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Abstract

In this paper we present an econometric framework aimed at obtaining projections of income growth in Europe at the regional level. We account for model uncertainty in terms of the choice of explanatory variables, as well as the nature of the spatial spillovers of output growth and human capital investment. Building on recent advances in Bayesian model averaging, we construct projected trajectories of income and human capital simultaneously, while integrating out the effects of other covariates. This approach allows us to assess the potential contribution of future educational attainment to economic growth and income convergence among European regions over the next decades. Our findings suggest that income convergence dynamics and human capital act as important drivers of income growth for the decades to come. In addition we find that the relative return of improving educational attainment levels in terms of economic growth appears to be higher in peripheral European regions.

Keywords: Income projections, model uncertainty, spatial filtering, European regions.

JEL Codes: C11, C15, C21, O52.

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1 Introduction

Economic growth differentials in Europe over the last six decades have led to a substantive reduction of income per capita gaps across regions of the European Union (EU). In the last five years, however, the process of convergence of income per capita in the EU has decelerated significantly as a consequence of the economic crisis in Europe. Understanding the future challenges facing regional policy in Europe requires the development of reliable quantitative tools (usually in the form of income projections) which are able to assess the reaction of economic growth differences to economic policy at the national and regional level. In order to create such tools, in turn, a set of robust determinants of income growth and income convergence in Europe needs to be unveiled and their influence quantified robustly. The main purpose of this paper is to provide a methodological framework aimed at obtaining income projections for European NUTS-2 regions which accounts for model uncertainty and can be used for policy analysis. Although we do not attempt to identify the pure causal effects of economic policies on economic growth, we believe that the methods put forward in this piece of research to obtain income projections based on model averaging can provide useful information for the design of European regional policy and contribute to integrated assessment models that require income projection scenarios, such as those used in the context of climate change research by the Intergovernmental Panel on Climate Change (Kriegler et al., 2012). By concentrating on subnational units, the framework put forward here provides more detailed information than existing long-run income projection methods which are currently at use in global integrated assessment models (see, for example Crespo Cuaresma, 2015; Leimbach et al., 2015) .

A large literature has dealt empirically with the analysis of economic growth and income convergence across European regions (see Sala-i-Martin (1996) for a seminal contribution). Several issues related to the econometric modelling of economic growth in sub-national units have dominated the modern empirical literature aimed at studying income dynamics at the regional level. First, spatial spillovers play a particularly important role as a determinant of income growth at the regional level (see e.g. Fischer and Stirböck (2006) or Niebuhr (2001)). In spite of the fact that many explanatory factors for regional economic performance appear correlated in space, they do not tend to be sufficient to explain the economic growth clusters observed in European NUTS-2 regions. Even after controlling for economic growth determinants in cross-sectional regional datasets, residuals tend to present correlation structures in space. Such a property of regional growth data requires the use of econometric models that account explicitly for spatially autocorrelated dependent variables and/or errors. These specifications have thus become the workhorse of econometricians dealing with the analysis of growth patterns at the regional level. Boldrin and Canova (2001), Fischer and Stirböck (2006), Ertur and Koch (2006), Ertur et al. (2006), Ertur et al. (2007) or Ertur and Koch (2007), for instance, are some prominent examples of studies using spatial econometric methods to model the growth and convergence process in European regions.

When estimating economic growth regressions in a spatial econometric framework, one is confronted with at least two dimensions of model uncertainty. One dimension is linked to the fact that the theoretical literature only offers limited guidance when it comes to the variables that should be included in the econometric model. Recently, the systematic assessment of model uncertainty has featured prominently in the empirical analysis of economic growth regressions, both for assessing differences in income growth across countries and across regions. The contributions by Fernández et al. (2001b) and Sala-i-Martin et al. (2004) gave rise to a large number of studies that assess the robustness of economic growth determinants to model specification in terms of the set of variables that are controlled for in linear economic growth regression models. LeSage and Fischer (2008), Crespo Cuaresma et al. (2014) or Crespo Cuaresma and Feldkircher (2013) are recent studies which explicitly deal with this issue for European regions and also address the uncertainty attached to the economic growth spillovers across regions.

