), 382-417.
- [3] Hendry DF. 1995. *Dynamic Econometrics*. Oxford: OUP.

Acknowledgements:

Study prepared within the research grant 03-34 of the Foundation for Population, Migration and Environment (BMU-PME) from Zurich, with the support of the stipend for young scientists of the Foundation for Polish Science (FNP). I am grateful to Prof. Jacek Osiewalski and Prof. Marek Kupiszewski for their comments. The usual disclaimer applies.