The determinants of economic growth in European regions*

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Abstract

This paper uses Bayesian Model Averaging (BMA) to find robust determinants of economic growth in a new dataset of 255 European regions between 1995 and 2005. The paper finds that income convergence *between* countries is dominated by the catching-up of regions in new member states in Central and Eastern Europe (CEE), whereas convergence *within* countries is driven by regions in old EU member states. Regions containing capital cities are growing faster, particularly in CEE countries, as do regions with a large share of workers with higher education. The results are robust to allowing for spatial spillovers among European regions.

Keywords: Bayesian Model Averaging (BMA), Spatial Autoregressive (SAR) model, determinants of economic growth, European regions.

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1 Introduction

This paper investigates determinants of *regional* economic growth based on a new data set of 255 EU regions at the NUTS (Nomenclature of Territorial Units) level 2 of disaggregation spanning the period 1995-2005. The paper uses Bayesian Model Averaging to assess the robustness of growth determinants in a systematic way, drawing explicit attention to the spatial interactions among European regions. The paper also investigates potential parameter heterogeneity due to the inclusion of regions from member countries in Central and Eastern Europe, which experienced a deep economic transformation process in the period under study. This study presents to the best knowledge of the authors the most comprehensive empirical investigation hitherto of the robustness of economic growth determinants in European regions.

Following Barro (1991), several studies have included a large number of explanatory variables in so-called 'kitchen sink' regressions based on cross-country data sets.[1] A problem with this approach is that theories of economic growth are often not mutually exclusive and the validity of one theory does not necessarily imply that another theory is false. Brock and Durlauf (2001) refer to this problem as 'open-endedness' of growth theories. Empirical models of economic growth are therefore plagued by problems of model uncertainty concerning the choice of explanatory variables and model specification. Levine and Renelt (1992) questioned the robustness of growth determinants by using a version of extreme bounds analysis (EBA) developed by Leamer (1983). Sala-i-Martin (1997) criticizes the extreme bounds as being too strict and proposes to analyze the entire distribution of coefficients of interest, which supported the importance of a wider set of growth determinants.

A recent and quickly growing literature addresses this problem of model uncertainty in growth empirics systematically by using Bayesian Model Averaging (henceforth BMA).[2] Fernández et al. (2001b) investigate the robustness of the growth determinants by using BMA on the dataset collected by Sala-i-Martin (1997). Following Leamer (1978), Sala-i-Martin et al. (2004) use Bayesian Averaging of Classical Estimates (BACE) which uses least-squares (classical) estimates and sample-dominated model weights that are positively related to the Bayesian Information Criterion (BIC) developed by Schwarz (1978).[3] Other studies study the importance of parameter heterogeneity in the uncertain growth process (see Crespo Cuaresma and Doppelhofer (2007), or Doppelhofer and Weeks (2009)). Despite this focus on various aspects of model uncertainty, the literature paid little attention to regional aspects of the uncertain growth process.

A number of recent studies have investigated model uncertainty in the context of robustness of growth determinants and income convergence patterns at the *regional* level. The empirical assessment of regional growth determinants has the added complication that spatial correlation is present in the data to a much higher extent than in cross-country data. Recently, a branch

[1] Barro and Sala-i-Martin (2004) give an excellent overview of empirical analysis for regional data (Chapter 11) and cross-sections of countries (Chapter 12).

[2] See Hoeting et al. (1999) for an excellent tutorial introduction to BMA and the survey by Doppelhofer (2008) that discusses both Bayesian and frequentist techniques.

[3] Raftery (1995) also proposes to combine BIC model weights and maximum likelihood estimates for model selection, with a method which differs from Sala-i-Martin et al. (2004) in the specification of prior probabilities over the model space and sampling method.

of literature has developed Bayesian tools for the analysis of spatially correlated data under model uncertainty. LeSage and Parent (2007) give an excellent introduction to BMA for spatial econometric models, and LeSage and Fischer (2008) apply BMA to investigate determinants of income in EU regions, with particular emphasis on sectoral factors. Knowledge spillovers from patent activity between EU regions, one of the most important growth determinants according to endogenous growth theory, is the focus of the analysis in LeSage and Parent (2008).

Many other empirical studies analyze regional growth determinants and income convergence in Europe but do not deal with the issue of model uncertainty and spatial spillovers simultaneously.[4] Boldrin and Canova (2001), for instance, investigate income convergence in EU regions and its relationship to regional policies, concluding with a critical assessment of regional economic policies. Becker et al. (2008) find evidence for growth, but not employment effects of regions receiving structural funds as so-called Objective 1 regions. Canova (2004) and Ertur et al. (2006) test for convergence clubs in European regions and finds evidence for convergence poles characterized by different economic conditions. Corrado et al. (2005) use an alternative technique to identify clusters of convergence in European regions and sectors. Carrington (2003) investigates convergence among EU regions and finds evidence of *negative* spatial spillovers among neighboring regions. Basile (2008) estimates a semiparametric spatial model for European regions and finds evidence for nonlinear effects associated with initial income and human capital investments, as well as some indication for global and local spillovers.

This paper contributes to the literature on determinants of regional growth in several aspects. First, we investigate a set of 50 possible growth determinants in 255 NUTS 2 regions of the EU. Compared to the limited set of variables considered in the existing empirical literature, the paper rigorously assesses model uncertainty over a much larger set of determinants of regional growth. Second, the paper uses BMA to investigate the robustness of determinants of regional growth between and within countries, as well as allowing for spatial spillovers. In particular, three different specifications are estimated to describe the growth process in EU regions: (1) the *baseline case* of a pure cross-section of EU regions, (2) the *baseline plus country fixed effects*, and (3) the baseline combined with a *spatial autoregressive* (SAR) structure.[5] Third, this paper uses a particular prior structure for interaction terms that fulfills the *strong heredity principle* put forward by Chipman (1996) when designing priors over the model space for related variables (see Crespo Cuaresma (2011) for a recent discussion on the use of interaction terms in BMA). Thus, the specification allows for heterogeneous effects of selected growth determinants in recent accession countries in Central and Eastern Europe (CEE) – Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovenia and Slovak Republic –, and also in capital cities. Finally, the paper allows for uncertainty over spatial weights by conducting a sensitivity analysis with respect to alternative spatial distance measures.

The main findings of the paper can be summarized as follows:

1. Conditional income convergence is a robust driving force of income growth across European regions. In the cross-section of regions, there is evidence for conditional convergence with a speed of around two percent. However, the precision of the estimated speed of convergence is strongly affected by the growth experience of CEE countries. The convergence process *between* European regions is dominated by the catching up process of regions in

[4]For an overview of convergence in EU regions at NUTS-2 level see European Commission (2008).
[5]See Anselin (1988) and LeSage and Pace (2009) for textbook discussions of the SAR model.

'new' EU member states in CEE countries, whereas convergence *within* countries is mostly a characteristic of regions in 'old' EU member states.

2. Regions with capital cities grow on average by one percentage point faster than non-capital city regions. This result, however, hides very strong differences between the experience of old and new EU member states. Regions containing capital cities in Central and Eastern Europe grew on average 1.8 percentage points faster, compared to only 0.4 percentage growth bonus in capital regions in old EU member states. Together with the observed convergence patterns in EU regions, this observations lends empirical support to the so-called 'Williamson hypothesis'. According to Williamson (1965), economic growth concentrates in regions with urban agglomerations as the catching-up process progresses, reverting the process in later stages of development. While this effect is very robust, it should be noted that these growth patterns may be related to the fact that the period under analysis (1995-2005) was characterized by rapid income growth in Eastern Europe.

3. Human capital, measured as population share of workers with higher (tertiary) education, has a robust positive association with regional economic growth. The estimates imply that an increase of 10 percent in the population share of workers with higher education is associated with a 0.6 percentage points higher annual growth rate of GDP *per capita.* The positive effect of human capital remains a robust determinant of regional growth within countries, but the parameter is not as well estimated as in the case without fixed country effects.

4. Allowing for spatial autocorrelation *a priori*, the paper finds evidence for positive spatial spillovers (growth clusters) in EU regions. However, spatial lags of growth determinants under consideration do not play a substantial role in explaining economic growth in European regions. The spatial spillovers are not operating through the explanatory variables at hand, but rather reflect some residual spatial effects which cannot be accounted by the explanatory variables or their spatial lags.

5. Statistical and economic inference on the determinant of regional economic growth is robust to alternative spatial weighting schemes for the economic growth spillovers. This robustness is also supported by a recent study by Crespo Cuaresma and Feldkircher (2010), which uses a different method to assess spatial link uncertainty in the regional growth process and investigates a wider set of weighting matrices.

The paper is structured as follows. Section 2 presents the setting of the BMA exercise carried out in the paper. Section 3 presents the empirical results concerning the robustness of growth determinants in the EU at the regional level and checks for the robustness of the results to variations in the spatial weighting matrix and in the nature of the potential parameter heterogeneity. Section 4 concludes.

2 The econometric model: Specification and prior structures

The robustness of regional growth determinants is analyzed using three different specifications. First, the *baseline case* pools the full cross-section of regions, taking into account variation of regional growth both between and within countries. Second, the *baseline case with country* *fixed effects* concentrates on regional variation of growth rates *within* countries by including country fixed effects in the model. Third, the *baseline case with a spatial autoregressive (SAR) structure* allows explicitly for possible spatial spillover effects from one region to another. The SAR specification adds confidence regarding the robustness of empirical findings since numerous studies point to non-negligible spatial correlation in regional growth data sets causing standard models to yield flawed inference (e.g. Fischer and Stirböck (2006), LeSage and Fischer (2008), Ertur and Koch (2006)). Note that since country effects themselves already constitute a spatial specification in the wider sense, the SAR model is employed for the cross section of regions (without fixed effects only.

