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Jesús Crespo Cuaresma, Gernot Doppelhofer & Martin Feldkircher

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The Determinants of Economic Growth in European Regions

JESÚS CRESPO CUARESMA*†‡§, GERNOT DOPPELHOFER¶ and MARTIN FELDKIRCHER‖
**Department of Economics, Vienna University of Economics and Business (WU), Augasse 2–6, A-1090 Vienna, Austria. Email: jcrespo@wu.ac.at*
†World Population Program, International Institute of Applied Systems Analysis (IIASA), Laxenberg, Austria
‡Wittgenstein Centre for Demography and Global Human Capital (WIC), Vienna, Austria
§Austrian Institute for Economic Research (WIFO), Vienna, Austria
¶Department of Economics, Norwegian School of Economics (NHH), Helleveien 30, N-5045 Bergen, Norway. Email: gernot.doppelhofer@nhh.no
‖Oesterreichische Nationalbank, Otto-Wagner-Platz 3, A-1090, Vienna, Austria. Email: martin.feldkircher@oenb.at

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CRESPO CUARESMA J., DOPPELHOFER G. and FELDKIRCHER M. The determinants of economic growth in European regions, *Regional Studies*. This paper uses Bayesian model averaging (BMA) to find robust determinants of economic growth between 1995 and 2005 in a new data set of 255 European regions. It finds that income convergence between countries is dominated by the catching-up of regions in new member states in Central and Eastern Europe, whereas convergence within countries is driven by regions in old European Union member states. Regions containing capital cities are growing faster, particularly in Central and Eastern European countries, as do regions with a large share of workers with a higher education. The results are robust when allowing for spatial spillovers among European regions.

Bayesian model averaging (BMA)   Spatial autoregressive (SAR) model   Determinants of economic growth   European regions

CRESPO CUARESMA J., DOPPELHOFER G. and FELDKIRCHER M. 欧洲区域经济成长的决定因素，*区域研究*。本论文使用贝式模型平均法(BMA)，在欧洲255个区域的新数据集中，寻找1995至2005年间经济成长的决定要素。研究发现，各国所得的趋同，主要是由中、东欧新成员国区域的追赶所引发；而国家内部的趋同则是由几个资深欧盟成员国所在区域所促动。首都城市所在之区域成长较为快速，尤其对中欧及东欧国家而言是如此；受过高等教育劳工比例较高的区域成长亦较为快速。考虑欧洲区域的空间外溢，以上研究结果是相当坚实的。

贝式模型平均法(BMA)   空间条件自回归模型(SAR)   经济成长要素   欧洲区域

CRESPO CUARESMA J., DOPPELHOFER G. et FELDKIRCHER M. Les déterminants de la croissance économique dans les régions d'Europe, *Regional Studies*. Cet article emploie la méthode du 'Bayesian Model Averaging' (BMA) afin de dévoiler, à partir d'un nouvel ensemble de données auprès de 255 régions d'Europe, les déterminants fiables de la croissance économique entre 1995 et 2005. Il s'avère que la convergence des revenus sur le plan international est dominée par le rattrapage des régions situés dans les nouveaux pays membres de l'Europe centrale et orientale, alors que la convergence au sein des pays est pilotée par les régions dans les anciens pays membres de l'Union européenne. Les régions qui englobent les capitales semblent croître plus rapidement, surtout dans les pays de l'Europe centrale et orientale, comme le fait les régions dotées d'une part importante des travailleurs qualifiés. Quand on tient compte des retombées géographiques parmi les régions européennes, les résultats s'avèrent fiables.

'Bayesian Model Averaging'   Modèle auto-régressif géographique   Déterminants de la croissance économique   Régions européennes

CRESPO CUARESMA J., DOPPELHOFER G. und FELDKIRCHER M. Determinanten des Wirtschaftswachstums in europäischen Regionen, *Regional Studies*. In diesem Beitrag ermitteln wir anhand eines neuen Datensatzes von 255 europäischen Regionen mit Hilfe der Methode des Bayesian Model Averaging (BMA) robuste Determinanten des Wirtschaftswachstums im Zeitraum von 1995 bis 2005. Wir stellen fest, dass die Einkommenskonvergenz zwischen verschiedenen Ländern von einem Aufholen der Regionen in den neuen mittel- und osteuropäischen Mitgliedstaaten der Europäischen Union beherrscht wird, während die Konvergenz innerhalb eines Landes von den Regionen der alten EU-Mitgliedstaaten ausgeht. Regionen mit Hauptstädten wachsen insbesondere in mittel- und osteuropäischen Ländern schneller; dasselbe gilt für Regionen mit einem hohen Anteil von Arbeitnehmern mit Hochschulbildung. Die Ergebnisse sind auch bei Berücksichtigung von räumlichen Übertragungen zwischen europäischen Regionen robust.

Bayesian Model Averaging (BMA) Räumliches autoregressives Modell (SAR-Modell) Determinanten des Wirtschaftswachstums Europäische Regionen

Crespo Cuaresma J., Doppelhofer G. y Feldkircher M. Los determinantes del crecimiento económico en las regiones europeas, *Regional Studies*. En este artículo utilizamos los promedios de modelo bayesiano para averiguar los determinantes sólidos del crecimiento económico entre 1995 y 2005 en un nuevo grupo de datos de 255 regiones europeas. Observamos que la convergencia de ingresos entre los países está dominada por la convergencia de las regiones en los nuevos Estados miembros en Europa central y oriental, mientras que la convergencia dentro de los países está determinada por las regiones en los antiguos Estados miembros de la Unión Europea. Las regiones con capitales crecen más rápidamente, sobre todo en los países de Europa central y oriental, igual que las regiones con un alto porcentaje de trabajadores con un alto nivel de estudios. Los resultados son sólidos cuando se tienen en cuenta desbordamientos espaciales entre las regiones europeas.

Promedios de modelo bayesiano Modelo autorregresivo espacial Determinantes del crecimiento económico Regiones europeas

JEL classifications: C11, C21, O52, R11

INTRODUCTION

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

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

A recent and quickly growing literature addresses this problem of model uncertainty in growth empirics systematically by using BMA.[2] Fernández *et al.* (2001b) investigated the robustness of the growth determinants by using BMA on the data set collected by Sala-i-Martin (1997). Following Leamer (1978), Sala-i-Martin *et al.* (2004) used Bayesian averaging of classical estimates (BACE), which uses least-squares (classical) estimates and sample-dominated model weights that are positively related to the Bayesian information criterion (BIC) developed by Schwarz (1978).[3] Other studies look at the importance of parameter heterogeneity in the uncertain growth process (Crespo Cuaresma and Doppelhofer, 2007; or Doppelhofer and Weeks, 2009). Despite this focus on various aspects of model uncertainty, the literature has paid little attention to regional aspects of the uncertain growth process.

A number of recent studies have investigated model uncertainty in the context of robustness of growth determinants and income convergence patterns at the *regional* level. The empirical assessment of regional growth determinants has the added complication that spatial correlation is present in the data to a much higher extent than in cross-country data. Recently, a branch of literature has developed Bayesian tools for the analysis of spatially correlated data under model uncertainty. LeSage and Parent (2007) gave an excellent introduction to BMA for spatial econometric models; and LeSage and Fischer (2008) applied BMA to investigate determinants of income in European Union regions, with particular emphasis on sectoral factors. Knowledge spillovers from patent activity between European Union regions, one of the most important growth determinants according to endogenous growth theory, is the focus of the analysis in LeSage and Parent (2008).

Many other empirical studies analyse regional growth determinants and income convergence in Europe but do not deal with the issue of model uncertainty and spatial spillovers simultaneously.[4] BOLDRIN and CANOVA (2001), for instance, investigated income convergence in European Union regions and its relationship to regional policies, and concluded with a critical assessment of regional economic policies. BECKER *et al.* (2010) found evidence for growth, but not employment effects of regions receiving Structural Funds as so-called Objective 1 regions. CANOVA (2004) and ERTUR *et al.* (2006) tested for convergence clubs in European regions and found evidence for convergence poles characterized by different economic conditions. CORRADO *et al.* (2005) used an alternative technique to identify clusters of convergence in European regions and sectors. CARRINGTON (2003) investigated convergence among European Union regions and found evidence of *negative* spatial spillovers among neighbouring regions. BASILE (2008) estimated a semi-parametric spatial model for European regions and found evidence for non-linear effects associated with initial income and human capital investments, as well as some indication for global and local spillovers.

