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The Determinants of Economic Growth in European Regions

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This paper was prepared as a background study to the statistical analysis on the factors of regional economic growth coordinated by the Vienna Institute for International Economic Studies (www.wiiw.ac.at) in the framework of the project 'Analysis of the Main Factors of Regional Growth: An in-depth study of the best and worst performing European regions' (contract no. 2007.CE.16.0.AT.029). Financial support from the European Community, DG Regional Policy, is gratefully acknowledged. We would like to thank Carlo Altavilla, Roger Bivand, Manfred Fischer, Jim LeSage, Robert Stehrer, Stefan Zeugner and participants of the wiiw Workshop on Regional Growth, CESifo Macro Area Conference, III World Conference of Spatial Econometrics in Barcelona and the Bergen Econometrics group for helpful comments. The opinions in this paper are those of the authors and do not necessarily coincide with those of the Oesterreichische Nationalbank or the EU Commission.

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The Determinants of Economic Growth in European Regions

Contents

Abstract

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JEL classification: *C11, C15, C21, R11, O52.*

The determinants of economic growth in European regions*

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September 8, 2009

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. Our results indicate that the income 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 find robust evidence of asymmetric growth performance within countries, with a growth bonus in regions containing capital cities which is particularly sizable in CEE countries, as well as a robust positive effect of education. The results are robust if we allow for spatial spillovers *a priori*. In this setting, we also find robust evidence of positive spillovers leading to growth clusters.

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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 two percent 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).[2]

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.[3] Fernández et al. (2001b) use *Bayesian Model Averaging* (henceforth 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

[1] Barro and Sala-i-Martin (2003) give an excellent overview of empirical analysis for regional data (chapter 11) and cross-sections of countries (chapter 12).

[2] For an overview of convergence in EU regions at NUTS-2 level see European Commission (2008).

[3] 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.

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 (2009). Following Brown et al. (1998), Ley and Steel (2009) 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 (2009). We also improve on past attempts to assess parameter heterogeneity[4] 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. 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) 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 semi-parametric 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. A very recent literature has developed Bayesian tools for the analysis of spatially correlated data. LeSage and Parent (2007) give an excellent introduction to BMA for spatial econometric models. LeSage and Fischer (2008) 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) and **?** for textbook discussions of the SAR model).

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 use a new methodology to assess parameter heterogeneity based on the strong heredity principle when assessing the model space in the BMA setting. We allow for heterogeneous effects of selected growth determinants in recent accession countries in Central and Eastern Europe (CEE) and also for capital cities. Fourth, we allow for uncertainty over spatial weights by conducting a sensitivity analysis with respect to alternative spatial distance measures.

The main findings of the paper are as follows:

[4] See Crespo Cuaresma and Doppelhofer (2007) and Doppelhofer and Weeks (2009) for recent contributions to parameter heterogeneity in the framework of BMA.

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 systematically higher than in non-capital city regions. This result, however, hides very strong differences between the experience of old and new EU member states. The growth bonus of capital city regions in Central and Eastern Europe is much more sizable than in old member states, which can be seen as empirical support to the Williamson hypothesis (Williamson, 1965). According to the Williamson hypothesis, as the catching-up process progresses, economic growth concentrates in regions where urban agglomerations are present, reverting the process in later stages of development.

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.

5. Statistical and economic inference are robust 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 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

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, $\mathbf{X}_k = (\mathbf{x}_1 \ldots \mathbf{x}_k)$ is a matrix whose columns are stacked data for k explanatory variables, $\vec{\beta}_k = (\beta_1 \ldots \beta_k)'$ 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.[5] For the moment, let us assume ε to be an N-dimensional 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[6] 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 economic 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,

[5]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 below using within-transformed data.

[6]For the estimation we use great circle distances between i and j measured in kilometers.

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

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

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

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

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 (2009) 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 this approach allows for very different prior structures on model size (see examples in Ley and Steel (2009)).

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[7]. The posterior distributions of interest over the model space can be then obtained using Markov Chain

[7] For more details see the Technical Appendix.

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 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 (2009) 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.[8]

3 Empirical results

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 dataset covers information on 255 European regions, and each income growth observation refers to the average annual growth rate in the period 1995-2005, deflated using national price data. The set of variables can be roughly divided into variables approximating *factor accumulation and convergence* (the usual economic growth determinants implied by the neoclassical (Solow) growth model), *human capital* variables, *technological innovation* variables, variables measuring *sectoral structure and employment*, *infrastructure* and *socio-geographical* variables.[9] All explanatory variables are measured at the year 1995 or the earliest existing year for those covariates for which no data are available in 1995.

We identify potential growth drivers for regions *between* countries as well as for regions

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

[9] We do not consider structural funds programs allocating transfers to NUTS-2 regions and associated classification into so-called Objective 1 regions 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.

within countries of the EU 27. Consequently 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 addition we employ the SAR model to capture growth spillovers among EU regions with different choices for the spatial weight matrix **W**. The SAR model should add confidence regarding the robustness of empirical findings since numerious studies (eg Fischer and Stirböck (2006), LeSage and Fischer (2008)) point to nonnegligible spatial correlation in regional growth data sets causing the standard model to yield flawed inference. 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.

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.

3.1 Economic growth determinants for European Regions

Table 3 presents findings based on the cross section of regions for three different model specifications. In each column we report the posterior inclusion probabilities of each regressor, together with the 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 $K/2$ regressors.[10] A variable whose PIP exceeds the 0.5 threshold (and thus has a higher inclusion probability after observing the data than its prior inclusion probability) is identified as robust.[11] We start by obtaining estimates using the cross section of regions drawing on the 54 variables listed in the appendix. The first set of columns in Table 3 reveal that initial income (GDPCAP0), a proxy for human capital (ShSH) and a dummy for capital cities (Capital) are robust drivers of economic growth for European regions. Posterior parameter means show the expected signs for the robust determinants and posterior standard deviations are relatively small. In this setting, the results imply that income convergence took place among European regions in the period considered, with a model-averaged estimate of the speed of convergence[12] of roughly 2%. Given that our 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.

[10]Since we use the hierarchical prior over the model size, our results do not appear sensitive to the choice of this hyperparameter.

[11]Eicher et al. (2009) translate the scale of evidence put forward by Kass and Raftery (1995) into four categouries: weak (50-75% PIP), substantial (75-95%), strong (95-99%) and decisive (99%+) evidence.

[12]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.

Consequently, we further elaborate on the issue of parameter heterogeneity between Eastern and Western European regions in the second 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, access to roads, output density, a human capital proxy variable, population density and employment density. The results in the second set of columns in Table 3 present striking evidence for the inclusion of the CEE dummy variable, whose effect on economic growth is positive and well estimated. In this setting, the estimated income convergence coefficient loses importance in terms of its posterior inclusion probability and the estimated speed of convergence falls radically after including the CEE dummy. Furthermore, the speed of income convergence is not estimated with a reasonable degree of certainty anymore. The top panel of Figure 3 illustrates the impact of explicitely modeling heterogeneity in the intercept across European regions. The left hand side of Figure 3 (top panel) shows the posterior distribution of the coefficient attached to the initial income variable based on the 500 models with largest posterior support (in terms of posterior model probability). The distribution is tightly concentrated around the model-averaged estimated 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 3). The posterior distribution of the parameter 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, we find 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 member states.

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. In the third column we allow for heterogenous 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 3, middle and bottom panels, showing the posterior distributions along with respective PIPs 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 theoretically a well known empirical stylized fact which can be interpreted in the framework of the Williamson hypothesis (Williamson (1965)), which states that countries in an early stage of catching up the growth push in economic acitivity should be concentrated in few poles (corresponding, for instance, to urban agglomerations around capital cities).

Similarly, the positive effect of human capital on economic growth is reflected in a robust positive parameter estimate attached to the variable quantifying the population share of highly educated workers. The size of the model averaged estimate in the model with interactions (third column in Table 3) implies that on average a ten percent increase of the share of highly educated in working age population 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 caveats mentioned in Vandenbussche et al. (2006) regarding the comparability of this proxy are however in place. In principle, some of the variation in the shares of highly educated people - measured as those who completed tertiary education - might be attributed to the fact that education systems vary across countries. Notice however that this variable remains important in explaining growth differences also in the specification including country-fixed effects (see next subsection), where heterogeneity in national education systems is controlled for.

