Economic Growth Determinants for European Regions: Is Central and Eastern Europe Different?

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We investigate the robustness of economic growth determinants for European regions in the period from 1995 to 2005. In particular we focus on the systematic differences in growth triggers for Central and Eastern European (CEE) regions as compared to regions belonging to the older EU Member States. Our method is based on the Bayesian model averaging of cross-sectional growth regressions, where we draw attention to (1) the spatial correlation structure of economic growth among European regions and (2) model uncertainty. The spatial autoregressive model (SAR) is employed to capture growth spillovers among European regions. We find that the regional income convergence process between countries is dominated by the catching-up process of CEE regions. Human capital, measured as the population share of highly educated workers, and income convergence appear to be robust driving forces of income growth. Capital cities grow faster, on average, with an additional growth bonus for those located in CEE. On top of this, the spatial model specification reveals a range of infrastructure variables as important growth determinants. Our results are robust with respect to different econometric model specifications.

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1 Introduction

In this paper we investigate the determinants of economic growth in European regions in the period from 1995 to 2005 with a special focus on the subset of Central and Eastern European (CEE) regions. We identify growth drivers for regions *between* countries as well as for regions *within* countries of the EU-27. Econometric inference concerning the determinants of economic growth depends strongly on the spatial disaggregation level at which economic units (countries, regions, cities, etc.) are observed.[2] In this contribution, we concentrate on economic growth patterns in Europe at the regional level. 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 income convergence is almost 2% and relatively constant both over time and also across countries.

Determinants of regional growth and convergence patterns have been studied by Boldrin and Canova (2001), who investigate income convergence and its relationship to regional policies, concluding with a critical assessment of regional economic policies. Canova (2004) tests 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. Becker et al. (2008) find evidence

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[2] *Barro (1991) and Sala-i-Martin et al. (2004) give an excellent overview of empirical analysis for regional data and cross-sections of countries.*

for growth (but not employment) effects for regions receiving structural funds. Basile (2008) finds positive (nonlinear) effects of schooling for EU-15 regions, whereas LeSage and Fischer's (2008) results indicate that industry diversity impacts negatively on European growth rates and that there is no evidence that human capital is robustly related to economic growth. A detailed study focusing on the identification of policy levers in the CEE regions to attain sustainable growth rates has been carried out by the European Commission (2004). The results show decreasing income inequality *between* regions of different countries, whereas increasing trends in inequality are found *within* CEE countries. This is confirmed by the results in Béla (2007), who shows that in the early stage of catching up, regional inequalities tend to increase.

An important challenge the empirical economic growth literature faces 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 the "open-endedness" of growth theories. Hence theory is of little guidance regarding which variables should be included in the analysis, and empirical results point to different growth determinants. Over 140 different variables have been used in country-based empirical growth studies since the 1990s (Durlauf et al., 2005). Empirical models of economic growth are therefore plagued by the problem of *model uncertainty* concerning the choice of explanatory variables and model specification.

In this paper we will deal with model uncertainty in regional growth regressions by applying Bayesian model averaging (BMA). The strength of BMA is rooted in the statistically sound way in which model uncertainty is overcome. Basing inference on a weighted average across sufficiently many models as opposed to picking a single best model provides a robust modeling strategy, with weights arising naturally in the Bayesian framework as the posterior model probabilities.[3] As such, BMA has received a lot of attention in the statistical literature (e.g. Raftery, 1995) and became popular among econometricians in the field of growth empirics (Sala-i-Martin et al., 2004, and Fernández et al., 2001b). A very recent literature has developed Bayesian tools in the analysis of spatially correlated data. The location and interaction of observations (countries, regions) might play a crucial role from a statistical point of view as well as regarding the economic interpretation of growth drivers. Spatial models have been already widely applied in the context of growth regressions (e.g. Fischer and Stirböck, 2006, and Niebuhr, 2001) and allow the researcher to interpret the source and strength of spatial dependence. LeSage and Fischer (2008) apply BMA to investigate determinants of income in EU regions, with particular emphasis on sectoral factors. In our model specifications we explicitly model spatial effects using the method put forward by LeSage and Parent (2007).