This paper contributes to the literature on determinants of regional growth in several aspects. First, it investigates a set of forty-eight possible growth determinants in 255 NUTS-2 regions of the European Union. Compared with the limited set of variables considered in the existing empirical literature, the paper rigorously assesses model uncertainty over a much larger set of determinants of regional growth. Second, the paper uses BMA to investigate the robustness of determinants of regional growth between and within countries, as well as allowing for spatial spillovers. In particular, three different specifications are estimated to describe the growth process in European Union regions: (1) the *baseline case* of a pure cross-section of European Union regions; (2) the *baseline plus country fixed effects*; and (3) the baseline combined with a *spatial autoregressive* (SAR) structure.[5] Third, this paper uses a particular prior structure for interaction terms that fulfils the *strong heredity principle* put forward by CHIPMAN (1996) when designing priors over the model space for related variables (for a recent discussion on the use of interaction terms in BMA, see CRESPO CUARESMA, 2012). Thus, the specification allows for heterogeneous effects of selected growth determinants in recent accession countries in CEE – Bulgaria, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovenia and the Slovak Republic – and also in capital cities. Finally, the paper allows for uncertainty over spatial weights by conducting a sensitivity analysis with respect to alternative spatial distance measures.

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

- Conditional income convergence is a robust driving force of income growth across European regions. In the cross-section of regions, there is evidence for conditional convergence with a speed of around 2% per year. However, the precision of the estimated speed of convergence is strongly affected by the growth experience of CEE countries. The convergence process *between* European regions is dominated by the catching-up process of regions in 'new' European Union member states in CEE countries, whereas convergence *within* countries is mostly a characteristic of regions in 'old' European Union member states.
- Regions with capital cities grow on average by 1 percentage point faster than non-capital city regions. This result, however, hides very strong differences between the experience of old and new European Union member states. Regions containing capital cities in CEE grew on average 1.8 percentage points faster, compared with only 0.4 percentage growth bonus in capital regions in old European Union member states. Together with the observed convergence patterns in European Union regions, this observation lends empirical support to the so-called 'Williamson hypothesis'. According to WILLIAMSON (1965), economic growth concentrates in regions with urban agglomerations as the catching-up process progresses, reverting the process in later stages of development. While this effect is very robust, it should be noted that these growth patterns may be related to the fact that the period under analysis (1995–2005) was characterized by rapid income growth in Eastern Europe.
- Human capital, measured as the population share of workers with higher (tertiary) education, has a robust positive association with regional economic growth. The estimates imply that an increase of 10% in the population share of workers with higher education is associated with a 0.6 percentage point higher annual growth rate of gross domestic product per capita. The positive effect of human capital remains a robust determinant of regional growth within countries, but the parameter is not as well estimated as in the case without fixed country effects.
- Allowing for spatial autocorrelation a priori, the paper finds evidence for positive spatial spillovers (growth clusters) in European Union regions. However, spatial lags of growth determinants under consideration do not play a substantial role in explaining economic growth in European regions. The spatial spillovers are not operating through the explanatory variables at hand, but rather reflect some residual spatial effects which cannot be accounted by the explanatory variables or their spatial lags.
- Statistical and economic inference on the determinant of regional economic growth is robust to alternative spatial weighting schemes for the economic growth spillovers. This robustness is also supported by a recent study by CRESPO CUARESMA and FELDKIRCHER (2012), which used a different method to assess spatial link uncertainty in the regional growth

process and investigated a wider set of weighting matrices.

The paper is structured as follows. The next section presents the setup for the BMA exercise carried out in the paper. The following section presents the empirical results concerning the robustness of growth determinants in the European Union 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. The final section concludes.

THE ECONOMETRIC MODEL: SPECIFICATION AND PRIOR STRUCTURES

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

All three specifications can be nested within a general SAR model of the form:

$$y = \alpha\iota_N + \rho W y + X_k\vec{\beta}_k + \varepsilon \qquad (1)$$

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; $X_k = (x_1, \ldots, x_k)$ 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 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.[6] The residuals ε are assumed to be drawn form an N-dimensional shock process with zero mean and diagonal variance–covariance matrix $\Sigma = \sigma I_N$.[7]

A typical element of the spatial weight matrix W is given by $[W]_{ij} = 0$ and $[W]_{ij} = d_{ij}^{-1}$ for $i \neq j$, where d_{ij} is the distance[8] between observations i and j. The number and identity of the variables in X_k are assumed to be 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 $M_k \in M$ is defined by the choice of a group of variables (and thus, the size of the model), so the total number of models is card(M) = 2^K. Notice that X_K may also contain spatially weighted explanatory variables of the form WX_k.

Inference on the parameters attached to the variables in X_k which explicitly takes into account model uncertainty can be based on weighted averages of parameter estimates of individual models:

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

with $Y = (X,y)$ denoting the data. The weights – the posterior model probabilities – are given by:

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

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

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

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

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

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

Note that g scales up prior variance of β-coefficients reflecting the strength of the prior belief regarding the regression coefficients. In the application, prior coefficient means are set to zero reflecting an agnostic prior about the sign of coefficients, $\underline{\beta_k} = \vec{0}$, and following FERNÁNDEZ *et al.* (2001a), the hyperparameter for the g-prior is set to $g = \max\{N, K^2\}$, which in the present case implies that $g = K^2$ for all the settings presented below. This so-called benchmark prior over g implies for linear regression models that the relative size of the sample as compared with the number of candidate regressors will determine whether models are compared based on the BIC (SCHWARZ, 1978) or risk inflation criterion (RIC; FOSTER and GEORGE, 1994). As in LESAGE and PARENT (2007), this paper combines a benchmark prior for β_k with a beta prior distribution for ρ.

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

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

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

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

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

The posterior standard deviation (PSD) is defined accordingly as:

$$PSD_k = \sqrt{\mathrm{var}(\beta_k|Y)}$$

The posterior distributions of the β-parameters for the SAR specification are calculated for the ρ that maximizes the integrated likelihood $p(p|Y,W)$ (equation (7) in Appendix A) over a grid of ρ values. The posterior distributions of interest over the model space can be then obtained using Markov chain Monte Carlo model composition (MC^3) methods in a straightforward manner (LESAGE and PARENT, 2007). In particular, a random-walk step is used in every replication of the MC^3 procedure, constructing an alternative model to the active one in each step of the chain by adding or subtracting a regressor from the active model. The chain then moves to the alternative model with the probability given by the product of Bayes factor and prior odds resulting from the binomial-beta prior distribution. The posterior inference is based on the models visited by the Markov chain instead of on the complete (potentially untractable) model space (for a more detailed description of this strategy, see FERNÁNDEZ *et al.*, 2001a). Appendix A describes the implemented BMA procedure and the MC^3 sampling method implemented in the empirical analysis in more detail.

For the evaluation of potential non-linear effects by inclusion of interaction terms, the MC^3 method is adapted as follows to ensure that CHIPMAN's (1996) *strong heredity principle* is fulfilled. Positive prior inclusion probability is assigned only to models which include no interaction terms or models with interaction terms, but interacted variables also appearing linearly. In practice, an MC^3 sampler is implemented, which adds the individual interacted variables linearly to those models in which the interaction is included, so as to ensure that only the independent effect of the interaction is evaluated. This approach imposes a particular prior distribution over the model space, removing the prior probability mass from all the models where interactions are present, but the corresponding linear terms are not part of the model. This prior probability mass is correspondingly redistributed to models where the interaction appears together with the interacted variables and can thus be properly interpreted. CRESPO CUARESMA (2012) presented evidence that this type of *interaction sampling* method has better properties than standard MC^3 in the sense that the latter may spuriously detect interaction effects which are not present in the data. This sampling procedure implies a particular dilution prior over the model space which assigns zero prior probability to models containing interactions whose parent variables are missing in the specification.[9] This prior structure ensures that the interactive effects found relate to the pure interaction term and are not masking the effect of the (potentially correlated) parent variables.

EMPIRICAL RESULTS

The data set covers information on 255 European regions listed in Table B1. Appendix B lists the full set of regions and available variables, together with a brief definition, descriptive statistics and the source for each of them. The dependent variable refers to observations of the average annual growth rate of each region in the period 1995–2005, deflated using national price data.[10] Note that five variables expressed in shares serve as reference group (denoted by asterisks (*) in Table B2) and are therefore not included in the regressions. This results in forty-eight explanatory variables which can be roughly divided into several thematic groups:

- *Factor accumulation and convergence:* these variables correspond to the usual economic growth determinants implied by neoclassical growth models (initial income, population growth and investment in physical capital).
- *Human capital:* population shares of workers with high (tertiary), medium (secondary) and low (primary) educational attainment, as well as a lifelong learning variable.
- *Technological innovation:* patent statistics, as well as the share of workers employed in the science and technology sector.
- *Sectoral structure and employment:* sectoral shares in gross domestic product; employment, unemployment and activity rates.
- *Infrastructure:* firm access to websites and telecommunications; access to sea, roads, air and rail transport.
- *Socio-geographical:* settlement structure; output, employment and population density; geographical location variables; Objective 1 regions;[11] capital city region.