All three specifications can be nested within a general spatial autoregressive model of the form

$$y = \alpha \iota_N + \rho \mathbf{W} y + \mathbf{X}_k \vec{\beta}_k + \varepsilon, \tag{1}$$

where y is an N-dimensional column vector of stacked growth rates of income per capita for N regions, α is the intercept term, ι_N is an N-dimensional column vector of ones, $\mathbf{X}_k = (\mathbf{x}_1 \dots \mathbf{x}_k)$ is a matrix whose columns are stacked data for k explanatory variables, $\vec{\beta}_k = (\beta_1 \dots \beta_k)'$ is the k-dimensional parameter vector corresponding to the variables in $\mathbf{X}_k$, $\mathbf{W}$ specifies the spatial dependence structure among y observations, ρ is a scalar indicating the degree of spatial autocorrelation and ε is an error term which may contain country-specific fixed effects.[6] The residuals ε are assumed to be drawn form an N-dimensional shock process with zero mean and diagonal variance-covariance matrix $\Sigma = \sigma \mathbf{I}_N$.[7]

A typical element of the spatial weight matrix $\mathbf{W}$ is given by $[\mathbf{W}]_{ii} = 0$ and $[\mathbf{W}]_{ij} = d_{ij}^{-1}$ for $i \neq j$, where d_{ij} is the distance[8] between observation i and observation j. The number and identity of the variables in $\mathbf{X}_k$ is assumed unknown, so that the columns in $\mathbf{X}_k$ are taken to be k variables from a larger set of (K) potential explanatory variables, grouped in $\mathbf{X}_K$, with $K \geq k$. A model $M_k \in \mathcal{M}$ is defined by the choice of a group of variables (and thus, the size of the model), so the total number of models is card($\mathcal{M}$)=2^K. Notice that $\mathbf{X}_K$ may also contain spatially-weighted explanatory variables of the form $\mathbf{W}\mathbf{x}_k$.

Inference on the parameters attached to the variables in $\mathbf{X}_k$ which explicitly takes into account model uncertainty can be based on weighted averages of parameter estimates of individual models

$$p(\beta_j|\mathbf{Y}) = \sum_{k=1}^{2^K} p(\beta_j|\mathbf{Y}, M_k) p(M_k|\mathbf{Y}), \tag{2}$$

with $\mathbf{Y} = (X, y)$ denoting the data. The weights - the posterior model probabilities - are given

[6] The generalization of the BMA strategy here to other error structures with fixed effects is straightforward after application of the Frisch-Waugh-Lovell theorem (Frisch and Waugh, 1933). The estimation of country fixed effects can be carried out by estimating the model using within-country-transformed data.

[7] See Doppelhofer and Weeks (2011) for a modelling strategy which allows for a more general distribution of regression errors in the context of model uncertainty and heteroskedasticity due to neglected heterogeneity and outliers.

[8] The estimation uses great-circle distances between regions i and j measured in kilometers. The great-circle distance is the shortest distance between two points i and j on the surface of a sphere and is measured along a *path on the surface* of the sphere.

by

$$p(M_j|\mathbf{Y}) = \frac{p(\mathbf{Y}|M_j)p(M_j)}{\sum_{k=1}^{2^K} p(\mathbf{Y}|M_k)p(M_k)}. \tag{3}$$

For the sake of illustration, consider the particular case of two models. In this case, the former expression boils down to the product of the Bayes factor $p(\mathbf{Y}|M_1)/p(\mathbf{Y}|M_2)$ with the prior odds $p(M_1)/p(M_2)$. Since the Bayes factor involves the marginal likelihoods unter the respective models it serves as a measure of differences in fit (with a penalty for model size embedded).

Model weights can thus be obtained using the marginal likelihood of each individual model after eliciting a prior over the model space. The marginal likelihood of model M_j is in turn given by

$$p(\mathbf{Y}|M_j) = \int_0^\infty \int_{-\infty}^\infty \int_{-\infty}^\infty \int_{-\infty}^\infty p(\mathbf{Y}|\alpha, \vec{\beta}_k, \rho, \sigma, M_j)p(\alpha, \vec{\beta}_k, \rho, \sigma|M_j) \; \mathrm{d}\alpha \; \mathrm{d}\vec{\beta}_k \; \mathrm{d}\rho \; \mathrm{d}\sigma. \tag{4}$$

The priors for the regression model provided in equation (1) are elicited by using a noninformative improper prior on the parameters common in all models, α and σ, and by using so-called g-prior (Zellner, 1986) on the β-coefficients:

$$p(\vec{\beta}_k|\alpha, \rho, \sigma, M_j) \sim \mathbf{N}(\underline{\beta_k}, \sigma^2 g(\mathbf{X}_k'\mathbf{X}_k)^{-1}),$$

Note that g scales up prior variance of β-coefficients reflecting the strength of the prior belief regarding the regression coefficients. In the application, prior coefficient means are set to zero reflecting an agnostic prior about the sign of coefficients, $\underline{\beta_k} = \vec{0}$, and following Fernández et al. (2001a) the hyperparameter for the g-prior is set to $g = \max\{N, K^2\}$, which in our case implies that $g = K^2$ for all the settings presented below. This so-called benchmark prior over g implies for linear regression models that the relative size of the sample as compared to the number of candidate regressors will determine whether models are compared based on the BIC (Bayesian Information Criterion, Schwarz (1978)) or RIC (Risk Inflation Criterion, Foster and George (1994)). As in LeSage and Parent (2007), this paper combines a benchmark prior for $\vec{\beta}_k$ with a beta prior distribution for ρ.

Lastly, a prior on the model space $p(M_j)$ has to be elicited. Many studies rely on a noninformative prior assigning equal probabilities to all possible models. Note that this implies a prior inclusion probability for a variable of 0.5 and thus in turn a mean prior model size of $K/2$ regressors. In contrast, some researchers prefer to give more prior weight to relatively parsimonious models by assuming Bernoulli distributions with fixed parameter π on the inclusion probability for each variable. The prior can then be anchored on the expected model size πK (see Sala-i-Martin et al. (2004)). Following Brown et al. (1998), Ley and Steel (2009) propose the use of a binominal-beta prior distribution, where a beta distribution is assumed as a hyperprior on π. This hyperprior is then elicited using a prior expected model size, which we fix to $K/2$. The flexibility of this approach allows the prior on the inclusion probability of a variable to be relatively agnostic (see examples in Ley and Steel (2009)) and further robustify our inference.

The empirical application presents the following statistics of interest for a variable $\mathbf{x}_k$. The *posterior inclusion probability* (**PIP**) is given by the sum of probabilities of models including variable $\mathbf{x}_k$. A PIP close to unity indicates the importance of the respective variable in explaining the process of regional growth. Note that the PIP can be interpreted as measure of evidence of including the variable contingent on other variables being included. The *posterior mean* of the distribution of β_k (**PM**) is the sum of model-weighted means of the model specific posterior distributions of the parameter:

$$E(\beta_k|\mathbf{Y}) = \sum_{l=1}^{2^K} p(M_l|\mathbf{Y}) E(\beta_k|\mathbf{Y}, M_l).$$

The *posterior variance* of β_k is the model-weighted sum of conditional variances plus an additional term capturing the uncertainty of the (estimated) posterior mean across models

$$\begin{aligned} \text{var}(\beta_k|\mathbf{Y}) &= \sum_{l=1}^{2^K} p(M_l|\mathbf{Y})\text{var}(\beta_k|\mathbf{Y}, M_l) + \\ &+ \sum_{l=1}^{2^k} p(M_l|\mathbf{Y})(E(\beta_k|Y, M_l) - E(\beta_k|\mathbf{Y}))^2. \end{aligned}$$

The *posterior standard deviation* is defined accordingly as $\mathbf{PSD_k} = \sqrt{\text{var}(\beta_\mathbf{k}|\mathbf{Y})}$.

The posterior distributions of the β-parameters for the SAR specification are calculated for the ρ that maximizes the integrated likelihood $p(\rho|\mathbf{Y}, \mathbf{W})$ (equation (A.2) in the Technical Appendix) over a grid of ρ values. The posterior distributions of interest over the model space can be then obtained using Markov Chain Monte Carlo Model Composition (MC^3) methods in a straightforward manner (see LeSage and Parent (2007)). In particular, a random-walk step is used in every replication of the MC^3 procedure, constructing an alternative model to the active one in each step of the chain by adding or subtracting a regressor from the active model. The chain then moves to the alternative model with probability given by the product of Bayes factor and prior odds resulting from the binomial-beta prior distribution. The posterior inference is based on the models visited by the Markov chain instead of on the complete (potentially untractable) model space (see Fernández et al. (2001a) for a more detailed description of this strategy). The Technical Appendix describes the implemented BMA procedure and the MC^3 sampling method implemented in the empirical analysis in more detail.

For the evaluation of potential nonlinear effects by inclusion of interaction terms, the MC^3 method is adapted as follows to ensure that Chipman's (1996) *strong heredity principle* is fulfilled. Positive prior inclusion probability is assigned only to models which include no interaction terms or models with interaction terms, but interacted variables also appearing linearly. In practice, an MC^3 sampler is implemented which adds the individual interacted variables linearly to those models in which the interaction is included, so as to ensure that only the independent effect of the interaction is evaluated. This approach imposes a particular prior distribution over the model space, removing the prior probability mass from all the models where interactions are present, but the corresponding linear terms are not part of the model. This prior probability mass is correspondingly redistributed to models where the interaction appears together with the interacted variables and can thus be properly interpreted. Crespo Cuaresma (2011) presents evidence that this type of *interaction sampling* method has better properties than standard MC[3] in the sense that the latter may spuriously detect interaction effects which are not present in the data. This sampling procedure implies a particular dilution prior over the model space which assigns zero prior probability to models containing interactions whose parent variables are missing in the specification.[9] This prior structure ensures that the interactive effects found relate to the pure interaction term and are not masking the effect of the (potentially correlated) parent variables.

3 Empirical results

The dataset covers information on 255 European regions listed in Table B.1. The Data Appendix lists the full set of regions and available variables, together with a brief definition, descriptive statistics and the source for each one of them. The dependent variable refers to observations of the average annual growth rate of each region in the period 1995-2005, deflated using national price data.[10] Note that three variables expressed in shares serve as reference group (denoted by asterisks (*) in Table B.2) and are therefore not included in the regressions. This results in 50 explanatory variables which can be roughly divided into several thematic groups:

1. *Factor accumulation and convergence:* These variables correspond to the usual economic growth determinants implied by neoclassical growth models (initial income, population growth, and investment in physical capital);

2. *Human capital:* Population shares of workers with high (tertiary), medium (secondary) and low (primary) educational attainment, as well as a life long learning variable;

3. *Technological innovation:* Patent statistics, as well as the share of workers employed in the science and technology sector;

4. *Sectoral structure and employment:* Sectoral shares in GDP; employment, unemployment and activity rates;

5. *Infrastructure:* Firm access to websites and telecommunications; access to sea, roads, air and rail transport;

6. *Socio-geographical:* Settlement structure; output, employment and population density; geographical location variables; Objective 1 regions[11]; capital city region.

All explanatory variables are measured at (or as close as possible) to the beginning of the sample period 1995 to capture the initial state of EU regions. Endogeneity in the relationship between regional growth and several potential determinants may be a concern in empirical work on economic growth at the subnational level. The dataset therefore measures regressors at (or as close as possible to) the beginning of the sample period to partly mitigate problems of endogeneity. The estimation by least squares therefore treats the regressors as predetermined.

[9] See the Technical Appendix for details.