We contribute to the literature as follows: First, we investigate a set of 60 potential growth determinants in 255 NUTS 2 regions of the EU, which represents a much larger dataset than in the available empirical literature (see the annex for a list of variables and data sources). Second, we use BMA to investigate the robustness of regional growth determinants with an emphasis on spatial modeling, using SAR and different prior assumptions. Third, we allow for heterogeneity by

[3] *See Doppelhofer (2008) for a discussion of both Bayesian and frequentist techniques.*

estimating different elasticities of economic growth to some selected determinants in CEE EU Member States. Furthermore, we use a new methodology to assess parameter heterogeneity based on the strong heredity principle when constructing the prior over space of potential models. Fourth, we allow also 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 paper is structured as follows. Section 2 presents the setting of the BMA exercise carried out in the paper, while section 3 shows the empirical set-up and the choice of the interaction terms. Section 4 presents the empirical results concerning the robustness of growth determinants in the EU at the regional level. Section 5 checks for the robustness of the results to variations in the spatial weighting matrix and in the nature of the potential parameter heterogeneity. Section 6 concludes.

2 The Econometric Model: Specification and Prior Structures

In order to investigate the robustness of potential determinants of regional economic growth, we propose using models that can be nested within a general spatial autoregressive model (SAR) of the form:

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

where y is an N-dimensional column vector of growth rates of income per capita for N regions, α is the intercept term, ι_N is an N-dimensional column vector of ones, $X_k=(x_1...x_k)$ 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 X_k, 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 shock process with zero mean and a diagonal variance-covariance matrix $\Sigma=\sigma I_N$.

Spatial dependence can be attributed to economic interactions such as trade or commuting between observations (e.g. countries, regions). From a more statistical point of view, omitted variables can cause residual spatial autocorrelation. Hence standard regression techniques lead to inefficient or biased estimates (Anselin, 1988) under the presence of spatial correlation. Note that there exist several ways of specifying the correlation structure among the observations. We assume that observations (regions) are tied to each other by an inverse distance relationship. Thus the similarity of regions decreases with distance. A typical element of W is then given by $[W]_{ij} = d_{ij}^{-1}$ for $i \neq j$ and $[W]_{ii} = 0$, where d_{ij} is the distance between observation i and observation j. We use airline distances measured in kilometers, although any other distance metric could be embedded into the analysis as well (e.g. travel times). Since our inference in the spatial set-up will be conditional upon the spatial link matrix, a sensitivity analysis is essential when drawing con-

[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.*

clusions. We also introduce later a different way of specifying neighborhood relationships and carry out a robustness analysis.

The number and identity of the variables in X_k is assumed unknown so that the columns in X_k are taken to be k variables from a larger set of K potential explanatory variables, grouped in X_K, with $K \geq k$. A model in our setting $M_k \in M$ is defined by the choice of a group of variables (and thus, the size of the model), so card$(M)=2^K$. Inference on the parameters attached to the variables in X_k, which explicitly takes into account model uncertainty, can be thus based on weighted-averaged parameter estimates of individual models,

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

with Y denoting the data. Posterior model probabilities $p(M_k \mid Y)$ constituting the weights in equation (2) are given by

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

In the empirical application we are interested in the following statistics for a variable x_k. The *posterior inclusion probability (PIP)* is given by the sum of probabilities of models including variable x_k. Hence it reflects the variable's relative importance in explaining the phenomenon under study – in our case the growth process. 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

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

The *posterior standard deviation (PSD)* of β_k is the square root of the model-weighted sum of conditional variances plus an additional term capturing the uncertainty of the (estimated) posterior mean across models.

We have to decide how to elicit prior structures in order to calculate the sum in equation (2). In most empirical applications the cardinality of the model space renders direct evaluation of equation (2) infeasible. Markov Chain Monte Carlo Model Composition (MC3) algorithms evaluate subsets of the model space with non-negligible posterior mass. This stochastic search algorithm traverses the model space, thereby visiting the models in the "right proportion" in the sense that models with high posterior model probabilities are frequented more often than those to which small posterior model probabilities are attributed. Furthermore we have to put priors on the coefficient vector, the variance and the model space. In this paper, we use the 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). For more details see the annex and Crespo Cuaresma et al. (2009).

