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The determinants of economic growth in European regions*

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Abstract

We use Bayesian Model Averaging (BMA) to evaluate the robustness of determinants of economic growth in a new dataset of 255 European regions in the 1995-2005 period. We use three different specifications based on (1) the cross-section of regions, (2) the cross-section of regions with country fixed effects and (3) the cross-section of regions with a spatial autoregressive (SAR) structure. We investigate the existence of parameter heterogeneity by allowing for interactions of potential explanatory variables with geographical dummies as extra regressors. We find remarkable differences between the determinants of economic growth implied by differences between regions and those within regions of a given country. In the cross-section of regions, we find evidence for conditional convergence with speed around two percent. The convergence process *between* countries is dominated by the catching up process of regions in Central and Eastern Europe (CEE), whereas convergence *within* countries is mostly a characteristic of regions in old EU member states. We also find robust evidence of positive growth of capital cities, a highly educated workforce and a negative effect of population density.

Keywords: Model uncertainty, spatial autoregressive model, determinants of economic growth, European regions. **JEL Classifications:** C11, C15, C21, R11, O52.

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1 Introduction

This paper investigates the determinants of economic growth in European regions in the 1995-2005 period. There is a very large literature on determinants of economic growth across countries and regions.[1] Barro and Sala-i-Martin (1991) test for convergence of income per capita among European regions between 1950 and 1985 and find that the speed of convergence near 2% is relatively constant both over time and also across countries. In this paper, we revisit this question using a new and larger set of 255 EU regions at the NUTS (Nomenclature of Territorial Units) level 2 of disaggregation, including regions in recent EU member countries in Central and Eastern Europe (CEE).

Beyond the question of convergence, the empirical growth literature has investigated a wider set of potential growth determinants. Following Barro (1991), several studies have included a large number of explanatory variables in so-called "kitchen sink" regressions. 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. The robustness of growth determinants was questioned by Levine and Renelt (1992) by employing a version of extreme bounds analysis (EBA) developed by Leamer (1983). Levine and Renelt concluded that almost no variable survives the EBA test of having a two standard deviation interval around the coefficient of the same sign across different models. Sala-i-Martin (1997) criticizes the EBA test as being too strict and proposes to analyze the entire distribution of coefficients of interest. Not surprisingly, Sala-i-Martin (1997) finds evidence for the importance of a wider set of growth determinants.

A recent and quickly growing literature has applied model averaging to address the issue of model uncertainty in the empirical growth literature.[2] Fernández et al. (2001b) use Bayesian Model Averaging (BMA) to investigate the robustness of the growth determinants 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 proportional to the Bayesian Information Criterion (BIC) developed by Schwarz (1978). 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. Fernández et al. (2001a) propose a set of benchmark priors on the parameters of the linear model for implementing BMA, which has been revisited recently by Ley and Steel (2008). Following Brown et al. (1998), Ley and Steel (2008) propose a hierarchical prior over the model size. In this paper, we use benchmark prior structures on the parameter space based on Fernández et al. (2001a) coupled with the hierarchical prior distribution over the model size used by Ley and Steel (2008). We also improve on past

[1] Barro (1991) and Sala-i-Martin et al. (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 (2009) that discusses both Bayesian and frequentist techniques.

attempts to assess parameter heterogeneity[3] by using a particular sampling procedure for interaction terms that fulfills the *strong heredity principle* put forward by Chipman (1996) when designing priors over the model space for related variables.

Determinants of regional growth and convergence patterns have also been investigated by a number of recent studies. Boldrin and Canova (2001) investigate convergence in EU regions and its relationship to regional policies, concluding with a critical assessment of regional economic policies. Canova (2004) 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. A very recent literature has developed Bayesian tools in the analysis of spatially correlated data. LeSage and Parent (2007) give an excellent introduction to BMA for spatial econometric models. LeSage and Fischer (2007) apply BMA to investigate determinants of income in EU regions, with particular emphasis on sectoral factors. LeSage and Parent (2008) investigate knowledge spillovers from patent activity between EU regions. In our model specifications we will explicitly model spatial effects using spatial autoregressive (SAR) structures (see Anselin (1988), for a textbook discussion).

This paper contributes to the literature as follows: First, we investigate a set of 67 potential growth determinants in 255 NUTS 2 regions of the EU, a much larger dataset than in the available empirical literature (see Data Appendix for list of variables and data sources). Second, we use BMA to investigate the robustness of determinants of regional growth with emphasis on spatial modeling using SAR and different prior assumptions. Third, we allow for heterogeneity between countries by allowing for different elasticities of economic growth to some selected determinants in recent accession countries in Central and Eastern Europe (CEE), as well as periphery countries in Southern Europe (Greece, Portugal and Spain). Furthermore, we use a new methodology to assess parameter heterogeneity based on the strong heredity principle when sampling interaction terms in the Markov Chain Monte Carlo procedure. Fourth, we allow for uncertainty over spatial weights by conducting a sensitivity analysis with respect to alternative spatial distance measures. While most studies using spatial models stick to a single spatial structure, we confirm the robustness of our results to the use of different spatial matrices.

The main findings of the paper are as follows:

1. Conditional income convergence appears as the most robust driving force of income growth across European regions. In the cross-section of regions, we find evidence for conditional convergence with speed of around two percent. However, the precision of the estimated speed of convergence is strongly affected by the growth experience of Central and Eastern European countries. The convergence process *between* regions is dominated by the catching up process of regions in Central and Eastern European (CEE), whereas convergence *within* countries is mostly a characteristic of regions in old EU member states.

2. On average, the growth rate of income per capita in regions with capital cities is over

[3] See Crespo-Cuaresma and Doppelhofer (2007) and Doppelhofer and Weeks (2008) for recent contributions to parameter heterogeneity in the framework of BMA.

one percentage point higher than in non-capital city regions, after controlling for all other factors. On the other hand, densely populated regions in Western Europe tended to present a weaker growth performance.

3. Human capital, measured as population share of highly educated workers, has a robust positive association with regional economic growth. The estimates imply that an increase of 10 percent in the share of high educated in working age population increase GDP per capita growth on average by 0.6 percent. 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*, we find evidence for positive spatial spillovers or growth clusters in EU regions. Allowing for a spatial autoregressive term diminishes the evidence for parameter heterogeneity between old and new EU member states.

5. Infrastructure plays an important role as a determinant of growth, in particular infrastructure related to air transport. The effect of infrastructure is weaker if we allow for heterogenous effects in regions in CEE countries.

6. Statistical and economic inference are not very sensitive to alternative spatial weights.

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. Section 4 checks for the robustness of the results to variations in the spatial weighting matrix and in the nature of the potential parameter heterogeneity. Section 5 concludes.

2 The econometric model: Specification and prior structures

To investigate the robustness of potential determinants of regional economic growth, we propose using models which 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.[4] For the moment, let us assume ε to be an N-dimensional

[4]The generalization of the BMA strategy here to other error structures with fixed effects is straightforward after application of the Frisch-Waugh-Lovell theorem. In a panel setting, the estimation of fixed effect models can be carried out by estimating the model proposed above using within-transformed data.

shock process with zero mean and diagonal variance-covariance matrix $\Sigma = \sigma \mathbf{I}_N$.

A typical element of $\mathbf{W}$ is given by $[\mathbf{W}]_{ii} = 0$ and $[\mathbf{W}]_{ij} = d_{ij}^{-1}$ for $i \neq j$, where d_{ij} is the distance[5] 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 in our setting, $M_k \in \mathcal{M}$ is defined by the choice of a group of variables (and thus, the size of the model), so 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 thus based on weighted-averaged 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 $\mathbf{Y}$ denoting the data. Posterior model probabilities $p(M_k|\mathbf{Y})$ are given by

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

In the empirical application we are interested in 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 $\mathbf{x}_k$. Hence it reflects the variable's relative importance in explaining the phenomenon - in our case the growth process - under study. 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,

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

We define the posterior standard deviation accordingly as **PSD**=$\sqrt{\text{var}(\beta_x|\mathbf{Y})}$.

[5]For the estimation we use airline distances between i and j measured in kilometers.

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

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

Given a model (say M_j, which corresponds to size k), we can rely on the results in Fernández et al. (2001a) and use a noninformative improper prior on α and σ in (1) and a g-prior (Zellner (1986)) on the β-coefficients, which implies that

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

with $g = 1/\max\{N, K^2\}$. This benchmark prior over g implies that the relative size of the sample as compared to the number of covariates will determine whether models are compared based on BIC (Bayesian Information Criterion, Schwarz (1978)) or RIC (Risk Inflation Criterion, Foster and George (1994)). We follow LeSage and Parent (2007)'s proposal and use a beta prior distribution for ρ.

Several approaches to the elicitation of prior information on model size have been proposed by the modern literature on BMA. Many studies rely on a diffuse prior setting which assigns equal probability to all possible models, thereby imposing a mean prior model size of $K/2$. In contrast, some authors give more prior weight to relatively pragmatic models by assuming Bernoulli distributions with fixed parameter π on the inclusion probability for each variable and using the expected model size, πK, to elicit the prior (see Sala-i-Martin et al. (2004)). Following Brown et al. (1998), Ley and Steel (2008) propose the use of a Binominal-Beta prior distribution, where a Beta distribution is assumed as a hyperprior on π, the parameter of the Bernoulli distribution for the inclusion of each regressor. The flexibility of the Beta distribution allows for very different prior structures on model size using the Binomial-Beta distribution (see examples in Ley and Steel (2008)).

The posterior distributions of the β-parameters for the SAR specification are calculated as the β that maximizes the likelihood calculated over a grid of ρ values[6]. The posterior distributions of interest over the model space can be then obtained using Markov Chain Monte Carlo Model Composite (MC^3) methods in a straightforward manner (see LeSage and Parent (2007)). In particular, we use a random-walk step 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 the product of Bayes factor and prior odds resulting from the Beta-Binomial 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).