All explanatory variables are measured at (or as close as possible) to the beginning of the sample period 1995 to capture the initial state of European Union regions. Endogeneity in the relationship between regional growth and several potential determinants may be a concern in empirical work on economic growth at the sub-national level. The data set therefore measures regressors at (or as close as possible to) the beginning of the sample period partly to mitigate problems of endogeneity. The estimation by least squares therefore treats the regressors as predetermined. This – as well as the use of country fixed effects in the within specification – should reduce the problem of endogeneity that is potentially associated with the use of some of the potential growth determinants. Given this maintained assumption, one should be careful not to attach a direct causal interpretation to the estimated effects. Alternatively, a researcher might consider using lagged values of regressors as potential instruments, although the high persistence of many regressors could imply the well-known weak instruments problem. Combined with likely measurement errors of regional growth and its determinants, HAUK and WACZIARG (2009) warned against the naive use of lagged values of regressors as instrumental variables, since this could imply larger biases than the much simpler ordinary least squares (OLS) estimator considered in this paper.[12]

The paper evaluates the robustness of potential growth determinants for European regions by using BMA in three different specifications: (1) the *baseline case* pools all regions and analyses variation across regions and *between* countries; (2) the baseline plus country fixed effects focuses on regional variation *within* countries of the EU-27; and (3) the baseline combined with an SAR specification is employed to capture growth spillovers among European Union regions with different choices for the spatial weight matrix W. The evaluation of non-linearities 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 Appendix A.

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

ECONOMIC GROWTH DETERMINANTS FOR EUROPEAN REGIONS

This section first considers the estimates based on the baseline case using a pooled cross-section of regions. The first column in Table 1 reveals that initial income per capita, the share of workers with higher education

Table 1. Bayesian model averaging (BMA) results for baseline setting

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

Notes: PIP, posterior inclusion probability; PM, posterior mean; PSD, posterior standard deviation. All calculations are based on Markov chain Monte Carlo model composition (MC^3) sampling with 2 million burn-ins and 3 million posterior draws. Model 1: Cross-section of regions (baseline). Model 2: Cross-section of regions including the Central and Eastern Europe (CEE) dummy variable and related interaction terms. Model 3: Cross-section of regions further including the interaction term of the capital city dummy with the CEE dummy variable. Under Models 2 and 3 the 'strong heredity prior' was employed.

Bold values refer to PIP values above 0.5.

and the dummy variable for capital cities are robust covariates for explaining economic growth differences among European regions. Posterior parameter means show the expected signs for the robust determinants and PSDs are relatively small. The parameter estimate associated with initial income implies that income convergence took place among European regions in the period considered, with a model-averaged estimate of the speed of convergence of roughly 2% per year.

Given that the data set 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. The possibility of different growth processes in CEE countries was explicitly assessed by expanding the set of covariates to contain interactions between a dummy for CEE countries and a group of selected variables. Consequently, the second column of Table 1 further elaborates on the issue of parameter heterogeneity between Eastern and Western European regions. The set of potential covariates now includes the original forty-nine covariates as well as a dummy variable for regions belonging to CEE countries (Bulgaria, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovenia and the Slovak Republic), together with the interaction of this variable with initial income per capita, investment, population growth, road access, output density, the share of workers in science/technology, population density, and employment density. The results in Table 1 present striking evidence for the importance of the CEE dummy variable, whose effect on economic growth is positive and well estimated. When including the CEE dummy, the estimated income convergence coefficient loses importance in terms of its PIP and the estimated speed of convergence is significantly lower. Furthermore, the speed of income convergence is no longer estimated with a reasonable degree of confidence. The third column of Table 1 further expands the set of covariates to include the interaction between the capital city and the CEE dummy. The results when this variable is included indicate that the positive growth effect of containing the capital city tend to be concentrated in CEE countries.

Table 1 also presents the proportion of total posterior model probability which is represented by the model with highest posterior probability, as well as the best twenty-five and fifty models. The posterior model probability tends to be concentrated on relatively few specifications. Table 2 presents the single best models (in terms of highest posterior probability) for each setting, together with some regression diagnostics. The single best models can explain differences in income per capita growth well, with adjusted R^2 statistics ranging from roughly 0.57 to 0.60. The best models, however, fail to produce residuals which are free of spatial autocorrelation, as measured by the results of Moran's I tests.

The top panel of Fig. 1 illustrates the impact of explicitly modelling heterogeneity in the intercept across European regions. The left-hand side of Fig. 1 (top panel) shows the posterior distribution[17] of the slope coefficient for the initial income variable based on the 500 models sampled in the MC^3 procedure with largest posterior support (in terms of posterior model probability). The posterior distribution is tightly concentrated around the model-averaged estimate of –0.02 with a PIP 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 Fig. 1). The figure presents a large mass of probability around zero. These results show that the

Table 2. Models with the highest posterior probability: baseline setting

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

Notes: Standard errors are given in parentheses; ***significance at the 1% level. Moran's I test and the Shapiro–Wilk test have as a null hypothesis the absence of spatial autocorrelation and residual normality, respectively.

CEE, Central and Eastern Europe.

recent income convergence experience in Europe has been mostly driven by significantly higher growth in Eastern European regions. In addition, there is no posterior support for the variable interacting initial income with the regional dummy variable. This indicates that the initial income level of Eastern European regions was not systematically able to discriminate the differential economic growth experiences of regions within the group of new European Union member states.

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

The differential growth dynamics of regions where the capital city of the country is located also appears as a relevant characteristic of the data set. On average, after controlling for all other variables and explicitly taking into account model uncertainty, the annual growth rate of income per capita in regions with capital cities is over 1 percentage point higher than in non-capital city regions. The specification in the third column allows for heterogeneous effects of capital cities in old versus new European Union member countries. The results show that regions containing capital cities in CEE countries grew on average 1.8 percentage points faster per year when compared with 0.4 percentage points in old European Union countries. This is further illustrated in Fig. 1, 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 a well-known empirical fact which can be interpreted in the framework of the Williamson hypothesis (WILLIAMSON, 1965), which states that for countries in an early stage of catching up the growth push in economic activity should be concentrated in few poles corresponding, for instance, to urban agglomerations around capital cities (also HENDERSON *et al.*, 2001, and references therein). Note that the period under study was characterized by a very strong economic growth push in CEE. The positive effect of urban agglomerations may be particularly important during boom times such as the decade considered here. Such a differential effect between Eastern and Western Europe further stresses the importance of modelling the regional growth process in Europe using data-generating processes which allow for such heterogeneity.

The positive effect of human capital on economic growth is reflected in a robust positive parameter estimate attached to the variable measuring the share of workers with higher (tertiary) education. The size of the model-averaged estimate in the model with interactions (the third set of columns in Table 1) implies that on average a 10% increase of the share of the working-age population with tertiary education is associated with a 0.5% higher growth rate of gross domestic product per capita. Compared with the sample average annual growth rate of 2.2% for all regions in the sample, the effect is quantitatively substantial. The bottom panel of Fig. 2 shows the regional distribution of mean estimates of the effect of the human capital variable across regions. The strongest effects of human capital on economic growth are located in the central regions in Germany, the Benelux countries and Scandinavia, as well as southern regions in the UK. When comparing economic effects of education (and other growth determinants), the model assumes that European Union regions have similar access to technologies (VANDENBUSSCHE *et al.*, 2006). In principle, some of the variation in the shares of workers with higher education – measured as those who completed tertiary education – might be attributed to the fact that education systems vary across countries. The next subsection shows that human capital remains important in explaining growth differences also in the specification including country-fixed effects, where heterogeneity in national education systems is controlled for.