As explained above and reported in Table 3, 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.

3.2 Growth determinants within countries

For the BMA exercise reported in Table 4 we concentrate on regional differences *within* countries in order to assess the robustness of economic growth determinants. The BMA estimates are thus based on specifications which contain country fixed effects and therefore account for unobserved time-invariant country specific characteristics which could affect the process of economic growth. Note that the dynamics of income convergence in this specification are to be interpreted as taking place in regions within a country towards a country-specific steady state. Comparing columns 1 and 2 in Table 4 indicates 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 by the interaction term linking the dummy variable for CEE regions to initial income. The coefficient attached to the dummy variable 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 4, top panel. As in the between specification, controllning for spatial htereogeneity reveals a bimodal shape of the posterior distribution of the initial income parameter. However, in contrast to the between specification, including the CEE dummy variable is necessary to establish income convergence for regions within European countries. This is in further evidence in line with Williamson (1965) and empirically confirmed by Béla (2007), which shows 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 diminishing returns to scale other backward regions become more attractive for investment leading to regional convergence. Our 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.[13] Our quantitative estimates imply a model averaged estimate of the coefficient attached to initial income of -0.029, larger in magnitude than in the *between* model specification. This translates into a speed of convergence of around 3.4%. While the capital dummy variable is not precisely estimated in the first two specifications (columns 1 and 2), it receives large posterior support in the third one (third column): Here, the capital city and CEE dummy variable plus its linear interaction term receive a high posterior inclusion probability, meaning that once we control for spatial heterogeneity (in terms of East/West-specific parameters), the capital city effect appears robust in the data. Figure 4, middle and bottom panel, shows the posterior distribution of the parameters for initial income, the capital city and the CEE dummy variables, as well as the interaction term. The distribution illustrates that 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 4.

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 illustrated in the top panel of Figure 1 which shows the spatial distribution of the quantitative effect of initial income on economic growth within European regions.[14] The figure 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. The bottom panel of Figure 1 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, Benelux countries and Scandinavia as well as Southern regions in the UK.

[13]Furthermore note that the CEE dummy in Table 4 is *by construction* significant according to its PIP. This is because we use the strong heredity principle that forces the dummy to be included whenever an interaction term enters the regression. However, its coefficient is merely zero, as is expected after including country fixed effects.

[14]To help reading the maps we have scaled regressors as follows. The top panel of Figure 1 plots the partial effect of the *levels* (not log-levels) of initial income. Similarly, the share of highly skilled workers (ShSH) is scaled by a factor of 100.

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 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 5 the results of the BMA exercise for the class of SAR models are presented. We use 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.

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.

Since economic theory does not offer much of a guidance concerning a particular choice of spatial weighting matrix $\mathbf{W}$ we assess the robustness of our findings with respect to the choice of the spatial link matrix.[15] 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 value $\phi = 2$, which implies a faster decay 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.[16] Such a spatial structure implies that growth developments in a given region are affected by the growth process in all (first-order) contiguous regions.

[15]See Crespo Cuaresma and Feldkircher (2009) for a recent contribution dealing with uncertainty with respect to the choice of spatial weight matrix in a BMA framework.

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

Figures 8 summarizes the results of the robustness exercise by plotting in the top panel the posterior inclusion probabilities (PIP) and in the bottom panel standardized 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 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.[17]

Finally - as a further robustness check - we allow for spillovers to occur via the explanatory variables, as in the Spatial Durbin model. Thus we have re-estimated the between and within models with an enlarged set of potential growth determinants by introducing further spatial lags. From Tables 6 and 7 it becomes evident that results obtained in sections 3.2 and 3.1 are still present under the enlarged set of variables[18].

4 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 via interaction terms.

Our results imply that conditional income convergence appears as the most robust driving 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, and this assymetry is particularly sizable in Eastern European economies, lending 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. We also find evidence for positive spatial spillovers leading to growth clusters in EU regions.

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

[18] Results for the SAR model with enlarged set of covariates are available upon request from the authors.

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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.[19] 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:

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

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.

[19] 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[20]

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

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,

$$\hat{\beta}_{SAR} = \hat{\beta}_{OLS} - \rho\hat{\beta}_d \qquad (8)$$

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

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.

[20]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	Yuzhentsentralen
Cyprus	Cyprus	
Czech Republic	Jihovýchod	Severozápad
	Jihozápad	Strední Cechy
	Moravskoslezsko	Stredn Morava
	Praha	Severovýchod
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	Schleswig-Holstein
	Freiburg	Schwaben
	Giessen	Stuttgart
	Hamburg	Thüringen
	Hannover	Trier
	Karlsruhe	Tübingen
	Kassel	Unterfranken
	Koblenz	Weser-Ems

	Köln	Leipzig
Greece	Anatoliki Makedonia, Thraki Attiki Dytiki Ellada Dytiki Makedonia Ionia Nisia Ipeiros Kentriki Makedonia	Kriti Notio Aigaio Peloponnisos Sterea Ellada Thessalia Voreio Aigaio
Hungary	Dél-Alföld Dél-Dunántúl Észak-Alföld Észak-Magyarország	Közép-Dunántúl Közép-Magyarország Nyugat-Dunántúl
Ireland	Border, Midlands and Western Southern and Eastern	
Italy	Abruzzo Basilicata Calabria Campania Emilia-Romagna Friuli-Venezia Giulia Lazio Liguria Lombardia Marche Molise	Piemonte Bolzano-Bozen Trento Puglia Sardegna Sicilia Toscana Umbria Valle d'Aosta Veneto
Latvia	Latvia	
Lithuania	Lithuania	
Luxembourg	Luxembourg (Grand-Duch)	
Malta	Malta	
Netherlands	Drenthe Flevoland Friesland Gelderland Groningen Limburg (NL)	Noord-Brabant Noord-Holland Overijssel Utrecht Zeeland Zuid-Holland
Poland	Dolnoslaskie Kujawsko-Pomorskie Ldzkie Lubelskie Lubuskie Malopolskie Mazowieckie Opolskie	Podkarpackie Podlaskie Pomorskie Slaskie Swietokrzyskie Warminsko-Mazurskie Wielkopolskie Zachodniopomorskie
Portugal	Alentejo Algarve Centro (PT)	Lisboa Norte
Romania	Bucuresti - Ilfov Centru Nord-Est Nord-Vest	Sud - Muntenia Sud-Est Sud-Vest Oltenia Vest
Slovak Republic	Bratislavský kraj Stredné Slovensko	Východné Slovensko Západné Slovensko
Slovenia	Slovenia	
Spain	Andalucia Aragón Cantabria	Extremadura Galicia 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 1: European regions in the sample