For the evaluation of potential nonlinear effects by inclusion of interaction terms, we adapt the MC^3 method as follows to ensure that Chipman's (1996) *strong heredity principle* is

[6] For more details see the technical appendix.

fulfilled. We only assign positive prior inclusion probability to models which include no interaction terms or models with interaction terms, but interacted variables also appearing linearly. In practice, we just implement an MC^3 sampler 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. If we interpret this approach as imposing a particular prior distribution over the model space, our design implies that we are removing the prior probability mass from all the models where interactions are present but the corresponding linear terms are not part of the model and redistributing this prior probability mass correspondingly to the models where the interaction appears together with the interacted variables and can thus be interpreted. Crespo-Cuaresma (2008) 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.[7]

3 The empirical setting: variables and interactions

The Data Appendix lists the full set of regions and available variables, together with a brief definition and the source for each one of them. The dataset covers information on 255 European regions, and each income growth observation refers to the average annual growth rate in the period 1995-2005. The set of variables can be roughly divided into variables approximating *factor accumulation and convergence* (the usual economic growth determinants implied by the original Solow growth model), *human capital* variables, *technological innovation* variables, variables measuring *sectoral structure and employment*, *infrastructure* and *socio-geographical* variables.

In order to assess the potential differences between determinants of economic growth differences across regions in different countries and between regions within a country, the BMA exercise is carried out both using a single intercept term in the specification and country-specific intercepts, that is, country fixed effects. In the same manner, we use sets of explanatory variables both including and excluding spatially lagged regressors (in addition to the spatially lagged dependent variable). As a benchmark comparison, we also report results based on specifications without spatial autoregressive lags.

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 using the interaction MC^3 sampler described above.

3.1 BMA results: models without spatial autocorrelation

Table 1 presents the BMA results for models without spatial autoregressive lags. In each column we report the posterior inclusion probabilities of each regressor, together with the

[7]See the Technical Appendix for more details on the BMA procedure and the MC^3 sampling method implemented in the empirical analysis.

mean and standard deviation of the posterior distribution for the associated parameter. The results were obtained from 3,000,000 draws of the MC^3 sampler, after a burn-in phase of 2,000,000 iterations. In all cases we use a Binomial-Beta prior for model size with expected size equal to seven regressors.[8] The first set of columns in Table 1 presents the results of the model averaging procedure for the cross-section of regions without country fixed effects. The second set of results relate to the same specification but adding to the set of potential regressors also a group of spatially lagged regressors. In particular, we include spatial lags of the three Solow model variables (initial income per capita, capital formation and population growth), an infrastructure variable (road density), a technology innovation variable (human resources in science and technology) and three variables measuring production polarization (output, population and employment density). We assess the issue of parameter heterogeneity between Eastern and Western European regions in the third set of columns. In this case, we include a dummy variable for regions belonging to CEE countries (Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovenia and Slovak Republic), as well as the interaction of this variable with initial income per capita, capital formation, population growth, road density, output density, population density and employment density. We repeat the same exercise using a specification including country-specific fixed effects, and thus concentrating on the determinants of economic growth *within* countries for European regions. The results are presented in Table 2, which has the same structure as Table 1.

There are remarkable differences between the determinants of economic growth implied by the differences between regions and those of regions within a given country. For the case of models without country fixed effects, conditional income convergence appears as the most robust driving force of income across European regions, with a model-averaged estimate of the speed of convergence[9] around 2% for the setting without spatially-lagged variables and 1.8% if spatially-lagged variables are included in the group of potential explanatory variables. The conditional β-convergence parameter associated with the initial income variable (GDPCAP0) is also very precisely estimated. Note that this estimate contains information of the convergence process of European income per capita both within and between countries. Furthermore, the precision of the estimate is strongly affected by the growth experience of Central and Eastern European countries. Figure 1 contrasts the unconditional posterior distribution of the coefficient associated with initial income. The top panel of Figure 1 shows the effect when including spatial lags of a number of variables as explained above. The bottom panel of Figure 1 shows the posterior distribution when allowing a dummy variable for Eastern European countries as potential additional regressor.[10] In this case, the posterior inclusion probability associated with initial income drops from 1.000 to 0.257 (shown as red bar above the distribution), and the mean and median of the posterior distribution

[8]Because we use the hierarchical prior over the model size, our results are not sensitive to the choice of this hyperparameter. The expected mean model size of seven regressors selected from a set of 67 candidate explanatory variables, implies a prior inclusion probability of $7/67 = 0,105$. In Tables 1 to 4 variables with posterior inclusion probability (PIP) exceeding the prior of 10% are highlighted in **bold** font.

[9]Log-linearizing a standard neoclassical (Solow) growth model around a steady state implies a coefficient $\beta = -(1 - e^{-\gamma T})/T$ for the logarithm of initial income (see Barro and Sala-i-Martin (1991)). The speed of convergence γ is therefore given by $ln(1 + \beta T)/T$ where the number of years T is 10 in this paper.

[10]In this setting, the dummy achieves a posterior inclusion probability, mean and standard deviation which are very close to those for CEE dummy in the third set of estimates in Table 1.

are much closer to zero, indicating that there is considerably less evidence for the existence of conditional β-convergence between European regions. This implies that the evidence for income convergence found in the setting without country fixed effects under the assumption of homogeneity in the growth process between new and old member states seems to be driven by the recent growth experience of Central and Eastern European economies.

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 estimate is precise and appears robust to the inclusion of spatially lagged explanatory variables in the model and to the relaxation of the assumption of parameter homogeneity between old and new EU member countries. Similarly, the positive effect of human capital on economic growth is reflected in a robust positive parameter estimate attached to the variable quantifying the share of high educated in working age population. The size of the model averaged estimate in the model with interactions implies that on average a ten percent increase of the share of highly educated in working age population is associated with a 0.6 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 inclusion of spatially lagged variables in the set of regressors gives robust evidence of the existence of convergence poles in Europe. On average, regions which are geographically close to lower income geographical zones experience a higher convergence speed. The estimate is however not very precise, and a plot of the posterior distribution of the corresponding parameter presents a bimodal shape (see Figure 2) with a heavy mass around zero. The parameter heterogeneity observed in Figure 2 appears to be driven by convergence poles in Eastern Europe, since after allowing for a different global trend in GDP per capita growth in CEE countries the evidence for geographical agglomeration of converging regions disappears (see inclusion probabilities in the third set of BMA estimates of Table 1).

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, as well as the mean in the posterior distribution of the parameter associated to 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.

For the BMA exercise reported in Table 2 we concentrate on regional differences *within* countries in order to assess the robustness of economic growth determinants. The specifications we consider contain thus country fixed effects that account for unobserved country specific characteristics which affect the process of economic growth and are assumed to be time-invariant. It should be noticed that the dynamics of convergence in this specification are to be interpreted as taking place in regions within a country towards a country-specific steady state. The results in Table 2 indicate that, while CEE regions contributed mostly to the regional income convergence process between countries, income convergence within countries is mostly a characteristic of old EU member states, as can be inferred from the results of the specifications with interaction effects. Human capital 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).

The finding of heterogeneous dynamics of convergence is also illustrated in Figures 3 (top panel) which show the spatial distribution of the quantitative effect of initial income on economic growth within European regions. Figure 3 shows the posterior mean estimates for models with interactions terms for the CEE dummy, as well as country fixed effects.[11] Figure 3 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. Figure 3 (bottom panel) shows the regional distribution of mean estimates of the effect of the share of highly educated workers (ShSH) within countries. The strongest effects on economic growth are located in the central regions in Germany and Benelux countries as well as Southern regions in the UK. Figure 4 shows that the effect associated with the share of firms with own website (INTF) is strongest for regions within Germany, the Netherlands, England and Sweden.

3.2 BMA results: models with 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 institutional membership of regions in countries may not be the best way of modeling spatial relationships in our dataset. Alternatively, we use actual geographical distance in the framework of SAR models such as those presented above to relate the growth process of different regions.

In Table 3 the results of the BMA exercise for the SAR model including spatial regressors (first set of columns) and spatial regressors and interactions with the CEE dummy (second set of columns) are presented. The number of robust variables when spatial autocorrelation is explicitly modeled is higher than in any other setting, with a posterior mean of model size over 11. Figure 7 presents the prior and posterior model size distribution. The prior distribution corresponds to a Beta-Binomial distribution with expected value equal to 7 (see Ley and Steel (2008), for examples of prior model size distributions based on Beta-Binomial

[11]To help reading the maps we have scaled regressors as follows. The top panels of Figures 3 and 5 are plotting the partial effect of the *levels* (not log-levels) of initial income. Similarly, the share of highly skilled workers (ShSH) in the bottom panels of Figures 3 and 5 and the proportion of firms with own website (INTF) in Figure 4 are scaled by a factor of 100. Population density (POPDENS0) is scaled by a factor of 10,000.

distributions), while the mass of the posterior distribution is very concentrated on model sizes between 6 and 18. 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. On top of this result, there is also evidence of the importance of technology poles (as measured by the spatially lagged variable measuring resources in science and technology) as determinants of long-run growth, although the estimated elasticity is not too precise. Regions also profit in terms of economic growth from growing populations in nearby regions. For the first time, infrastructure variables appear strongly related to growth. In particular, regions which possess infrastructure related to air transport present higher growth rates of income. Interestingly, once that spatial autocorrelation is taken into account, there is no robust parameter heterogeneity in the speed of income convergence, although the CEE region dummy does appear robustly related to growth (albeit with a more uncertain parameter estimate).

Figure 5 shows the spatial distribution of effects associated with initial income and human capital with the spatial autoregressive specification and interaction effects for CEE countries. The effects are mostly similar to the fixed effects results in Figure 3: regions in Central and Eastern Europe and Portugal are strongly catching up with other EU regions and the share of highly skilled workers has the largest effect on growth in core EU regions, England and Nordic countries (Denmark, Sweden and Finland). Figure 6 shows the distribution of the effect of population density on economic growth. Notice that the posterior mean coefficient of population density is negative (-0.0098) and marginally significant. The most lightly colored regions (in Germany, the Netherlands and Southern UK) indicate the strongest negative impacts associated with high population density.

4 Robustness checks

In this section we allow for different settings in the specifications which are averaged upon, so as to ensure that the results presented above are robust to different decay parameters in the distance matrix and that the parameter heterogeneity evidence we find is exclusive to CEE countries and not present in older peripheral member states.

Economic theory does not offer any guidance concerning a particular choice of spatial weighting matrix $\mathbf{W}$. 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 our results, we repeat the BMA exercise for parameter values $\phi = 2, 3, 4$, which imply faster decays of weights with distance. We also show results obtained from imposing contiguity weights using a first-order queen contiguity matrix with positive (equal) weights assigned only to bordering regions.[12] 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 8 summarizes the results of the robustness exercise by plotting the PIP and standardized coefficients (PM/PSD) corresponding to each variable for the cases $\phi = 1, 2, 3, 4$ and for the queen contiguity matrix. Posterior inclusion probabilities of the regressors in our analysis are surprisingly insensitive to alternative weighting matrices. Statistical and economic inference, measured by standardized coefficients, does not change qualitatively if the weighting design is varied within decaying weighting schemes.[13] The results including a contiguity matrix result in general in lower PIP and —PM/PSD— values, although the relative importance of growth determinants is left practically unaffected.