We also improve on past attempts to assess parameter heterogeneity[5] by using a particular prior over the model space that fulfills the *strong heredity principle* put forward by Chipman (1996) and which is aimed at assessing the importance of interaction terms in BMA. We implement this prior using a modified sampling procedure in the MC3 algorithm. In particular, under strong heredity, we only assign positive prior inclusion probabilities to models that (1) do not include interaction terms and (2) include *all* variables related to the interactions. To be more specific, if the term A*B (interacting variables A and B multiplicatively) enters the regression, variables A and B will also be part of the model. Thus we ensure that variables A, B and A*B enter the regression jointly for the evaluation of interaction terms, so as to ensure that only the independent effect of the interaction is evaluated. 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. Crespo Cuaresma (2008) points out that this approach can protect the analysis from spuriously detected interaction effects.

3 The Empirical Setting: Variables and Interactions

Table 2 lists the full set of 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 from 1995 to 2005, deflated by national price data. Note that over the larger part of the sample period, the CEE regions have not yet been EU members. This implies that potential structural breaks related to formal EU membership play a negligible role in this dataset.[6] 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. Wherever possible, variables are measured at their initial levels in order to limit the potential endogeneity of some of our explanatory variables.

We aim at assessing the potential differences between determinants of economic growth differences both across regions in different European countries and regions within a given country. Therefore the BMA exercise is carried out using both a single intercept term in the specification and country-specific intercepts, i.e. country-fixed effects. As a benchmark comparison, we report results based on the specification without a spatial correlation structure. 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 following the strong heredity principle described above.

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

[6] *See Crespo Cuaresma et al. (2008) for an assessment of EU membership as a growth determinant.*

4 Estimation Results

Table 1 presents the BMA results for three model specifications: Model 1 is the baseline estimation excluding both the spatial autoregressive lag and country-fixed effects. Model 2 incorporates country-fixed effects, and model 3 is the SAR. The SAR model is estimated without country-fixed effects, since the within transformation imposes some spatial structure a priori, which makes the SAR term not properly interpretable. Consequently, model 2 assumes that regions interact solely within countries and neglects any correlation that results from economic interaction beyond the countries' borders. The structure of the table is as follows: 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. In all cases we use a Binomial-Beta prior for model size with an expected size equal to seven regressors. Due to the hierarchical prior structure imposed over the model size, our results do not appear sensitive to the choice of this hyperparameter. The expected mean model size of seven regressors selected from a set of 60 candidate explanatory variables implies a prior inclusion probability of 7/60, which is approximately 0.10. Consequently variables with posterior inclusion probability (PIP) exceeding the prior of 10% are highlighted in bold font. We assess the issue of parameter heterogeneity between Eastern and Western European regions by explicitly including a dummy variable for regions belonging to CEE (Bulgaria, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovenia and Slovakia). The dummy is (linearly) interacted with initial income per capita, capital formation, population growth, access to roads, output density, capital cities, the share of highly educated labor, population density and employment density. In particular, these variables reflect the three Solow model variables (initial income per capita, capital formation and population growth), an infrastructure variable (road access), a human capital/technology innovation variable (share of highly educated labor), three variables measuring production polarization (output, population and employment density) and a dummy variable for capital cities.[7]

4.1 Cross-Section of Regions

Model 1 reveals a model-averaged estimate of the speed of convergence[8] – i.e. the rate at which per capita income in a region approaches its steady state relative to its distance from its steady state – of around 0.4%. Note that this estimate contains information on the convergence process of European income per capita both within and between countries. In this sense, it is not surprising that the estimate implies such a slow convergence process to the steady state: A higher speed of convergence is obtained below for the case of country-specific intercepts (and thus country-specific steady states). Furthermore, including the CEE dummy in the set of regressors shows that the precision of the estimate is strongly affected by the

[7] *We decided to include only a limited set of interactions so as to avoid models in which too many parameters would have to be estimated exclusively in the CEE subsample. Model spaces which include specifications with too many interactions as well as running two separate regressions for the CEE and non-CEE subsamples would result in many models which run out of degrees of freedom.*