[10] The starting year of the observation period is determined by the lack of reliable and comparable regional data for the first part of the 1990s for Central and Eastern European countries.

[11] Structural funds programs allocating transfers to NUTS-2 regions and associated classification into so-called Objective 1 regions are not considered for obvious concerns about endogeneity. A recent study by Becker et al. (2008) uses a regression discontinuity approach to identify the impact of structural funds and finds growth, but no employment effects.

This - as well as the use of country fixed effects in the within specification - should reduce the problem of endogeneity that is potentially associated with the use of some of the potential growth determinants. Given this maintained assumption, one should be careful not to attach a direct causal interpretation to the estimated effects. Alternatively, a researcher might consider to use lagged values of regressors as potential instruments, although the high persistence of many regressors could imply the well-known weak instruments problem. Combined with likely measurement errors of regional growth and its determinants, Hauk and Wacziarg (2009) warn against the naive use of lagged values of regressors as instrumental variables, since this could imply larger biases than the much simpler ordinary least-squares estimator considered in this paper.[12]

The paper evaluates the robustness of potential growth determinants for European regions by using BMA in three different specifications: (1) the *baseline case* pools all regions and analyzes variation across regions and *between* countries; (2) the baseline plus country fixed effects focusses on regional variation *within* countries of the EU 27; (3) the baseline combined with a spatial autoregressive (SAR) specification is employed to capture growth spillovers among EU regions with different choices for the spatial weight matrix $\mathbf{W}$. The evaluation of nonlinearities in the regional growth processes is assessed using interactions of pairs of variables as extra explanatory variables. Model averaging in a model space which includes specifications with interacted variables takes place imposing the strong heredity principle by modifying the standard MC^3 sampler as described in the Technical Appendix.

We present the empirical findings based on the three different model specifications discussed above. In the tables we report the posterior inclusion probabilities (PIP) of each regressor, together with the mean (PM) and standard deviation (PSD) of the posterior distribution for the associated parameter. The results are obtained from three million draws of the MC^3 sampler, after a burn-in phase of two million iterations. We use in all cases a binomial-beta prior where the expected model size equals $K/2$ regressors.[13] For easier readability, we restrict the variables shown in the tables to those that have a posterior inclusion probability above 0.5 (which we label *robust* in at least one of the specifications used.[14] Such robust variables have a higher inclusion probability after observing the data than their prior inclusion probability. One can use the scales proposed by Kass and Raftery (1995), to classify evidence of robustness of growth determinants into four categories (see also Eicher et al. (2011)): weak (50-75% PIP), substantial (75-95%), strong (95-99%) and decisive (99%+) evidence.[15] Alternatively, the economic significance of growth determinants can also be assessed by looking at their *transformed coefficients*, defined as PM/PSD. Masanjala and Papageorgiou (2008), for instance, label explanatory variables with absolute values of transformed coefficients greater than 1.3 as 'effective'.[16]

[12]Unfortunately, our dataset does not contain lagged observations of the data, we therefore leave extensions in this dimension to future work.

[13]The hyperparameters for the binomial-beta distribution are set to $a = b = 1$.

[14]The full set of results is available from the authors upon request.

[15]Note that this scale is based on a prior inclusion probability of 0.5 for each regressor which is implied by the binomial-beta prior anchored around an expected model size of K/2. The variables are sorted by posterior inclusion probabilities in the first set of columns in each Table of results.

[16]Brock and Durlauf (2001) provide decision-theoretic foundations for using such transformed coefficients. Even though the particular cutoff values for PIPs and transformed coefficients are specific to the assumed prior structure, the results are robust to alternative choice of prior parameters.

	Model 1			Model 2			Model 3		
	PIP	PM	PSD	PIP	PM	PSD	PIP	PM	PSD
Capital city	**1.000**	0.018	0.002	**0.984**	0.011	0.003	**1.000**	0.004	0.003
Initial income	**1.000**	-0.020	0.002	0.245	-0.003	0.005	0.387	-0.004	0.005
Higher education workers (share)	**0.977**	0.048	0.012	**0.999**	0.063	0.011	**0.996**	0.053	0.010
	0.001	0.003	0.000	0.001					
Distance to Frankfurt	0.005	0.001	0.000	0.388	0.001	0.000	**0.590**	0.001	0.000
CEE Dummy Interactions									
CEE dummy				**0.982**	0.019	0.006	**1.000**	0.016	0.005
CEE dummy × Capital city							**0.996**	0.018	0.004
Share of post. prob. (best model)		0.53			0.31			0.46	
Share of post. prob. (best 25 models)		0.89			0.86			0.86	
Share of post. prob. (best 50 models)		0.92			0.90			0.90	

PIP stands for 'posterior inclusion probability', PM stands for 'posterior mean' and PSD stands for 'posterior standard deviation'. All calculations based on MC^3 sampling with 2,000,000 burn-ins and 3,000,000 posterior draws. Model 1: Cross section of regions (baseline). Model 2: Cross section of regions including the CEE dummy variable and related interaction terms. Model 3: Cross section of regions further including the interaction term of the capital city dummy with the CEE dummy variable. Under models 2 and 3 the 'strong heredity prior' has been employed.

Table 1: BMA results for baseline setting

	Model 1	Model 2	Model 3
Intercept	0.205***	0.001	0.001
	(0.012)	(0.002)	(0.002)
Capital city	0.018***	0.009***	0.009***
	(0.002)	(0.002)	(0.002)
Initial income	-0.020***		
	(0.001)		
Higher education workers (share)	0.048***	0.059***	0.059***
	(0.009)	(0.009)	(0.009)
Distance to Frankfurt		0.001***	0.001***
		(0.000)	(0.000)
CEE dummy		0.023***	0.023***
		(0.002)	(0.002)
Observations	255	255	255
Adjusted R^2	0.567	0.597	0.597
Moran's I test (p-value)	0.001	0.011	0.011
Shapiro-Wilk test (p-value)	0.001	0.001	0.001

Standard errors in parenthesis, *** indicates significance at the 1% level. Moran's I test and the Shapiro-Wilk test have as a null hypothesis the absence of spatial autocorrelation and residual normality, respectively.

Table 2: Models with highest posterior probability: baseline setting

3.1 Economic growth determinants for European regions

We consider first the estimates based on the baseline case using a pooled cross section of regions. The first column in Table 1 reveals that initial income per capita, the share of workers with higher education and the dummy variable for capital cities are robust covariates for explaining economic growth differences among European regions. Posterior parameter means show the expected signs for the robust determinants and posterior standard deviations are relatively small. The parameter estimate associated with initial income implies that income convergence took place among European regions in the period considered, with a model-averaged estimate of the speed of convergence of roughly 2%.

Given that the dataset contains information on a relatively heterogeneous set of countries, the assumption of parameter homogeneity (at least for CEE countries versus Western European nations) may be too far-fetched. In particular, the speed of income convergence may differ across countries and the effect of urban agglomerations in capital cities may depend on the overall level of development. We explicitly assess the possibility of different growth processes in Central and Eastern European countries by expanding the set of covariates to contain interactions between a dummy for CEE countries and a group of selected variables. Consequently, the second column of Table 1 further elaborates on the issue of parameter heterogeneity between Eastern and Western European regions. The set of potential covariates includes now the original 50 covariates as well as a dummy variable for regions belonging to CEE countries (Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovenia and Slovak Republic), together with the interaction of this variable with initial income per capita, investment, population growth, road access, output density, the share of workers in science/technology, population density and employment density. The results in Table 1 present striking evidence for the importance of the CEE dummy variable, whose effect on economic growth is positive and well estimated. When including the CEE dummy, the estimated income convergence coefficient loses importance in terms of its posterior inclusion probability and the estimated speed of convergence is significantly lower. Furthermore, the speed of income convergence is no longer estimated with a reasonable degree of confidence. In the third column of Table 1 we further expand the set of covariates to include the interaction between the capital city and the CEE dummy. The results when this variable is included indicate that the positive growth effect of containing the capital city tend to be concentrated in Central and Eastern European countries.

Table 1 also presents the proportion of total posterior model probability which is represented by the model with highest posterior probability, as well as the best 25 and 50 models. The posterior model probability tends to be concentrated on relatively few specifications. In Table 2 the single best models (in terms of highest posterior probability) for each setting are presented, together with some regression diagnostics. The single best models are able to explain differences in income per capita growth well, with adjusted R^2 statistics ranging from roughly 0.57 to 0.6. The best models, however, fail to produce residuals which are free of spatial autocorrelation, as measured by the results of Moran's I tests.

The top panel of Figure 1 illustrates the impact of explicitly modelling heterogeneity in the intercept across European regions. The left hand side of Figure 1 (top panel) shows the posterior distribution[17] of the slope coefficient for the initial income variable based on the 500 models sampled in the MC^3 procedure with largest posterior support (in terms of posterior model probability). The posterior distribution is tightly concentrated around the model-averaged estimate of -0.02 with a posterior inclusion probability close to 1. Including the CEE dummy variable seriously affects the estimate of the coefficient attached to initial income (right hand side, top panel of Figure 1). The figure presents a large mass of probability around zero. These results show that the recent income convergence experience in Europe has been mostly driven by significantly higher growth in Eastern European regions. In addition, there is no posterior support for the variable interacting initial income with the regional dummy variable. This indicates that the initial income level of Eastern European regions was not systematically able to discriminate the differential economic growth experiences of regions within the group of new EU member states.

The finding of heterogeneous dynamics of convergence is illustrated in the top panel of Figure 2 which shows the spatial distribution of the quantitative effect of initial income on economic growth in European regions.[18] Figure 2 clearly shows that regions within CEE countries are strongly catching up. Most regions in Eastern Germany, Greece, Italy, Portugal and Spain with low initial income are growing relatively more rapidly, but the convergence patterns are more heterogeneous across regions as compared to Eastern Europe.

The differential growth dynamics of regions where the capital city of the country is located also appears as a relevant characteristic of the dataset. On average, after controlling for all other variables and explicitly taking into account model uncertainty, the growth rate of income per capita in regions with capital cities is over one percentage point higher than in non-capital city regions. The specification in the third column allows for heterogeneous effects of capital cities in old versus new EU member countries. The results show that regions containing capital cities in CEE countries grew on average 1.8 percentage points faster, compared to 0.4 percentage points in old EU countries. This is further illustrated in Figure 1, middle and bottom panels, showing the posterior distributions along with respective posterior inclusion probabilities for the capital city variable, as well as its interaction term with the regional CEE dummy variable. The results present a clear picture of the spatial distribution of economic growth in Europe for the period 1995-2005: income convergence across regions was driven by the strong growth experience in Eastern Europe and economic growth was systematically skewed towards regions with urban agglomerations (capital cities). Such an asymmetric distribution of economic growth in transition economies is a well known empirical fact which can be interpreted in the framework of the Williamson hypothesis (Williamson (1965)), which states that for countries in an early stage of catching up the growth push in economic activity should be concentrated in few poles (corresponding, for instance, to urban agglomerations around capital cities).[19] Note that the period under study was characterized by a very strong economic growth push in Central and Eastern Europe. The positive effect of urban agglomerations may be particularly important during boom times such as the decade we consider here. Such a differential effect between

[17]For illustration purposes a smoothed histogram of the posterior coefficients is used in the following figures. The histogram is based on the coefficients for the best 500 models and serves as approximation for the posterior distribution.