An econometric framework for spatially correlated data typically requires a predefined spatial weight matrix, which defines the geographical links between the observations. Since inference may be sensitive with respect to the structure of the spatial dependence, the choice of a particular spatial weight matrix is a crucial task (LeSage and Pace 2009). LeSage and Fischer (2008) account for both dimensions of uncertainty using Bayesian model averaging techniques. The computational burden of the procedure put forward by LeSage and Fischer (2008), however, is severe when large sets of potential covariates and/or spatial weight matrices are considered, since the method involve numerical integration techniques. To circumvent numerical integration, Crespo Cuaresma and Feldkircher (2013) make use of spatial eigenvector filtering, which can be used to reduce spatial econometric models to non-spatial specifications and thus attain a higher degree of computational efficiency.

Our contribution builds on these recent developments in the field of econometric modelling under model uncertainty and spatial correlation of unknown form in order to obtain projections of income per capita levels and growth rates for European NUTS-2 regions for the period 2011-2070. These projections are based on Bayesian averaging of predictive densities of spatial autoregressive specifications based on the estimation sample given by the period 2001-2010. Our results confirm the importance of convergence forces and human capital accumulation as a driver of income growth in Europe (see LeSage and Fischer 2008, Crespo Cuaresma et al. 2014 or Crespo Cuaresma and Feldkircher 2013) once that we integrate away the uncertainty emanating from both the selection of covariates and of spatial linkage structures. In addition, as compared to other specification classes entertained in the literature, we propose to account explicitly for the simultaneous determination of income growth and human capital accumulation, thus generalizing the Bayesian model averaging applications put forward by LeSage and Fischer (2008), Crespo Cuaresma et al. (2014) or Crespo Cuaresma and Feldkircher (2013).

The paper is structured as follows. Section 2 describes the econometric framework, based on Bayesian averaging of econometric specifications for spatially correlated data, as well as the results concerning the in-sample robust determinants of regional growth in Europe. Section 3 presents the results of the income projection exercise and Section 4 concludes.

2 The econometric framework

Due to the uncertainty surrounding the data generating process of income growth and human capital accumulation at the regional level, we take a Bayesian stance and account for model uncertainty by resorting to model averaging methods. While many econometric applications aimed at modelling income growth at the regional level tend to assume that human capital is exogenous to income growth, we take a more coherent approach and propose a model that is capable of accounting for simultaneity in the relationship between human capital and output growth. Given the importance of educational attainment as a robust determinant of regional economic growth in Europe (see for instance the results in Crespo Cuaresma and Feldkircher, 2013; Crespo Cuaresma et al., 2014), accounting for the simultaneous determination of human capital accumulation and economic growth at the regional level in Europe appears as an important generalization of the Bayesian model averaging exercises carried out hitherto in the literature.

2.1 A spatial model of regional income growth and human capital in Europe

Consider a spatial autoregressive specification aimed at modelling the process of income growth and human capital accumulation for a cross section of regions indexed by $i = 1, \ldots, N$,

$$y_{i\tau} = \rho^y \sum_{j=1}^{N} w_{ij}^y y_{j\tau} + \tilde{\beta}_0^y + \boldsymbol{x}'_{it_0}\tilde{\boldsymbol{\beta}}^y + \tilde{u}_{i\tau}^y \tag{2.1}$$

$$h_{i\tau} = \tilde{\gamma} y_{i\tau} + \rho^h \sum_{j=1}^{N} w_{ij}^h h_{j\tau} + \tilde{\beta}_0^h + \boldsymbol{x}'_{it_0}\tilde{\boldsymbol{\beta}}^h + \tilde{u}_{i\tau}^h, \tag{2.2}$$