[8] *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.*

growth experience of CEE countries.[9] This suggests that income convergence is mainly driven by the catching-up process of CEE regions, as can be further seen by the large inclusion probability of the CEE dummy. Some variables present a robust (partial) correlation with growth: a proxy for human capital (the share of highly educated labor), a gravity/spatial measure (the distance to Frankfurt) and the interaction of the CEE dummy with the capital city dummy. The positive effect of human capital on economic growth is reflected in a robust positive parameter estimate attached to the variable quantifying the highly educated share in the working-age population. The empirical literature concerning the importance of human capital accumulation for economic growth provides very mixed results both at the country level (see the important contribution by Krueger and Lindahl, 1999) and at the regional level. Focusing on the recent empirical literature dealing with regional growth, LeSage and Fischer (2008), for instance, find no significant effects of education on growth, while Sterlacchini (2008) concludes that human capital and R&D are the most effective growth-enhancing factors in Western European regions. Nonlinear effects of human capital on economic growth are found by Basile (2008). Since these deviations can be at least partly attributed to differences in the model employed (as well as in the data set), the use of techniques which are robust to model uncertainty is particularly important when studying the relationship between education and economic development at the regional level.

The size of the model-averaged estimate implies that on average a 10% increase in the share of highly educated people in the working-age population is associated with a 0.5% higher growth rate of GDP per capita. The caveats mentioned in Vandenbussche et al. (2006) regarding the comparability of this proxy are however in place. In principle, a proportion of the variations 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 below), where heterogeneity in national education systems is controlled for.

The significant interaction term with capital cities can be interpreted as confirming the theory put forward by Williamson (1965) and empirically confirmed by Béla (2007), which states that in an early stage of catching up, regional inequalities within countries increase. This is also in line with the results found by the European Commission (2004). A possible explanation is the general scarcity of infrastructure that countries face at the beginning of the convergence process. As countries are catching up, agglomerations (e.g. capital cities) become congested. Due to diminishing returns to scale, other backward regions become more attractive for investment, leading to regional convergence. Our results confirm this phenomenon, indicating that CEE regions are in an earlier stage of convergence than the old EU Member States. The data reveal that capital cities in CEE regions (agglomerations) gain a growth bonus that is about four times higher than for non-CEE capital cities. Furthermore the positive coefficient on the CEE dummy shows that on average these regions grow faster than the rest of the sample.

[9] *Estimation results are available from the authors upon request.*

4.2 Cross-Section of Regions with Country-Fixed Effects

In model 2 we repeat the same exercise using a specification including country-fixed effects, and thus concentrating on the determinants of economic growth *within* countries for European regions. It should be noted 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. Furthermore country-fixed effects account for unobserved country-specific characteristics which affect the process of economic growth and are assumed to be equal across regions. Variables that are country-specific are thus conditioned out and should yield no posterior support. Note that the strong heredity principle can, by construction, lead to a large posterior inclusion probability of the CEE dummy in case that there are important interaction variables. However, if it is only the interaction that matters, the effect (i.e. the coefficient) of the dummy should be close to zero. There are some differences between the determinants of economic growth implied by the differences *between* regions and those of regions *within* a given country. For the first time an infrastructure variable appears strongly related to growth (INTF). Model 2 further indicates that human capital remains a robust determinant of growth in this setting, although the parameter is not as well estimated as in the case without country-fixed effects. This result is not surprising, given that a large part of the variation in educational outcomes is driven by cross-country differences (as opposed to cross-regional differences within countries). A 10% increase in the highly educated share in the labor force in CEE regions leads to a remarkable growth bonus of 1.2%.

4.3 Results 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 country, in the economic growth process. To the extent that country borders are not a large obstacle in the growth process of EU regions, country-fixed effects may not be the best way to model spatial relationships in our dataset. Alternatively, we use actual geographical distances in the framework of SAR models such as those presented above to relate the growth process of different regions.