[18]To help reading the maps, the regressors are scaled as follows. The top panel of Figure 2 plots the partial effect of the *levels* (not log-levels) of initial income. Similarly, the share of workers with higher education in the bottom panel is scaled by a factor of 100.

[19]See also Henderson et al. (2001) and the references therein.

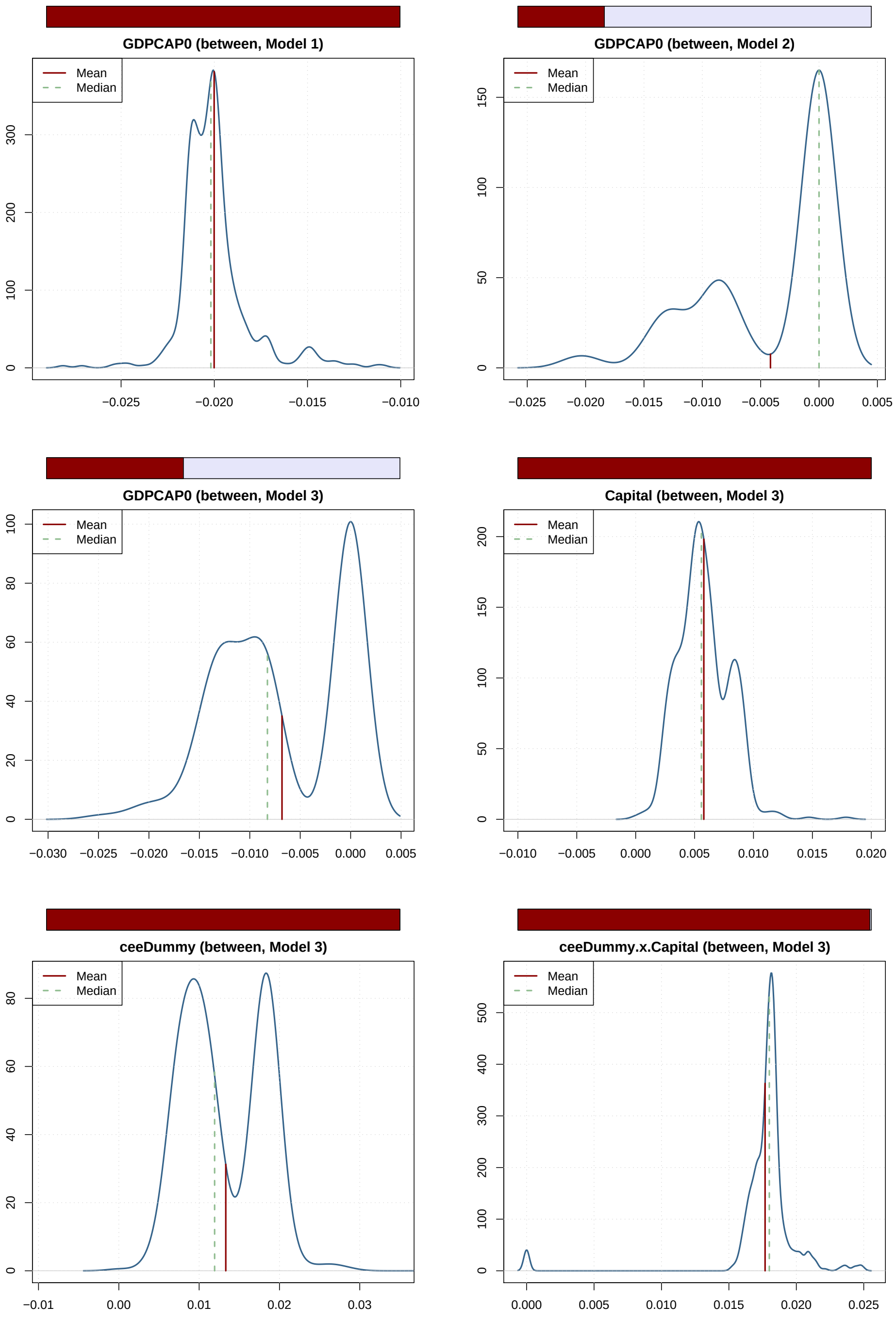


Figure 1: Unconditional posterior distribution (500 best models). The bar on top of each distribution refers to the posterior inclusion probability of the respective regressor. Top panel, left side shows the posterior distribution of the initial income variable based on the model specification not including the CEE dummy variable (Table 1, first column). Top panel, right side is based on the model including the CEE dummy variable (Table 1, second column). Middle and bottom panel are based on the estimation given in Table 1, third column. Posterior distributions are shown for the initial income variable , the capital city dummy and its linear interaction term (Capital $\times$ CEE dummy).

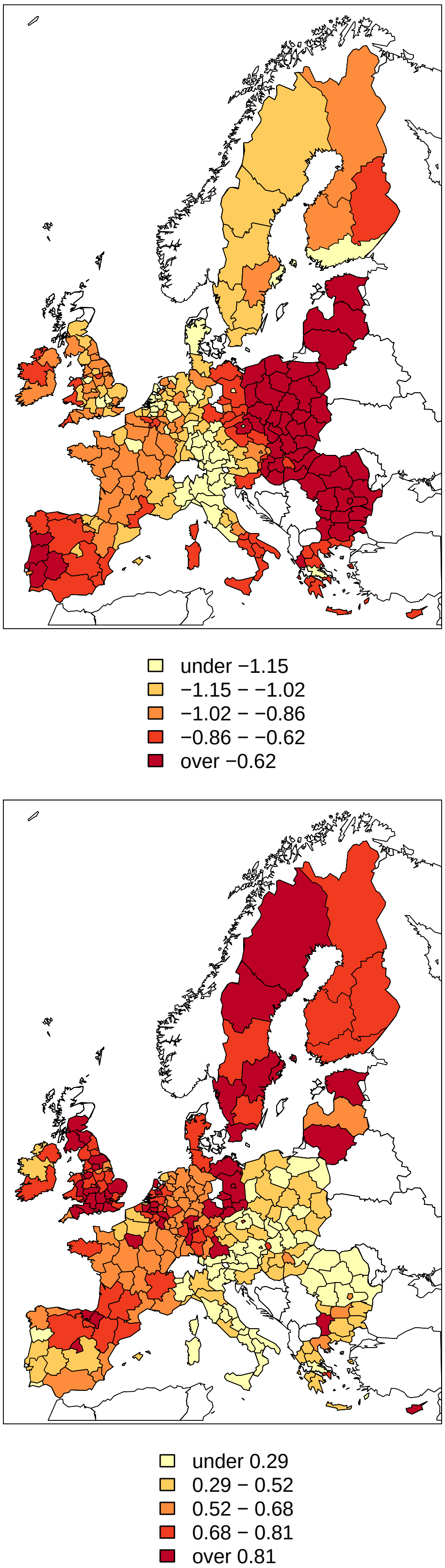


Figure 2: Spatial distribution of the estimated effect due to income convergence and human capital accumulation for the cross section specification (Table 1, third column). Top panel shows the spatial distribution of the coefficient on GDP per capita, the bottom panel the one for a human capital proxy.

Eastern and Western Europe further stresses the importance of modelling the regional growth process in Europe using data generating processes which allow for such heterogeneity.

The positive effect of human capital on economic growth is reflected in a robust positive parameter estimate attached to the variable measuring the share of workers with higher (tertiary) education. The size of the model averaged estimate in the model with interactions (third set of columns in Table 1) implies that on average a ten percent increase of the share of the working age population with tertiary education is associated with a 0.5 percent higher growth rate of GDP per capita. Compared to the sample average growth rate of 2.2 percent for all regions in the sample, the effect is quantitatively substantial. The bottom panel of Figure 2 shows the regional distribution of mean estimates of the effect of the human capital variable across regions. The strongest effects of human capital on economic growth are located in the central regions in Germany, Benelux countries and Scandinavia as well as Southern regions in the UK. When comparing economic effects of education (and other growth determinants), the model assumes that EU regions have similar access to technologies (Vandenbussche et al. (2006)). In principle, some of the variation in the shares of workers with higher education - measured as those who completed tertiary education - might be attributed to the fact that education systems vary across countries. The next subsection shows that human capital remains important in explaining growth differences also in the specification including country-fixed effects, where heterogeneity in national education systems is controlled for.

As explained above and reported in Table 1, when parameter heterogeneity between old and new member states is allowed for, the evidence concerning robust convergence decreases, reflected also in the mean of the posterior distribution of the coefficient associated with initial income. The results of the most general specification setting therefore confirm the importance of human capital formation as an engine of economic growth among European regions and the over-proportional growth performance of regions containing the capital city. On the other hand, the strong growth performance of emerging economies in Central Eastern Europe appears as the main responsible for the existence of robust income convergence across regions in Europe and for the evidence of convergence poles at the regional level in Europe in the period 1995-2005.

3.2 Regional growth determinants within countries

The results shown in Table 3 are based on BMA with models containing country fixed effects that concentrate on regional differences of growth and its determinants *within* countries. The specification can therefore account for unobserved time-invariant country specific characteristics that could affect the process of economic growth. Note that in this specification the dynamics of income convergence, associated with the coefficient of initial income per capita, should be interpreted as taking place in regions *within* a country towards a country-specific steady state[20]. Comparing the results in Tables 1 and 3, CEE regions contributed mostly to the regional income convergence process *between* countries, whereas income convergence *within* countries is mostly a characteristic of old EU member states. This evidence is in line with the trends in income

[20]Note that the CEE dummy variable is not identified when including fixed effects. We consequently exclude the CEE dummy for the estimations provided in Table 3 and do not employ the strong heredity prior for the linear interaction terms. Furthermore note that the capital city dummy does not suffer from identification problems since the case that all regions of a country (when there is more than one) contain national capital cities is ruled out by definition.

convergence described in ? and hints at the fact that the spatial concentration of economic activity in Eastern European economies may foster growth but at the same time increase within-country inequality at the regional level (see ? and ?).