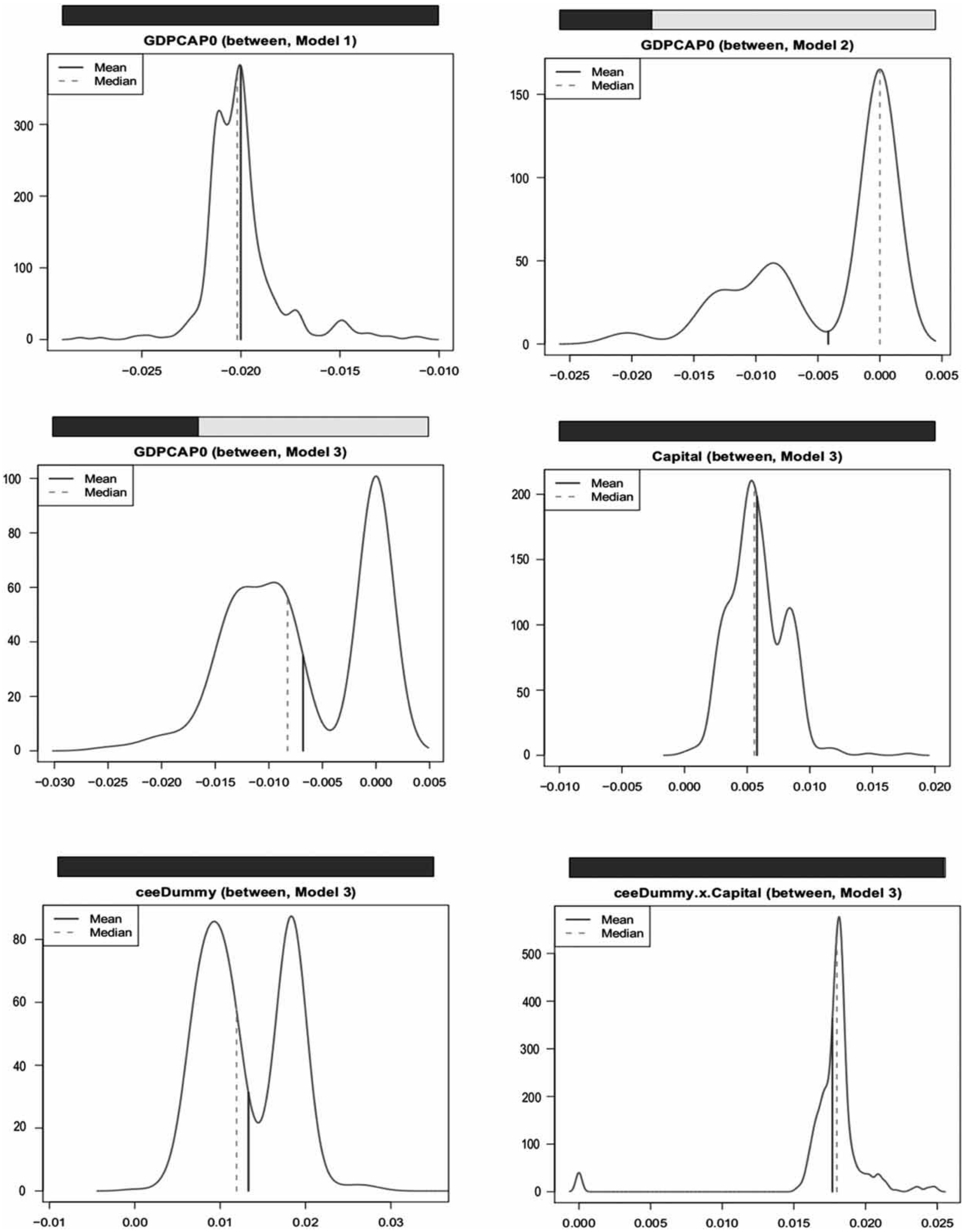

Fig. 1. Unconditional posterior distribution (500 best models). The bar on top of each distribution refers to the posterior inclusion probability of the respective regressor. The top panel, left side, shows he posterior distribution of the initial income variable based on the model specification not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

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

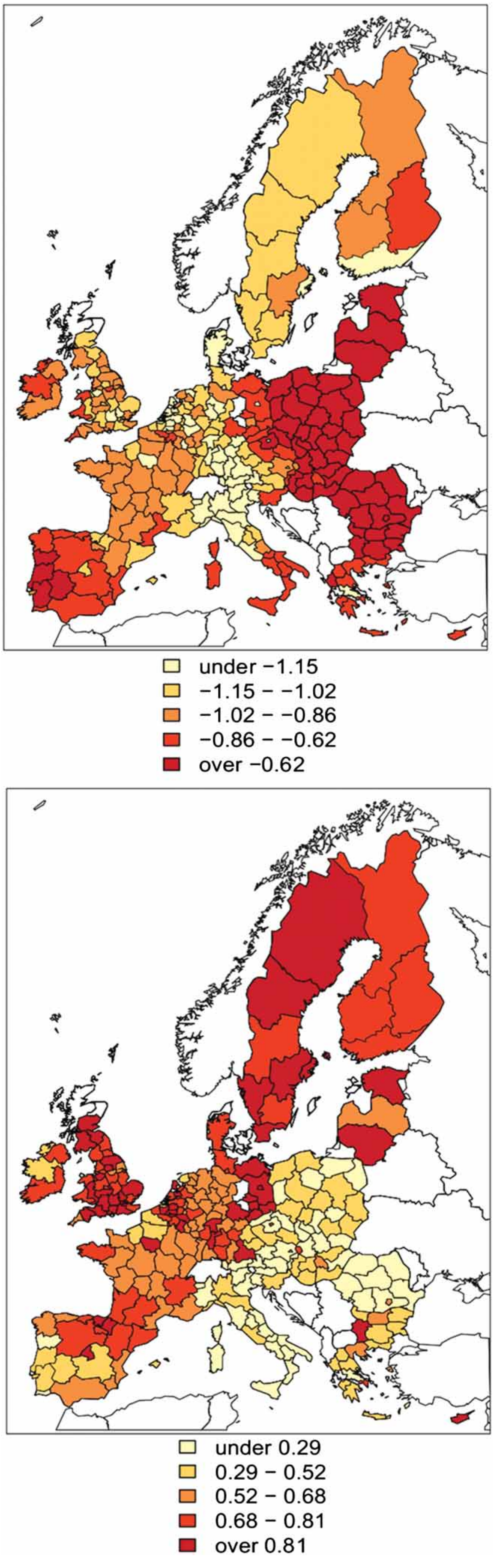

Fig. 2. Spatial distribution of the estimated effect due to income convergence and human capital accumulation for the cross-section specification (Table 1, third column). The top panel shows the spatial distribution of the coefficient on gross domestic product per capita; the bottom panel the one for a human capital proxy

Table 3. Bayesian model averaging (BMA) results for baseline setting with country fixed effects

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

Notes: PIP, posterior inclusion probability; PM, posterior mean; PSD, posterior standard deviation. All calculations are based on Markov chain Monte Carlo model composition (MC^3) sampling with 2 million burn-ins and 3 million posterior draws. Model 1: Baseline with country fixed effects. Model 2: Baseline with country fixed effects including interaction terms of the Central and Eastern Europe (CEE) dummy variable. Model 3: Baseline with country fixed effects including the interaction term of the capital city dummy with the CEE dummy variable. Under Models 2 and 3 the strong heredity prior was employed.

Bold values refer to PIP values above 0.5.

in CEE appears as the main factor 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.

REGIONAL GROWTH DETERMINANTS WITHIN COUNTRIES

The results shown in Table 3 are based on BMA with models containing country fixed effects that concentrate on regional differences of growth and its determinants *within* countries. The specification can therefore account for unobserved time-invariant country-specific characteristics that could affect the process of economic growth. Note that in this specification the dynamics of income convergence, associated with the coefficient of initial income per capita, should be interpreted as taking place in regions *within* a country towards a country-specific steady-state.[19] Comparing the results in Tables 1 and 3, CEE regions contributed mostly to the regional income convergence process *between* countries, whereas income convergence *within* countries is mostly a characteristic of old European Union member states. This evidence is in line with the trends in income convergence described in PUGA (2002) and hints at the fact that the spatial concentration of economic activity in Eastern European economies may foster growth but at the same time increase within-country inequality at the regional level (MARTIN, 1998; CRESPO CUARESMA *et al.*, 2010).