We also check for the sensitivity of results concerning the CEE dummy and its interaction terms. In principle, it could be argued that the effects found in the analysis may not be particular of CEE economies, but also be present in the subset of old member states with lower income levels. We do so by obtaining BMA estimates from the SAR specification allowing for parameter heterogeneity between periphery EU member states in Southern Europe (Greece, Portugal and Spain). The results are shown in Table 4 and indicate that all interaction terms have negligible posterior inclusion probabilities and thus old EU periphery countries do not feature significantly different growth determinants or elasticities compared to other European regions. Our results imply thus that the difference in the determinants of growth dynamics between old and new member states is exclusive to this subsample division, and no evidence of such heterogeneity in coefficients appears in peripherial Southern EU member states.

5 Conclusions

We analyze the nature of robust determinants of economic growth in EU regions in the presence of model uncertainty using model averaging techniques. Our paper contains some important novelties compared to previous studies in the topic. On the one hand, we use the most comprehensive dataset existing (to the knowledge of the authors) on potential determinants of economic growth in European regions. On the other hand, we apply the most recent Bayesian Model Averaging techniques to assess the issue of robustness of growth determinants. In particular, we use 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.

Our results imply that conditional income convergence appears as the most robust driving

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

[13]Brock and Durlauf (2001) discuss a decision-theoretic foundation for using such standardized coefficients. In Masanjala and Papageorgiou (2008), for instance, explanatory variables with values of —PM/PSD— above 1.3 are dubbed "effective".

force of income across European regions and has been fueled by the growth experience in Eastern Europe. Convergence within countries, on the other hand, is concentrated in Western European economies. Regions with capital cities present a systematic better performance than other regions, although densely populated regions in Western Europe tend to present a weaker growth performance. 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. We also find evidence for positive spatial spillovers leading to growth clusters in EU regions. Once this feature of the data is properly modeled, new insights on the regional growth process are gained: infrastructure plays an important role as a determinant of growth and regions tend to profit from population growth in neighboring regions. All results appear robust to alternative definitions of the spatial weight matrix.

References

Anselin, L. (1988). *Spatial Econometrics: Methods and Models*. Kluwer Academic Publishers.

Barro, R. J. (1991). Economic Growth in a Cross Section of Countries. *The Quarterly Journal of Economics*, 106, No. 2:407–443.

Barro, R. J. and Sala-i-Martin, X. (1991). Convergence across States and Regions. *Brookings Papers on Economic Activity*, 1:107–182.

Boldrin, M. and Canova, F. (2001). Inequality and Convergence in Europe'sRegions: Reconsidering European Regional Policies. *Economic Policy*, 16:205–253.

Brock, W. and Durlauf, S. (2001). Growth Empirics and Reality. *World Bank Economic Review*, 15:229–272.

Brown, P., Vannucci, M., and Fearn, T. (1998). Multivariate Bayesian Variable Selection and Prediction. *Journal of the Royal Statistical Society B*, 60:627–641.

Canova, F. (2004). Testing for convergence clubs in income per capita: A predictive density approach. *International Economic Review*, 45:49–77.

Chipman, H. (1996). Bayesian Variable Selection with Related Predictors. *Canadian Journal of Statistics*, 24:1736.

Corrado, L., Martin, R., and Weeks, M. (2005). Identifying and Interpreting Regional Convergence Clusters across Europe. *Economic Journal*, 115:C133–C160.

Crespo-Cuaresma, J. (2008). How different is Africa? *mimeo, University of Innsbruck*.

Crespo-Cuaresma, J. and Doppelhofer, G. (2007). Nonlinearities in Cross-Country Growth Regressions: A Bayesian Averaging of Thresholds (BAT) Approach. *Journal of Macroeconomics*, 29:541–554.

Doppelhofer, G. (2009). *The New Palgrave Dictionary of Economics. Second Edition*, chapter Model Averaging. Palgrave Macmillan.

Doppelhofer, G. and Weeks, M. (2008). Jointness of Growth Determinants. *Journal of Applied Econometrics, forthcoming.*

Eklund, J. and Karlsson, S. (2007). Computational Efficiency in Bayesian Model and Variable Selection. Working Paper 4, Örebro University.

Fernández, C., Ley, E., and Steel, M. F. (2001a). Benchmark Priors for Bayesian Model Averaging. *Journal of Econometrics*, 100:381–427.

Fernández, C., Ley, E., and Steel, M. F. (2001b). Model Uncertainty in Cross-Country Growth Regressions. *Journal of Applied Econometrics*, 16:563–576.

Foster, D. P. and George, E. I. (1994). The Risk Inflation Criterion for Multiple Regression. *The Annals of Statistics*, 22:1947–1975.

Hoeting, J. A., Madigan, D., Raftery, A. E., and Volinsky, C. T. (1999). Bayesian Model Averaging: A Tutorial. *Statistical Science*, 14, No. 4:382–417.

Koop, G. (2003). Introduction to Bayesian Econometrics. *John Wiley.*

Leamer, E. (1978). *Specification Searches.* John Wiley and Sons, New York.

Leamer, E. (1983). Let's take the Con out of Econometrics. *American Economic Review*, 73:31–43.

LeSage, J. P. and Fischer, M. (2007). Spatial Growth Regressions, Model Specification, Estimation, and Interpretation. *mimeo.*

LeSage, J. P. and Parent, O. (2007). Bayesian Model Averaging for Spatial Econometric Models. *Geographical Analysis*, 39:3:241–267.

LeSage, J. P. and Parent, O. (2008). Using the Variance Structure of the Conditional Spatial Specfcation to Model Knowledge Spillovers. *Journal of Applied Econometrics*, 23:235–256.

Levine, R. and Renelt, D. (1992). A Sensitivity Analysis of Cross-Country Growth Regressions. *American Economic Review*, 82:942–963.

Ley, E. and Steel, M. F. (2008). On the Effect of Prior Assumptions in Bayesian Model Averaging with Applications to Growth Regressions. *Journal of Applied Econometrics*, (forthcoming).

Masanjala, W. and Papageorgiou, C. (2008). Rough and Lonely Road to Prosperity: A Reexamination of the Sources of Growth in Africa Using Bayesian Model Averaging. *Journal of Applied Econometrics*, 23:671–682.

Pace, R. and Barry, R. (1998). Qick Computation of Spatially Autoregressive Estimators. *Geographical Analysis*, 29(3):232–247.

Raftery, E. A. (1995). *Sociological Methodology*, volume 25. Blackwell Publishing.

Sala-i-Martin, X. (1997). I Just Ran 2 Million Regressions. *American Economic Review*, 87:178–183.

Sala-i-Martin, X., Doppelhofer, G., and Miller, R. I. (2004). Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach. *American Economic Review*, 94:813–835.

Schwarz, G. (1978). Estimating the Dimensions of a Model. *Annals of Statistics*, 6(2):461–464.

Zellner, A. (1986). *Inference and Decision Techniques: Essays in Honor of Bruno de Finetti*, chapter On Assessing Prior Distributions and Bayesian Regression Analysis with g-Prior Distributions. North-Holland: Amsterdam.

Technical Appendix

MCMC sampler

This section briefly discusses the MCMC sampler we are using throughout the paper. Exploring the model space can be done via a range of search algorithms, here we use Markov Chain Monte Carlo methods, 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. We use a a birth/death MC^3 search algorithm to explore the model space. In each iteration step a candidate regressor is drawn from $k_c \sim U(1, K)$. We add *(birth step)* 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)*. In this sense, the new model is always drawn from a neighborhood of the current one and differs from it only by a single regressor.[14] To compare the sampled candidate model to the current one we calculate the posterior odds ratio resulting into the following acceptance probability,

$$\tilde{p}_{ij} = \min\left[1, \frac{p(M_i)p(\mathbf{Y}|M_i)}{p(M_j)p(\mathbf{Y}|M_j)}\right]. \tag{6}$$

MCMC and interaction terms

We have modified the birth/death MCMC sampler assigning positive prior model probabilities solely to models that include all "relevant" regressors. That is, in case we have (multiplicative) interaction terms all variables that belong to the interaction variable are forced to enter the regression equation. Suppose we have a linear regression model with covariate matrix X, which contains some element(s) from the set {A, B, C, AB} and we draw 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 we draw a single regressor A. If the current model is $X_{current} = \{$ A, B, AB, C $\}$, we would drop variables A *and* AB. Hence we do not allow for models including interaction terms without their "parents" variables. This sampling method fulfills Chipman's (1996) strong heredity property, a possible guiding principle for model choice and model averaging with related variables.

[14]See Eklund and Karlsson (2007) for a comparison of various sampling schemes with respect to computational time and convergence properties.

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

We elicit a beta prior for ρ, Zellner's g-prior for the coefficient vector $\vec{\beta}$ (see text), and a gamma prior for the variance σ^2,

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

where we set $a_1 = a_2 = 1.01$ for the beta prior and $\nu = 1$, $\sigma^2 = 1$ for the variance corresponding to diffuse prior settings.

The log integrated likelihood (equation 4) is given by[15]

$$p(\rho|\mathbf{Y}, \mathbf{W}) = K_2\left(\frac{g}{1+g}\right)^{k/2}|\mathbf{I}_N - \rho\mathbf{W}|[\nu\bar{s}^2 + S(\rho) + Q(\rho)]^{-\frac{N+\nu-1}{2}}p(\rho) \tag{7}$$

with

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

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) we use 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,

$$\hat{\beta}_{SAR} = \hat{\beta}_{OLS} - \rho\hat{\beta}_d \tag{8}$$

$$\beta_d = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{W}y. \tag{9}$$

Equation 9 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 ($\rho = 0$) we hold the spatial lag term Wy 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.