	Model 1			Model 2			Model 3		
	PIP	PM	PSD	PIP	PM	PSD	PIP	PM	PSD
Investment	**0.627**	0.023	0.020	0.003	0.001	0.001	0.020	0.001	0.003
Capital city	**0.500**	0.004	0.005	0.010	0.001	0.001	0.001	0.001	0.001
Higher education workers (share)	0.499	0.038	0.041	**0.922**	0.055	0.019	0.459	0.023	0.026
Low education workers (share)	0.258	-0.010	0.018	0.082	-0.003	0.010	**0.514**	-0.018	0.019
Websites	0.016	0.001	0.004	**1.000**	0.077	0.013	**1.000**	0.087	0.012
GDPCAP0	0.009	0.001	0.001	**1.000**	-0.030	0.005	**1.000**	-0.031	0.004
CEE Dummy Interactions									
CEE Dummy × Capital city							**0.999**	0.032	0.003
CEE Dummy × Investment				**0.996**	0.090	0.019	0.028	0.001	0.009
CEE Dummy × Initial income				**1.000**	0.038	0.005	0.007	0.001	0.002
Share of post. prob. (best model)		0.14			0.37			0.61	
Share of post. prob. (best 25 models)		0.79			0.88			0.88	
Share of post. prob. (best 50 models)		0.85			0.93			0.92	

PIP stands for "posterior inclusion probability", PM stands for "posterior mean" and PSD stands for "posterior standard deviation". All calculations based on MC^3 sampling with 2,000,000 burn-ins and 3,000,000 posterior draws. Model 1: Baseline with country fixed effects. Model 2: Baseline with country fixed effects including interaction terms of the CEE dummy variable. Model 3: Baseline with country fixed effects including the interaction term of the capital city dummy with the CEE dummy variable. Under models 2 and 3 the strong heredity prior has been employed.

Table 3: BMA results for baseline setting with country fixed effects

This heterogeneity of the catching-up process can be further illustrated by looking at the interaction term linking the CEE Dummy and initial income. This coefficient (Table 3) plus the initial income coefficient yield a positive total effect pointing to regional *divergence* in CEE regions, whereas convergence occurs within the old EU member states. This is further illustrated in Figure 3, top panel. As in the between specification, controlling for spatial heterogeneity reveals a bimodal shape of the posterior distribution of the initial income parameter. However, in contrast to the between specification, including interaction terms related to the CEE dummy variable is necessary to establish income convergence for regions within European countries. This is further in line with Williamson (1965) and empirically confirmed by Barrios and Strobl (2009), who show that in an early stage of catching up regional inequalities increase. The general scarcity of (modern) infrastructure that countries face at the beginning of the convergence process may lead to congestion in urban agglomerations. Due to decreasing returns to scale other backward regions become more attractive for investment leading to regional convergence. The results confirm that, concerning this phenomenon, CEE regions are not yet in the phase of balancing regional equality, as opposed to old EU member states.The quantitative estimates imply a model averaged estimate of the coefficient attached to initial income of -0.030, larger in magnitude than in the *between* model specification. This translates into a faster speed of convergence of around 3.4% which is in line with other studies using fixed effects. Note that this changes also the interpretation of the speed of convergence, because regions within each country converge to their own country-specific steady state.

While the capital city dummy variable is not precisely estimated in all three specifications (set of columns 1 to 3) of Table 3, its linear interaction term with the CEE dummy variable

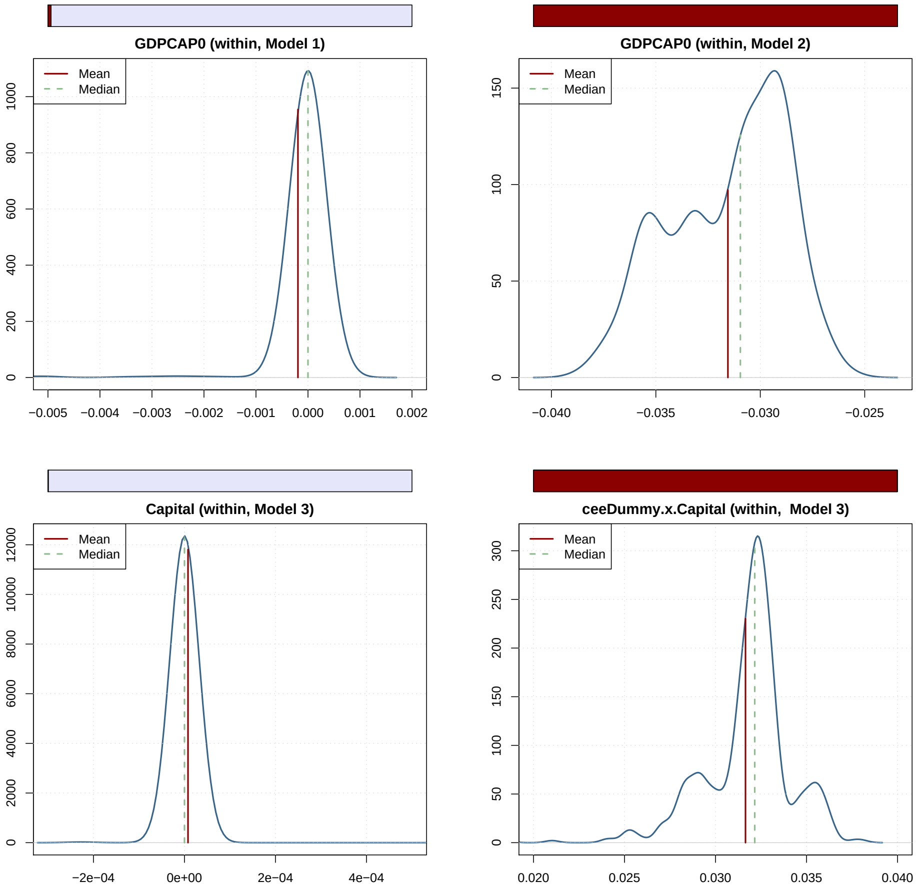


Figure 3: Unconditional posterior distribution based on models with fixed effects (500 best models). The bar on top of each distribution refers to the posterior inclusion probability of the respective regressor. Top panel, left side shows the posterior distribution of the initial income variable based on the model specification not including interaction effects (Table 3, first column). Top panel, right side refers to the specification including linear interaction terms related to the CEE dummy variable (Table 3, second column). The bottom panel further includes the interaction of the Capital dummy with the CEE dummy variable (Table 3, third column) showing posterior distributions of the capital city dummy and its linear interaction term (Capital $\times$ CEE dummy).

receives a high posterior inclusion probability in the third specification. This implies - as in the between specification - that regions hosting a capital city that are further located in CEE receive an additional growth bonus. Figure 3 corroborates our findings: The top panel, left side, shows the posterior distribution of the parameter for initial income. After controlling for spatial heterogeneity (in terms of East / West-specific parameters) by including linear interaction terms related to the CEE dummy variable income convergence appears robust in the data: The corresponding graph in Figure 3, top panel, right side shows a bimodal posterior distribution with both mean and median negative indicating income convergence taking place. The bottom panel, left and right side shows the posterior distribution of the parameters for the capital city as well as the corresponding linear interaction term with the CEE dummy variable. The distribution illustrates that CEE regions with a capital city tend to perform relatively better than other regions, with an additional and sizable bonus implied by the right shift of the distribution shown at the bottom right panel of Figure 3.

	Model 1	Model 2	Model 3
Higher education workers (share)	0.091***	0.060***	
	(0.012)	(0.011)	
Initial income		-0.029***	-0.031***
		(0.004)	(0.004)
Websites		0.073***	0.089***
		(0.011)	(0.011)
Low education workers (share)			-0.035***
			(0.008)
CEE dummy × Investment		0.090***	
		(0.018)	
CEE dummy × Initial income		0.038***	
		(0.005)	
CEE dummy × Capital city			0.033***
			(0.003)
Observations	255	255	255
Adjusted R^2 (within)	0.186	0.448	0.452
Moran's I test (p-value)	0.950	0.643	0.759
Shapiro-Wilk test (p-value)	0.000	0.000	0.000

Standard errors in parenthesis, *** indicates significance at the 1% level. Moran's I test and the Shapiro-Wilk test have as a null hypothesis the absence of spatial autocorrelation and residual normality, respectively.

Table 4: Models with highest posterior probability: baseline + country fixed effects setting

Our human capital variable remains a robust determinant of growth in this setting, although the parameter is not as well estimated as in the case without fixed country effects. This result is not surprising, given that a large part of the variation of educational outcomes is driven by cross-country differences (as opposed to cross-region differences within countries).

Table 4 shows the single models with highest posterior probabilities in each setting. The inclusion of country fixed effects is able to account for enough spatial autocorrelation in the economic growth data as for Moran's I test not to be able to reject its null hypothesis. As compared to models which explicitly model spatial autocorrelation, using these specifications we are however not able to extract information about the nature of the growth spillovers (such as, for example, the degree of spatial autocorrelation of economic growth at the regional level). In the next subsection we overcome this limitation by considering BMA in the framework of SAR models for regional growth in Europe.

3.3 Growth spillovers in Europe - Robust growth determinants under spatial autocorrelation

The model with country fixed effects presented above assesses the issue of spatial correlation of income growth by assuming a country-specific intercept, common to all regions within a nation, in the economic growth process. To the extent that country borders are not a large obstacle in the growth process of EU regions, using membership of regions in countries may not be the best way of modeling spatial relationships in the dataset. Alternatively, actual geographical distance can be used in the framework of SAR models such as those presented above to relate the growth process of different regions.

Table 5 presents the results of the BMA exercise for the class of SAR models, using inverse distances to construct the matrix of spatial weights $\mathbf{W}$. The number of robust variables when spatial autocorrelation is explicitly modeled is higher than in any other setting. The model averaged estimate of the spatial autocorrelation parameter ρ reveals positive spatial autocorrelation in income growth across European regions. The results obtained in the specifications without spatial autocorrelation are still present in the estimates from the SAR specification: regions with capital cities, regions with lower income and regions with a relatively educated labor force tend to present higher growth rates of income. Strikingly, initial income appears also as robust in the preferred specification that allows for capital city effects together with regional heterogeneity captured by the CEE dummy variable. This finding contrasts the results of the linear model and underscores the importance of 'correct' modeling of spatial correlation.

The posterior estimates using the SAR specification are close to the ones using the linear regression model. In particular, regions containing capital cities in CEE countries grew on average 2 percentage points faster, compared to 0.6 percentage points in old EU countries. Furthermore, a ten percent increase of the share of workers with higher education is associated with a 0.4 percent higher growth rate of GDP per capita, a finding that is very close to that reported in Section 3.1. As for the specifications above, we also present the models with the highest posterior probability, which are shown in Table 6. For the case of SAR specifications, the posterior model probability appears more spread across models than in the cases without spatial autoregressive terms, and there appears to be a large degree of variability in spatial autocorrelation estimates (see the differences in estimates of ρ in Table 6. Thus, a rigorous assessment of model uncertainty is important when considering spatial models for regional economic growth in Europe.