where $y_{i\tau}$ and $h_{i\tau}$ denote the log-level of gross value added per capita and tertiary education attainment in region i at time τ, respectively. τ denotes the final time point in our estimation period (which in our dataset corresponds to the year 2010). The explanatory variables are stored in a $K \times 1$ vector $\boldsymbol{x}_{it_0}$. The scalars $\tilde{\beta}_0^y$ and $\tilde{\beta}_0^h$ denote the intercept parameters and $\tilde{\gamma}$ denotes a parameter which establishes a contemporaneous relationship between $y_{i\tau}$ and $h_{i\tau}$. The K-dimensional parameter vector associated with the exogenous variables stored in $\boldsymbol{x}_{it_0}$ is denoted by $\tilde{\boldsymbol{\beta}}^l$, with t_0 denoting the initial yearin the period considered (for our application, the year 2000). The vector $\boldsymbol{x}_{it_0}$ is composed by variables which are chosen from a set of potential predictors of both economic output and tertiary education attainment. In addition, $\boldsymbol{x}'_{it_0}$ includes both y_{it_0} and h_{it_0}, so as to allow for conditional convergence patterns in the data. The error terms $\tilde{u}_{i\tau}^y$ and $\tilde{u}_{i\tau}^h$ are assumed to fulfil the usual assumptions of the linear regression model and their variances are given by $\tilde{\lambda}^y$ and $\tilde{\lambda}^h$, respectively. Finally, w_{ij}^l for $l \in \{y, h\}$ denotes the ijth element of an $N \times N$ row-stochastic spatial weight matrix $\boldsymbol{W}^l$. The spatial weight matrix $\boldsymbol{W}^l$ summarizes the spatial linkages across regions and $\rho^l \in (-1, 1)$ measures the degree of spatial autocorrelation. $w_{ij}^l \geq 0$ for $i \neq j$ if region i and j are considered neighbors. By construction, we assume that $w_{ii}^l = 0$.

Due to the simultaneity across dependent variables in equation (2.1) and equation (2.2), it is well known that standard methods of posterior inference in the presence of spatial autocorrelation cannot be used, since posterior distributions over parameters are of no well-known form (see LeSage and Pace 2009). We overcome this problem by approximating the terms which capture spatial spillovers by means of the spatial eigenvector filtering techniques proposed by Griffith (2000a) and Griffith (2000b) which reduce spatially autoregressive specifications to linear modelling frameworks. To illustrate this approach, it proves convenient to rewrite equations (2.1) and (2.2) in terms of full data matrices,

$$\boldsymbol{y}_\tau = \rho^y \boldsymbol{W}^y \boldsymbol{y}_\tau + \boldsymbol{\iota}_N \tilde{\beta}_0^y + \boldsymbol{X}_{t_0} \tilde{\boldsymbol{\beta}}^y + \tilde{\boldsymbol{u}}_\tau^y \tag{2.3}$$

$$\boldsymbol{h}_\tau = \tilde{\gamma} \boldsymbol{y}_\tau + \rho^h \boldsymbol{W}^h \boldsymbol{h}_\tau + \boldsymbol{\iota}_N \tilde{\beta}_0^h + \boldsymbol{X}_{t_0} \tilde{\boldsymbol{\beta}}^h + \tilde{\boldsymbol{u}}_\tau^h, \tag{2.4}$$

with $\boldsymbol{y}_\tau = (y_{1\tau}, \ldots, y_{N\tau})'$ and $\boldsymbol{h}_\tau = (h_{1\tau}, \ldots, h_{N\tau})'$ denoting N-dimensional vectors of stacked observations and $\boldsymbol{X}_{t_0} = (\boldsymbol{x}_{1t_0}, \ldots, \boldsymbol{x}_{Nt_0})'$ is an $N \times K$ matrix of stacked observations of explanatory variables. For $l \in \{y, h\}$, $\boldsymbol{u}_\tau^l$ denotes an N-dimensional error vector and $\boldsymbol{\iota}_N$ is an $N \times 1$ vector of ones.

Spatially filtered specifications use an approximation of this model, whereby the spatial autocorrelation term is substituted by a linear function of the eigenvectors of the appropriately transformed spatial linkage matrix (see Griffith 2000a and Griffith 2000b). Spatial eigenvector filtering relies on a set of eigenvectors to approximate equations (2.3) and (2.4). The spatial autoregressive term in the original specification is substituted by a linear combination of the eigenvectors in the spatially filtered model,

$$\boldsymbol{y}_\tau = \boldsymbol{E}^y \boldsymbol{\psi}^y + \boldsymbol{\iota}_N \beta_0^y + \boldsymbol{X}_{t_0} \boldsymbol{\beta}^y + \boldsymbol{u}_\tau^y \tag{2.5}$$

$$\boldsymbol{h}_\tau = \gamma \boldsymbol{y}_\tau + \boldsymbol{E}^h \boldsymbol{\psi}^h + \boldsymbol{\iota}_N \beta_0^h + \boldsymbol{X}_{t_0} \boldsymbol{\beta}^h + \boldsymbol{u}_\tau^h, \tag{2.6}$$