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

Data Appendix

Country	Region	
Austria	Burgenland	Salzburg
	Kärnten	Steiermark
	Niederösterreich	Tirol
	Oberösterreich	Vorarlberg
	Wien	
Belgium	Prov. Antwerpen	Prov. Luxembourg (B)
	Prov. Brabant Wallon	Prov. Namur
	Prov. Hainaut	Prov. Oost-Vlaanderen
	Prov. Liège	Prov. Vlaams Brabant
	Prov. Limburg (B)	Prov. West-Vlaanderen
	Région de Bruxelles-Capitale	
Bulgaria	Severen tsentralen	Yugoiztochen
	Severoiztochen	Yugozapaden
	Severozapaden	Yuzhen tsentralen
Cyprus	Cyprus	Severovýchod
Czech Republic	Jihovýchod	Severozápad
	Jihozápad	Strední Cechy
	Moravskoslezsko	Stredn Morava
	Praha	
Denmark	Denmark	
Estonia	Estonia	
Finland	land	Länsi-Suomi
	Etelä-Suomi	Pohjois-Suomi
	Itä-Suomi	
France	Alsace	Île de France
	Aquitaine	Languedoc-Roussillon
	Auvergne	Limousin
	Basse-Normandie	Lorraine
	Bourgogne	Midi-Pyrénées
	Bretagne	Nord - Pas-de-Calais
	Centre	Pays de la Loire
	Champagne-Ardenne	Picardie
	Corse	Poitou-Charentes
	Franche-Comté	Provence-Alpes-Côte d'Azur
	Haute-Normandie	Rhône-Alpes
Germany	Arnsberg	Lüneburg
	Berlin	Mecklenburg-Vorpommern
	Brandenburg - Nordost	Mittelfranken
	Brandenburg - Südwest	Münster
	Braunschweig	Niederbayern
	Bremen	Oberbayern
	Chemnitz	Oberfranken
	Darmstadt	Oberpfalz
	Detmold	Rheinhessen-Pfalz
	Dresden	Saarland
	Düsseldorf	Saarland
	Freiburg	Schleswig-Holstein
	Giessen	Schwaben
	Hamburg	Stuttgart
	Hannover	Thüringen
	Karlsruhe	Trier

	Kassel	Tübingen
	Koblenz	Unterfranken
	Köln	Weser-Ems
	Leipzig	
Greece	Anatoliki Makedonia, Thraki	Kriti
	Attiki	Notio Aigaio
	Dytiki Ellada	Peloponnisos
	Dytiki Makedonia	Sterea Ellada
	Ionia Nisia	Thessalia
	Ipeiros	Voreio Aigaio
	Kentriki Makedonia	
Hungary	Dél-Alföld	Közép-Dunántúl
	Dél-Dunántúl	Közép-Magyarország
	Észak-Alföld	Nyugat-Dunántúl
	Észak-Magyarország	
Ireland	Border, Midlands and Western	
	Southern and Eastern	
Italy	Abruzzo	Molise
	Basilicata	Piemonte
	Calabria	Bolzano-Bozen
	Campania	Trento
	Emilia-Romagna	Puglia
	Friuli-Venezia Giulia	Sardegna
	Lazio	Sicilia
	Liguria	Toscana
	Lithuania	Umbria
	Lombardia	Valle d'Aosta
	Marche	Veneto
Latvia	Latvia	
Lithuania	Lithuania	
Luxembourg	Luxembourg (Grand-Duch)	
Malta	Malta	
Netherlands	Drenthe	Noord-Brabant
	Flevoland	Noord-Holland
	Friesland	Overijssel
	Gelderland	Utrecht
	Groningen	Zeeland
	Limburg (NL)	Zuid-Holland
Poland	Dolnoslaskie	Podkarpackie
	Kujawsko-Pomorskie	Podlaskie
	Ldzkie	Pomorskie
	Lubelskie	Slaskie
	Lubuskie	Swietokrzyskie
	Malopolskie	Warminsko-Mazurskie
	Mazowieckie	Wielkopolskie
	Opolskie	Zachodniopomorskie
Portugal	Alentejo	Lisboa
	Algarve	Norte
	Centro (PT)	
Romania	Bucuresti - Ilfov	Sud - Muntenia
	Centru	Sud-Est
	Nord-Est	Sud-Vest Oltenia
	Nord-Vest	Vest
Slovak Republic	Bratislavský kraj	Východné Slovensko

	Stredné Slovensko	Západné Slovensko
Slovenia	Slovenia	
Spain	Andalucia	Extremadura
	Aragón	Galicia
	Cantabria	Illes Balears
	Castilla y León	La Rioja
	Castilla-la Mancha	Pais Vasco
	Cataluña	Principado de Asturias
	Comunidad de Madrid	Región de Murcia
	Comunidad Foral de Navarra	Comunidad Valenciana
Sweden	Mellersta Norrland	Småland med öarna
	Norra Mellansverige	Stockholm
	Östra Mellansverige	Sydsverige
	Övre Norrland	Västsverige
United Kingdom	Bedfordshire, Hertfordshire	Kent
	Berkshire, Bucks and Oxfordshire	Lancashire
	Cheshire	Leicestershire, Rutland and Northants
	Cornwall and Isles of Scilly	Lincolnshire
	Cumbria	Merseyside
	Derbyshire and Nottinghamshire	North Yorkshire
	Devon	Northern Ireland
	Dorset and Somerset	Northumberland, Tyne and Wear
	East Anglia	Outer London
	East Riding and North Lincolnshire	Shropshire and Staffordshire
	East Wales	South Western Scotland
	Eastern Scotland	South Yorkshire
	Essex	Surrey, East and West Sussex
	Gloucestershire, Wiltshire and North Somerset	Tees Valley and Durham
	Greater Manchester	West Midlands
	Hampshire and Isle of Wight	West Wales and The Valleys
	Herefordshire, Worcestershire and Warks	West Yorkshire
	Inner London	

Table A.1: European regions in the sample

Variable name	Description	Source
Dependent variable		
gGDPCAP	Growth rate of real GDP per capita	Eurostat
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
AccessRail	Potential accessibility rail	ESPON
AccessRoad	Potential accessibility road	ESPON
AccessMulti	Potential accessibility multimodal	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	
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
ShSM	Share of medium 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
ShJK0	Initial share of NACE J to K (Business services)	Eurostat
EREH0	Employment rate - high	Eurostat LFS
EREM0	Employment rate - medium	Eurostat LFS
EREL0	Employment rate - low	Eurostat LFS
ERET0	Employment rate - total	Eurostat LFS
URH0	Unemployment rate - high	Eurostat LFS
URM0	Unemployment rate - medium	Eurostat LFS
URL0	Unemployment rate - low	Eurostat LFS
URT0	Unemployment rate - total	Eurostat LFS
ARH0	Activity rate high	Eurostat LFS
ARM0	Activity rate medium	Eurostat LFS
ARL0	Activity rate low	Eurostat LFS
ART0	Activity rate total	Eurostat LFS

Table A.2: Variables, description and sources

	Cross-section of regions			Cross-section of regions, spatial lags			Cross-section of regions, spatial lags and CEE inter.		
Variable	**PIP**	**PM**	**PSD**	**PIP**	**PM**	**PSD**	**PIP**	**PM**	**PSD**
AccessAir	0.010	0.0001	0.0009	0.049	0.0005	0.0023	0.007	0.0000	0.0006
AccessRoad	0.023	-0.0001	0.0007	0.046	-0.0003	0.0014	**0.358**	-0.0020	0.0028
AirportDens	0.074	0.3739	1.4379	0.063	0.3488	1.4590	0.025	0.1060	0.7249
Airports	0.046	0.0000	0.0002	0.049	0.0000	0.0002	0.037	0.0000	0.0002
ARH0	0.030	0.0013	0.0082	0.014	0.0006	0.0054	0.013	0.0006	0.0055
ARL0	0.011	-0.0002	0.0032	0.006	-0.0001	0.0021	0.002	0.0000	0.0004
ART0	0.007	0.0001	0.0029	0.004	0.0001	0.0019	0.002	0.0000	0.0007
Capital	**1.000**	0.0178	0.0019	**1.000**	0.0178	0.0020	**0.975**	0.0105	0.0035
ConnectAir	0.013	0.0000	0.0004	0.017	-0.0001	0.0004	0.007	0.0000	0.0003
ConnectSea	0.003	0.0000	0.0000	0.002	0.0000	0.0000	0.002	0.0000	0.0000
Distde71	0.005	0.0000	0.0000	0.007	0.0000	0.0000	**0.422**	0.0000	0.0000
DistCap	0.002	0.0000	0.0000	0.002	0.0000	0.0000	0.004	0.0000	0.0000
EMPDENS0	0.009	0.0001	0.0012	0.025	0.0003	0.0022	0.004	0.0000	0.0003
EREH0	0.025	0.0006	0.0042	0.011	0.0002	0.0027	0.004	0.0001	0.0015
EREL0	0.007	0.0000	0.0026	0.003	0.0000	0.0014	0.002	0.0000	0.0005
ERET0	0.043	0.0010	0.0052	0.018	0.0004	0.0036	0.005	0.0001	0.0011
GDPCAP0	**1.000**	-0.0202	0.0016	**1.000**	-0.0177	0.0033	**0.257**	-0.0030	0.0056
gPOP	0.005	0.0008	0.0141	0.003	0.0003	0.0094	0.003	0.0005	0.0115
Hazard	0.002	0.0000	0.0000	0.002	0.0000	0.0000	0.003	0.0000	0.0000
HRSTcore	0.002	0.0000	0.0006	0.003	0.0000	0.0007	0.001	0.0000	0.0003
INTF	0.005	0.0001	0.0016	0.003	0.0000	0.0010	0.004	0.0000	0.0009
OUTDENS0	0.002	0.0000	0.0000	0.005	0.0000	0.0000	0.007	0.0000	0.0000
PatentBIO	0.002	0.0000	0.0051	0.003	0.0004	0.0098	0.001	0.0000	0.0041
PatentHT	0.005	0.0002	0.0032	0.012	0.0006	0.0066	0.002	0.0000	0.0017
PatentICT	0.004	0.0001	0.0020	0.010	0.0004	0.0040	0.002	0.0000	0.0013
PatentShBIO	0.002	0.0000	0.0007	0.002	0.0000	0.0008	0.002	0.0000	0.0006
PatentShHT	0.002	0.0000	0.0004	0.002	0.0000	0.0004	0.001	0.0000	0.0002
PatentShICT	0.004	0.0000	0.0005	0.003	0.0000	0.0004	0.002	0.0000	0.0002
PatentT	0.003	0.0000	0.0004	0.007	0.0001	0.0012	0.002	0.0000	0.0005
POPDENS0	0.010	-0.0001	0.0010	0.031	-0.0003	0.0021	0.012	0.0000	0.0003
RailDens	0.002	0.0000	0.0006	0.002	0.0000	0.0007	0.002	0.0000	0.0010
RegBoarder	0.003	0.0000	0.0001	0.003	0.0000	0.0001	0.002	0.0000	0.0000
RegCoast	0.002	0.0000	0.0002	0.003	0.0000	0.0002	0.001	0.0000	0.0001
RegObj1	0.004	0.0000	0.0002	0.007	0.0000	0.0003	0.007	0.0000	0.0004
RegPent27	0.003	0.0000	0.0002	0.004	0.0000	0.0003	0.004	0.0000	0.0002