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

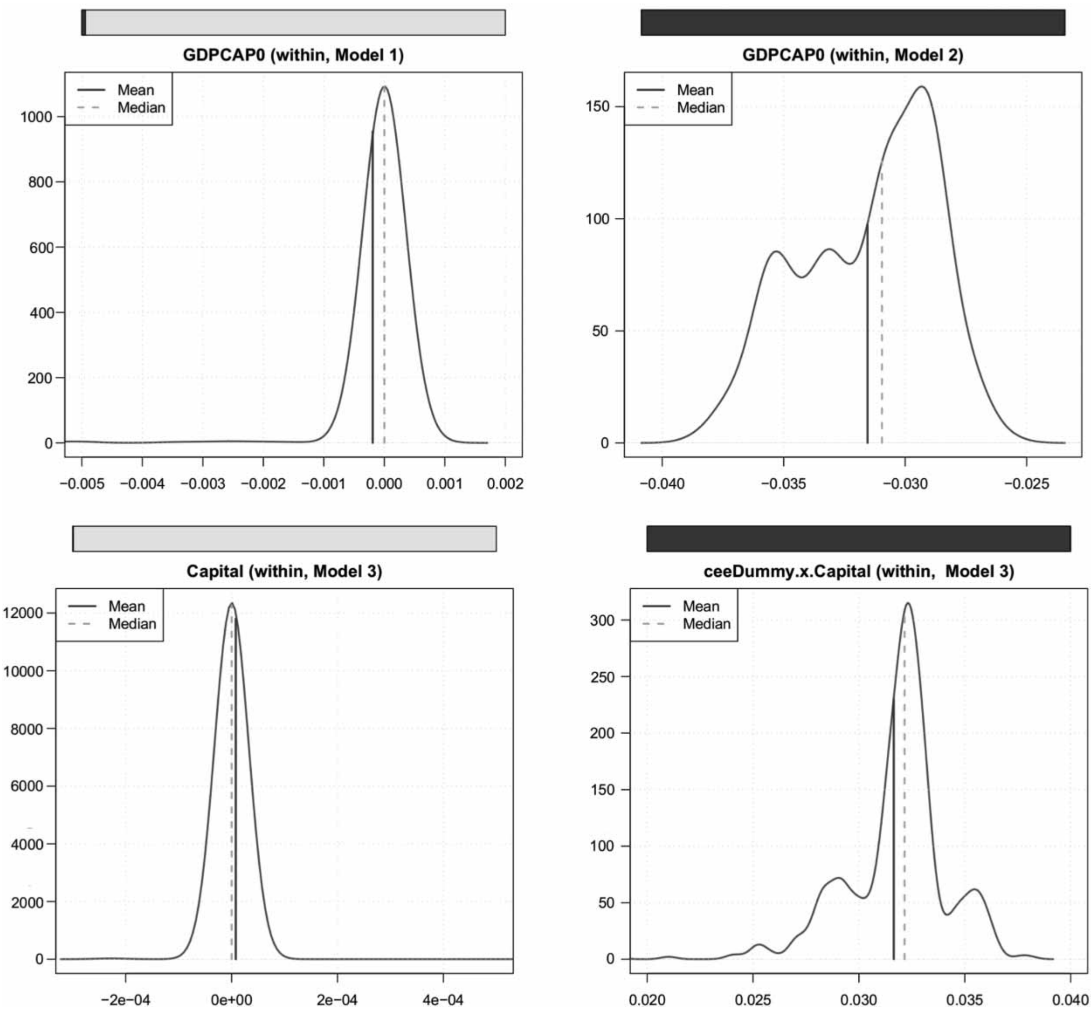

Fig. 3. Unconditional posterior distribution based on models with fixed effects (500 best models). The bar on top of each distribution refers to the posterior inclusion probability of the respective regressor. The top panel, left side, shows the posterior distribution of the initial income variable based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

While the capital city dummy variable is not precisely estimated in all three specifications (set of Models 1–3) of Table 3, its linear interaction term with the CEE dummy variable receives a high PIP in the third specification. This implies – as in the between specification – that regions hosting a capital city that are further located in CEE receive an additional growth bonus. Fig. 3 corroborates the findings: the top panel, left side, shows the posterior distribution of the parameter for initial income. After controlling for spatial heterogeneity (in terms of East/West-specific parameters) by including linear interaction terms related to the CEE dummy variable income convergence appears robust in the data: The corresponding graph in Fig. 3, top panel, right side, shows a bimodal posterior distribution with both mean and median negative indicating income convergence taking place. The bottom panel, left and right side, shows the posterior distribution of the parameters for the capital city as well as the corresponding linear interaction term with the CEE dummy variable. The distribution illustrates that CEE regions with a capital city tend to perform relatively better than other regions, with an additional and sizable bonus implied by the right shift of the distribution shown at the bottom-right panel of Fig. 3.

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

Table 4 shows the single models with highest posterior probabilities in each setting. The inclusion of country fixed effects can account for enough spatial autocorrelation in the economic growth data as for

Table 4. *Models with the highest posterior probability: baseline plus country fixed effects setting*

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

Note: Standard errors are given in parentheses; ***significance at the 1% level. Moran's I test and the Shapiro–Wilk test have as a null hypothesis the absence of spatial autocorrelation and residual normality, respectively.

Moran's I test not to reject its null hypothesis. As compared with models which explicitly model spatial autocorrelation, by using these specifications one cannot, however, extract information about the nature of the growth spillovers (such as, for example, the degree of spatial autocorrelation of economic growth at the regional level). The next subsection overcomes this limitation by considering BMA in the framework of SAR models for regional growth in Europe.

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 European Union regions, using membership of regions in countries may not be the best way of modelling spatial relationships in the data set. Alternatively, actual geographical distance can be used in the framework of SAR models such as those presented above to relate the growth process of different regions.

Table 5 presents the results of the BMA exercise for the class of SAR models, using inverse distances to construct the matrix of spatial weights W. The number of robust variables when spatial autocorrelation is explicitly modelled 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 labour force tend to present higher growth rates of income. Strikingly, initial income also appears as robust in the preferred specification that allows for capital city effects together with regional heterogeneity captured by the CEE dummy variable. This finding contrasts with the results of the linear model and underscores the importance of 'correct' modelling of spatial correlation.

Table 5. *Bayesian model averaging (BMA) results for spatial autoregressive (SAR) setting*

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

Notes: PIP, posterior inclusion probability; PM, posterior mean; PSD, posterior standard deviation. All calculations are based on Markov chain Monte Carlo model composition (MC^3) sampling with 2 million burn-ins and 3 million posterior draws. Model 1: SAR specification. Model 2: SAR specification including interaction terms using the Central and Eastern Europe (CEE) dummy variable. Model 3: SAR specification including the interaction term of the capital city dummy with the CEE dummy variable. Under Models 2 and 3 the strong heredity prior was employed.

Bold values refer to PIP values above 0.5.

The posterior estimates using the SAR specification are close to those using the linear regression model. In particular, regions containing capital cities in CEE countries grew on average 2 percentage points faster per year compared with 0.6 percentage points in old European Union countries. Furthermore, a 10% increase of the share of workers with higher education is associated with a 0.4% higher growth rate of gross domestic product per capita, a finding that is very close to that reported in the cross-sectional analysis in Tables 1 and 2. As for the specifications above, the models with the highest posterior probability are also presented (Table 6). For the case of SAR specifications, the posterior model probability appears more spread across models than in the cases without SAR terms, and there appears to be a large degree of variability in spatial autocorrelation estimates (see the differences in estimates of ρ in Table 6. Thus, a rigorous assessment of model uncertainty is important when considering spatial models for regional economic growth in Europe.

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

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

where d_{ij} is the distance between regions i and j; and the parameter ϕ embodies the sensitivity of weights to distance, and thus the decay of the weighting scheme. The benchmark value $\phi = 1$ implies that weights are an inverse function of distance, while higher values of ϕ lead to a stronger decay of weights with distance. To test the sensitivity of results, the BMA exercise is repeated for parameter value $\phi = 2$, which implies a faster decay of weights with distance. Also, results are shown obtained from imposing contiguity weights using a first-order queen contiguity matrix with positive (equal) weights assigned only to bordering regions.[20] Such a spatial structure implies that growth developments in a given region are affected by the growth process in all (first-order) contiguous regions.

Table 6. Models with highest posterior probability: spatial autoregressive (SAR) setting

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

Notes: Standard errors are given in parentheses; *** (**) and [*] indicates significance at the 1% (5%) and [10%] levels, respectively. The Shapiro–Wilk test has as a null hypothesis residual normality.

CEE, Central and Eastern Europe.