where P^l eigenvectors are stored in the $N \times P^l$ matrix $\boldsymbol{E}^l$, $\boldsymbol{\psi}^l$ is a $P^l \times 1$ vector of the corresponding parameters and $\boldsymbol{u}_\tau^l \sim \mathcal{N}(\boldsymbol{0}, \lambda^l \boldsymbol{I}_N)$. The tilde-superscripts are henceforth dropped in order to indicate the parameters given by the spatially filtered specification in equations (2.5) and (2.6). The set of P^l eigenvectors is identified using an algorithm proposed by Tiefelsdorf and Griffith (2007) and Pace et al. (2013) which iteratively includes the eigenvectors associated with the highest eigenvalues as covariates in a regression model of the dependent variable until the change in the Moran's I statistic drops below a predefined threshold (usually set to 0.1 in existing applications).[1]

Defining a 2×1 vector $\boldsymbol{z}_{i\tau} = (y_{i\tau}, h_{i\tau})'$ and collecting all terms corresponding to time τ on the left-hand side of equations (2.1) and (2.2) yields

$$\boldsymbol{A} \boldsymbol{z}_{i\tau} = \boldsymbol{\Phi} \boldsymbol{z}_{i\tau}^* + \boldsymbol{B} \boldsymbol{x}_{it_0} + \boldsymbol{\varepsilon}_{i\tau}. \tag{2.7}$$

$\boldsymbol{A}$ is a 2×2 lower triangular matrix with ones on the main diagonal and element $(2, 1)$ is given by $-\gamma$. Moreover, define $\boldsymbol{\Phi} = \text{diag}(\boldsymbol{\psi}^y, \boldsymbol{\psi}^h)'$, and let $\boldsymbol{B} = (\boldsymbol{\beta}^y, \boldsymbol{\beta}^h)'$ denote a $2 \times K$

[1]One potential drawback of the approach is that the threshold has to be specified prior to estimation. In a large simulation study, Pace et al. (2013) show that for low to moderate spatial autocorrelation, spatial eigenvector filtering performs very well in approximating the slope parameters in models such as those entertained in this application.

matrix of stacked coefficients. Information on the eigenvectors for the ith observation are stored in a vector $\boldsymbol{z}^*_{i\tau} = (E^y_i, E^h_i)$. Finally, $\boldsymbol{\varepsilon}_{i\tau} = (u^y_{i\tau}, u^h_{i\tau})' \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma})$ is an error vector with variance-covariance matrix $\boldsymbol{\Sigma}$ given by

$$\boldsymbol{\Sigma} = \begin{pmatrix} \lambda^y & 0 \\ 0 & \lambda^h \end{pmatrix}. \tag{2.8}$$

Equation (2.8) implies that the shocks are contemporaneously uncorrelated and homoskedastic. Note that while we assume that $y_{i\tau}$ enters equation (2.2), we do not assume that human capital influences output contemporaneously, but only with a lag. This identification assumption is predicated by the fact that output usually reacts sluggishly to changes in human capital, leading to returns in terms of economic growth only after several years. It is moreover worth noting that the diagonal variance-covariance matrix of the structural form of the model given by equation (2.7) implies that we can treat the estimation problem as two separate problems, simplifying the computational burden required for posterior analysis enormously.

Since we are ultimately interested in producing a sequence of projections in the form of conditional expectations, we have to solve the model in equation (2.7) for the reduced form

$$\boldsymbol{z}_{i\tau} = \boldsymbol{\Pi}\boldsymbol{z}^*_{i\tau} + \boldsymbol{\Lambda}\boldsymbol{x}_{it_0} + \boldsymbol{e}_{i\tau}. \tag{2.9}$$

where $\boldsymbol{\Pi} = \boldsymbol{A}^{-1}\boldsymbol{\Phi}$ and $\boldsymbol{\Lambda} = \boldsymbol{A}^{-1}\boldsymbol{B}$ denote the reduced form $2 \times K$ coefficient matrices. The reduced form innovations are denoted by $\boldsymbol{e}_{i\tau} = \boldsymbol{A}^{-1}\boldsymbol{\varepsilon}_{i\tau} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Omega})$ with variance-covariance matrix given by $\boldsymbol{\Omega} = (\boldsymbol{A}^{-1})\boldsymbol{\Sigma}(\boldsymbol{A}^{-1})'$.

This framework explicitly deals with the complex relationship between income and human capital in a flexible fashion which allows for Bayesian inference under model uncertainty regarding covariate selection and spatial spillovers. In addition, since the right-hand side of equation (2.9) comprises only variables evaluated in the initial year, it is possible to produce projections conditional on $\boldsymbol{x}_{it_0}$.