RoadDens	0.002	0.0000	0.0003	0.002	0.0000	0.0003	0.002	0.0000	0.0002
Seaports	0.004	0.0000	0.0002	0.003	0.0000	0.0001	0.005	0.0000	0.0002
Settl	0.002	0.0000	0.0001	0.002	0.0000	0.0001	0.001	0.0000	0.0001
ShAB0	0.002	0.0000	0.0010	0.002	0.0000	0.0011	0.002	0.0000	0.0013
ShCE0	0.017	0.0004	0.0038	0.008	0.0002	0.0023	0.002	0.0000	0.0006
shGFCF	0.004	0.0000	0.0007	0.003	0.0000	0.0006	0.013	0.0003	0.0034
ShLLL	0.016	0.0005	0.0045	0.008	0.0002	0.0031	0.002	0.0000	0.0010
ShSH	**0.976**	0.0475	0.0119	**0.495**	0.0238	0.0250	**0.983**	0.0599	0.0134
ShSL	0.023	-0.0003	0.0025	**0.511**	-0.0151	0.0152	0.019	-0.0005	0.0036
TELF	0.015	0.0000	0.0002	0.018	0.0000	0.0003	**0.272**	-0.0006	0.0011
TELH	0.002	0.0000	0.0000	0.002	0.0000	0.0000	0.002	0.0000	0.0000
Temp	0.003	0.0000	0.0001	0.007	0.0000	0.0003	0.002	0.0000	0.0001
URH0	0.006	0.0000	0.0026	0.004	0.0000	0.0019	0.002	0.0000	0.0011
URL0	0.028	-0.0006	0.0040	0.013	-0.0003	0.0026	0.008	-0.0001	0.0018
URT0	**0.181**	-0.0067	0.0153	0.075	-0.0027	0.0102	0.007	-0.0002	0.0026
W×EMPDENS0				0.004	0.0000	0.0015	0.009	0.0002	0.0019
W×GDPCAP0				**0.461**	-0.0271	0.0308	0.014	-0.0007	0.0064
W×gPOP				**0.499**	3.1943	3.3842	0.065	0.1865	0.8660
W×HRSTcore				0.086	0.0186	0.0643	0.017	0.0028	0.0236
W×OUTDENS0				0.004	0.0000	0.0000	0.013	0.0000	0.0001
W×POPDENS0				0.003	0.0000	0.0006	0.005	0.0001	0.0009
W×RoadDens				0.003	0.0000	0.0031	0.006	0.0003	0.0043
W×shGFCF				0.004	-0.0002	0.0039	0.016	-0.0024	0.0207
CEEDummy							**0.963**	0.0190	0.0060
CEEDummy×EMPDENS0							0.000	0.0000	0.0000
CEEDummy×GDPCAP0							0.001	0.0000	0.0002
CEEDummy×gPOP							0.000	0.0000	0.0000
CEEDummy×OUTDENS0							0.000	0.0000	0.0000
CEEDummy×POPDENS0							0.000	0.0000	0.0001
CEEDummy×RoadDens							0.000	0.0000	0.0000
CEEDummy×shGFCF							0.000	0.0000	0.0001
CEEDummy×HRSTcore							0.000	0.0000	0.0007
Model size (post. Mean)		3.65			4.64			4.61	
Countries/Obs.		27/255			27/255			27/255	

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 3,000,000 replications (after 2,000,000 burnin draws). PIPs over 10% are in bold font.

Table 1: BMA results, cross-section of regions

	Cross-section of regions			**Cross-section of regions, spatial lags**			**Cross-section of regions, spatial lags and CEE inter.**		
Variable	**PIP**	**PM**	**PSD**	**PIP**	**PM**	**PSD**	**PIP**	**PM**	**PSD**
AccessAir	**0.313**	0.0029	0.0046	**0.237**	0.0022	0.0042	0.010	0.0000	0.0005
AccessRoad	0.031	-0.0002	0.0011	0.022	-0.0001	0.0010	0.003	0.0000	0.0002
AirportDens	**0.200**	0.9465	1.9991	**0.179**	0.8524	1.9243	0.002	0.0019	0.0711
Airports	0.008	0.0000	0.0000	0.006	0.0000	0.0000	0.002	0.0000	0.0000
ARH0	0.002	0.0000	0.0010	0.001	0.0000	0.0009	0.002	0.0000	0.0007
ARL0	0.008	-0.0001	0.0018	0.006	-0.0001	0.0015	0.004	0.0000	0.0009
ART0	0.014	-0.0018	0.0301	0.010	-0.0013	0.0259	0.003	0.0000	0.0011
Capital	**0.489**	0.0043	0.0047	**0.440**	0.0040	0.0048	0.024	0.0001	0.0009
ConnectAir	0.005	0.0000	0.0002	0.004	0.0000	0.0002	0.006	0.0000	0.0002
ConnectSea	0.002	0.0000	0.0000	0.002	0.0000	0.0000	0.002	0.0000	0.0000
Distde71	0.037	0.0000	0.0000	0.025	0.0000	0.0000	0.024	0.0000	0.0000
DistCap	0.002	0.0000	0.0000	0.001	0.0000	0.0000	0.002	0.0000	0.0000
EMPDENS0	0.007	0.0001	0.0009	0.004	0.0000	0.0007	0.002	0.0000	0.0001
EREH0	0.004	-0.0001	0.0017	0.003	-0.0001	0.0014	0.001	0.0000	0.0006
EREL0	0.006	-0.0001	0.0012	0.004	-0.0001	0.0011	0.012	0.0002	0.0019
ERET0	0.005	0.0014	0.0309	0.004	0.0010	0.0265	0.011	0.0002	0.0025
GDPCAP0	0.007	0.0000	0.0007	0.004	0.0000	0.0006	**1.000**	-0.0288	0.0045
gPOP	0.004	-0.0006	0.0116	0.002	-0.0002	0.0075	0.001	0.0000	0.0041
Hazard	0.009	0.0000	0.0000	0.005	0.0000	0.0000	0.004	0.0000	0.0000
HRSTcore	0.002	0.0000	0.0004	0.001	0.0000	0.0004	0.001	0.0000	0.0003
INTF	0.013	0.0003	0.0032	0.010	0.0002	0.0027	**1.000**	0.0728	0.0125
OUTDENS0	0.010	0.0000	0.0000	0.006	0.0000	0.0000	0.002	0.0000	0.0000
PatentBIO	0.004	0.0005	0.0112	0.003	0.0004	0.0096	0.004	0.0004	0.0087
PatentHT	0.004	0.0001	0.0028	0.003	0.0001	0.0023	0.010	0.0004	0.0046
PatentICT	0.005	0.0001	0.0022	0.003	0.0001	0.0016	0.010	0.0003	0.0030
PatentShBIO	0.002	0.0000	0.0006	0.001	0.0000	0.0004	0.002	0.0000	0.0005
PatentShHT	0.002	0.0000	0.0004	0.002	0.0000	0.0003	0.003	0.0000	0.0004
PatentShICT	0.003	0.0000	0.0004	0.002	0.0000	0.0004	0.004	0.0000	0.0005
PatentT	0.012	0.0002	0.0018	0.008	0.0001	0.0014	0.016	0.0002	0.0020
POPDENS0	0.016	0.0000	0.0004	0.008	0.0000	0.0002	0.002	0.0000	0.0000
RailDens	0.003	0.0000	0.0007	0.001	0.0000	0.0005	0.006	-0.0001	0.0015
RegBoarder	0.016	0.0000	0.0003	0.012	0.0000	0.0003	0.005	0.0000	0.0001
RegCoast	0.002	0.0000	0.0001	0.001	0.0000	0.0000	0.002	0.0000	0.0000
RegObj1	0.032	0.0001	0.0008	0.023	0.0001	0.0007	0.002	0.0000	0.0001
RegPent27	0.003	0.0000	0.0002	0.003	0.0000	0.0001	0.004	0.0000	0.0001