Variable name	Description	Source	Min	Mean	Max
Dependent variable					
gGDPCAP	Growth rate of real GDP per capita Deflated by national prices, Price base year is 2000	Eurostat	-0.006	0.022	0.083
Factor accumulation/convergence					
GDPCAP0	Initial real GDP per capita (in logs) Price base year is 2000	Eurostat	8.261	9.599	10.690
gPOP	Growth rate of population	Eurostat	0.000	0.000	0.000
shGFCF	Initial share of GFCF in GVA	Cambridge Econometrics	0.075	0.213	0.528
Infrastructure					
INTF	Proportion of firms with own website	ESPON	0.021	0.467	0.990
TELH	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
TELF	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
AirportDens	Airport density Number of airports divided by area in square km	ESPON	0.000	0.000	0.002
RoadDens	Road density Length of road network (in km) divided by area	ESPON	0.000	0.151	0.913
RailDens	Rail density Length of rail network (in km) divided by area	ESPON	0.000	0.063	0.321
ConnectAir	Connectivity to commercial airports by car of the capital or centroid representative of the NUTS3, in hours	ESPON	0.000	1.053	2.766
ConnectSea	Connectivity to commercial seaports by car of the capital or centroid representative of the NUTS3, in hours	ESPON	0.010	0.598	3.000
AccessAir	Potential accessibility air ESPON space = 100 ESPON AcAiE01N3; model output	ESPON	0.377	0.937	1.770
AccessRail	Potential accessibility rail ESPON space = 100 ESPON AcRaE01N3; model output	ESPON	0.040	0.946	2.170
AccessRoad	Potential accessibility road ESPON space = 100 ESPON AcRoE01N3; model output	ESPON	0.035	0.964	2.032
AccessMulti	Potential accessibility multimodal ESPON space = 100 ESPON AcME01N3; model output	ESPON	0.378	0.940	1.770
Socio-geographical variables					
Settl	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; Dummy variable for regions with centers (1 = regions with centers)	ESPON	0.000	0.729	1.000
OUTDENS0	Initial output density; GDP in mio. / area in km2; initial year; Price base for GDP is 2000	WIIW	0.043	7.919	365.100
EMPDENS0	Initial employment density Employed persons in 1000/ area in km2; initial year	WIIW	0.001	0.179	7.805
POPDENS0	Initial population density Population in 1000 / area in km2; initial year	WIIW	0.002	0.338	8.299
RegCoast	Coast 0: No Coast, 1: Coast	ESPON	0.000	0.463	1.000
RegBorder	Border 0: No Border, 1: Border	ESPON			
RegPent27	Pentagon EU 27 plus 2 The Pentagon is shaped by London, Paris, Munich, Milan and Hamburg.	ESPON	0.000	0.322	1.000
RegObj1	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	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
Temp	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
Distde71	Distance to Frankfurt in km				
DistCap	Distance to capital city in km		0.000	241.400	883.100
Technological innovation					
PatentT	Number of patents total per 1000 persons	Eurostat	0.000	0.078	0.545
PatentHT	Number of patents in high technology per 1000 persons	Eurostat	0.000	0.011	0.186
PatentICT	Number of patents in ICT per 1000 persons	Eurostat	0.000	0.017	0.315
PatentBIO	Number of patents in biotechnology per 1000 persons	Eurostat	0.000	0.003	0.058
PatentShHT	Share of patents in high technology in total patents	Eurostat	0.000	0.109	0.505
PatentShICT	Share of patents in ICT	Eurostat in total patents	0.000	0.156	0.728
PatentShBIO	Share of patents in biotechnology in total patents	Eurostat	0.000	0.039	0.226
HRSTcore	Human resources in science and technology (core), share in persons employed	Eurostat LFS	0.036	0.126	0.816
Human capital					
ShSH	Share of high educated in working age population	Eurostat LFS	0.044	0.156	0.390
ShSM*	Share of medium educated in working age population	Eurostat LFS	0.106	0.467	0.742
ShSL	Share of low educated in working age population	Eurostat LFS	0.135	0.378	0.837
ShLLL	Life long learning	Eurostat LFS	0.003	0.068	0.263
Sectoral structure/employment					
ShAB0	Initial share of NACE A and B (Agriculture), Share in nominal gross value added	Eurostat	0.000	0.046	0.202
ShCE0	Initial share of NACE C to E (Mining, Manufacturing and Energy), Share in nominal gross value added	Eurostat	0.022	0.195	0.304
ShJK0	Initial share of NACE J to K (Business services), Share in nominal gross value added	Eurostat	0.048	0.163	0.433
EREH0	Employment rate of high educated (initial)	Eurostat LFS	0.609	0.819	0.964
EREM0	Employment rate of medium educated (initial)	Eurostat LFS	0.359	0.665	0.869
EREL0	Employment rate of low educated (initial)	Eurostat LFS	0.168	0.447	0.718
ERET0	Employment rate total (initial)	Eurostat LFS	0.391	0.618	0.836
URH0	Unemployment rate of high educated (initial)	Eurostat LFS	0.004	0.054	0.273
URM0*	Unemployment rate of medium educated (initial)	Eurostat LFS	0.020	0.099	0.293
URL0	Unemployment rate of low educated (initial)	Eurostat LFS	0.018	0.136	0.484
URT0	Unemployment rate total (initial)	Eurostat LFS	0.025	0.096	0.294
ARH0	Activity rate of high educated (initial)	Eurostat LFS	0.761	0.865	0.964
ARM0*	Activity rate of medium educated (initial)	Eurostat LFS	0.473	0.735	0.888
ARL0	Activity rate of low educated (initial)	Eurostat LFS	0.246	0.513	0.797
ART0	Activity rate total (initial)	Eurostat LFS	0.497	0.682	0.872

Table 2: Table 2: Data Description. Data are from ESPON (European Spatial Planning Observation Network, http://www.espon.eu), Cambridge Econometrics (http://www.camecon.com), WIIW (http://www.wiiw.ac.at/), Eurostat and Eurostat LFS (Eurostat Labor Force Survey, http://epp.eurostat.ec.europa.eu/). Variables expressed in shares additionally denoted by asterisks (*) are not included in the regressions and hence serve as a reference group

	PIP	PM	PSD	PIP	PM	PSD	PIP	PM	PSD
Capital	1.000	0.018	0.002	0.984	0.011	0.003	1.000	0.004	0.003
GDPCAP0	1.000	-0.020	0.002	0.245	-0.003	0.005	0.387	-0.004	0.005
ShSH	0.975	0.047	0.012	0.999	0.063	0.011	0.996	0.053	0.010
URT0	0.200	-0.007	0.016	0.010	0.000	0.003	0.011	0.000	0.003
AirportDens	0.082	0.420	1.526	0.039	0.172	0.926	0.014	0.045	0.423
Airports	0.055	0.000	0.000	0.053	0.000	0.000	0.045	0.000	0.000
ERET0	0.045	0.001	0.006	0.007	0.000	0.001	0.004	0.000	0.001
ARH0	0.032	0.001	0.009	0.025	0.001	0.008	0.010	0.000	0.004
URL0	0.030	-0.001	0.004	0.011	0.000	0.002	0.012	0.000	0.002
ShSL	0.029	0.000	0.003	0.006	0.000	0.001	0.004	0.000	0.001
EREH0	0.027	0.001	0.004	0.008	0.000	0.002	0.007	0.000	0.002
AccessRoad	0.027	0.000	0.001	0.402	-0.002	0.003	0.306	-0.002	0.003
TELF	0.020	0.000	0.000	0.369	-0.001	0.001	0.090	0.000	0.001
ShCE0	0.019	0.000	0.004	0.003	0.000	0.001	0.003	0.000	0.001
ShLLL	0.016	0.001	0.004	0.002	0.000	0.001	0.003	0.000	0.001
AccessAir	0.014	0.000	0.001	0.009	0.000	0.001	0.019	0.000	0.001
ConnectAir	0.013	0.000	0.000	0.010	0.000	0.000	0.013	0.000	0.000
POPDENS0	0.013	0.000	0.001	0.021	0.000	0.000	0.003	0.000	0.000
ARL0	0.013	0.000	0.003	0.002	0.000	0.000	0.002	0.000	0.001
EMPDENS0	0.011	0.000	0.001	0.006	0.000	0.000	0.002	0.000	0.000
EREL0	0.008	0.000	0.003	0.003	0.000	0.001	0.003	0.000	0.001
ART0	0.008	0.000	0.003	0.003	0.000	0.001	0.003	0.000	0.001
URH0	0.006	0.000	0.003	0.002	0.000	0.001	0.003	0.000	0.001
INTF	0.006	0.000	0.002	0.004	0.000	0.001	0.020	0.001	0.005
Distde71	0.005	0.000	0.000	0.388	0.000	0.000	0.590	0.000	0.000
gPOP	0.005	0.001	0.014	0.004	0.001	0.013	0.025	0.007	0.045
PatentICT	0.005	0.000	0.002	0.002	0.000	0.001	0.005	0.000	0.002
PatentHT	0.004	0.000	0.003	0.002	0.000	0.002	0.006	0.000	0.004
RegObj1	0.004	0.000	0.000	0.011	0.000	0.000	0.006	0.000	0.000
shGFCF	0.004	0.000	0.001	0.009	0.000	0.002	0.007	0.000	0.001
RegPent27	0.004	0.000	0.000	0.005	0.000	0.000	0.005	0.000	0.000
Seaports	0.004	0.000	0.000	0.009	0.000	0.000	0.007	0.000	0.000
PatentShICT	0.004	0.000	0.000	0.003	0.000	0.000	0.002	0.000	0.000
Temp	0.003	0.000	0.000	0.002	0.000	0.000	0.002	0.000	0.000
RegCoast	0.003	0.000	0.000	0.003	0.000	0.000	0.004	0.000	0.000
ShAB0	0.003	0.000	0.001	0.003	0.000	0.001	0.006	0.000	0.003
DistCap	0.003	0.000	0.000	0.006	0.000	0.000	0.009	0.000	0.000
OUTDENS0	0.003	0.000	0.000	0.010	0.000	0.000	0.003	0.000	0.000
TELH	0.003	0.000	0.000	0.002	0.000	0.000	0.003	0.000	0.000
PatentShBIO	0.003	0.000	0.001	0.002	0.000	0.001	0.002	0.000	0.001
Settl	0.002	0.000	0.000	0.002	0.000	0.000	0.002	0.000	0.000
HRSTcore	0.002	0.000	0.001	0.002	0.000	0.000	0.002	0.000	0.000
PatentT	0.002	0.000	0.000	0.003	0.000	0.001	0.003	0.000	0.001
PatentShHT	0.002	0.000	0.000	0.002	0.000	0.000	0.003	0.000	0.000
RegBoarder	0.002	0.000	0.000	0.002	0.000	0.000	0.002	0.000	0.000
ConnectSea	0.002	0.000	0.000	0.003	0.000	0.000	0.004	0.000	0.000
PatentBIO	0.002	0.000	0.006	0.002	0.000	0.005	0.003	0.000	0.008
RoadDens	0.002	0.000	0.000	0.003	0.000	0.000	0.003	0.000	0.000
RailDens	0.002	0.000	0.001	0.003	0.000	0.001	0.003	0.000	0.001
Hazard	0.002	0.000	0.000	0.004	0.000	0.000	0.002	0.000	0.000
ceeDummy				0.982	0.019	0.006	1.000	0.016	0.005
ceeDummy.x.Capital							0.996	0.018	0.004
ceeDummy.x.AccessRoad				0.011	0.000	0.002	0.004	0.000	0.001
ceeDummy.x.gPOP				0.000	0.000	0.000	0.000	0.000	0.001
ceeDummy.x.EMPDENS0				0.000	0.000	0.000	0.000	0.000	0.000
ceeDummy.x.POPDENS0				0.000	0.000	0.000	0.000	0.000	0.000
ceeDummy.x.shGFCF				0.000	0.000	0.000	0.000	0.000	0.000
ceeDummy.x.OUTDENS0				0.000	0.000	0.000	0.000	0.000	0.000
ceeDummy.x.GDPCAP0				0.001	0.000	0.000	0.001	0.000	0.000
ceeDummy.x.HRSTcore				0.000	0.000	0.001	0.000	0.000	0.000