Since economic theory does not offer much guidance concerning a particular choice of spatial weighting matrix $\mathbf{W}$, the paper finally assesses the robustness of the findings with respect to the choice of the spatial link matrix. While the inverse distance matrix used hitherto is a recurrent choice in spatial econometric applications, it can be thought of as a special case of a more general weighting matrix $\mathbf{W}(\phi)$ with a characteristic element

$$[\mathbf{W}]_{ij} = [d_{ij}]^{-\phi}, \tag{5}$$

where d_{ij} is the distance between regions i and j and the parameter ϕ embodies the sensitivity of weights to distance, and thus the decay of the weighting scheme. The benchmark value ($\phi = 1$) implies that weights are an inverse function of distance, while higher values of ϕ lead to a stronger decay of weights with distance. To test the sensitivity of results, the BMA exercise is repeated for parameter value $\phi = 2$, which implies a faster decay of weights with distance.

	Model 1			Model 2			Model 3		
	PIP	PM	PSD	PIP	PM	PSD	PIP	PM	PSD
Capital city	**1.000**	0.018	0.002	**0.999**	0.013	0.003	**1.000**	0.006	0.003
Initial income	**1.000**	-0.017	0.002	**0.509**	-0.005	0.005	**0.894**	-0.012	0.007
Higher education workers (share)	**0.973**	0.045	0.013	**0.999**	0.063	0.012	**0.951**	0.044	0.016
Airport density	**0.832**	6.350	3.445	0.457	2.854	3.499	0.086	0.281	1.086
Population density	**0.812**	-0.010	0.006	0.438	-0.003	0.005	0.038	0.001	0.001
Employment density	**0.766**	0.011	0.007	0.308	0.003	0.006	0.034	0.001	0.001
Air accessibility	**0.528**	0.005	0.006	0.144	0.001	0.003	0.094	0.001	0.002
Telecommunication (firms)	0.153	0.001	0.001	**0.594**	-0.001	0.001	0.232	0.001	0.001
CEE Dummy Interactions									
CEE Dummy				**0.980**	0.013	0.014	**1.000**	0.008	0.008
CEE Dummy × Capital city							**1.000**	0.020	0.004
ρ		0.650			0.413			0.622	
Share of post. prob. (best model)		0.05			0.06			0.18	
Share of post. prob. (best 25 models)		0.60			0.61			0.69	
Share of post. prob. (best 50 models)		0.81			0.79			0.82	

PIP stands for "posterior inclusion probability", PM stands for "posterior mean" and PSD stands for "posterior standard deviation". All calculations based on MC^3 sampling with 2,000,000 burn-ins and 3,000,000 posterior draws. Model 1: SAR specification. Model 2: SAR specification including interaction terms using the CEE dummy variable. Model 3: SAR specification including the interaction term of the capital city dummy with the CEE dummy variable. Under models 2 and 3 the strong heredity prior has been employed.

Table 5: BMA results for SAR setting

Also results are shown obtained from imposing contiguity weights using a first-order queen contiguity matrix with positive (equal) weights assigned only to bordering regions.[21] Such a spatial structure implies that growth developments in a given region are affected by the growth process in all (first-order) contiguous regions.

Figures 4 summarizes the results of the robustness exercise by plotting in the top panel the posterior inclusion probabilities (PIP) and in the bottom panel transformed coefficients (PM/PSD) corresponding to each variable for the cases $\phi = 1, 2$ and for the queen contiguity matrix. Posterior inclusion probabilities of the regressors in the empirical analysis are insensitive to alternative weighting matrices. Statistical and economic inference, measured by transformed coefficients, does not change qualitatively if the weighting design is varied within decaying weighting schemes. Our results concerning the driving factors of economic growth in EU regions are also confirmed in recent work by Crespo Cuaresma and Feldkircher (2010), who employ a different method to integrate out uncertainty in spatial linkages in economic growth across regions. In their work, a larger set of spatial linkage matrices is employed and their results reinforce our conclusions concerning the pivotal role played by human capital and income convergence in regional economic growth.

3.4 Further robustness checks

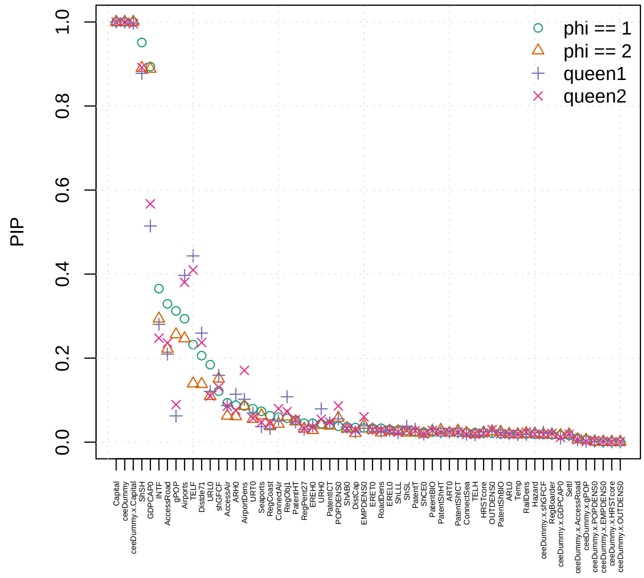
The common denominator of our results indicates that human capital differences and income convergence across and within countries are able to robustly explain differences in income per capita growth at the regional level in Europe. Several robustness checks were carried out in

[21] For a discussion of various weighting schemes see Anselin (1988).

	Model 1	Model 2	Model 3
Intercept	0.1640***	0.0224**	-0.0228
	(0.0229)	(0.0104)	(0.0160)
Air accessibility	0.0129***		
	(0.0029)		
Road accessibility	-0.0139***	-0.0031	-0.0041***
	(0.0025)	(0.0023)	(0.0013)
Capital city	0.0152***	0.0112***	0.0106***
	(0.0019)	(0.0019)	(0.0018)
Initial income	-0.0126***		
	(0.0021)		
Coastal	-0.0024*		
	(0.0013)		
Pentagon	0.0071***		
	(0.0020)		
Low education workers (share)	-0.0308***	-0.0113*	
	(0.0047)	(0.0059)	
Telecommunications (firms)	-0.0027***	-0.0025***	-0.0026***
	(0.0007)	(0.0006)	(0.0005)
Distance to Frankfurt		0.0001	
		(0.0001)	
Higher education workers (share)		0.0555***	0.0745***
		(0.0112)	(0.0091)
Activity rate (higher education)			0.0458**
			(0.0179)
CEE dummy		0.0173***	0.0185***
		(0.0024)	(0.0020)
ρ	-0.013	0.035	0.104
	(0.316)	(0.349)	(0.324)
Observations	255	255	255
Shapiro-Wilk test (p-value)	0.010	0.000	0.000

Standard errors in parenthesis, ***(**)[*] indicates significance at the 1% (5%)[10%] level. The Shapiro-Wilk test has as a null hypothesis residual normality.

Table 6: Models with highest posterior probability: SAR setting



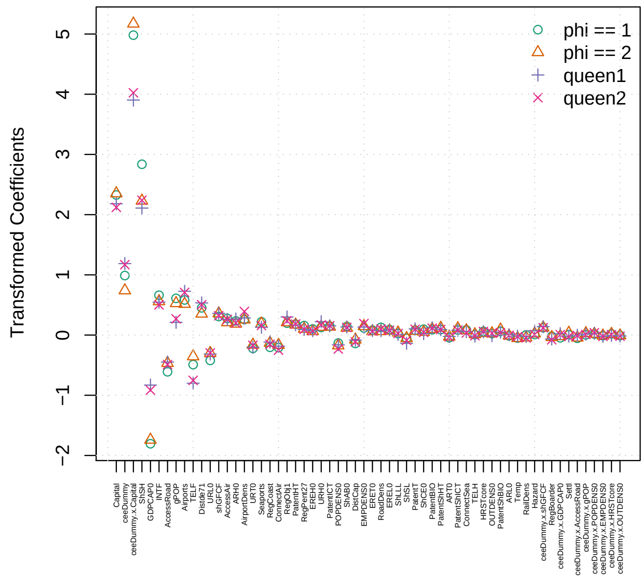


Figure 4: Posterior inclusion probabilities and transformed coefficients based on the SAR model (cross section of regions) with four different **W** specifications employed: inverse distances, inverse distances squared ($\phi = 1, 2$) and a first order and second order queen contiguity matrix.

order to ensure that our results do not depend on the particular setting put forward in this study.

To further investigate the transmission channels of growth spillovers, we allowed spatial spillovers to occur via the explanatory variables, as in the unrestricted Spatial Durbin model. Thus, the benchmark setting and the benchmark with country fixed effects setting were re-estimated with an enlarged set of potential growth determinants by introducing spatial lags of the potential covariates. The results presented above are left unchanged under the enlarged set of variables.[22] The spatially lagged explanatory variables do not appear as robust determinants of regional growth. This suggests that the positive correlation found from the SAR specification is driven by other factors not captured by the variables under consideration.

A further criticism that could be exercised on our analysis is related to the fact that many of our covariates are highly correlated. This could lead to multicollinearity problems in single specifications which would lead to inflated estimates of the uncertainty surrounding single parameter estimates. Some solutions to deal with correlated regressors in the framework of BMA have been proposed in the literature. In particular, Durlauf et al. (2008) propose to use a dilution prior of the type put forward in George (2007). They propose to use the determinant of the correlation matrix of regressors multiplicatively in the prior model probability. This dilution prior punishes models that contain highly collinear variables. The determinant of an uncorrelated set of regressors will be close to 1, while highly correlated regressors will result in a determinant close to 0. We repeated our analysis using this prior specification and the results did not change qualitatively as compared to those presented above. Our results appear thus also robust to the explicit assessment of potential multicollinearity among covariates.

4 Conclusions

This paper analyzes the nature of robust determinants of economic growth in EU regions in the presence of model uncertainty using model averaging techniques. The paper contains some important novelties compared to previous studies on the topic. On the one hand, the paper uses the most comprehensive dataset existing (to the knowledge of the authors) on potential determinants of economic growth in European regions. On the other hand, the paper applies the most recent Bayesian Model Averaging techniques to assess the issue of robustness of growth determinants. In particular, the empirical estimation framework allows for spatial autoregressive structures, hyperpriors on model size to robustify the prior choice on the model space and introduce a new methodology to treat the issue of subsample parameter heterogeneity via interaction terms.