The very right column in table 1 presents the results of the BMA exercise for the SAR model (without country-fixed effects). 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 around 9. With a coefficient of approximately 0.6, the model-averaged estimate of ρ points to positive spillovers among European regions. Thus regions benefit from a neighborhood that is characterized by high growth rates. The results obtained in the specifications without spatial autocorrelation are still present in the estimates from the SAR model: 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 infrastructure variables and socio-geographical variables as determinants of long-run growth. In terms of economic growth, regions also profit from a growing population. Taking spatial autocorrelation into account, there is no robust parameter heterogeneity in the speed of income convergence. The CEE region dummy does no longer appear robustly related to growth since we explicitly modeled the spatial arrangement of the data by the econometric framework we set up.

The issue of the estimates of income convergence speed under spatial autocorrelation deserves further comment. If spatial spillovers are not included in the specification but exist in the data, the speed of convergence will tend to be overestimated (see Crespo Cuaresma and Feldkircher, 2009). In this sense, the choice of a spatial link matrix is particularly important in order to get reliable estimates of the speed of convergence. Crespo Cuaresma and Feldkircher (2009) analyze this issue by allowing uncertainty concerning the spatial link matrix. While our results here are derived using an inverse distance matrix, in the following subsection we perform a robustness analysis using other spatial link matrices.[10]

5 Robustness Checks

In this section we allow for a different setting in the neighborhood specification so as to ensure that the results presented above are robust with respect to the connectivity matrix. Economic theory does not offer any guidance concerning a particular choice of spatial weighting matrix 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 $W(\varphi)$ with a characteristic element

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

where d_{ij} is the distance between regions i and j and the parameter $\o$ embodies the sensitivity of weights to distance, and thus the decay of the weighting scheme. The benchmark value ($\varphi=1$) implies that weights are an inverse function of distance, while higher values of φ lead to a stronger decay of weights with distance. Using inverse distance weighting, one needs to specify "centers of economic activities," where we use the region's capital cities. This can be circumvented when using binary contiguity matrices as weighting schemes. Here neighborhood is defined by the regions sharing a common border (or vertex). A first-order queen contiguity matrix therefore reflects spatial interactions of contiguous regions only. This implies that growth developments in a given region are affected by the growth process in all (first-order) contiguous regions and not by those that do not share a common border with the region under consideration. A typical element of W for two neighboring regions is then given by $[W]_{ij}=1$ for $i \neq j$, $[W]_{ii}=0$ and $[W]_{ij}=0$ for i and j not sharing a common border. A second-order queen contiguity matrix assigns positive (equal) weights not only to contiguous regions but also to the neighbors of the neighbors. The main difference to inverse distance weighting lies in the common treatment of neighbors by assigning equal weights.

To test the sensitivity of our results, we repeat the BMA exercise for the parameter value $\o=2$, which implies a faster decay of weights with distance. We also obtain results from imposing contiguity weights using a first-order and

[10] *Pfaffermayr (2009) shows, furthermore, that local spatial interactions in the Solow model lead to heterogeneity in the speed of convergence. Further empirical research in this field could profit from the methods presented in this paper as well as those in Crespo Cuaresma and Feldkircher (2009).*

second-order queen contiguity matrix.[11] Chart 1 summarizes the results of the robustness exercise by plotting the PIP corresponding to each variable for the cases *ø=1,2* and for the first- and second-order queen contiguity matrices. Posterior inclusion probabilities of the regressors in our analysis are surprisingly insensitive to alternative weighting matrices. The same applies to statistical and economic inference, measured by standardized coefficients (PM/PSD): No qualitative changes for varied weighting designs can be detected.[12]

6 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 on the topic. On the one hand, we use the most comprehensive dataset existing (to our knowledge) 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 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.

We find evidence for conditional convergence across European regions both between regions of different countries and between regions within individual countries. In the cross-section of regions with spatial specification, the estimated speed of convergence is around 1.3%. However, the precision of the estimated speed of convergence is strongly affected by the growth experience of CEE countries. The convergence process *between* regions is dominated by the catching-up process of regions in CEE. In all model specifications, the growth rate of income per capita is higher in regions with capital cities than it is in non-capital city regions, after controlling for all other factors. On top of this, there is an additional growth bonus for capital cities in CEE regions. Allowing for spatial autocorrelation a priori, we find evidence for positive spatial spillovers in EU regions. These growth clusters have become a stylized fact in the empirical literature on economic growth (e.g. LeSage and Fischer, 2008).