Table 3: Cross Section of Regions (linear regression model). 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.

	PIP	PM	PSD	PIP	PM	PSD	PIP	PM	PSD
shGFCF	0.619	0.023	0.020	0.454	0.003	0.008	0.032	0.001	0.004
ShSH	0.501	0.038	0.041	0.881	0.053	0.023	0.431	0.022	0.026
Capital	0.498	0.004	0.005	0.031	0.000	0.001	0.998	0.000	0.002
AccessAir	0.338	0.003	0.005	0.014	0.000	0.001	0.008	0.000	0.000
ShSL	0.254	-0.010	0.018	0.108	-0.004	0.012	0.524	-0.018	0.018
AirportDens	0.210	0.988	2.030	0.004	0.004	0.101	0.003	0.003	0.089
Distde71	0.042	0.000	0.000	0.041	0.000	0.000	0.008	0.000	0.000
AccessRoad	0.035	0.000	0.001	0.005	0.000	0.000	0.004	0.000	0.000
RegObj1	0.035	0.000	0.001	0.003	0.000	0.000	0.005	0.000	0.000
ART0	0.025	-0.007	0.064	0.004	0.000	0.001	0.005	0.000	0.001
POPDENS0	0.019	0.000	0.000	0.003	0.000	0.000	0.007	0.000	0.000
RegBoarder	0.018	0.000	0.000	0.010	0.000	0.000	0.007	0.000	0.000
INTF	0.015	0.000	0.004	1.000	0.074	0.013	1.000	0.087	0.012
ShAB0	0.015	-0.001	0.006	0.003	0.000	0.001	0.020	0.001	0.006
ERET0	0.013	0.007	0.067	0.014	0.000	0.003	0.010	0.000	0.002
URT0	0.013	0.004	0.041	0.020	-0.001	0.004	0.008	0.000	0.002
OUTDENS0	0.012	0.000	0.000	0.004	0.000	0.000	0.004	0.000	0.000
PatentT	0.012	0.000	0.002	0.028	0.000	0.003	0.027	0.000	0.002
Hazard	0.011	0.000	0.000	0.006	0.000	0.000	0.011	0.000	0.000
ARL0	0.010	0.000	0.002	0.004	0.000	0.001	0.003	0.000	0.001
URH0	0.010	0.000	0.004	0.004	0.000	0.002	0.005	0.000	0.002
EMPDENS0	0.009	0.000	0.001	0.003	0.000	0.000	0.004	0.000	0.000
Airports	0.008	0.000	0.000	0.003	0.000	0.000	0.004	0.000	0.000
GDPCAP0	0.008	0.000	0.001	1.000	-0.029	0.005	1.000	-0.031	0.004
ShCE0	0.007	0.000	0.002	0.005	0.000	0.001	0.003	0.000	0.001
EREL0	0.007	0.000	0.002	0.013	0.000	0.002	0.005	0.000	0.001
PatentICT	0.006	0.000	0.002	0.015	0.000	0.004	0.022	0.001	0.005
ConnectAir	0.006	0.000	0.000	0.008	0.000	0.000	0.003	0.000	0.000
EREH0	0.005	0.000	0.002	0.002	0.000	0.001	0.003	0.000	0.001
PatentHT	0.005	0.000	0.003	0.016	0.001	0.006	0.028	0.001	0.008
PatentBIO	0.004	0.001	0.012	0.005	0.001	0.011	0.008	0.001	0.014
gPOP	0.004	-0.001	0.012	0.003	0.000	0.006	0.003	0.000	0.007
RoadDens	0.004	0.000	0.000	0.004	0.000	0.000	0.003	0.000	0.000
RegPent27	0.003	0.000	0.000	0.005	0.000	0.000	0.003	0.000	0.000
PatentShICT	0.003	0.000	0.000	0.007	0.000	0.001	0.029	0.000	0.002
Seaports	0.003	0.000	0.000	0.003	0.000	0.000	0.003	0.000	0.000
ShLLL	0.003	0.000	0.003	0.006	0.000	0.004	0.005	0.000	0.003
Temp	0.002	0.000	0.000	0.005	0.000	0.000	0.003	0.000	0.000
DistCap	0.002	0.000	0.000	0.003	0.000	0.000	0.003	0.000	0.000
URL0	0.002	0.000	0.001	0.115	-0.003	0.008	0.032	-0.001	0.004
TELF	0.002	0.000	0.000	0.005	0.000	0.000	0.003	0.000	0.000
ConnectSea	0.002	0.000	0.000	0.003	0.000	0.000	0.003	0.000	0.000
RailDens	0.002	0.000	0.001	0.008	0.000	0.002	0.003	0.000	0.001
PatentShHT	0.002	0.000	0.000	0.004	0.000	0.001	0.012	0.000	0.001
RegCoast	0.002	0.000	0.000	0.002	0.000	0.000	0.002	0.000	0.000
Settl	0.002	0.000	0.000	0.003	0.000	0.000	0.003	0.000	0.000
TELH	0.002	0.000	0.000	0.004	0.000	0.000	0.004	0.000	0.000
ARH0	0.002	0.000	0.001	0.002	0.000	0.001	0.002	0.000	0.001
PatentShBIO	0.002	0.000	0.001	0.003	0.000	0.001	0.003	0.000	0.001
HRSTcore	0.002	0.000	0.000	0.002	0.000	0.000	0.002	0.000	0.000
ceeDummy				1.000	0.000	0.001	1.000	0.000	0.001
ceeDummy.x.Capital							0.998	0.032	0.004
ceeDummy.x.AccessRoad				0.000	0.000	0.000	0.000	0.000	0.000
ceeDummy.x.gPOP				0.000	0.000	0.007	0.000	0.000	0.001
ceeDummy.x.EMPDENS0				0.000	0.000	0.000	0.000	0.000	0.000
ceeDummy.x.POPDENS0				0.000	0.000	0.000	0.000	0.000	0.000
ceeDummy.x.shGFCF				0.424	0.036	0.044	0.001	0.000	0.003
ceeDummy.x.OUTDENS0				0.000	0.000	0.000	0.000	0.000	0.000
ceeDummy.x.GDPCAP0				1.000	0.040	0.005	0.011	0.000	0.002
ceeDummy.x.HRSTcore				0.000	0.000	0.002	0.000	0.000	0.000

Table 4: Cross Section of regions with country fixed effects (linear regression model). 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.

