Spatial Filtering, Model Uncertainty and the Speed of Income Convergence in Europe

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Structure of the presentation

- **Our research question:** Evaluating robust effects of covariates on regional growth under model uncertainty in terms of
  - the choice of explanatory variables
  - the choice of a spatial weight matrix
- In particular, we are interested in obtaining robust estimates of the *proper* speed of income convergence (free of spatial spillovers) in Europe and thus quantifying the role of spatial spillovers in European regional growth
- **Structure:**
  - Model uncertainty
    - Spatial autocorrelation and model uncertainty
    - BMA, spatial weight uncertainty and spatial filtering
  - Growth and convergence in EU regions
    - The determinants of regional growth under model uncertainty
    - The speed of income convergence under model uncertainty
  - Conclusions

The problem of model uncertainty

- A stereotype SAR specification:

$$y = \alpha + \rho \mathbf{W} y + \mathbf{X}_k \vec{\chi}_k + \sigma \varepsilon,$$

  where y_i refers to regional growth and $\mathbf{X}_k = x_1, \ldots, x_k$ are k variables which belong to the set $\mathbf{X}$ of possible determinants of y and ε is an error term
- How important is a variable x_j in explaining y if we do not know which model is the true model: robustness of growth determinants
- Estimating the speed of convergence (purged of spatial feedback)
- Bayesian Model Averaging (BMA) presents a fully-fledged systematic approach to dealing with model uncertainty
- How can we integrate uncertainty about $\mathbf{W}$ in the BMA framework?

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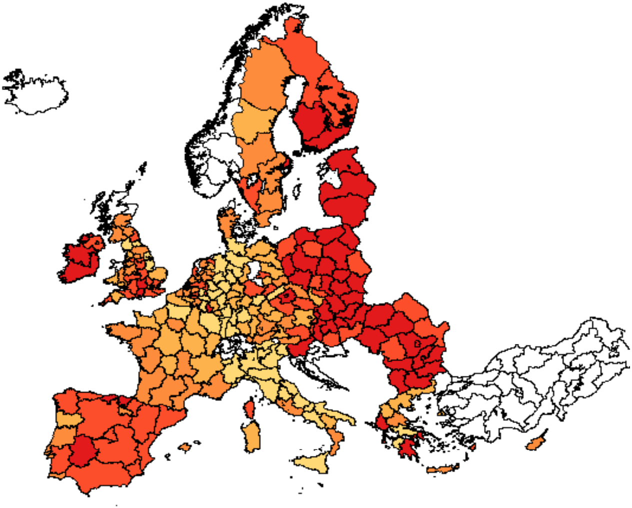
Economic growth in European regions 1995-2005



Bayesian Model Averaging

- Assume

$$y = \alpha + \rho \mathbf{W}_f y + \sum_{k=1}^{n} \beta_k x_k + \sigma \varepsilon,$$

and a set of competing models, $\{M_1, \ldots, M_M\}$ defined by the choice of variables in $\mathbf{X}$ and a spatial weight matrix $\mathbf{W}_f$.

- Our quantity of interest is the effect of variable x_j, β_j

$$\mathrm{P}(\beta_j|\mathbf{Y}) = \sum_{m=1}^{M} \mathrm{P}(\beta_j|\mathbf{Y}, M_m)\mathrm{P}(M_m|\mathbf{Y}),$$

where $\mathrm{P}(M_k|\mathbf{Y})$ are the posterior model probabilities,

$$\mathrm{P}(M_k|\mathbf{Y}) = \frac{\mathrm{P}(\mathbf{Y}|M_k)\mathrm{P}(M_k)}{\sum_{m=1}^{M} \mathrm{P}(\mathbf{Y}|M_m)\mathrm{P}(M_m)}$$

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Bayesian Model Averaging

- The Bayes factor can be approximated as

$$\frac{\mathrm{P}(\mathbf{Y}|M_2)}{\mathrm{P}(\mathbf{Y}|M_1)} = N^{(k_1-k_2)/2}\left(\frac{Lik_2}{Lik_1}\right),$$

- Using $\mathrm{P}(M_k|\mathbf{Y})\ \forall k$ we can compute $\mathrm{P}(\beta_j|\mathbf{Y})$
- We can also obtain the posterior inclusion probability (PIP) of each variable as the sum of the probabilities of models including it
- The cardinality of the model space makes the computation of all posteriors intractable: MC^3 methods
- The problem is enlarged by the estimation of each individual SAR model