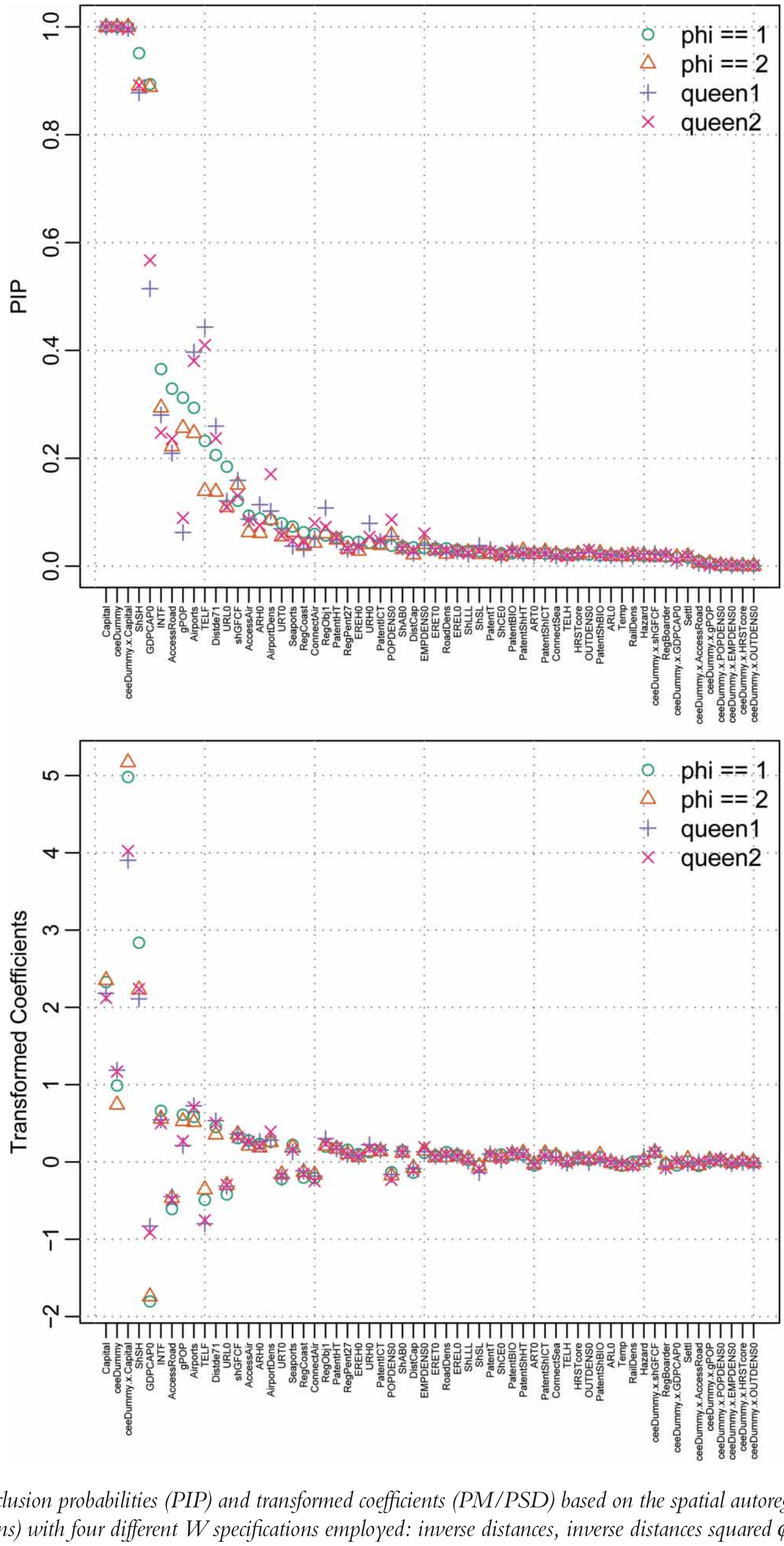

Fig. 4. Posterior inclusion probabilities (PIP) and transformed coefficients (PM/PSD) based on the spatial autoregressive (SAR) model (cross-section of regions) with four different W specifications employed: inverse distances, inverse distances squared $\phi = 1, 2$), and a first-order and second-order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

Fig. 4 summarizes the results of the robustness exercise by plotting in the top panel the PIP and in the bottom panel transformed coefficients (PM/PSD) corresponding to each variable for the cases $\phi = 1$, 2 and for the queen contiguity matrix. PIPs of the regressors in the empirical analysis are insensitive to alternative weighting matrices. Statistical and economic inference, measured by transformed coefficients, does not change qualitatively if the weighting design is varied within decaying weighting schemes. The results concerning the driving factors of economic growth in European Union regions are also confirmed in recent work by Crespo Cuaresma and Feldkircher (2012), who employed a different method to integrate out uncertainty in spatial linkages in economic growth across regions. In their work, a larger set of spatial linkage matrices is employed and their results reinforce the conclusions concerning the pivotal role played by human capital and income convergence in regional economic growth.

FURTHER ROBUSTNESS CHECKS

The common denominator of the results indicates that human capital differences and income convergence across and within countries can robustly explain differences in income per capita growth at the regional level in Europe. Several robustness checks were carried out in order to ensure that the results do not depend on the particular setting put forward in this study.

To investigate further the transmission channels of growth spillovers, spatial spillovers were allowed to occur via the explanatory variables, as in the unrestricted spatial Durbin model. Thus, the benchmark setting and the benchmark with country fixed effects setting were re-estimated with an enlarged set of potential growth determinants by introducing spatial lags of the potential covariates. The results presented above are left unchanged under the enlarged set of variables.[21] The spatially lagged explanatory variables do not appear as robust determinants of regional growth. This suggests that the positive correlation found from the SAR specification is driven by other factors not captured by the variables under consideration.

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

CONCLUSIONS

This paper analyses the nature of robust determinants of economic growth in European Union regions in the presence of model uncertainty using model averaging techniques. The paper contains some important novelties compared with previous studies on the topic. On the one hand, it uses the most comprehensive data set existing (to the knowledge of the authors) on potential determinants of economic growth in European regions. On the other hand, it applies the most recent BMA techniques to assess the issue of robustness of growth determinants. In particular, the empirical estimation framework allows for SAR structures, hyperpriors on model size to make inference more robust to the prior choice over models, and it introduces a new methodology to treat the issue of subsample parameter heterogeneity via interaction terms.

The results imply that conditional income convergence appears to be a robust driving force of income growth across European regions. Between European Union regions of different countries, this catching-up process has been fuelled by the growth experience in Eastern Europe. Convergence within countries, on the other hand, is concentrated in Western European economies. Regions with capital cities exhibit a significantly higher growth performance than other regions (between specification), and this asymmetry is particularly sizable in Eastern European economies (between and within specification), which lends further support to the differential regional dynamics proposed by the Williamson hypothesis in the catching-up process. The importance of education as a growth engine also appears clearly in the data, which show that a higher share of educated workers in the labour force is positively associated with regional economic growth. The paper also finds evidence for positive spatial economic growth spillovers among European Union regions.

The BMA method used in this paper allows for further generalizations which can be very fruitful as future research avenues: (1) exploiting alternative spatial weights matrices, as done by Crespo Cuaresma and Feldkircher (2012), can help one further understand the nature of economic growth spillovers in Europe; (2) combining the methods proposed here with BMA settings which allow for non-linear data-generating processes (for example, Crespo Cuaresma and Doppelhofer, 2007) could shed light on the heterogeneity of growth processes within the European Union beyond the East/West differences highlighted in this study; and (3) the availability of further data may allow for the use of instrumental variable methods in the framework of BMA explicitly to assess potential endogeneity in the link between economic growth and its determinants.

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APPENDIX A

Markov chain Monte Carlo (MC³) sampler

This section briefly discusses the MC³ sampler used throughout the paper. Exploring the model space can be done via a range of search algorithms, here MC³ methods are used, which have been shown to have good properties in the framework of BMA. The Markov chain is designed to wander efficiently through the model space, where it draws attention solely to models with non-negligible posterior mass.

The sampler uses a birth/death MC³ search algorithm to explore the model space (Madigan and York, 1995). In each iteration step a candidate regressor is drawn from $k_c \sim U(1,K)$. A (*birth step*) adds 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 (the *death step*). This is in the vein of Madigan and York (1995), with the new model always being drawn from a neighbourhood of the current one differing only by a single regressor. To compare the sampled candidate model M_i with the current one, the posterior odds ratio is calculated implying the following acceptance probability:

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

MC³ and interaction terms

The birth/death MC³ sampler is modified by assigning positive prior model probabilities solely to models that include all 'relevant' regressors. That is, in case there are (multiplicative) interaction terms, all variables that belong to the interaction variable are forced to enter the regression equation. Candidate regressors are again drawn from $k_c \sim U(1,K)$. Consider now a linear regression model with regressor matrix X, which contains some element(s) from the set {A,B,C,AB} and a draw of the interaction term AB. The following cases arise:

$X_{current}$ = {C}	⇒	$X_{candidate}$ = {**A**,**B**,C,**AB**}	(birth step)
$X_{current}$ = {A,C}	⇒	$X_{candidate}$ = {A,**B**,C,**AB**}	(birth step)
$X_{current}$ = {A,B,C}	⇒	$X_{candidate}$ = {A,B,C,**AB**}	(birth step)
$X_{current}$ = {A,B,AB}	⇒	$X_{candidate}$ = {A,B}	(death step)
$X_{current}$ = {A,B,C,AB}	⇒	$X_{candidate}$ = {A,B,C}	(death step)