	PIP	PM	PSD	PIP	PM	PSD	PIP	PM	PSD
Capital	1.000	0.017	0.002	0.999	0.013	0.003	1.000	0.006	0.003
GDPCAP0	1.000	-0.017	0.002	0.509	-0.005	0.005	0.894	-0.012	0.007
ShSH	0.971	0.044	0.013	0.999	0.063	0.012	0.951	0.044	0.016
AirportDens	0.815	6.200	3.529	0.457	2.854	3.499	0.086	0.281	1.086
POPDENS0	0.792	-0.010	0.006	0.438	-0.003	0.005	0.038	0.000	0.001
EMPDENS0	0.743	0.011	0.007	0.308	0.003	0.006	0.034	0.000	0.001
AccessAir	0.516	0.005	0.006	0.144	0.001	0.003	0.094	0.001	0.002
ShCE0	0.423	0.014	0.018	0.044	0.001	0.005	0.024	0.000	0.003
AccessRoad	0.266	-0.001	0.003	0.378	-0.002	0.003	0.329	-0.001	0.002
TELF	0.161	0.000	0.001	0.594	-0.001	0.001	0.232	0.000	0.001
URT0	0.135	-0.004	0.015	0.056	-0.001	0.007	0.080	-0.002	0.010
ShSL	0.119	-0.002	0.005	0.040	0.000	0.002	0.028	0.000	0.001
ConnectAir	0.111	0.000	0.001	0.060	0.000	0.001	0.060	0.000	0.001
RegCoast	0.098	-0.001	0.002	0.042	0.000	0.001	0.063	0.000	0.002
ERET0	0.088	0.002	0.012	0.040	0.001	0.005	0.033	0.000	0.005
Seaports	0.082	0.000	0.002	0.061	0.000	0.001	0.073	0.000	0.002
Airports	0.072	0.000	0.000	0.156	0.000	0.000	0.294	0.000	0.000
shGFCF	0.072	0.001	0.004	0.091	0.001	0.005	0.121	0.002	0.007
ARL0	0.070	-0.001	0.007	0.020	0.000	0.002	0.019	0.000	0.002
RoadDens	0.067	0.001	0.003	0.032	0.000	0.001	0.033	0.000	0.001
OUTDENS0	0.065	0.000	0.000	0.081	0.000	0.000	0.022	0.000	0.000
ARH0	0.064	0.002	0.012	0.138	0.006	0.017	0.088	0.003	0.013
INTF	0.054	0.001	0.005	0.031	0.000	0.003	0.365	0.013	0.019
URL0	0.054	-0.001	0.005	0.049	-0.001	0.004	0.185	-0.004	0.010
EREL0	0.050	-0.001	0.006	0.024	0.000	0.002	0.030	0.000	0.003
URH0	0.047	0.001	0.012	0.029	0.001	0.007	0.044	0.001	0.010
EREH0	0.045	0.001	0.009	0.048	0.001	0.006	0.045	0.001	0.008
RegPent27	0.044	0.000	0.001	0.048	0.000	0.001	0.045	0.000	0.001
PatentShICT	0.040	0.000	0.002	0.022	0.000	0.001	0.023	0.000	0.001
Distde71	0.039	0.000	0.000	0.122	0.000	0.000	0.206	0.000	0.000
ART0	0.038	0.000	0.010	0.026	0.000	0.005	0.024	0.000	0.005
gPOP	0.035	0.004	0.033	0.035	0.005	0.035	0.312	0.090	0.147
PatentICT	0.034	0.001	0.006	0.029	0.001	0.005	0.042	0.001	0.007
PatentHT	0.033	0.001	0.008	0.024	0.000	0.007	0.052	0.002	0.012
PatentShHT	0.032	0.000	0.002	0.020	0.000	0.001	0.024	0.000	0.001
PatentShBIO	0.031	0.000	0.003	0.020	0.000	0.002	0.020	0.000	0.002
Hazard	0.030	0.000	0.000	0.031	0.000	0.000	0.019	0.000	0.000
RegObj1	0.030	0.000	0.000	0.062	0.000	0.001	0.057	0.000	0.001
RailDens	0.030	0.000	0.004	0.027	0.000	0.003	0.019	0.000	0.002
ShLLL	0.028	0.000	0.003	0.021	0.000	0.002	0.029	0.000	0.003
PatentT	0.026	0.000	0.002	0.024	0.000	0.002	0.024	0.000	0.002
ShAB0	0.025	0.000	0.004	0.020	0.000	0.003	0.036	0.001	0.007
RegBoarder	0.024	0.000	0.000	0.018	0.000	0.000	0.018	0.000	0.000
TELH	0.023	0.000	0.000	0.019	0.000	0.000	0.023	0.000	0.000
Settl	0.023	0.000	0.000	0.019	0.000	0.000	0.016	0.000	0.000
Temp	0.022	0.000	0.000	0.020	0.000	0.000	0.019	0.000	0.000
ConnectSea	0.022	0.000	0.000	0.020	0.000	0.000	0.023	0.000	0.000
HRSTcore	0.022	0.000	0.002	0.035	0.000	0.002	0.022	0.000	0.002
PatentBIO	0.021	0.000	0.018	0.017	0.000	0.016	0.024	0.002	0.023
DistCap	0.019	0.000	0.000	0.020	0.000	0.000	0.035	0.000	0.000
ceeDummy				0.980	0.013	0.014	1.000	0.008	0.008
ceeDummy.x.Capital							1.000	0.020	0.004
ceeDummy.x.AccessRoad				0.047	-0.001	0.003	0.010	0.000	0.001
ceeDummy.x.gPOP				0.001	0.000	0.010	0.006	0.000	0.028
ceeDummy.x.EMPDENS0				0.018	-0.001	0.010	0.001	0.000	0.001
ceeDummy.x.POPDENS0				0.041	0.001	0.007	0.001	0.000	0.001
ceeDummy.x.shGFCF				0.004	0.000	0.002	0.018	0.001	0.006
ceeDummy.x.OUTDENS0				0.006	0.000	0.000	0.001	0.000	0.000
ceeDummy.x.GDPCAP0				0.019	0.000	0.001	0.016	0.000	0.001
ceeDummy.x.HRSTcore				0.016	0.002	0.013	0.001	0.000	0.002
ρ		0.6475			0.4126			0.6221	

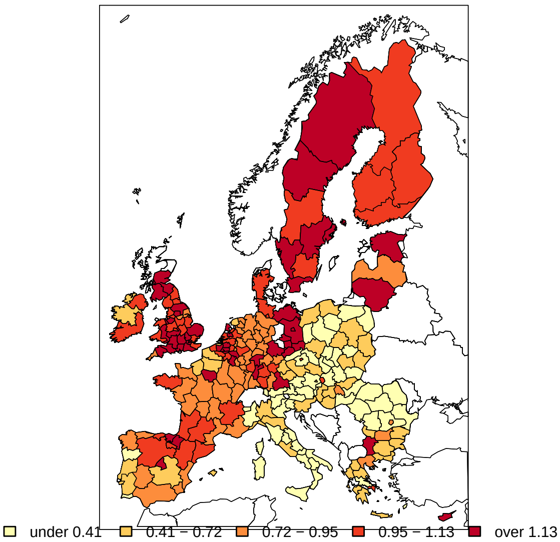
Table 5: SAR Model (inverse distances). PIP stands for “Posterior inclusion probability”, PM stands for “Posterior mean” and PSD stands for “Posterior standard deviation”. All calculations based on MC^3 sampling with 2,000,000 burn-ins and 3,000,000 posterior draws.