RoadDens	0.004	0.0000	0.0005	0.002	0.0000	0.0003	0.002	0.0000	0.0003
Seaports	0.003	0.0000	0.0001	0.002	0.0000	0.0001	0.002	0.0000	0.0000
Settl	0.002	0.0000	0.0001	0.001	0.0000	0.0000	0.002	0.0000	0.0000
ShAB0	0.015	-0.0007	0.0060	0.012	-0.0005	0.0053	0.003	0.0000	0.0011
ShCE0	0.007	-0.0002	0.0021	0.004	-0.0001	0.0017	0.003	0.0000	0.0010
shGFCF	**0.597**	0.0221	0.0198	**0.516**	0.0192	0.0200	**0.283**	0.0018	0.0065
ShLLL	0.003	0.0001	0.0029	0.002	0.0001	0.0024	0.003	0.0001	0.0026
ShSH	**0.514**	0.0396	0.0413	**0.576**	0.0464	0.0424	**0.900**	0.0555	0.0220
ShSL	**0.235**	-0.0091	0.0173	**0.177**	-0.0069	0.0156	0.091	-0.0033	0.0110
TELF	0.002	0.0000	0.0001	0.002	0.0000	0.0001	0.003	0.0000	0.0001
TELH	0.001	0.0000	0.0000	0.001	0.0000	0.0000	0.003	0.0000	0.0001
Temp	0.002	0.0000	0.0001	0.001	0.0000	0.0001	0.003	0.0000	0.0001
URH0	0.009	0.0003	0.0041	0.006	0.0002	0.0033	0.002	0.0000	0.0012
URL0	0.001	0.0000	0.0005	0.001	0.0000	0.0004	0.068	-0.0016	0.0063
URT0	0.005	0.0009	0.0191	0.003	0.0006	0.0164	0.012	-0.0003	0.0032
$\mathbf{W}\times$EMPDENS0				0.004	0.0001	0.0014	0.002	0.0000	0.0006
$\mathbf{W}\times$GDPCAP0				0.001	0.0000	0.0006	0.003	-0.0001	0.0017
$\mathbf{W}\times$gPOP				0.004	0.0079	0.1532	0.025	0.0668	0.4697
$\mathbf{W}\times$HRSTcore				0.002	-0.0002	0.0077	0.002	-0.0001	0.0054
$\mathbf{W}\times$OUTDENS0				0.006	0.0000	0.0000	0.003	0.0000	0.0000
$\mathbf{W}\times$POPDENS0				0.002	0.0000	0.0005	0.002	0.0000	0.0003
$\mathbf{W}\times$RoadDens				0.003	-0.0002	0.0046	0.001	0.0000	0.0015
$\mathbf{W}\times$shGFCF				0.013	-0.0023	0.0216	0.014	-0.0019	0.0173
CEEDummy							0.000	0.0000	0.0009
CEEDummy×EMPDENS0							**1.000**	0.0000	0.0009
CEEDummy×GDPCAP0							0.000	0.0000	0.0000
CEEDummy×gPOP							**1.000**	0.0406	0.0050
CEEDummy×OUTDENS0							0.000	0.0000	0.0013
CEEDummy×POPDENS0							0.000	0.0000	0.0000
CEEDummy×RoadDens							0.000	0.0000	0.0000
CEEDummy×shGFCF							0.000	0.0000	0.0002
CEEDummy×HRSTcore							**0.255**	0.0219	0.0388
Model size (post. Mean)		2.68			2.38			5.87	
Countries/Obs.		27/255			27/255			27/255	

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 3,000,000 replications (after 2,000,000 burnin draws). PIPs over 10% in bold.

Table 2: BMA results, cross-section of regions with country fixed effects

	Cross-section of regions spatial lags			Cross-section of regions, spatial lags and CEE inter.		
Variable	**PIP**	**PM**	**PSD**	**PIP**	**PM**	**PSD**
AccessAir	**0.953**	0.0129	0.0049	**0.670**	0.0087	0.0070
AccessRoad	**0.532**	-0.0036	0.0040	**0.580**	-0.0042	0.0043
AirportDens	**0.927**	6.3298	2.4831	**0.661**	4.2991	3.4936
Airports	0.030	0.0000	0.0001	0.073	0.0000	0.0002
ARH0	0.027	0.0004	0.0053	0.042	0.0012	0.0078
ARL0	0.023	-0.0001	0.0023	0.016	0.0000	0.0015
ART0	0.021	-0.0001	0.0037	0.020	0.0001	0.0024
Capital	**1.000**	0.0175	0.0022	**1.000**	0.0154	0.0029
ConnectAir	0.042	-0.0001	0.0006	0.052	-0.0001	0.0007
ConnectSea	0.019	0.0000	0.0001	0.018	0.0000	0.0001
Distde71	0.036	0.0000	0.0000	0.083	0.0000	0.0000
DistCap	0.020	0.0000	0.0000	0.019	0.0000	0.0000
EMPDENS0	**0.920**	0.0141	0.0053	**0.610**	0.0082	0.0075
EREH0	0.025	-0.0001	0.0039	0.026	0.0001	0.0041
EREL0	0.019	0.0000	0.0014	0.019	0.0000	0.0015
ERET0	0.020	0.0001	0.0041	0.024	0.0002	0.0025
GDPCAP0	**1.000**	-0.0158	0.0031	**0.900**	-0.0122	0.0056
gPOP	0.045	-0.0073	0.0427	**0.250**	-0.0437	0.0998
Hazard	**0.108**	0.0000	0.0000	0.064	0.0000	0.0000
HRSTcore	0.020	0.0000	0.0014	0.034	0.0000	0.0019
INTF	0.022	0.0001	0.0018	0.025	0.0002	0.0027
OUTDENS0	0.065	0.0000	0.0001	**0.199**	0.0000	0.0001
PatentBIO	0.021	0.0012	0.0185	0.018	0.0009	0.0173
PatentHT	0.056	0.0022	0.0122	0.052	0.0022	0.0123
PatentICT	0.063	0.0018	0.0090	0.065	0.0020	0.0095
PatentShBIO	0.026	0.0003	0.0027	0.021	0.0002	0.0023
PatentShHT	0.019	0.0000	0.0010	0.020	0.0000	0.0011
PatentShICT	0.020	0.0000	0.0008	0.020	0.0001	0.0009
PatentT	0.039	0.0004	0.0026	0.058	0.0008	0.0039
POPDENS0	**0.967**	-0.0133	0.0037	**0.799**	-0.0094	0.0060
RailDens	0.020	0.0000	0.0024	0.018	-0.0001	0.0025
RegBoarder	0.036	0.0001	0.0004	0.028	0.0000	0.0003
RegCoast	**0.109**	-0.0005	0.0017	0.081	-0.0003	0.0015
RegObj1	0.065	0.0002	0.0008	0.070	0.0002	0.0010
RegPent27	0.072	0.0003	0.0012	0.088	0.0004	0.0014

RoadDens	0.061	0.0006	0.0026	0.049	0.0004	0.0022
Seaports	0.058	0.0002	0.0013	0.048	0.0002	0.0012
Settl	0.020	0.0000	0.0002	0.016	0.0000	0.0002
ShAB0	0.026	0.0004	0.0044	0.046	0.0015	0.0087
ShCE0	**0.187**	0.0051	0.0120	0.064	0.0014	0.0064
shGFCF	0.073	0.0012	0.0049	0.099	0.0021	0.0076
ShLLL	**0.151**	-0.0051	0.0137	0.095	-0.0029	0.0105
ShSH	0.055	0.0011	0.0059	**0.455**	0.0220	0.0261
ShSL	**0.992**	-0.0283	0.0076	**0.620**	-0.0153	0.0135
TELF	**0.390**	-0.0008	0.0012	**0.290**	-0.0006	0.0011
TELH	0.032	0.0000	0.0002	0.027	0.0000	0.0002
Temp	**0.300**	0.0011	0.0018	**0.166**	0.0006	0.0014
URH0	0.059	0.0017	0.0087	0.047	0.0014	0.0086
URL0	0.026	-0.0002	0.0021	0.035	-0.0004	0.0031
URT0	0.025	-0.0003	0.0043	0.031	-0.0006	0.0051
$\mathbf{W}\times$EMPDENS0	0.067	-0.0014	0.0107	0.031	-0.0004	0.0060
$\mathbf{W}\times$GDPCAP0	**0.684**	-0.0395	0.0305	**0.252**	-0.0127	0.0250
$\mathbf{W}\times$gPOP	**0.968**	5.2825	1.8965	**0.840**	3.5716	2.2578
$\mathbf{W}\times$HRSTcore	**0.603**	0.1523	0.1428	**0.283**	0.0672	0.1189
$\mathbf{W}\times$OUTDENS0	0.046	0.0000	0.0002	0.025	0.0000	0.0001
$\mathbf{W}\times$POPDENS0	**0.118**	-0.0022	0.0076	0.047	-0.0007	0.0043
$\mathbf{W}\times$RoadDens	0.094	-0.0068	0.0255	0.043	-0.0021	0.0148
$\mathbf{W}\times$shGFCF	0.026	0.0002	0.0109	0.045	-0.0053	0.0330
CEEDummy				**0.708**	0.0072	0.0090
CEEDummy×EMPDENS0				**0.109**	-0.0072	0.0389
CEEDummy×GDPCAP0				0.011	0.0000	0.0006
CEEDummy×gPOP				0.002	-0.0002	0.0167
CEEDummy×OUTDENS0				**0.129**	-0.0003	0.0009
CEEDummy×POPDENS0				**0.252**	0.0129	0.0266
CEEDummy×RoadDens				0.005	-0.0004	0.0068
CEEDummy×shGFCF				0.002	0.0000	0.0008
CEEDummy×HRSTcore				0.012	0.0011	0.0113
Model size (post. Mean)		12.45			11.62	
Countries/Obs.		27/255			27/255	
ρ estimate		0.3757			0.5036	

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 3,000,000 replications (after 2,000,000 burnin draws). PIPs over 10% in bold.

Table 3: BMA results, cross-section of regions, spatial autoregressive specification

	Spatial lags and Periphery dummy inter.		
Variable	PIP	PM	PSD
AccessAir	**0.924**	0.0125	0.0053
AccessRoad	**0.552**	-0.0038	0.0041
AirportDens	**0.884**	6.0723	2.7937
Airports	0.037	0.0000	0.0001
ARH0	0.024	0.0004	0.0043
ARL0	0.021	-0.0003	0.0034
ART0	0.017	-0.0001	0.0030
Capital	**1.000**	0.0177	0.0022
ConnectAir	0.041	-0.0001	0.0006
ConnectSea	0.017	0.0000	0.0001
Distde71	0.031	0.0000	0.0000
DistCap	0.019	0.0000	0.0000
EMPDENS0	**0.876**	0.0137	0.0061
EREH0	0.020	0.0000	0.0027
EREL0	0.022	-0.0001	0.0018
ERET0	0.022	0.0004	0.0055
GDPCAP0	**1.000**	-0.0159	0.0031
gPOP	**0.443**	-0.0713	0.1147
Hazard	0.074	0.0000	0.0000
HRSTcore	0.019	0.0000	0.0014
INTF	0.018	0.0001	0.0018
OUTDENS0	0.060	0.0000	0.0001
PatentBIO	0.021	0.0013	0.0188
PatentHT	0.059	0.0024	0.0133
PatentICT	0.061	0.0018	0.0093
PatentShBIO	0.023	0.0003	0.0026
PatentShHT	0.016	0.0000	0.0010
PatentShICT	0.016	0.0000	0.0008
PatentT	0.039	0.0004	0.0027
POPDENS0	**0.920**	-0.0129	0.0047
RailDens	0.018	0.0000	0.0023
RegBoarder	0.036	0.0001	0.0004
RegCoast	**0.111**	-0.0005	0.0017
RegObj1	0.052	0.0001	0.0008
RegPent27	0.074	0.0003	0.0013
RoadDens	0.048	0.0004	0.0023
Seaports	0.049	0.0002	0.0012
Settl	0.016	0.0000	0.0002
ShAB0	0.022	0.0004	0.0040
ShCE0	**0.135**	0.0035	0.0101
shGFCF	0.069	0.0011	0.0049
ShLLL	**0.141**	-0.0048	0.0134
ShSH	0.064	0.0016	0.0076
ShSL	**0.979**	-0.0269	0.0080
TELF	**0.329**	-0.0007	0.0011
TELH	0.030	0.0000	0.0002
Temp	**0.257**	0.0009	0.0017
URH0	0.045	0.0014	0.0084
URL0	0.022	-0.0002	0.0020
URT0	0.027	-0.0005	0.0053