Spatial filtering

- The spatial link matrix $\mathbf{W}$ is first transformed to satisfy symmetry and then entered in a quadratic form with the projector $M_1 = I - \iota_N(\iota_N'\iota_N)^{-1}\iota_N'$
- The eigenvectors $\vec{e}$ extracted from $[M_1 \frac{1}{2}(\mathbf{W} + \mathbf{W}')M_1]$ reflect spatial patterns and can be thought of as proxy variables for the spatial structure of the data
- A linear combination of a reasonable subset of the eigenvectors of the projection matrix is capable of proxying the omitted variables that tie the residuals spatially together or to approximate the spatial process in general
- Spatially filtered specification:

$$y = \alpha + \sum_{i=1}^{E} \gamma_i \vec{e}_i + \mathbf{X}_k \vec{\chi}_k + \sigma\varepsilon,$$

Markov Chain Monte Carlo Model Composite

- Start with a model as defined by a group of regressors and the set of eigenvalues associated to a spatial weighting matrix $\mathbf{W}^k$
- First step: A candidate regressor is drawn from the set of potential covariates and we add/drop the candidate regressor to/from the current model. The candidate model, M_c^k is accepted with probability:

$$\tilde{p}_{cj} = \min \left[1, \frac{\overline{p}(M_c^k) p(y|M_c^k, \theta_c, \mathbf{W}_k)}{\overline{p}(M_j^k) p(y|M_j^k, \theta_j, \mathbf{W}_k)} \right].$$

- Second step: Draw a candidate weighting matrix $\mathbf{W}^c$. The accepted model from step 1) is then compared with the model containing the same regressors and the eigenvalues corresponding to $\mathbf{W}_c$,

$$\hat{p}_{if} = \min \left[1, \frac{p(y|M_i^c, \theta_i, \mathbf{W}^c)}{p(y|M_f^j, \theta_f, \mathbf{W}^j)} \right].$$

- Repeat a large number of times and compute statistics based on the visited models

Is there life on Mars?

$$y = 0.6\mathbf{W}_j y + 1.5\mathsf{x}_1 + 2\mathsf{x}_4 - 0.5\mathsf{x}_{10} + 0.5\varepsilon,$$

- We simulate 10 potential covariates
- 4 settings for W:
  - case 1: $\mathbf{W}_j$ is a first order Queen contiguity matrix ($\mathbf{W}_1^Q$),
  - case 2: $\mathbf{W}_j$ is a four nearest neighbour weight matrix ($\mathbf{W}_4^{K-NN}$),
  - case 3: $\mathbf{W}_j$ is a 400 km distance band weight matrix ($\mathbf{W}_{400}^b$),
  - case 4: $\mathbf{W}_j$ is given by $0.5\mathbf{W}_1^Q + 0\mathbf{W}_4^{K-NN} + 0.5\mathbf{W}_{400}^b$.

A simulation

	$\mathbf{W}_1^Q$	$\mathbf{W}_4^{K-NN}$	$\mathbf{W}_{400}^b$
Case $j = 1$			
Percentage visited	99.66	0.34	0.00
Adj. R^2	0.47	0.37	0.23
# eigenvalues	25.50	23.46	9.02
Case $j = 2$			
Percentage visited	0.00	100.00	0.00
Adj. R^2	0.29	0.42	0.18
# eigenvalues	16.98	33.82	7.18
Case $j = 3$			
Percentage visited	0.00	0.00	100.00
Adj. R^2	0.09	0.12	0.19
# eigenvalues	2.56	6.56	10.44
Case $j = 4$			
Percentage visited	32.96	16.89	50.15
Adj. R^2	0.25	0.22	0.21
# eigenvalues	11.84	13.50	9.66

Empirical application: Economic growth in European regions

- Dependent variable: Growth rate of GDP per capita 1995-2005.
- Data for 255 NUTS-2 regions belonging to EU-27
- 50 potential covariates, evaluated in 1995
- 16 potential spatial weighting matrices