	PIP	PM	PSD		PIP	PM	PSD
ceeDummy	0.999	0.017	0.005	OUTDENS0	0.000	0.000	0.000
Capital	0.999	0.004	0.003	URH0	0.000	0.000	0.000
ShSH	0.998	0.053	0.009	W-AccessRoad	0.000	0.000	0.000
ceeDummy.x.Capital	0.985	0.018	0.004	ceeDummy.x.GDPCAP0	0.000	0.000	0.000
Distde71	0.700	0.000	0.000	W-URL0	0.000	0.000	0.003
GDPCAP0	0.211	-0.002	0.005	W-GDPCAP0	0.000	0.000	0.000
AccessRoad	0.191	-0.001	0.002	W-gPOP	0.000	0.001	0.047
TELF	0.035	0.000	0.000	W-TELF	0.000	0.000	0.000
Airports	0.016	0.000	0.000	W-HRSTcore	0.000	0.000	0.001
gPOP	0.006	0.002	0.022	W-EMPDENS0	0.000	0.000	0.000
W-ShSH	0.004	0.000	0.005	W-Airports	0.000	0.000	0.000
AirportDens	0.003	0.011	0.207	W-ShLLL	0.000	0.000	0.001
DistCap	0.003	0.000	0.000	W-ARH0	0.000	0.000	0.001
AccessAir	0.003	0.000	0.000	W-POPDENS0	0.000	0.000	0.000
INTF	0.003	0.000	0.002	W-URT0	0.000	0.000	0.001
shGFCF	0.003	0.000	0.001	W-ERET0	0.000	0.000	0.000
URL0	0.002	0.000	0.001	W-ShSL	0.000	0.000	0.000
ARH0	0.002	0.000	0.002	W-RegCoast	0.000	0.000	0.000
ShAB0	0.002	0.000	0.002	ceeDummy.x.EMPDENS0	0.000	0.000	0.000
ShLLL	0.002	0.000	0.001	ceeDummy.x.gPOP	0.000	0.000	0.000
URT0	0.002	0.000	0.001	ceeDummy.x.OUTDENS0	0.000	0.000	0.000
W-Capital	0.002	0.000	0.002	ceeDummy.x.POPDENS0	0.000	0.000	0.000
PatentHT	0.002	0.000	0.002	ceeDummy.x.shGFCF	0.000	0.000	0.000
RegObj1	0.001	0.000	0.000	ceeDummy.x.HRSTcore	0.000	0.000	0.000
ConnectSea	0.001	0.000	0.000	W-AccessAir	0.000	0.000	0.000
ShSL	0.001	0.000	0.000	W-AirportDens	0.000	0.000	0.000
ceeDummy.x.AccessRoad	0.001	0.000	0.000	W-ARL0	0.000	0.000	0.000
POPDENS0	0.001	0.000	0.000	W-ART0	0.000	0.000	0.000
ConnectAir	0.001	0.000	0.000	W-ConnectAir	0.000	0.000	0.000
ERET0	0.001	0.000	0.000	W-ConnectSea	0.000	0.000	0.000
Seaports	0.001	0.000	0.000	W-DistCap	0.000	0.000	0.000
PatentICT	0.001	0.000	0.001	W-EREH0	0.000	0.000	0.000
PatentT	0.001	0.000	0.000	W-EREL0	0.000	0.000	0.000
RegCoast	0.001	0.000	0.000	W-Hazard	0.000	0.000	0.000
HRSTcore	0.001	0.000	0.000	W-INTF	0.000	0.000	0.000
RegPent27	0.001	0.000	0.000	W-OUTDENS0	0.000	0.000	0.000
EREH0	0.001	0.000	0.001	W-PatentBIO	0.000	0.000	0.000
W-shGFCF	0.001	0.000	0.006	W-PatentHT	0.000	0.000	0.000
EMPDENS0	0.001	0.000	0.000	W-PatentICT	0.000	0.000	0.000
ART0	0.001	0.000	0.000	W-PatentShBIO	0.000	0.000	0.000
Settl	0.001	0.000	0.000	W-PatentShHT	0.000	0.000	0.000
PatentShICT	0.001	0.000	0.000	W-PatentShICT	0.000	0.000	0.000
RoadDens	0.001	0.000	0.000	W-PatentT	0.000	0.000	0.000
ARL0	0.001	0.000	0.000	W-RailDens	0.000	0.000	0.000
TELH	0.001	0.000	0.000	W-RegBoarder	0.000	0.000	0.000
PatentShHT	0.001	0.000	0.000	W-RegObj1	0.000	0.000	0.000
ShCE0	0.001	0.000	0.000	W-RegPent27	0.000	0.000	0.000
W-Distde71	0.001	0.000	0.000	W-RoadDens	0.000	0.000	0.000
RailDens	0.001	0.000	0.000	W-Seaports	0.000	0.000	0.000
Hazard	0.001	0.000	0.000	W-Settl	0.000	0.000	0.000
PatentBIO	0.001	0.000	0.003	W-ShAB0	0.000	0.000	0.000
EREL0	0.001	0.000	0.000	W-ShCE0	0.000	0.000	0.000
PatentShBIO	0.001	0.000	0.000	W-TELH	0.000	0.000	0.000
RegBoarder	0.000	0.000	0.000	W-Temp	0.000	0.000	0.000
Temp	0.000	0.000	0.000	W-URH0	0.000	0.000	0.000

Table 6: Cross section of regions (linear regression model) with full set of spatially lagged explanatory variables. 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.