2.2 Bayesian model averaging

Most empirical assessments of regional growth determinants carry out different model selection procedures to justify a particular choice of covariates and of the matrix $\boldsymbol{W}$ (see, for example, LeSage and Pace 2009). In a similar fashion, predictions or projections are eventually obtained using individual specifications, thus neglecting the uncertainty embodied by the choice of a single model in the space of potential specifications, leading to an underestimation of the uncertainty of the quantities of interest (Raftery 1995).

To cope with such issues we carry out inference and the projection exercise using Bayesian model averaging (BMA) techniques by eliciting suitable prior distributions on the parameters of the model given by equation (2.7). Different models in terms of included covariates are trivially obtained by setting the corresponding elements of $\boldsymbol{B}$ to zero. Alternative models are thus defined by selecting a given combination of columns of $\boldsymbol{X}_{t_0}$ for each equation, and a set of eigenvectors extracted from one particular spatial weight matrix.

Assuming that the constant term is included in all potential specifications, with K potential explanatory variables and R weight matrices, the cardinality of the model space $\mathcal{M}^l$ is $R\ 2^K$ for each one of the two equations assessed. Pooling all parameters in the vector $\boldsymbol{\theta}^l = \left[\beta_0^l \quad (\boldsymbol{\psi}^l)' \quad (\boldsymbol{\beta}^l)' \quad \lambda^l\right]$ for $l \in (y, h)$, the posterior distribution of interest conditional on a particular model $M_{qr}^l \in \mathcal{M}^l (q = 1, \ldots, 2^K; r = 1, \ldots, R)$ is given by

$$p(\boldsymbol{\theta}^l | M_{qr}^l, \mathcal{D}) = \frac{p(\mathcal{D}|\boldsymbol{\theta}^l, M_{qr}^l) p(\boldsymbol{\theta}^l | M_{qr}^l)}{p(\mathcal{D}|M_{qr}^l)}, \tag{2.10}$$

with $\mathcal{D}$ denoting the available data. Since the marginal likelihood $p(\mathcal{D}|M_{qr}^l)$ does not involve $\boldsymbol{\theta}^l$, the posterior for $\boldsymbol{\theta}^l$ conditional on model M_{qr}^l is thus proportional to the likelihood $p(\mathcal{D}|\boldsymbol{\theta}^l, M_{qr}^l)$ times the prior $p(\boldsymbol{\theta}^l|M_{qr}^l)$. The uncertainty regarding model choice can be integrated out by carrying out inference on weighted averages of model-specific posteriors using posterior model probabilities $p(M_{qr}^l|\mathcal{D})$ as weights,

$$p(\boldsymbol{\theta}^l|\mathcal{D}) = \sum_{q=1}^{2^K} \sum_{r=1}^{R} p(M_{qr}^l|\mathcal{D}) p(\boldsymbol{\theta}^l|M_{qr}^l, \mathcal{D}). \tag{2.11}$$

The posterior model probabilities, in turn, are given by

$$p(M_{qr}^y|\mathcal{D}) \quad \propto \quad p(\boldsymbol{y}|M_{qr}^y, \mathcal{D}) p(M_{qr}^y), \tag{2.12}$$
$$p(M_{qr}^h|\mathcal{D}) \quad \propto \quad p(\boldsymbol{h}|M_{qr}^y, \mathcal{D}) p(M_{qr}^h). \tag{2.13}$$

For the parameters on the constant terms β_0^l and the disturbance parameters λ^l, non-informative priors can be elicited. For the priors on the remaining slope parameters and the parameters corresponding to the eigenvectors we follow Fernández et al. (2001b) and impose multivariate normally distributed g-priors (see Zellner 1986):

$$\left[(\boldsymbol{\psi}_{qr}^l)' \quad (\boldsymbol{\beta}_{qr}^l)'\right]' | \lambda^l, M_{qr}^l \sim \mathcal{N}(\mathbf{0}, \lambda^l [g(\boldsymbol{Z}_{qr}^l)'(\boldsymbol{Z}_{qr}^l)]^{-1}, \tag{2.14}$$

where $\boldsymbol{Z}_{qr}^l$ is the matrix of observations on the eigenvectors and explanatory variables for model M_{qr}^l and $\left[(\boldsymbol{\psi}_{qr}^l)' \quad (\boldsymbol{\beta}_{qr}^l)'\right]'$ denotes the stacked vector of corresponding parameters. One virtue of the prior specification given in equation (2.14) is that the g-prior specification yields closed-form solutions for the marginal likelihood. Moreover, only the scalar prior hyperparameter g has to be elicited. We follow the suggestions of Fernández et al. (2001a) and set $g = 1/\max(N, K^2)$.