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

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

The beta prior for ρ, Zellner's g-prior for the coefficient vector $\vec{\beta}$ (see the text), and an inverted gamma prior for the variance σ^2 are elicited as follows:[22]

$$p(\sigma^2) \sim \frac{(\bar{s}^2\nu/2)^{(\nu/2)}}{\Gamma(\nu/2)} \sigma^{2(-\frac{\nu+2}{2})} \exp\left(-\frac{\nu\bar{s}^2}{2\sigma^2}\right)$$

$$p(\rho) \sim Beta(a_1, a_2)$$

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

The log integrated likelihood (4) is given by:[23]

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

with:

$$K_2 = \frac{\Gamma\left(\frac{N+\nu-1}{2}\right)}{\Gamma(\nu/2)} (\nu\bar{s}^2)^{\nu/2} \pi^{-\frac{N-1}{2}}$$

$$S(\rho) = \frac{g}{1+g}\left((I_N - \rho W)y - X\hat{\beta}(\rho) - \hat{\alpha}\iota_N\right)'\left((I_N - \rho W)y - X\hat{\beta}(\rho) - \hat{\alpha}\iota_N\right)$$

$$Q(\rho) = \frac{1}{1+g}\left((I_N - \rho W)y - \hat{\alpha}\iota_N\right)'\left((I_N - \rho W)y - \hat{\alpha}\iota_N\right)$$

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

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

$$\hat{\beta}_d = (X'X)^{-1}X'Wy \tag{9}$$

Equation (9) illustrates that the OLS estimator is nested in the SAR specification. Since OLS estimates are misleading if $\rho \neq 0$ and the SAR model collapses to OLS if observations are not spatially correlated ($\rho = 0$), the spatial lag term Wy is held fixed across SAR models. Thus, the null model (without covariates) for the SAR specification is a first-order SAR model including an intercept term.

APPENDIX B

Table B1. *Nomenclature des Unités Territoriales Statistiques (NUTS)-2 regions*

Austria		
Burgenland	Oberösterreich	Tirol
Kärnten	Salzburg	Wien
Niederösterreich	Steiermark	Vorarlberg
Belgium		
Antwerpen	Limburg (B)	Oost-Vlaanderen
Brabant Wallon	Région de Bruxelles-Capitale	Vlaams Brabant
Hainaut	Luxembourg (B)	West-Vlaanderen
Liège	Namur	
Bulgaria		
Severentsentralen	Severozapaden	Yugozapaden
Severoiztochen	Yugoiztochen	Yuzhentsentralen
Cyprus		
Cyprus		
Czech Republic		
Jihovýchod	Praha	Strední Morava
Jihozápad	Severozápad	Severovýchod
Moravskoslezsko	Strední Cechy	
Denmark[a]		
Denmark		
Estonia		
Estonia		
Finland		
Aland	Itä-Suomi	Pohjois-Suomi
Etelä-Suomi	Länsi-Suomi	
France		
Alsace	Corse	Midi-Pyrénées
Aquitaine	Franche-Comté	Nord–Pas-de-Calais
Auvergne	Haute-Normandie	Pays de la Loire
Basse-Normandie	Île de France	Picardie
Bourgogne	Languedoc-Roussillon	Poitou-Charentes
Bretagne	Limousin	Provence-Alpes-Côte d'Azur
Centre	Lorraine	Rhône-Alpes
Champagne-Ardenne		

(*Continued*)

Table B1. *Continued*

Germany		
Arnsberg	Hamburg	Oberfranken
Berlin	Hannover	Oberpfalz
Brandenburg – Nordost	Karlsruhe	Rheinhessen-Pfalz
Brandenburg – Südwest	Kassel	Saarland
Braunschweig	Koblenz	Schleswig-Holstein
Bremen	Köln	Schwaben
Chemnitz	Leipzig	Stuttgart
Darmstadt	Lüneburg	Thüringen
Detmold	Mecklenburg-Vorpommern	Trier
Dresden	Mittelfranken	Tübingen
Düsseldorf	Münster	Unterfranken
Freiburg	Niederbayern	Weser-Ems
Giessen	Oberbayern	
Greece		
Anatoliki Makedonia, Thraki	Ipeiros	Peloponnisos
Attiki	Kentriki Makedonia	Sterea Ellada
Dytiki Ellada	Kriti	Thessalia
Dytiki Makedonia	Notio Aigaio	Voreio Aigaio
Ionia Nisia		
Hungary		
Dél-Alföld	Észak-Magyarország	Közép-Magyarország
Dél-Dunántúl	Közép-Dunántúl	Nyugat-Dunántúl
Észak-Alföld		
Ireland		
Border, Midlands and Western	Southern and Eastern	
Italy		
Abruzzo	Liguria	Puglia
Basilicata	Lombardia	Sardegna
Calabria	Marche	Sicilia
Campania	Molise	Toscana
Emilia-Romagna	Piemonte	Umbria
Friuli-Venezia Giulia	Bolzano-Bozen	Valle d'Aosta
Lazio	Trento	Veneto
Latvia		
Latvia		
Lithuania		
Lithuania		
Luxembourg		
Luxembourg (Grand-Duché)		
Malta		
Malta		
Netherlands		
Drenthe	Groningen	Overijssel
Flevoland	Limburg (NL)	Utrecht
Friesland	Noord-Brabant	Zeeland
Gelderland	Noord-Holland	Zuid-Holland
Poland		
Dolnoslaskie	Mazowieckie	Slaskie
Kujawsko-Pomorskie	Opolskie	Swietokrzyskie
Lodzkie	Podkarpackie	Warminsko-Mazurskie
Lubelskie	Podlaskie	Wielkopolskie
Lubuskie	Pomorskie	Zachodniopomorskie
Malopolskie		
Portugal		
Alentejo	Centro (PT)	Norte
Algarve	Lisboa	

(*Continued*)

Table B1. *Continued*

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

Notes: A sample of 255 European regions (NUTS-2 level) was used in the analysis.

[a]Since the data set was based on the 2003 NUTS definitions, Denmark was considered to be composed by a single NUTS-2 region for the empirical analysis, although the current classification assigns five regions to the country at this level of sub-national disaggregation: Hovedstaden, Sjlland, Southern Denmark, Midtjylland and Nordjylland.

Table B2. *Data description*

Variable	Description	Source	Minimum	Mean	Maximum
Dependent variable					
Economic growth	Growth rate of real GDP per capita: deflated by national prices, price base year is 2000	Eurostat	–0.01	0.02	0.08
1. Factor accumulation/ convergence					
Initial income	Initial real GDP per capita (in logs): price base year is 2000	Eurostat	8.26	9.60	10.69
Population growth	Growth rate of population	Eurostat	0.00	0.00	0.00
Investment	Initial share of gross fixed capital formation (GFCF) in gross value added (GVA)	Cambridge Econometrics	0.08	0.21	0.53
2. Human capital					
Share of workers with higher education	Share of the population with higher education level in the working age population	Eurostat LFS	0.04	0.16	0.39
Share of workers with medium education*	Share of the population with medium education level in the working age population	Eurostat LFS	0.11	0.47	0.74
Share of workers with low education	Share of the population with low education level in the working age population	Eurostat LFS	0.14	0.38	0.84
Lifelong learning	Lifelong learning	Eurostat LFS	0.00	0.07	0.26

(*Continued*)