The results imply that conditional income convergence appears to be a robust driving force of income growth across European regions. Between EU regions of different countries, this catching-up process has been fuelled by the growth experience in Eastern Europe. Convergence within countries, on the other hand, is concentrated in Western European economies. Regions with capital cities exhibit a significantly higher growth performance than other regions (be-

[22]Detailed BMA results for the setting with an enlarged set of covariates are available upon request from the authors.

tween specification) and this asymmetry is particularly sizable in Eastern European economies (between and within specification), which lends further support to the differential regional dynamics proposed by the Williamson hypothesis in the catching-up process. The importance of education as a growth engine appears also clearly in the data, which show that a higher share of educated workers in the labor force is positively associated with regional economic growth. The paper also finds evidence for positive spatial economic growth spillovers among EU regions.

The BMA method used in the paper allows for further generalizations which can be very fruitful as future research avenues: (a) exploiting alternative spatial weights matrices, as is done in Crespo Cuaresma and Feldkircher (2010), can help us further understand the nature of economic growth spillovers in Europe; (b) combining the methods proposed here with BMA settings which allow for nonlinear data generating processes (see e.g. Crespo Cuaresma and Doppelhofer (2007)) could shed light on the heterogeneity of growth processes within the European Union beyond the East/West differences highlighted in this study; (c) the availability of further data may allow for the use of instrumental variable methods in the framework of BMA to explicitly assess potential endogeneity in the link between economic growth and its determinants.

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A Technical Appendix

A.1 MCMC sampler

This Section briefly discusses the MCMC sampler used throughout the paper. Exploring the model space can be done via a range of search algorithms, here Markov Chain Monte Carlo methods are used, which have been shown to have good properties in the framework of BMA. The Markov chain is designed to wander efficiently through the model space, where it draws attention solely to models with non-negligible posterior mass.

The sampler uses a birth/death MC^3 (Madigan and York, 1995) search algorithm to explore the model space. In each iteration step a candidate regressor is drawn from $k_c \sim U(1, K)$. A *(birth step)* is adding the candidate regressor to the current model M_j if that model did not already include k_c. On the other hand, the candidate regressor is dropped if it is already contained in M_j *(death step)*. This is in the vein of Madigan and York (1995) with the new model always being drawn from a neighborhood of the current one differing only by a single regressor. To compare the sampled candidate model M_i to the current one, the posterior odds ratio is calculated implying the following acceptance probability,

$$\tilde{p}_{ij} = \min\left[1, \frac{p(M_i)p(\mathbf{Y}|M_i)}{p(M_j)p(\mathbf{Y}|M_j)}\right]. \tag{A.1}$$

A.2 MCMC and interaction terms

The birth/death MCMC sampler is modified by assigning positive prior model probabilities solely to models that include all 'relevant' regressors. That is, in case there are (multiplicative) interaction terms, all variables that belong to the interaction variable are forced to enter the regression equation. Candidate regressors are again drawn from $k_c \sim U(1, K)$. Consider now a linear regression model with regressor matrix X, which contains some element(s) from the set {A, B, C, AB} and a draw of the interaction term AB. The following cases arise:

$$\begin{array}{llll}
X_{current} = \{\text{C}\} & \Rightarrow & X_{candidate}=\{\mathbf{A},\mathbf{B},\text{C},\mathbf{AB}\} & \text{(birth step)} \\
X_{current} = \{\text{A,C}\} & \Rightarrow & X_{candidate}=\{\text{A},\mathbf{B},\text{C},\mathbf{AB}\} & \text{(birth step)} \\
X_{current} = \{\text{A,B,C}\} & \Rightarrow & X_{candidate}=\{\text{A,B,C},\mathbf{AB}\} & \text{(birth step)} \\
X_{current} = \{\text{A,B,AB}\} & \Rightarrow & X_{candidate}=\{\text{A,B}\} & \text{(death step)} \\
X_{current} = \{\text{A,B,C,AB}\} & \Rightarrow & X_{candidate}=\{\text{A,B,C}\} & \text{(death step)}
\end{array}$$

Now suppose a single regressor A is drawn. If the current model is $X_{current} = \{$ A, B, AB, C $\}$, variables A *and* AB would be dropped. Hence, models that include interaction terms without their 'parent' variables are not allowed. This sampling method fulfills Chipman's (1996) strong heredity property, a possible guiding principle for model choice and model averaging with related variables.

A.3 Priors on the parameters and the log-marginal posterior for the SAR model

The beta prior for ρ, Zellner's g-prior for the coefficient vector $\vec{\beta}$ (see text), and an inverted gamma prior for the variance σ^2 are elicited as follows:[23]

$$
\begin{aligned}
p(\sigma^2) &\sim \frac{(\bar{s}^2\nu/2)^{(\nu/2)}}{\Gamma(\nu/2)}\sigma^{2(-\frac{\nu+2}{2})}\exp\left(-\frac{\nu\bar{s}^2}{2\sigma^2}\right),\\
p(\rho) &\sim \text{Beta}(a_1, a_2),
\end{aligned}
$$

with $a_1 = a_2 = 1.01$ for the beta prior, and $\nu = \bar{s}^2 = 0$ corresponding to a non-informative prior on the variance.

The log integrated likelihood (equation (4)) is given by[24]

$$
p(\rho|\mathbf{Y},\mathbf{W}) = K_2\left(\frac{1}{1+g}\right)^{k/2}|\mathbf{I}_N-\rho\mathbf{W}|[\nu\bar{s}^2+S(\rho)+Q(\rho)]^{-\frac{N+\nu-1}{2}}p(\rho), \tag{A.2}
$$

with

$$
\begin{aligned}
K_2 &= \frac{\Gamma\left(\frac{N+\nu-1}{2}\right)}{\Gamma(\nu/2)}(\nu\bar{s}^2)^{\nu/2}\pi^{-\frac{N-1}{2}},\\
S(\rho) &= \frac{g}{1+g}\Big((I_N-\rho\mathbf{W})y-\mathbf{X}\hat{\beta}(\rho)-\hat{\alpha}\iota_N\Big)'\Big((\mathbf{I}_N-\rho\mathbf{W})y-\mathbf{X}\hat{\beta}(\rho)-\hat{\alpha}\iota_N\Big),\\
Q(\rho) &= \frac{1}{1+g}\left((\mathbf{I}_N-\rho\mathbf{W})y-\hat{\alpha}\iota_N\right)'\left((\mathbf{I}_N-\rho\mathbf{W})y-\hat{\alpha}\iota_N\right).
\end{aligned}
$$

Here $\hat{\beta}(\rho) = \hat{\beta}_{OLS}$ conditional on a specific ρ and $\hat{\alpha}$ denotes the OLS estimate of the intercept term. In contrast to standard linear regression analysis, where analytical expressions for all necessary quantities exist (see e.g. Koop (2003)), the integrated likelihood for the SAR model still depends on the spatial parameter ρ. Following LeSage and Parent (2007), the sampler uses numerical integration over a fine grid of $\rho \in [-1, 1]$. The numerical integration part, and especially the calculation of the matrix determinant, results in additional computational burden for doing BMA in a SAR framework. It will become handy to write the SAR estimator (Pace and Barry (1998)) as the difference of two estimators,

$$
\begin{aligned}
\hat{\beta}(\rho)_{SAR} &= \hat{\beta}_{OLS}-\rho\hat{\beta}_d, &\text{(A.3)}\\
\hat{\beta}_d &= (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{W}y. &\text{(A.4)}
\end{aligned}
$$

[23] The use of an inverted gamma prior as opposed to employing a diffuse prior for the variance is advocated in LeSage and Parent (2007).

[24] See LeSage and Parent (2007) for the exact derivation.

Equation A.4 illustrates that the ordinary least squares estimator is nested in the SAR specification. Since OLS estimates are misleading if $\rho \neq 0$ and the SAR model collapses to OLS if observations are not spatially correlated ($\rho = 0$), the spatial lag term $\mathbf{W}y$ is held fixed across SAR models. Thus the null model (without covariates) for the SAR specification is a first order spatial autoregressive model including an intercept term.

B Data Appendix

Austria		
Burgenland	Oberösterreich	Tirol
Kärnten	Salzburg	Wien
Niederösterreich	Steiermark	Vorarlberg
Belgium		
Prov. Antwerpen	Prov. Limburg (B)	Prov. Oost-Vlaanderen
Prov. Brabant Wallon	Région de Bruxelles-Capitale	Prov. Vlaams Brabant
Prov. Hainaut	Prov. Luxembourg (B)	Prov. West-Vlaanderen
Prov. Liège	Prov. Namur	
Bulgaria		
Severen tsentralen	Severozapaden	Yugozapaden
Severoiztochen	Yugoiztochen	Yuzhentsentralen
Cyprus		
Cyprus		
Czech Republic		
Jihovýchod	Praha	
Jihozápad	Severozápad	Stredn? Morava
Moravskoslezsko	Strední Cechy	Severovýchod
Denmark[25]		
Denmark		
Estonia		
Estonia		
Finland		
Aland	Itä-Suomi	Pohjois-Suomi
Etelä-Suomi	Länsi-Suomi	
France		
Alsace	Champagne-Ardenne	Lorraine
Aquitaine	Corse	Midi-Pyrénées
Auvergne	Franche-Comté	Nord - Pas-de-Calais
Basse-Normandie	Haute-Normandie	Pays de la Loire
Bourgogne	Île de France	Picardie
Bretagne	Languedoc-Roussillon	Poitou-Charentes
Centre	Limousin	Provence-Alpes-Côte d'Azur
		Rhône-Alpes
Germany		
Arnsberg	Hamburg	Oberfranken
Berlin	Hannover	Oberpfalz
Brandenburg - Nordost	Karlsruhe	Rheinhessen-Pfalz
Brandenburg - Südwest	Kassel	Saarland
Braunschweig	Koblenz	Schleswig-Holstein
Bremen	Köln	Schwaben
Chemnitz	Leipzig	Stuttgart
Darmstadt	Lüneburg	Thüringen
Detmold	Mecklenburg-Vorpommern	Trier
Dresden	Mittelfranken	Tübingen
Düsseldorf	Münster	Unterfranken
Freiburg	Niederbayern	Weser-Ems
Giessen	Oberbayern	
Greece		
Anatoliki Makedonia, Thraki	Ipeiros	Sterea Ellada
Attiki	Kentriki Makedonia	Thessalia
Dytiki Ellada	Kriti	Voreio Aigaio
Dytiki Makedonia	Notio Aigaio	
Ionia Nisia	Peloponnisos	
Hungary		
Dél-Alföld	Észak-Magyarország	Nyugat-Dunántúl
Dél-Dunántúl	Közép-Dunántúl	
Észak-Alföld	Közép-Magyarország	
Ireland		
Border, Midlands and Western		
Southern and Eastern		
Italy		
Abruzzo	Liguria	

[25]Since our dataset is based on the 2003 NUTS definitions, we consider Denmark to be composed by a single NUTS2 region for our empirical analysis, although the current classification assigns five regions to the country at this level of subnational disaggregation- Hovedstaden, Sjlland, Southern Denmark, Midtjylland and Nordjylland.