For the priors on the model spaces $\mathcal{M}^l$, we follow Ley and Steel (2007) and elicit a binomial-beta prior

$$p(M_{qr}^l) \propto \Gamma(1 + \varphi_{qr}^l)\Gamma(1 + K - \varphi_{qr}^l), \tag{2.15}$$

with $\Gamma(\cdot)$ and φ_{qr}^l denoting the gamma function and the number of (non-constant) explanatory variables in model M_{qr}^l, respectively. Such setting allows for a flexible prior distribution over model size and in particular for an uninformative prior regarding the number of covariates included in the specification.

For out-of-sample projections, the quantity of interest is the predictive density of future values of $\boldsymbol{y}$ and $\boldsymbol{h}$ ($\hat{\boldsymbol{y}}$ and $\hat{\boldsymbol{h}}$, respectively), conditional on trajectories for other explanatory variables which are summarized in the matrix $\hat{\boldsymbol{X}}$. The predictive densities of $\hat{\boldsymbol{y}}$ and $\hat{\boldsymbol{h}}$ are given by:

$$p(\hat{\boldsymbol{y}}|\hat{\boldsymbol{X}},\mathcal{D}) = \sum_{q=1}^{2^K}\sum_{r=1}^{R} p(M^y_{qr}|\mathcal{D})p(\hat{\boldsymbol{y}}|\hat{\boldsymbol{X}},M^y_{qr},\mathcal{D}) \quad (2.16)$$

$$p(\hat{\boldsymbol{h}}|\hat{\boldsymbol{X}},\mathcal{D}) = \sum_{q=1}^{2^K}\sum_{r=1}^{R} p(M^h_{qr}|\mathcal{D})p(\hat{\boldsymbol{h}}|\hat{\boldsymbol{X}},M^h_{qr},\mathcal{D}). \quad (2.17)$$

The predictive densities are thus weighted averages of all model-specific predictive densities, where the weights are given by the corresponding posterior model probabilities.

3 On the determinants of regional economic growth in Europe

We start by applying BMA for spatially filtered specifications to a cross-section of regional economic growth in 273 NUTS-2 EU regions.[2] Our dependent variables are the gross value added per capita and the share of tertiary education attainment in the period 2010.[3]

Table 1 presents the definition of the variables, as well as the original source of the data. All explanatory variables are measured in the year 2000, with the exception of the growth rate of population and the unemployment rate, which are averages for the period 1996-2000. The majority of the empirical growth literature includes the initial level of income as an explanatory variable. As a proxy for human capital, we use tertiary education attainment shares measured by means of the share of working age population with higher education (ISCED levels 5-6).

To account for the industrial mix of the regions in the sample we moreover include the shares of employment in agriculture (NACE A and B), mining, manufacturing and energy (NACE C to E), construction services (NACE F) as well as employment in market services (NACE G to K) as additional explanatory variables. Our dataset moreover contains information for several other potential control variables which summarize information about the accumulation of classical factors of production, degree of urbanization, population structure, infrastructure and geography.

We consider 14 different spatial linkage matrices of three different classes: Queen contiguity matrices (first-order and second-order), k-nearest neighbour matrices (for $k = 5, \dots, 14$) and two matrices based on critical distance (where neighbours are defined as those regions with a distance below a critical threshold, defined alternatively as the first or second quintile of the distribution of distances between pairs of regions). In all cases geodesic distance measures are used to construct the spatial linkage matrices.

[2] See the Appendix for the list of NUTS-2 regions included in the data.

[3] To ensure that the projected tertiary educational attainment shares lie between 0 and 100%, the estimations are run using the transformed series $h_{it} = \log\left(\frac{\tilde{h}_{it}}{1-\tilde{h}_{it}}\right)$, where h_{it} and $\tilde{h}_{it}$ denotes the transformed and untransformed value of tertiary educational attainment for period t and region i, respectively.