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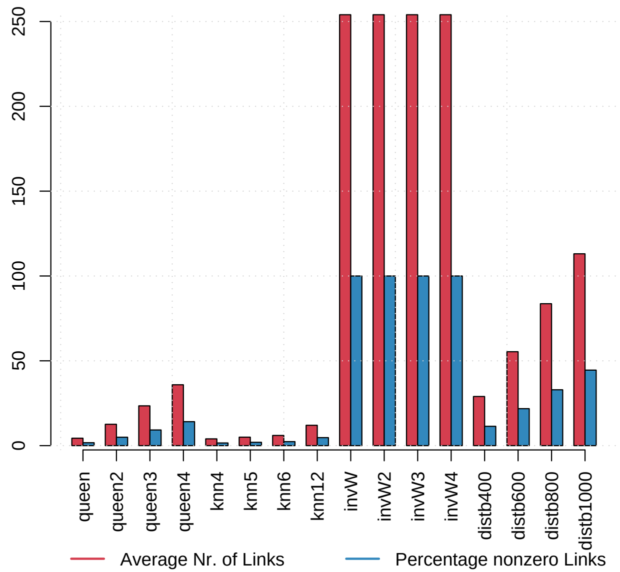
Variables

Variable name	Description	Source
Factor accumulation/convergence		
GDPCAP0	Initial real GDP per capita (in logs)	Eurostat
gPOP	Growth rate of population	Eurostat
shGFCF	Share of GFCF in GVA	Cambridge Econometrics
Infrastructure		
INTF	Proportion of firms with own website regression	ESPON
TELH	A typology of levels of household telecommunications uptake	ESPON
TELF	A typology of estimated levels of business telecommunications access and uptake	ESPON
Seaports	Regions with seaports	ESPON
AirportDens	Airport density	ESPON
RoadDens	Road density	ESPON
RailDens	Rail density	ESPON
ConnectAir	Connectivity to commercial airports by car	ESPON
ConnectSea	Connectivity to commercial seaports by car	ESPON
AccessAir	Potential accessibility air	ESPON
AccessRoad	Potential accessibility road	ESPON
Socio-geographical variables		
Settl	Settlement structure	ESPON
OUTDENS0	Initial output density	
EMPDENS0	Initial employment density	
POPDENS0	Initial population density	
RegCoast	Coast	ESPON
RegBorder	Border	ESPON
RegPent27	Pentagon EU 27 plus 2	ESPON
RegObj1	Objective 1 regions	ESPON
Capital	Capital city	
Airports	Number of airports	ESPON
Temp	Extreme temperatures	ESPON
Hazard	Sum of all weighted hazard values	ESPON
Distde71	Distance to Frankfurt	
DistCap	Distance to capital city	

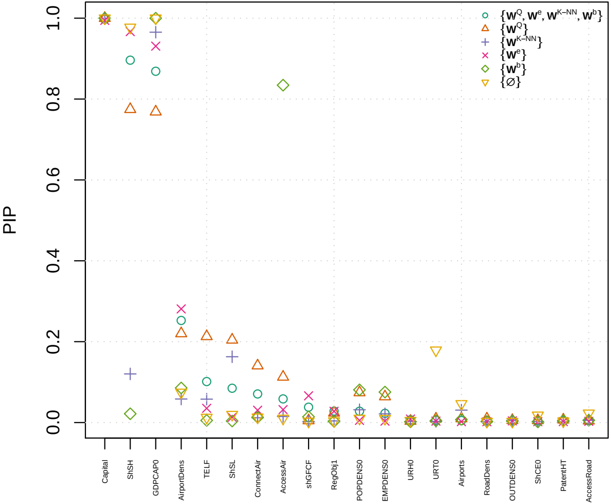
Variables

Variable name	Description	Source
Technological innovation		
PatentT	Number of patents total	Eurostat
PatentHT	Number of patents in high technology	Eurostat
PatentICT	Number of patents in ICT	Eurostat
PatentBIO	Number of patents in biotechnology	Eurostat
PatentShHT	Share of patents in high technology	Eurostat
PatentShICT	Share of patents in ICT	Eurostat
PatentShBIO	Share of patents in biotechnology	Eurostat
HRSTcore	Human resources in science and technology (core)	Eurostat LFS
Human capital		
ShSH	Share of high educated in working age population	Eurostat LFS
ShSL	Share of low educated in working age population	Eurostat LFS
ShLLL	Life long learning	Eurostat LFS
Sectoral structure/employment		
ShAB0	Initial share of NACE A and B (Agriculture)	Eurostat
ShCE0	Initial share of NACE C to E (Mining, Manufacturing and Energy)	Eurostat
EREH0	Employment rate - high	Eurostat LFS
EREL0	Employment rate - low	Eurostat LFS
ERET0	Employment rate - total	Eurostat LFS
URH0	Unemployment rate - high	Eurostat LFS
URL0	Unemployment rate - low	Eurostat LFS
URT0	Unemployment rate - total	Eurostat LFS
ARH0	Activity rate high	Eurostat LFS
ARL0	Activity rate low	Eurostat LFS
ART0	Activity rate total	Eurostat LFS