	PIP	PM	PSD		PIP	PM	PSD
GDPCAP0	1.000	-0.031	0.004	ARL0	0.000	0.000	0.000
INTF	1.000	0.086	0.012	ceeDummy.x.shGFCF	0.000	0.000	0.002
ceeDummy	1.000	0.000	0.001	ConnectSea	0.000	0.000	0.000
Capital	0.995	0.001	0.002	EREH0	0.000	0.000	0.000
ceeDummy.x.Capital	0.995	0.032	0.004	W-ShSH	0.000	0.000	0.001
ShSL	0.469	-0.016	0.018	W-Settl	0.000	0.000	0.000
ShSH	0.429	0.022	0.027	W-URL0	0.000	0.000	0.001
shGFCF	0.015	0.000	0.003	W-URT0	0.000	0.000	0.001
W-gPOP	0.014	0.037	0.330	W-PatentT	0.000	0.000	0.000
URL0	0.011	0.000	0.002	W-AirportDens	0.000	0.000	0.061
PatentShICT	0.011	0.000	0.001	W-AccessRoad	0.000	0.000	0.000
PatentHT	0.008	0.000	0.004	ceeDummy.x.EMPDENS0	0.000	0.000	0.000
PatentT	0.008	0.000	0.001	ceeDummy.x.gPOP	0.000	0.000	0.000
ceeDummy.x.GDPCAP0	0.007	0.000	0.003	ceeDummy.x.OUTDENS0	0.000	0.000	0.000
PatentICT	0.006	0.000	0.002	ceeDummy.x.POPDENS0	0.000	0.000	0.000
ShAB0	0.005	0.000	0.003	ceeDummy.x.AccessRoad	0.000	0.000	0.000
W-OUTDENS0	0.004	0.000	0.000	ceeDummy.x.HRSTcore	0.000	0.000	0.000
ERET0	0.004	0.000	0.001	W-AccessAir	0.000	0.000	0.000
PatentShHT	0.003	0.000	0.001	W-Airports	0.000	0.000	0.000
PatentBIO	0.003	0.000	0.010	W-ARH0	0.000	0.000	0.000
W-ShSL	0.003	0.000	0.004	W-ARL0	0.000	0.000	0.000
Airports	0.003	0.000	0.000	W-ART0	0.000	0.000	0.000
Hazard	0.003	0.000	0.000	W-Capital	0.000	0.000	0.000
Distde71	0.002	0.000	0.000	W-ConnectSea	0.000	0.000	0.000
POPDENS0	0.002	0.000	0.000	W-Distde71	0.000	0.000	0.000
URT0	0.002	0.000	0.001	W-DistCap	0.000	0.000	0.000
ART0	0.002	0.000	0.001	W-EMPDENS0	0.000	0.000	0.000
AccessAir	0.002	0.000	0.000	W-EREH0	0.000	0.000	0.000
ShLLL	0.002	0.000	0.002	W-EREL0	0.000	0.000	0.000
AccessRoad	0.002	0.000	0.000	W-ERET0	0.000	0.000	0.000
RegObj1	0.001	0.000	0.000	W-GDPCAP0	0.000	0.000	0.000
EREL0	0.001	0.000	0.000	W-Hazard	0.000	0.000	0.000
RegBoarder	0.001	0.000	0.000	W-HRSTcore	0.000	0.000	0.000
OUTDENS0	0.001	0.000	0.000	W-INTF	0.000	0.000	0.000
TELH	0.001	0.000	0.000	W-PatentBIO	0.000	0.000	0.000
W-ConnectAir	0.001	0.000	0.000	W-PatentHT	0.000	0.000	0.000
EMPDENS0	0.001	0.000	0.000	W-PatentICT	0.000	0.000	0.000
Seaports	0.001	0.000	0.000	W-PatentShBIO	0.000	0.000	0.000
AirportDens	0.001	0.001	0.047	W-PatentShHT	0.000	0.000	0.000
ShCE0	0.001	0.000	0.000	W-PatentShICT	0.000	0.000	0.000
Temp	0.001	0.000	0.000	W-POPDENS0	0.000	0.000	0.000
PatentShBIO	0.001	0.000	0.000	W-RailDens	0.000	0.000	0.000
URH0	0.001	0.000	0.001	W-RegBoarder	0.000	0.000	0.000
ConnectAir	0.001	0.000	0.000	W-RegCoast	0.000	0.000	0.000
ARH0	0.001	0.000	0.000	W-RegObj1	0.000	0.000	0.000
RoadDens	0.001	0.000	0.000	W-RegPent27	0.000	0.000	0.000
RegCoast	0.001	0.000	0.000	W-RoadDens	0.000	0.000	0.000
HRSTcore	0.001	0.000	0.000	W-Seaports	0.000	0.000	0.000
TELF	0.001	0.000	0.000	W-ShAB0	0.000	0.000	0.000
W-TELF	0.001	0.000	0.000	W-ShCE0	0.000	0.000	0.000
RegPent27	0.001	0.000	0.000	W-shGFCF	0.000	0.000	0.000
RailDens	0.001	0.000	0.000	W-ShLLL	0.000	0.000	0.000
Settl	0.001	0.000	0.000	W-TELH	0.000	0.000	0.000
gPOP	0.001	0.000	0.003	W-Temp	0.000	0.000	0.000
DistCap	0.000	0.000	0.000	W-URH0	0.000	0.000	0.000

Table 7: Cross section of regions (linear regression model) with fixed effects and full set of spatially lagged explanatory variables. 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.



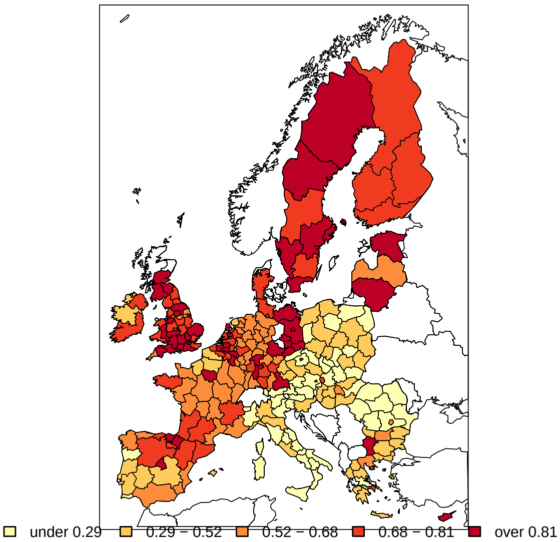
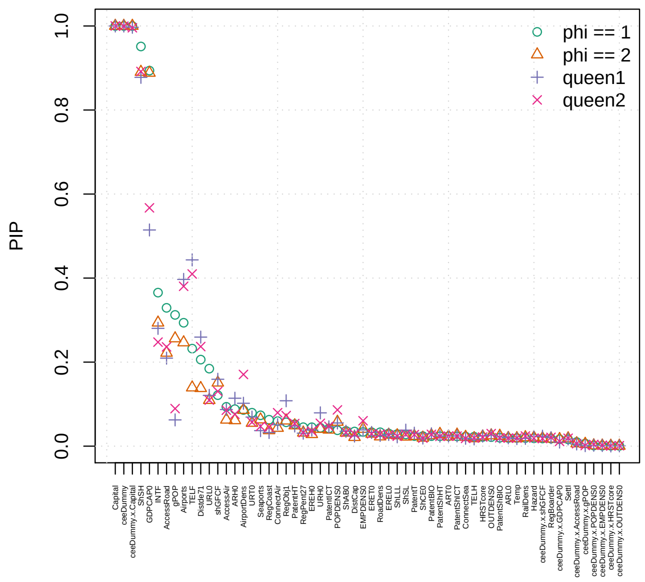


Figure 1: Spatial distribution of the estimated effect due to income convergence and human capital accumulation for the cross section specification (Table 3, third column). Top panel shows the spatial distribution of the coefficient on GDP per capita, bottom panel the one for human capital proxy (ShSH).



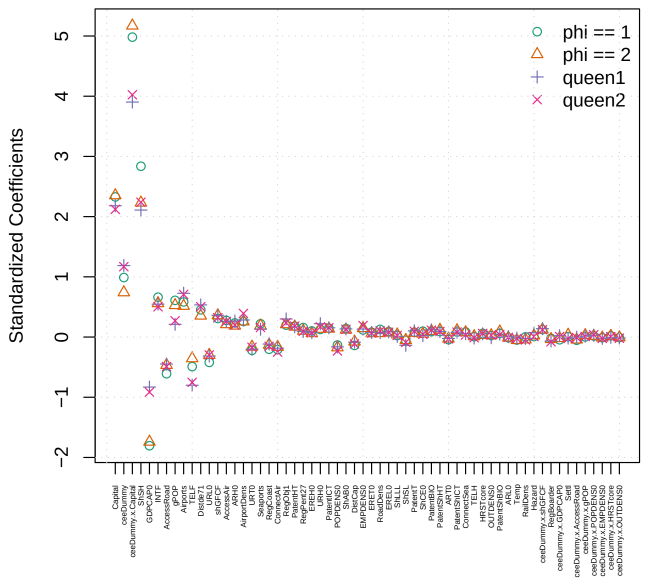


Figure 2: Posterior inclusion probabilities and standardized coefficients based on four different **W** specifications: inverse distances, inverse distances squared ($\phi = 1, 2$) and a first order and second order queen contiguity matrix.