Table 1: Explanatory variables: overview

Variable	Description
Initial income	Gross-value added divided by population, 2000. *Source*: Cambridge Econometrics
Physical capital investment	Gross fixed capital formation, 2000. *Source*: Cambridge Econometrics
Tertiary education attainment	Share of population (aged 25 and over, 2000) with higher education (ISCED levels 1-2). *Source*: Eurostat
Agricultural employment	Share of NACE A and B (agriculture) in total employment, 2000. *Source*: Cambridge Econometrics
Manufacturing employment	Share of NACE C to E (mining, manufacturing and energy) in total employment, 2000. *Source*: Cambridge Econometrics
Construction employment	Share of NACE F (construction) in total employment, 2000. *Source*: Cambridge Econometrics
Market services employment	Share of NACE G to K (market services) in total employment, 2000. *Source*: Cambridge Econometrics
Output density	Gross-value added per square km, 2000. *Source*: Eurostat
Employment density	Employed persons per square km, 2000. *Source*: Eurostat
Population density	Population per square km, 2000. *Source*: Eurostat
Population growth	Average growth rate of the population for 1996-2000. *Source*: Eurostat
Unemployment rate	Average unemployment rate for 1996-2000. Unemployment rate is defined as the share of unemployed persons of the economically active population *Source*: Eurostat
Labor force participation rate	Employed and unemployed persons as a share of total population, 2000. *Source*: Eurostat
Child dependency ratio	The ratio of the number of people aged 0-14 to the number of people aged 15-64, 2000. *Source*: Eurostat
Old-age dependency ratio	The ratio of the number of people aged 65 and over to the number of people aged 15-64, 2000. *Source*: Eurostat
Peripheriality	Measured in terms of distance to Brussels
Accessibility road	Potential accessibility road, ESPON space=100. *Source*: ESPON
Accessibility rail	Potential accessibility rail, ESPON space=100. *Source*: ESPON
Seaports	Dummy variable, 1 denotes region with seaport, 0 otherwise. *Source*: ESPON
Airports	Dummy variable, 1 denotes region with airport, 0 otherwise. *Source*: ESPON
Coastal region	Dummy variable, 1 denotes region with coast, 0 otherwise. *Source*: ESPON
Capital city	Dummy variable, 1 denotes region with capital city, 0 otherwise. *Source*: ESPON
Large city	Dummy variable, 1 denotes region with a city larger than $300,000$ inhabitants, 0 otherwise. *Source*: ESPON
Rural region	Dummy variable, 1 denotes region with a population density lower than 100 and without a city larger than $125,000$ inhabitants, 0 otherwise. *Source*: ESPON
Border region	Dummy variable, 1 denotes region with country borders, 0 otherwise. *Source*: ESPON
Pentagon region	Dummy variable, 1 if in London-Paris-Munich-Milan-Hamburg pentagon. *Source*: ESPON

Table 2 and Table 3 presents the results of the in-sample model averaging exercise for the income per capita and educational attainment equations, respectively. The results are based on evaluating 20 million models sampled using a Markov Chain Monte Carlo (MCMC) method after disregarding the first 5 million steps of the Markov chain as initial burn-ins.[4] We report the mean of the posterior distribution of the parameter associated to each one of the variables, as well as its corresponding standard deviation. In addition, we compute the posterior inclusion probability (PIP) of each covariate and each matrix of spatial linkages. The PIP is defined as the sum of posterior model probabilities of the specifications which include that particular variable or the set of eigenvectors corresponding to a particular matrix of spatial weights.

The results in Table 2 confirm and complement the conclusions of Crespo Cuaresma and Feldkircher (2013), who use a different time period and a larger set of potential covariates but do not consider the potential simultaneity in the education-growth link. In line with Crespo Cuaresma et al. (2014) and Crespo Cuaresma and Feldkircher (2013), the importance of (conditional) income convergence and human capital accumulation as driving forces

[4]The standard statistics used to evaluate the convergence of the Markov chain indicate that convergence was achieved. The correlation between simulated and analytical posterior model probabilities for the subset of best models, for example, is 0.998.