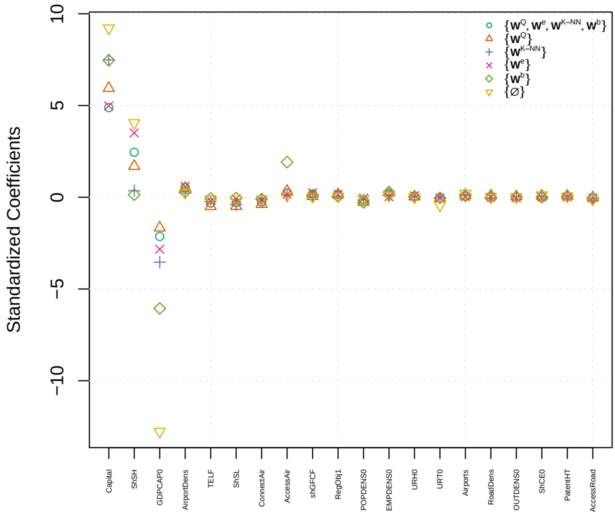
Spatial weighting matrices



Posterior inclusion probabilities



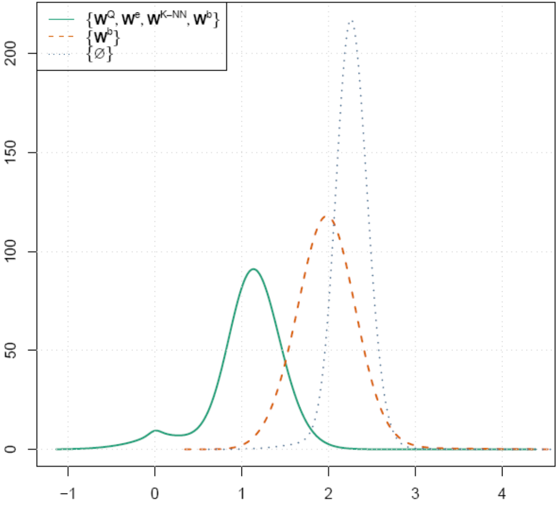
Posterior inclusion probabilities



Posterior inclusion probabilities

	$\mathbf{W}_1^Q$	$\mathbf{W}_2^Q$	$\mathbf{W}_3^Q$	$\mathbf{W}_4^Q$	$\mathbf{W}_4^{K-NN}$	$\mathbf{W}_5^{K-NN}$	$\mathbf{W}_6^{K-NN}$	$\mathbf{W}_{12}^{K-NN}$
PIP	0.0234	0.0000	1.7728	36.2936	0.0000	0.0016	0.0000	0.0000
	$\mathbf{W}_1^e$	$\mathbf{W}_2^e$	$\mathbf{W}_3^e$	$\mathbf{W}_4^e$	$\mathbf{W}_{400}^b$	$\mathbf{W}_{600}^b$	$\mathbf{W}_{800}^b$	$\mathbf{W}_{1000}^b$
PIP	0.0000	0.0000	61.8796	0.0000	0.0000	0.0290	0.0000	0.0000

Posterior distribution on the speed of convergence



Conclusions

- We put forward a Bayesian Model Averaging method for dealing with model uncertainty in the presence of potential spatial autocorrelation of unknown form.
- We propose using spatial filtering methods to achieve computational gains in the procedure.
- Evaluating growth determinants across European regions for the period 1995-2005, the choice of a particular class of spatial weighting matrices can have an important effect on the estimates of the parameters attached to the model covariates. Our posterior results emphasize the importance of human capital and convergence for economic growth in Europe at the regional level.

Conclusions

- Estimates of the speed of income convergence across European regions depend strongly on the form of the spatial patterns which are assumed to underly the dataset.
- The posterior distribution of the speed of convergence parameter has some probability mass around no convergence (0% speed of convergence) and a clear mode at a rate of convergence of 1%, approximately half of the value which is usually reported in the literature.