The interaction between growth and output agglomeration deserves further analysis. Williamson (1965) states that in countries in an early stage of catching up, the growth push in economic acitivity should be concentrated in few poles (for instance, urban agglomerations around capital cities).

Regarding regional growth determinants, our results imply that human capital, conditional income convergence and – to a minor extent – infrastructure variables appear as the most robust driving forces of income across European regions.

[11] *Detailed results are available upon request from the authors. Variations for the coefficient attached to initial income (GDPCAP0) might be due to multicollinearity with the CEE dummy variable.*

[12] *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."*

The importance of education as a growth engine appears clearly in the data and is also robust to the use of different spatial weight matrices.[13] Our estimates imply that an increase of 10% in the share of highly educated people in the working-age population leads to a rise in GDP per capita growth by 0.5% on average. 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 country-fixed effects. On top of this, regions belonging to CEE countries achieve on average higher returns to human capital. When it comes to policy choices, this result gives clear indications concerning the importance of policies aimed at increasing education levels as a key component of policy strategies toward sustainable long-term growth rates of income in CEE. Besides the fact that human capital accumulation appears to be a robust driver of growth, the differences in returns to education in terms of growth (which could be seen as an empirical sign concerning a certain degree of skill mismatch) implies that CEE regions can profit overproportionately from policies aimed at incentivizing investment in human capital accumulation.

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[13] *We conducted several extra robustness exercises using different spatial weight matrices, which are not presented here but are available from the authors upon request. The results concerning the robustness of human capital and income convergence appear robust across spatial weighting matrices.*

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Annex

A. Prior Structures

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 so-called g-prior (Zellner, 1986) for the coefficient vector:

$$p(\vec{\beta}_k \mid \alpha,\rho,\sigma) \sim N(\underline{0_k}, g\sigma^2 (X_{k'} X_k)^{-1}).$$

The prior is noninformative in the sense that the variable is thought of as having no influence on the dependent variable. The prior expected value of β is zero with variance equal to the ordinary least squares variance multiplied by the scalar g. Increasing g decreases the researcher's confidence in the prior guess, whereas a small g corresponds to a strong belief a priori. We use the benchmark prior for g put forward by Fernández et al. (2001a), setting $g = \max\{N, K^2\}$. 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, see Schwarz, 1978) or RIC (Risk Inflation Criterion, see Foster and George, 1994). We follow LeSage and Parent's (2007) proposal and use a beta prior distribution for ρ.

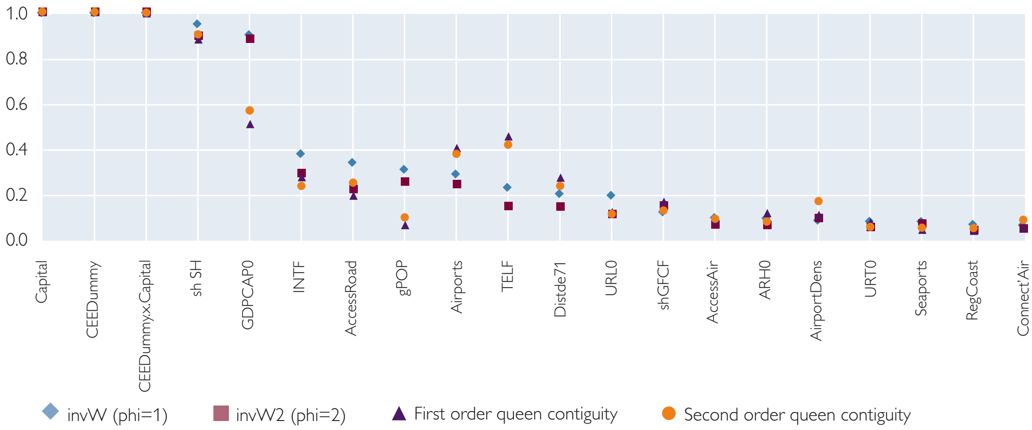
Several approaches to the elicitation of prior information on model size have been proposed by the modern literature on BMA. Many studies rely on a diffuse prior setting which assigns equal probability to all possible models, thereby imposing a mean prior model size of *K/2*. In contrast, some authors 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 Binomial-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, 2009