Basilicata	Lombardia	Sardegna
Calabria	Marche	Sicilia
Campania	Molise	Toscana
Emilia-Romagna	Piemonte	Umbria
Friuli-Venezia Giulia	Bolzano-Bozen	Valle d'Aosta
Lazio	Trento	Veneto
	Puglia	
Latvia		
Latvia		
Lithuania		
Lithuania		
Luxembourg		
Luxembourg (Grand-Duché)		
Malta		
Malta		
Netherlands		
Drenthe	Groningen	Overijssel
Flevoland	Limburg (NL)	Utrecht
Friesland	Noord-Brabant	Zeeland
Gelderland	Noord-Holland	Zuid-Holland
Poland		
Dolnoslaskie	Malopolskie	Slaskie
Kujawsko-Pomorskie	Mazowieckie	Swietokrzyskie
L?dzkie	Opolskie	Warminsko-Mazurskie
Lubelskie	Podkarpackie	Wielkopolskie
Lubuskie	Podlaskie	Zachodniopomorskie
	Pomorskie	
Portugal		
Alentejo	Centro (PT)	Norte
Algarve	Lisboa	
Romania		
Bucuresti - Ilfov	Nord-Vest	Sud-Vest Oltenia
Centru	Sud - Muntenia	Vest
Nord-Est	Sud-Est	
Slovak Republic		
Bratislavský kraj	Východné Slovensko	
Stredné Slovensko	Západné Slovensko	
Slovenia		
Slovenia		
Spain		
Andalucia	Comunidad de Madrid	La Rioja
Aragón	Comunidad Foral de Navarra	Pais Vasco
Cantabria	Extremadura	Principado de Asturias
Castilla y León	Galicia	Región de Murcia
Castilla-la Mancha	Illes Balears	Comunidad Valenciana
Cataluña		
Sweden		
Mellersta Norrland	Övre Norrland	Sydsverige
Norra Mellansverige	Småland med öarna	Västsverige
Östra Mellansverige	Stockholm	
United Kingdom		
Bedfordshire, Hertfordshire	Essex	North Yorkshire
Berkshire, Bucks and Oxfordshire	Gloucestershire, Wiltshire and	Northern Ireland
Cheshire	Greater Manchester	Northumberland, Tyne and Wear
Cornwall and Isles of Scilly	Hampshire and Isle of Wight	Outer London
Cumbria	Herefordshire, Worcestershire and Warks	Shropshire and Staffordshire
Derbyshire and Nottinghamshire	Inner London	South Western Scotland
Devon	Kent	South Yorkshire
Dorset and Somerset	Lancashire	Surrey, East and West Sussex
East Anglia	Leicestershire, Rutland and Northants	Tees Valley and Durham
East Riding and North Lincolnshire	Lincolnshire	West Midlands
East Wales	Merseyside	West Wales and The Valleys
Eastern Scotland	North Somerset	West Yorkshire

Table B.1: Sample of 255 European regions (NUTS level 2) used in the analysis

Variable name	Description	Source	Min	Mean	Max
Dependent variable					
Economic growth	Growth rate of real GDP per capita Deflated by national prices, Price base year is 2000	Eurostat	-0.006	0.022	0.083
1. Factor accumulation/ convergence					
Initial income	Initial real GDP per capita (in logs) Price base year is 2000	Eurostat	8.261	9.599	10.690
Population growth	Growth rate of population	Eurostat	0.000	0.000	0.000
Investment	Initial share of GFCF in GVA	Cambridge Econometrics	0.075	0.213	0.528
2. Human capital					
Share of workers with higher education	Share of population with higher education level in working age population	Eurostat LFS	0.044	0.156	0.390
Share of workers with medium education*	Share of population with medium education level in working age population	Eurostat LFS	0.106	0.467	0.742
Share of workers with low education	Share of population with low education level in working age population	Eurostat LFS	0.135	0.378	0.837
Life long learning	Life long learning	Eurostat LFS	0.003	0.068	0.263
3. Technological innovation					
Patents	Number of patents total per 1000 persons	Eurostat	0.000	0.078	0.545
High-tech patents	Number of patents in high technology per 1000 persons	Eurostat	0.000	0.011	0.186
ICT patents	Number of patents in ICT per 1000 persons	Eurostat	0.000	0.017	0.315
Biotechnology patents	Number of patents in biotechnology per 1000 persons	Eurostat	0.000	0.003	0.058
High-tech patents share	Share of patents in high technology in total patents	Eurostat	0.000	0.109	0.505
ICT patents share	Share of patents in ICT in total patents	Eurostat	0.000	0.156	0.728
Biotechnology patents share	Share of patents in biotechnology in total patents	Eurostat	0.000	0.039	0.226
Technology resources	Human resources in science and technology (core), share in persons employed	Eurostat LFS	0.036	0.126	0.816
4. Sectoral structure/ employment					
Agricultural share	Initial share of NACE A and B (Agriculture), Share in nominal gross value added	Eurostat	0.000	0.046	0.202
Manufacturing share	Initial share of NACE C to E (Mining, Manufacturing and Energy), Share in nominal gross value added	Eurostat	0.022	0.195	0.304
Services share*	Initial share of NACE J to K (Business services), Share in nominal gross value added	Eurostat	0.048	0.163	0.433
Employment rate (Higher education)	Employment rate of high educated (initial)	Eurostat LFS	0.609	0.819	0.964
Employment rate (Medium education)*	Employment rate of medium educated (initial)	Eurostat LFS	0.359	0.665	0.869
Employment rate (Low education)	Employment rate of low educated (initial)	Eurostat LFS	0.168	0.447	0.718
Employment rate	Employment rate total (initial)	Eurostat LFS	0.391	0.618	0.836
Unemployment rate (Higher education)	Unemployment rate of high educated (initial)	Eurostat LFS	0.004	0.054	0.273
Unemployment rate (Medium education)*	Unemployment rate of medium educated (initial)	Eurostat LFS	0.020	0.099	0.293
Unemployment rate (Low education)	Unemployment rate of low educated (initial)	Eurostat LFS	0.018	0.136	0.484
Unemployment rate	Unemployment rate total (initial)	Eurostat LFS	0.025	0.096	0.294
Activity rate (Higher education)	Activity rate of high educated (initial)	Eurostat LFS	0.761	0.865	0.964
Activity rate (Medium education)*	Activity rate of medium educated (initial)	Eurostat LFS	0.473	0.735	0.888
Activity rate (Low education)	Activity rate of low educated (initial)	Eurostat LFS	0.246	0.513	0.797

Activity rate	Activity rate total (initial)	Eurostat LFS	0.497	0.682	0.872
5. Infrastructure					
Websites	Proportion of firms with own website	ESPON	0.021	0.467	0.990
Telecommunications (households)	A typology of levels of household telecommunications uptake. 6=very high; 5=high; 3=moderately high; 3=moderate; 2=low; 1=very low; rescaled	ESPON	1.000	3.098	6.000
Telecommunications (firms)	A typology of estimated levels of business telecommunications access and uptake. 6=very high; 5=high; 3=moderately high; 3=moderate; 2=low; 1=very low; rescaled	ESPON	1.000	3.584	6.000
Seaports	Regions with seaports 1: regions with seaports; 0: no seaports	ESPON	0.000	0.424	1.000
Airport density	Airport density Number of airports divided by area in square km	ESPON	0.000	0.000	0.002
Road density	Road density Length of road network (in km) divided by area	ESPON	0.000	0.151	0.913
Rail density	Rail density Length of rail network (in km) divided by area	ESPON	0.000	0.063	0.321
Air connectivity	Connectivity to commercial airports by car of the capital or centroid representative of the NUTS3, in hours	ESPON	0.000	1.053	2.766
Sea connectivity	Connectivity to commercial seaports by car of the capital or centroid representative of the NUTS3, in hours	ESPON	0.010	0.598	3.000
Air accessibility	Potential accessibility air ESPON space = 100 ESPON AcAiE01N3; model output	ESPON	0.377	0.937	1.770
Road accessibility	Potential accessibility road ESPON space = 100 ESPON AcRoE01N3; model output	ESPON	0.035	0.964	2.032
6. Socio-geographical variables					
Settlement structure	Settlement structure Settlement Structure Typology (Six basic types defined by population density and situation regarding centres): 1: very densely populated with large centres, 2: densely populated with large centres, 3: densely populated with large centres, 4:densely populated without large centres, 5:less densely populated with centres, 6: less densely populated without centres;	ESPON	0.000	0.729	1.000
Output density	Initial output density; GDP in mio. / area in km2; initial year; Price base for GDP is 2000	WIIW	0.043	7.919	365.100
Employment density	Initial employment density Employed persons in 1000/ area in km2; initial year	WIIW	0.001	0.179	7.805
Population density	Initial population density Population in 1000 / area in km2; initial year	WIIW	0.002	0.338	8.299
Coastal	Coast 0: No Coast, 1: Coast	ESPON	0.000	0.463	1.000
Pentagon	Pentagon EU 27 plus 2 The Pentagon is shaped by London, Paris, Munich, Milan and Hamburg.	ESPON	0.000	0.322	1.000

Objective 1	Objective 1 regions Based on COM 'Second progress report on economic and social cohesion' (30 January 2003)	ESPON	0.000	0.408	1.000
Capital city	Capital city 0: region without capital cities; 1: capital cities		0.000	0.106	1.000
Airports	Number of airports	ESPON	0.000	1.608	17.000
Temperature	Extreme temperatures, 2=Low (Mean=2-2,75), 3=Moderate (Mean=2,75-3,25), 4=High (Mean=3,25-3,50); calculated from NUTS3 digit; weighted by population shares	ESPON	2.000	2.424	4.000
Hazard	Sum of all weighted hazard values alculated from NUTS3; weighted by population shares	ESPON	100.000	232.000	307.300
Distance to Frankfurt	Distance to Frankfurt in km				
Distance to capital	Distance to capital city in km		0.000	241.400	883.100

Table B.2: Data Description. Data are from ESPON (European Spatial Planning Observation Network), Cambridge Econometrics , WIIW, Eurostat and Eurostat LFS (Eurostat Labor Force Survey). Variables expressed in shares additionally denoted by asterisks (*) are not included in the regressions and hence serve as a reference group.