Table B2. *Continued*

Variable	Description	Source	Minimum	Mean	Maximum
3. Technological innovation					
Patents	Number of patents total per 1000 persons	Eurostat	0.00	0.08	0.55
High-technology patents	Number of patents in high-technology per 1000 persons	Eurostat	0.00	0.01	0.19
ICT patents	Number of patents in ICT per 1000 persons	Eurostat	0.00	0.02	0.32
Biotechnology patents	Number of patents in biotechnology per 1000 persons	Eurostat	0.00	0.00	0.06
High-technology patents share	Share of patents in high-technology in total patents	Eurostat	0.00	0.11	0.51
ICT patents share	Share of patents in ICT in total patents	Eurostat	0.00	0.16	0.73
Biotechnology patents share	Share of patents in biotechnology in total patents	Eurostat	0.00	0.04	0.23
Technology resources	Human resources in science and technology (core), share in persons employed	Eurostat LFS	0.04	0.13	0.82
4. Sectoral structure/ employment					
Agricultural share	Initial share of NACE A and B: (Agriculture), share in nominal gross value added	Eurostat	0.00	0.05	0.20
Manufacturing share	Initial share of NACE C–E: (Mining, manufacturing and energy), share in nominal gross value added	Eurostat	0.02	0.20	0.30
Services share*	Initial share of NACE J–K: (Business services), share in nominal gross value added	Eurostat	0.05	0.16	0.43
Employment rate (higher education)	Employment rate of high educated (initial)	Eurostat LFS	0.61	0.82	0.96
Employment rate (medium education)*	Employment rate of medium educated (initial)	Eurostat LFS	0.36	0.67	0.87
Employment rate (low education)	Employment rate of low educated (initial)	Eurostat LFS	0.17	0.45	0.72
Employment rate	Employment rate total (initial)	Eurostat LFS	0.39	0.62	0.84
Unemployment rate (higher education)	Unemployment rate of high educated (initial)	Eurostat LFS	0.00	0.05	0.27
Unemployment rate (medium education)*	Unemployment rate of medium educated (initial)	Eurostat LFS	0.02	0.10	0.29
Unemployment rate (low education)	Unemployment rate of low educated (initial)	Eurostat LFS	0.02	0.14	0.48
Unemployment rate	Unemployment rate total (initial)	Eurostat LFS	0.03	0.10	0.29
Activity rate (higher education)	Activity rate of high educated (initial)	Eurostat LFS	0.76	0.87	0.96
Activity rate (medium education)*	Activity rate of medium educated (initial)	Eurostat LFS	0.47	0.74	0.89
Activity rate (low education)	Activity rate of low educated (initial)	Eurostat LFS	0.25	0.51	0.80
Activity rate	Activity rate total (initial)	Eurostat LFS	0.50	0.68	0.87
5. Infrastructure					
Websites	Proportion of firms with their own website	ESPON	0.02	0.47	0.99
Telecommunications (households)	Typology of levels of household telecommunications uptake: 6 = very high; 5 = high; 4 = moderately high; 3 = moderate; 2 = low; 1 = very low; rescaled	ESPON	1.00	3.10	6.00
Telecommunications (firms)	Typology of estimated levels of business telecommunications access and uptake: 6 = very high; 5 = high; 4 = moderately high; 3 = moderate; 2 = low; 1 = very low; rescaled	ESPON	1.00	3.58	6.00
Seaports	Regions with seaports: 1 = regions with seaports; 0 = no seaports	ESPON	0.00	0.42	1.00
Airport density	Airport density: number of airports divided by area (km^2)	ESPON	0.00	0.00	0.00
Road density	Road density: length of road network (km) divided by area (km^2)	ESPON	0.00	0.15	0.91
Rail density	Rail density: length of rail network (km) divided by area (km^2)	ESPON	0.00	0.06	0.32
Air connectivity	Connectivity to commercial airports by car of the capital or centroid representative of the NUTS-3 (hours)	ESPON	0.00	1.05	2.77
Sea connectivity	Connectivity to commercial seaports by car of the capital or centroid representative of the NUTS-3 (hours)	ESPON	0.01	0.60	3.00
Air accessibility	Potential accessibility air: ESPON space = 100 ESPON AcAiE01N3; model output	ESPON	0.38	0.94	1.77

(*Continued*)

Table B2. *Continued*

Variable	Description	Source	Minimum	Mean	Maximum
Road accessibility	Potential accessibility road: ESPON space = 100 ESPON AcRoE01N3; model output	ESPON	0.04	0.96	2.03
6. Socio-geographical variables					
Settlement structure	Settlement structure typology (six basic types are 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; and 6 = less densely populated without centres	ESPON	0.00	0.73	1.00
Output density	Initial output density; GDP (millions)/area (km^2); initial year; price base for GDP is 2000	WIIW	0.04	7.92	365.10
Employment density	Initial employment density: employed persons (thousands)/area (km^2); initial year	WIIW	0.00	0.18	7.81
Population density	Initial population density: population (thousands)/area (km^2); initial year	WIIW	0.00	0.34	8.30
Coastal	Coast: 0 = no coast; 1 = coast	ESPON	0.00	0.46	1.00
Pentagon	Pentagon EU-27 plus 2: The pentagon is shaped by London, Paris, Munich, Milan and Hamburg	ESPON	0.00	0.32	1.00
Objective 1	Objective 1 regions: based on COM '*Second Progress Report on Economic and Social Cohesion*' (30 January 2003)	ESPON	0.00	0.41	1.00
Capital city	Capital city: 0 = region without capital cities; 1 = capital cities		0.00	0.11	1.00
Airports	Number of airports	ESPON	0.00	1.61	17.00
Temperature	Extreme temperatures: 2 = low (mean = 2.00–2.75); 3 = moderate (mean = 2.75–3.25); and 4 = high (mean = 3.25–3.50); calculated from NUTS-3 digit; weighted by population shares	ESPON	2.00	2.42	4.00
Hazard	Sum of all weighted hazard values: all calculated from NUTS-3; weighted by population shares	ESPON	100.00	232.00	307.30
Distance to Frankfurt	Distance to Frankfurt (km)				
Distance to capital	Distance to capital city (km)		0.00	241.40	883.10

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

GDP, gross domestic product; ICT, information and communication technology; NACE, Nomenclature statistique des activités économiques dans les Communautés Européennes; NUTS, Nomenclature des Unités Territoriales Statistiques

NOTES

1. Barro and Sala-i-Martin (2004) give an excellent overview of empirical analysis for regional data (Chapter 11) and cross-sections of countries (Chapter 12).
2. For an excellent tutorial introduction to BMA, see Hoeting *et al.* (1999); for a discussion of both Bayesian and frequentist techniques, see the survey by Doppelhofer (2008).
3. Raftery (1995) also proposed 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.
4. For an overview of convergence in European Union regions at the NUTS-2 level, see European Commission (2008).
5. For textbook discussions of the SAR model, see Anselin (1988) and LeSage and Pace (2009).
6. The generalization of the BMA strategy here to other error structures with fixed effects is straightforward after application of the Frisch–Waugh–Lovell theorem (Frisch and Waugh, 1933). The estimation of country fixed effects can be carried out by estimating the model using within-country-transformed data.
7. For a modelling strategy that allows for a more general distribution of regression errors in the context of model uncertainty and heteroskedasticity due to neglected heterogeneity and outliers, see Doppelhofer and Weeks (2011).
8. The estimation uses great-circle distances (km) between regions *i* and *j*. The great-circle distance is the shortest distance between two points *i* and *j* on the surface of a sphere and is measured along a *path on the surface* of the sphere.
9. See Appendix A for details.
10. The starting year of the observation period is determined by the lack of reliable and comparable regional data for the first part of the 1990s for CEE countries.
11. Structural Funds programmes allocating transfers to NUTS-2 regions and associated classification into so-called Objective 1 regions are not considered for obvious concerns about endogeneity. A recent study by

BECKER *et al.* (2010) used a regression discontinuity approach to identify the impact of Structural Funds and found growth, but no employment effects.

12. Unfortunately, the data set does not contain lagged observations of the data; extensions in this dimension are therefore left to future work.
13. The hyperparameters for the binomial-beta distribution were set to $a = b = 1$.
14. The full set of results is available from the authors upon request.
15. This scale is based on a prior inclusion probability of 0.5 for each regressor, which is implied by the binomial-beta prior anchored around an expected model size of $K/2$. The variables were sorted by posterior inclusion probabilities in the first set of columns in each table of results.
16. BROCK and DURLAUF (2001) provided decision-theoretic foundations for using such transformed coefficients. Even though the particular cut-off values for PIPs and transformed coefficients are specific for the assumed prior structure, the results are robust to alternative choice of prior parameters.
17. For illustration purposes a smoothed histogram of the posterior coefficients is used in the following figures. The histogram is based on the coefficients for the best 500 models and serves as approximation for the posterior distribution.
18. To help in reading the maps, the regressors are scaled as follows. The top panel of Fig. 1 plots the partial effect of the *levels* (not log-levels) of initial income. Similarly, the share of workers with higher education in the bottom panel is scaled by a factor of 100.
19. The CEE dummy variable is not identified when including fixed effects. The CEE dummy is consequently excluded for the estimations provided in Table 4, and the strong heredity prior is not employed for the linear interaction terms. Furthermore, the capital city dummy does not suffer from identification problems since the case that all regions of a country (when there is more than one) contain national capital cities is ruled out by definition.
20. For a discussion of various weighting schemes, see ANSELIN (1988).
21. Detailed BMA results for the setting with an enlarged set of covariates are available from the authors upon request.
22. The use of an inverted gamma prior as opposed to employing a diffuse prior for the variance is advocated by LESAGE and PARENT (2007).
23. For the exact derivation, see LESAGE and PARENT (2007).

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