B. Posterior Distribution SAR Model and MCMC algorithm

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. The posterior distributions of interest over the model space can be then obtained using Markov Chain Monte Carlo Model Composition (MC3) methods in a straightforward manner (see LeSage and Parent, 2007). In particular, we use a random-walk step in every replication of the MC3 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 the complete (potentially untractable) model space (see Fernández et al. (2001a) for a more detailed description of this strategy). All results were obtained from 1,100,000 draws of the MC3 sampler where we discarded the first 100,000 draws (burn-in phase).

Chart 1

Posterior Inclusion Probability under Different Weight Matrices



Source: Authors' calculations.

Table 1

Estimation Results

	Model 1			Model 2			Model 3		
	PIP	PM	PSD	PIP	PM	PSD	PIP	PM	PSD
AccessAir	0.017	0.000	0.001	0.008	0.000	0.000	0.094	0.001	0.002
AccessRoad	0.301	−0.002	0.003	0.004	0.000	0.000	0.324	−0.001	0.002
AirportDens	0.011	0.036	0.379	0.003	0.003	0.084	0.090	0.299	1.129
Airports	0.043	0.000	0.000	0.006	0.000	0.000	0.287	0.000	0.000
ARH0	0.009	0.000	0.004	0.002	0.000	0.001	0.092	0.003	0.013
ARL0	0.003	0.000	0.001	0.002	0.000	0.001	0.022	0.000	0.003
ART0	0.001	0.000	0.000	0.004	0.000	0.001	0.027	−0.000	0.006
Capital	0.998	0.005	0.003	0.677	0.000	0.002	1.000	0.006	0.003
ConnectAir	0.011	0.000	0.000	0.003	0.000	0.000	0.059	−0.000	0.001
ConnectSea	0.002	0.000	0.000	0.003	0.000	0.000	0.020	0.000	0.000
DistCap	0.009	0.000	0.000	0.002	0.000	0.000	0.036	0.000	0.000
Distde71	0.585	0.000	0.000	0.006	0.000	0.000	0.216	0.000	0.000
EMPDENS0	0.002	0.000	0.000	0.004	0.000	0.000	0.036	0.000	0.001
EREH0	0.006	0.000	0.002	0.002	0.000	0.001	0.042	0.001	0.007
EREL0	0.004	0.000	0.001	0.004	0.000	0.001	0.031	0.000	0.003
ERET0	0.004	0.000	0.001	0.008	0.000	0.002	0.035	0.001	0.006
GDPCAP0	0.389	−0.004	0.006	1.000	−0.030	0.004	0.888	−0.012	0.007
gPOP	0.025	0.007	0.045	0.003	−0.000	0.007	0.315	0.090	0.147
Hazard	0.002	0.000	0.000	0.010	0.000	0.000	0.019	0.000	0.000
HRSTcore	0.003	0.000	0.001	0.003	0.000	0.000	0.023	0.000	0.002
INTF	0.019	0.001	0.004	1.000	0.084	0.013	0.371	0.013	0.019
OUTDENS0	0.003	0.000	0.000	0.005	0.000	0.000	0.022	0.000	0.000
PatentBIO	0.002	0.000	0.007	0.007	0.001	0.013	0.025	0.002	0.024
PatentHT	0.005	0.000	0.004	0.017	0.001	0.006	0.050	0.002	0.011
PatentICT	0.006	0.000	0.002	0.019	0.001	0.004	0.043	0.001	0.007
PatentShBIO	0.001	0.000	0.001	0.002	0.000	0.001	0.019	0.000	0.002
PatentShHT	0.002	0.000	0.000	0.008	0.000	0.001	0.025	0.000	0.001
PatentShICT	0.003	0.000	0.000	0.022	0.000	0.001	0.022	0.000	0.001
PatentT	0.003	0.000	0.001	0.020	0.000	0.002	0.027	0.000	0.002
POPDENS0	0.003	0.000	0.000	0.004	0.000	0.000	0.039	−0.000	0.001
RailDens	0.001	0.000	0.001	0.003	0.000	0.001	0.020	0.000	0.002
RegBorder	0.001	0.000	0.000	0.007	0.000	0.000	0.017	0.000	0.000
RegCoast	0.004	0.000	0.000	0.002	0.000	0.000	0.060	−0.000	0.002