W×EMPDENS0	0.059	-0.0011	0.0105
W×GDPCAP0	**0.622**	-0.0352	0.0310
W×gPOP	**0.934**	5.1590	2.1749
W×HRSTcore	**0.520**	0.1276	0.1390
W×OUTDENS0	0.032	0.0000	0.0002
W×POPDENS0	0.093	-0.0017	0.0071
W×RoadDens	0.072	-0.0050	0.0222
W×shGFCF	0.023	0.0000	0.0100
Periphery Dummy	0.033	0.0001	0.0025
Periphery Dummy×EMPDENS0	0.001	0.0000	0.0012
Periphery Dummy×GDPCAP0	0.001	0.0000	0.0003
Periphery Dummy×gPOP	0.000	0.0000	0.0029
Periphery Dummy×HRSTcore	0.000	0.0000	0.0000
Periphery Dummy×OUTDENS0	0.000	0.0000	0.0000
Periphery Dummy×POPDENS0	0.001	0.0000	0.0006
Periphery Dummy×RoadDens	0.000	0.0000	0.0002
Periphery Dummy×shGFCF	0.000	0.0000	0.0005
Model size (post. Mean)		12.18	
Countries/Obs.		27/255	
ρ estimate		0.4413	

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 1,000,000 replications. PIPs over 10% in bold.

Table 4: BMA results, cross-section of regions, spatial autoregressive specification with Periphery Dummy

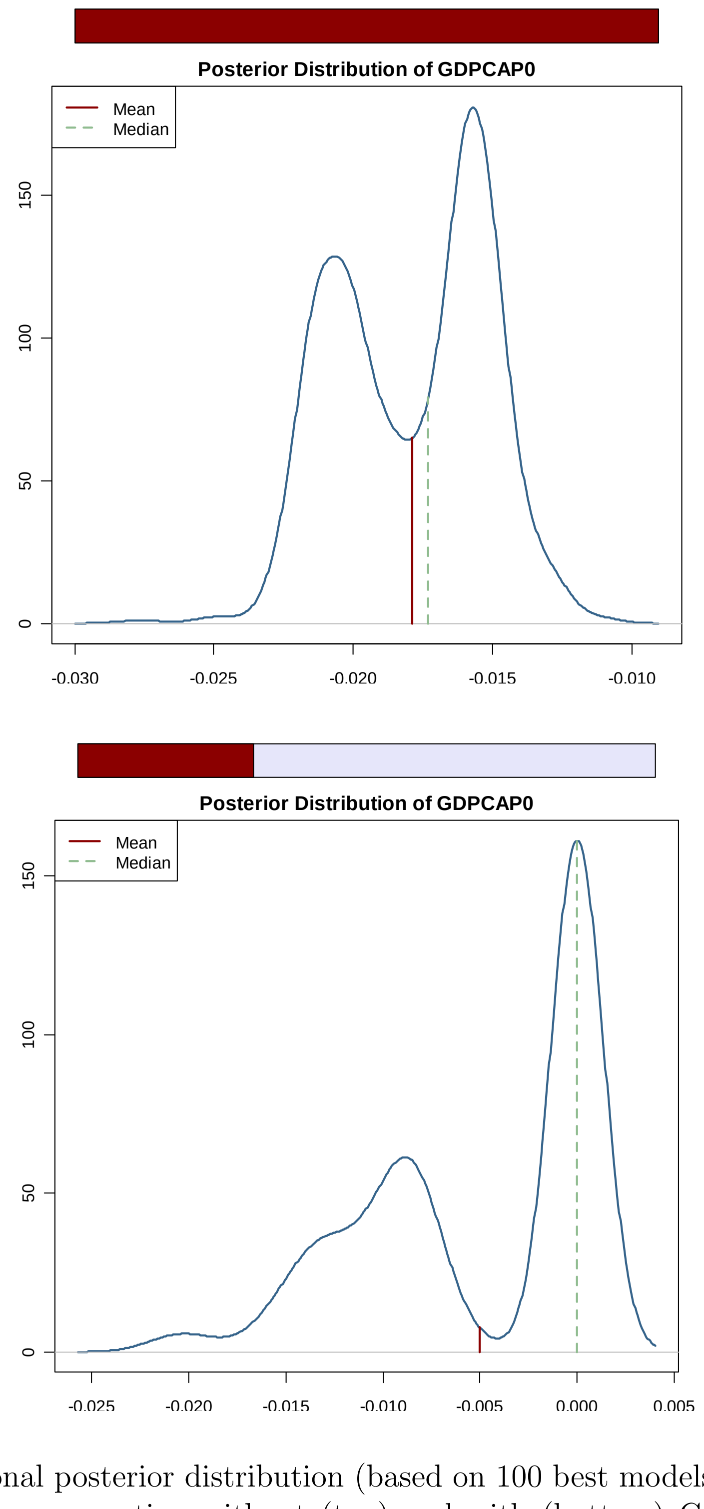


Figure 1: Unconditional posterior distribution (based on 100 best models), conditional convergence parameter: cross section without (top) and with (bottom) Central and Eastern European dummy as a covariate

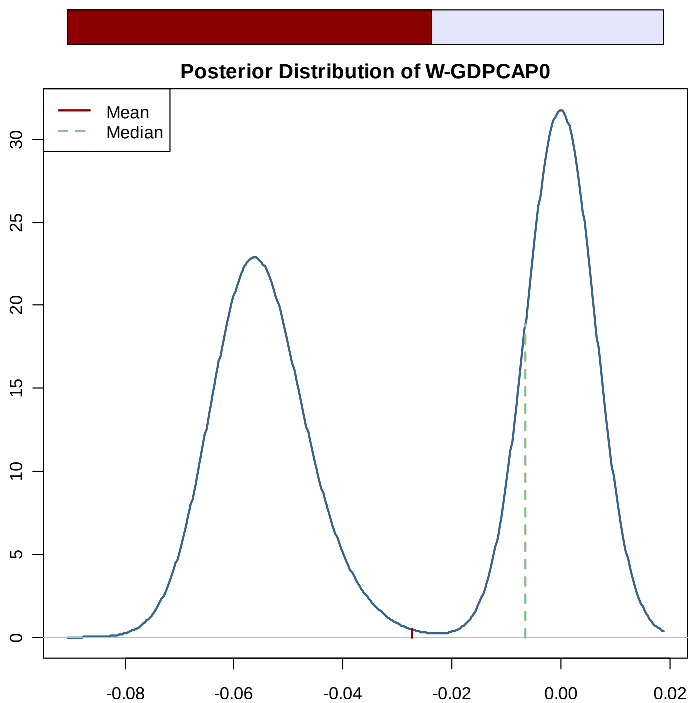
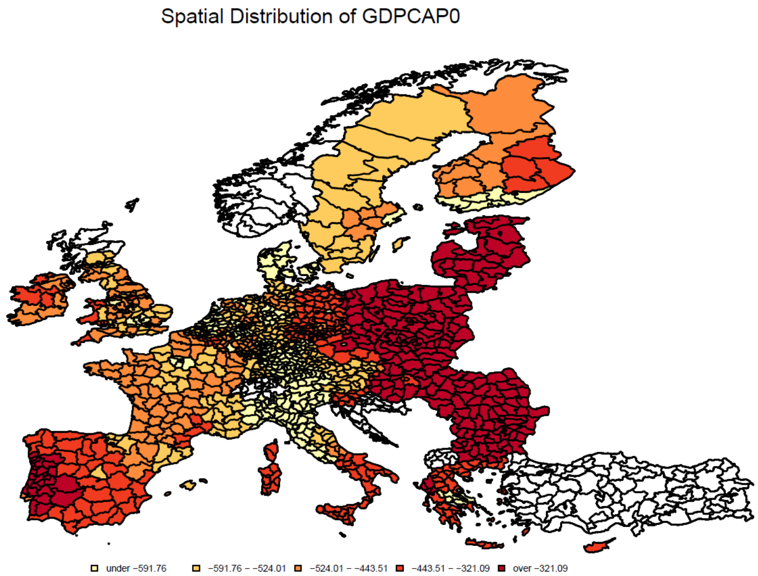