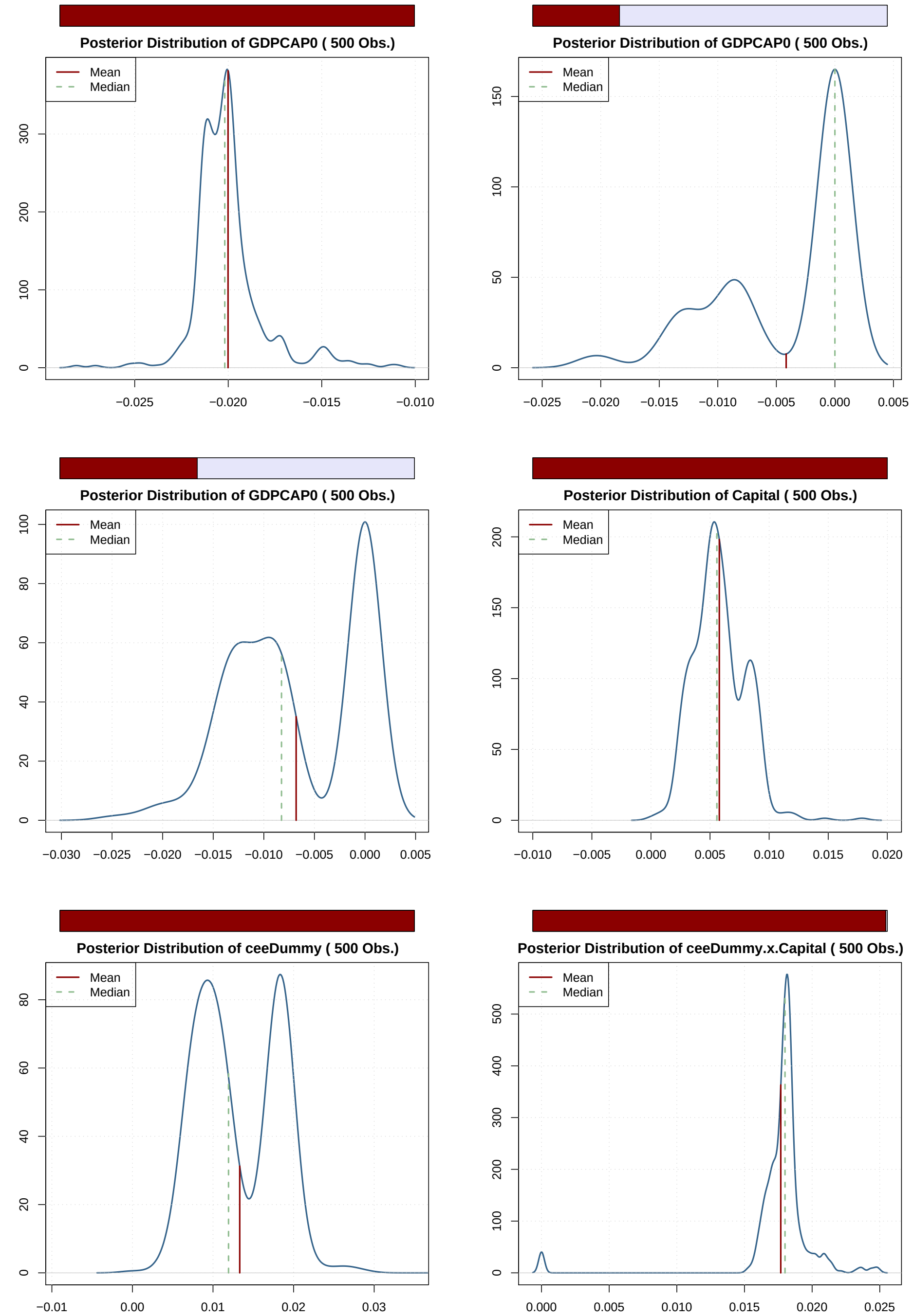


Figure 3: Unconditional posterior distribution (500 best models). Red bars on top of each distribution refer to the posterior inclusion probability of the respective regressor. Top panel, left side shows the posterior distribution of the initial income variable (GDPCAP0) based on the model specification not including the CEE dummy variable (Table 3, first column). Top panel, right side is based on the model including the CEE dummy variable (Table 3, second column). Middle and bottom panel are based on the estimation given in Table 3, third column. Distributions are shown for the initial income variable (GDP-CAP0), the capital city dummy (Capital) and its linear interaction term (Capital × CEE dummy).

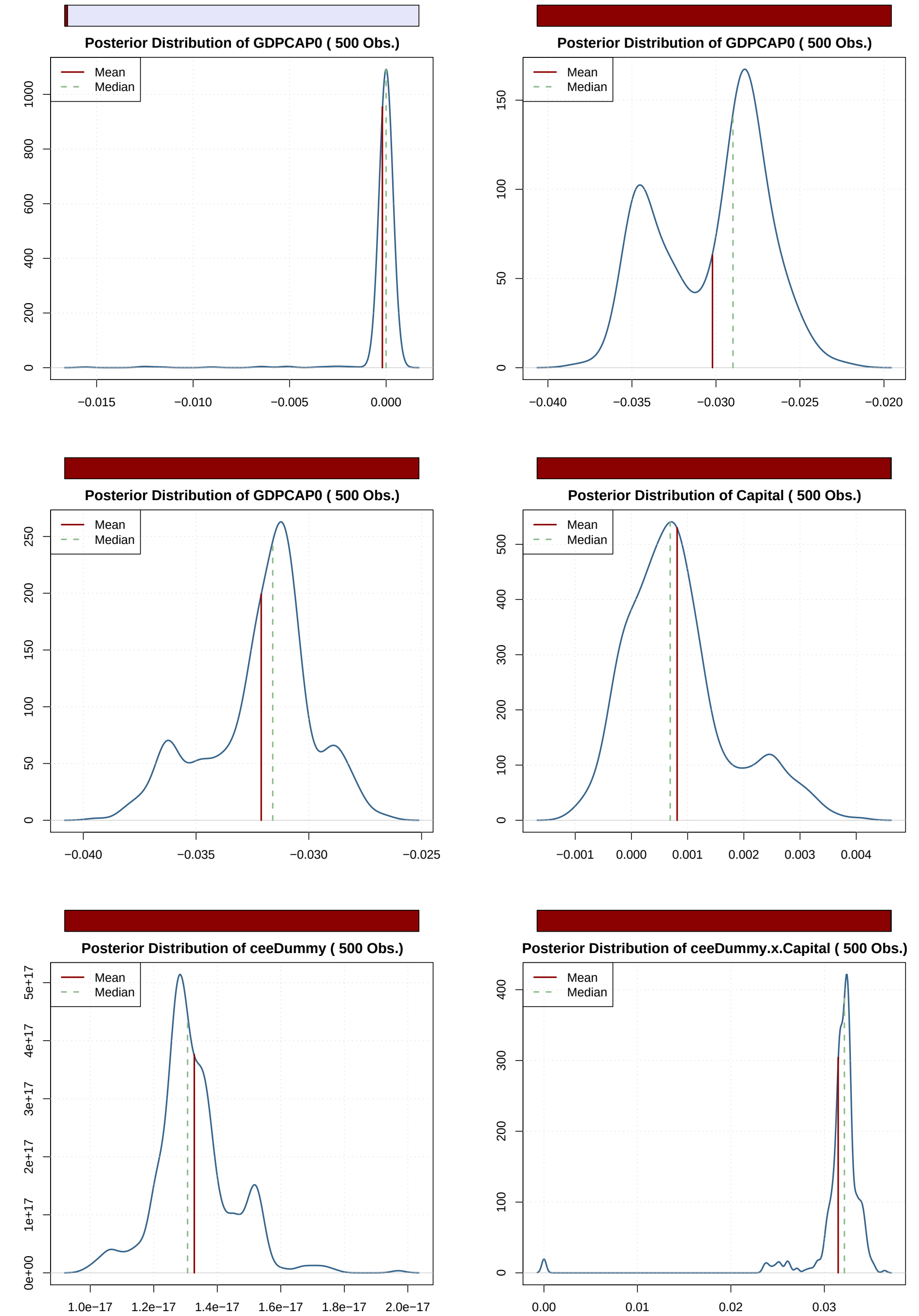


Figure 4: Unconditional posterior distribution based on models with fixed effects (500 best models). Red bars on top of each distribution refer to the posterior inclusion probability of the respective regressor. Top panel, left side shows the posterior distribution of the initial income variable (GDPCAP0) based on the model specification not including the CEE dummy variable (Table 4, first column). Top panel, right side is based on the model including the CEE dummy variable (Table 4, second column). Middle and bottom panel are based on the estimation given in Table 4, third column. Distributions are shown for the initial income variable (GDPCAP0), the capital city dummy (Capital) and its linear interaction term (Capital $\times$ CEE dummy).

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