RegObj1	0.006	0.000	0.000	0.004	0.000	0.000	0.052	0.000	0.001
RegPent27	0.005	0.000	0.000	0.003	0.000	0.000	0.043	0.000	0.001
RoadDens	0.003	0.000	0.000	0.003	0.000	0.000	0.029	0.000	0.001
Seaports	0.006	0.000	0.000	0.002	0.000	0.000	0.076	0.000	0.002
Settl	0.002	0.000	0.000	0.003	0.000	0.000	0.016	0.000	0.000
ShAB0	0.005	0.000	0.002	0.014	0.001	0.005	0.036	0.001	0.007
ShCE0	0.003	0.000	0.001	0.003	0.000	0.001	0.024	0.000	0.003
shGFCF	0.006	0.000	0.001	0.040	0.001	0.004	0.125	0.002	0.007
ShLLL	0.003	0.000	0.001	0.005	0.000	0.003	0.028	0.000	0.003
ShSH	0.996	0.053	0.010	0.612	0.030	0.026	0.951	0.044	0.016
ShSL	0.003	0.000	0.001	0.362	−0.012	0.017	0.025	−0.000	0.001
TELF	0.085	−0.000	0.001	0.003	0.000	0.000	0.243	−0.000	0.001
TELH	0.003	0.000	0.000	0.003	0.000	0.000	0.021	0.000	0.000
Temp	0.002	0.000	0.000	0.003	0.000	0.000	0.021	0.000	0.000
URH0	0.003	0.000	0.001	0.005	0.000	0.002	0.043	0.001	0.010
URL0	0.012	−0.000	0.002	0.023	−0.000	0.003	0.182	−0.004	0.010
URT0	0.009	−0.000	0.002	0.008	−0.000	0.002	0.081	−0.002	0.010
CEEDummy	1.000	0.016	0.006	1.000	0.000	0.001	1.000	0.008	0.008
CEEDummy.x.AccessRoad	0.005	−0.000	0.001	0.000	0.000	0.000	0.009	0.000	0.001
CEEDummy.x.Capital	0.993	0.018	0.004	0.676	0.022	0.015	1.000	0.021	0.004
CEEDummy.x.EMPDENS0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CEEDummy.x.GDPCAP0	0.001	0.000	0.000	0.011	0.000	0.002	0.020	0.000	0.001
CEEDummy.x.gPOP	0.000	0.000	0.002	0.000	0.000	0.003	0.005	0.000	0.025
CEEDummy.x.OUTDENS0	0.000	0.000	0.000	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	0.001	0.000	0.000
CEEDummy.x.shGFCF	0.000	0.000	0.000	0.005	0.000	0.005	0.019	0.001	0.006
CEEDummy.x.ShSH	0.005	0.000	0.005	0.324	0.096	0.141	0.027	−0.001	0.008
Spatial Rho	–	–	–	–	–	–	–	0.623	–

Source: Authors' calculations.

Note: PIP stands for Posterior Inclusion Probability, PM stands for Posterior Mean and PSD stands for Posterior Standard Deviation. All calculations based on MC3 sampling with 1,000,000 replications (after 100,000 burn-in draws).
PIPs over 10% in bold. Variables separated by .x. denote interaction terms.
Model 1: Cross-section of regions (no country-fixed effects); model 2: country-fixed effects; model 3: spatial autoregressive model (no country fixed effects).

Table 2

Data Description

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	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
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 highly 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	Lifelong 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

Source: Authors' compilation.

Note: Data are from ESPON (European Spatial Planning Observation Network, www.espon.eu), Eurostat and Eurostat LFS (Eurostat Labour Force Survey, http://epp.eurostat.ec.europa.eu/). Variables expressed in shares additionally denoted by asterisk (*) are not included in the regressions and serve hence as a reference group.