Figure 2: Posterior distribution, $\mathbf{W}\times$GDPCAP0 parameter



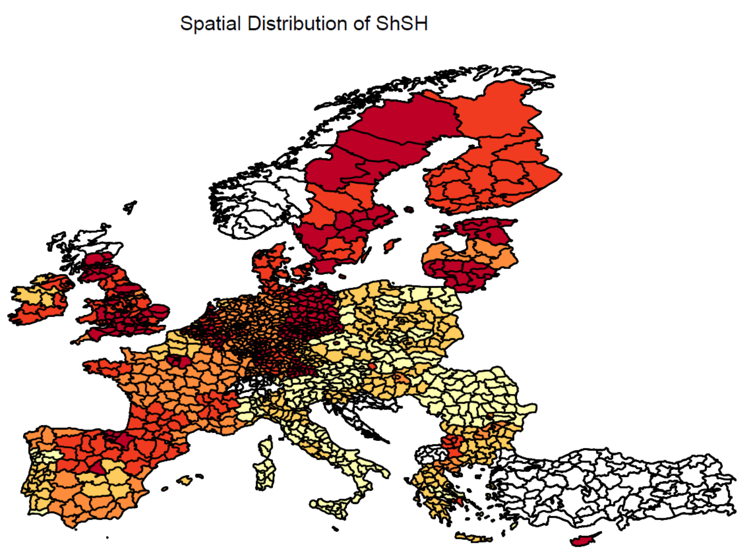


Figure 3: Spatial Distribution / No SAR but Interaction + country fixed effects

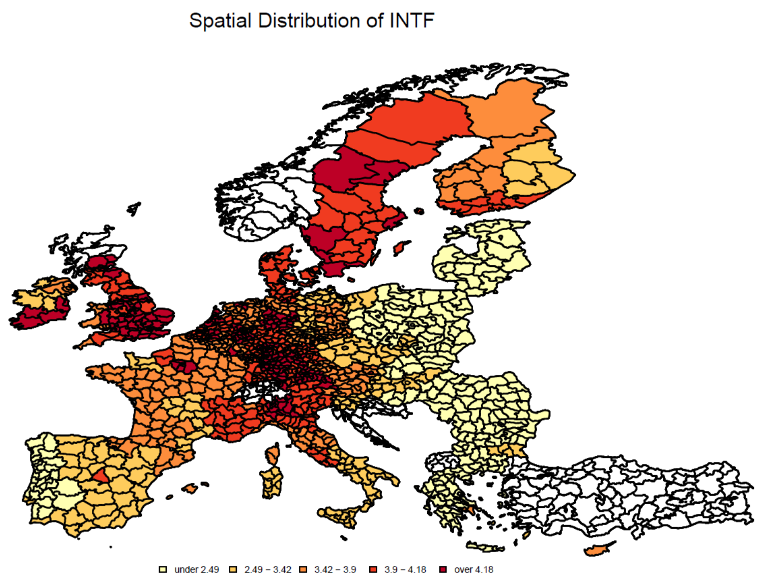


Figure 4: Spatial Distribution / No SAR but Interaction + country fixed effects

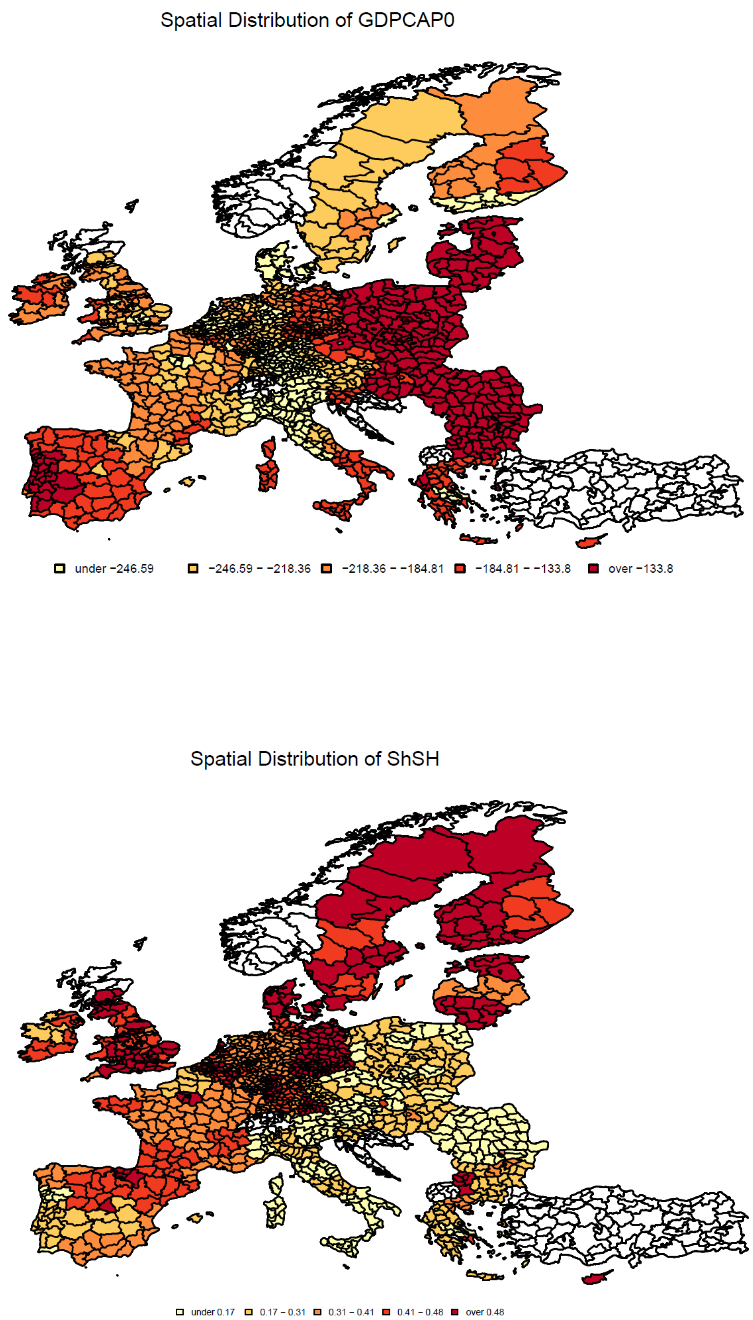


Figure 5: Spatial Distribution / SAR + Interaction but no country fixed effects

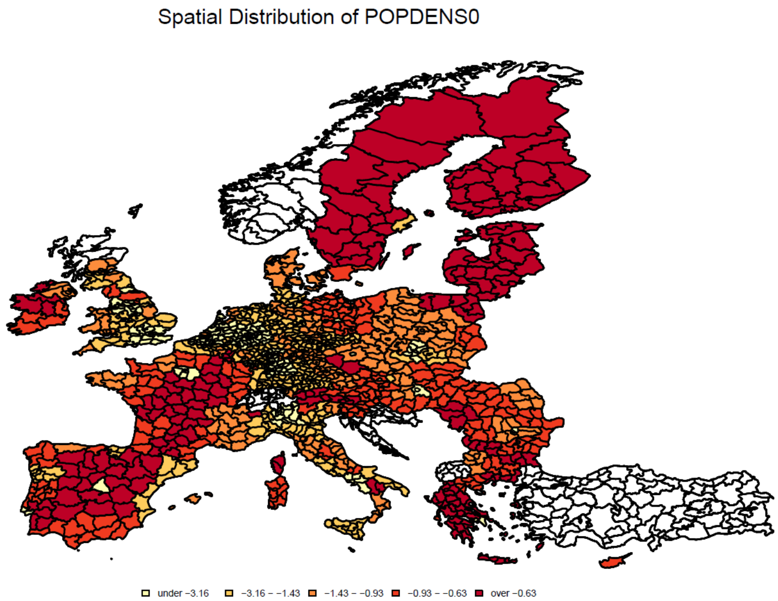


Figure 6: Spatial Distribution / SAR + Interaction but no country fixed effects

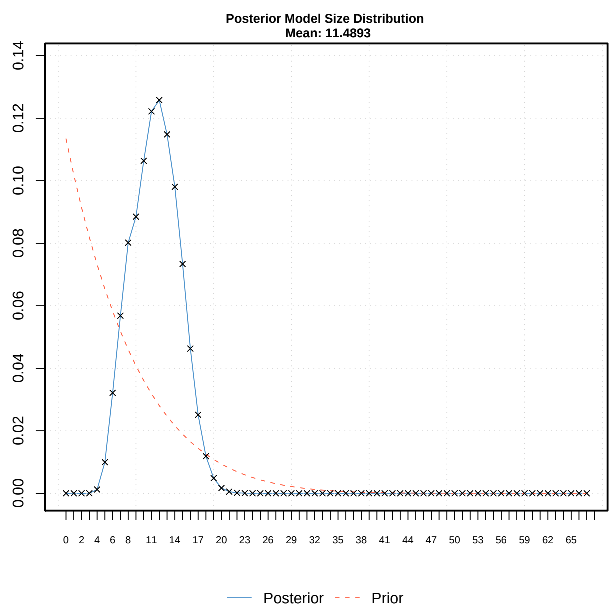
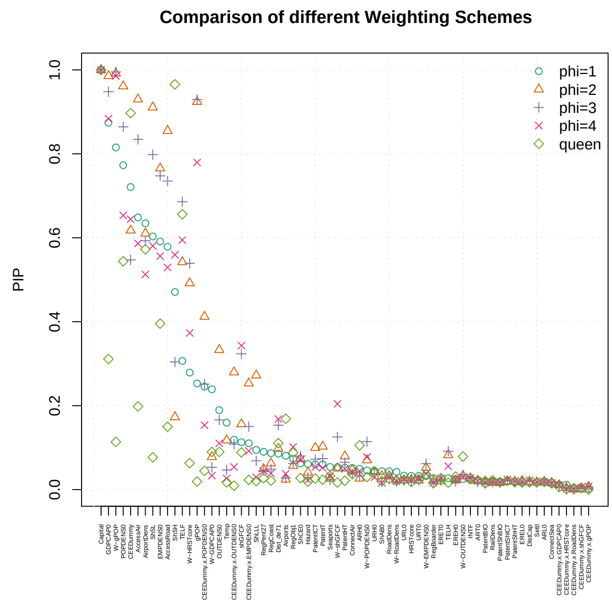


Figure 7: Prior (red-dotted) and Posterior (blue) Distribution of Model Size: Cross-section of regions, spatial autoregressive Specification with CEEDummy Interaction (Table 3, right panel)



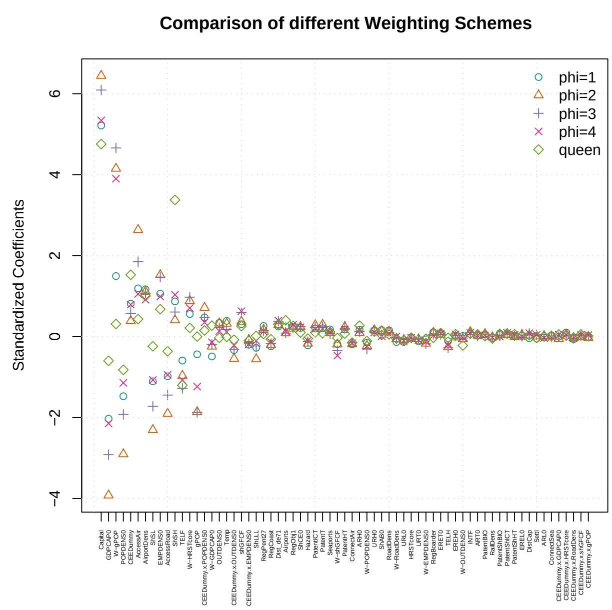


Figure 8: Posterior inclusion probabilities and standarized coefficients for different **W** matrices based on the estimation set up from Table 2 (Cross-section of regions, and CEE interaction). We have used four distance ($\phi = 1, \ldots, 4$) and one contiguity (first order queen contiguity, see Anselin (1988)) weighting schemes.

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