Table 2: GVA per capita equation

Variables	PIP	PM	PSD
Initial income	1.0000	0.8590	0.0229
Physical capital investment	0.0221	-0.0002	0.0020
Tertiary education attainment	0.9243	0.0575	0.0230
Employment agriculture	0.0278	0.0000	0.0004
Employment energy and manufacturing	0.2457	0.0007	0.0014
Employment construction	0.0122	0.0000	0.0005
Employment market services	0.6260	0.0028	0.0024
Output density	0.0128	0.0001	0.0017
Employment density	0.0517	0.0000	0.0103
Population density	0.0865	-0.0023	0.0122
Population growth	0.0106	-0.0001	0.0018
Unemployment rate	0.0140	0.0000	0.0003
Labor force participation rate	0.6018	0.0024	0.0021
Child dependency ratio	0.0232	0.0001	0.0005
Old-age dependency ratio	0.0624	-0.0002	0.0009
Peripheriality	0.0201	-0.0003	0.0028
Accessibility road	0.0135	0.0000	0.0000
Accessibility rail	0.0220	0.0000	0.0001
Seaports	0.0108	-0.0001	0.0019
Airports	0.0149	-0.0002	0.0023
Coastal region	0.0378	-0.0009	0.0052
Capital city	0.5283	0.0384	0.0402
Large city	0.0074	0.0000	0.0011
Rural region	0.0089	-0.0001	0.0020
Border region	0.0161	0.0002	0.0025
Pentagon region	0.0085	0.0001	0.0021
first-order (queen) contiguity	0.0001		
second-order (queen) contiguity	0.9999		
5-nearest neighbours	0.0000		
6-nearest neighbours	0.0000		
7-nearest neighbours	0.0000		
8-nearest neighbours	0.0000		
9-nearest neighbours	0.0000		
10-nearest neighbours	0.0000		
11-nearest neighbours	0.0000		
12-nearest neighbours	0.0000		
13-nearest neighbours	0.0000		
14-nearest neighbours	0.0000		
distance band 1st quintile	0.0000		
distance band 2nd quintile	0.0000		

PIP stands for 'posterior inclusion probability', PM stands for 'posterior mean' (mean of the posterior distribution of the corresponding parameter) and PSD stands for 'posterior standard deviation' (square root of the variance of the posterior distribution of the corresponding parameter). All calculations are based on MC^3 sampling using 15 million posterior draws after 5 million burn-in draws.

Table 3: Tertiary education attainment equation

Variables	PIP	PM	PSD
Income 2010	1.0000	0.5067	0.1148
Initial income	0.2588	-0.0752	0.1439
Physical capital investment	0.9515	-0.1453	0.0437
Tertiary education attainment	1.0000	0.7101	0.0257
Employment agriculture	0.9117	0.0053	0.0023
Employment energy and manufacturing	0.0146	0.0000	0.0002
Employment construction	0.0203	0.0001	0.0010
Employment market services	0.0132	0.0000	0.0002
Output density	0.9505	-0.1436	0.0445
Employment density	0.0879	0.0082	0.0362
Population density	0.9162	0.1614	0.0608
Population growth	0.1004	0.0039	0.0132
Unemployment rate	0.0414	-0.0001	0.0007
Labor force participation rate	0.0326	0.0001	0.0006
Child dependency ratio	0.1100	0.0007	0.0023
Old-age dependency ratio	0.2312	-0.0014	0.0028
Peripheriality	0.1142	-0.0068	0.0211
Accessibility road	0.8999	-0.0012	0.0008
Accessibility rail	0.1425	0.0002	0.0007
Seaports	0.2116	-0.0141	0.0304
Airports	0.0157	0.0002	0.0028
Coastal region	0.0350	-0.0012	0.0086
Capital city	0.0315	0.0016	0.0117
Large city	0.0126	0.0000	0.0026
Rural region	0.0169	-0.0003	0.0047
Border region	0.0253	-0.0006	0.0049
Pentagon region	0.0229	-0.0006	0.0084
first-order (queen) contiguity	0.2086		
second-order (queen) contiguity	0.0000		
5-nearest neighbours	0.0000		
6-nearest neighbours	0.7914		
7-nearest neighbours	0.0000		
8-nearest neighbours	0.0000		
9-nearest neighbours	0.0000		
10-nearest neighbours	0.0000		
11-nearest neighbours	0.0000		
12-nearest neighbours	0.0000		
13-nearest neighbours	0.0000		
14-nearest neighbours	0.0000		
distance band 1st quintile	0.0000		
distance band 2nd quintile	0.0000		

PIP stands for 'posterior inclusion probability', PM stands for 'posterior mean' (mean of the posterior distribution of the corresponding parameter) and PSD stands for 'posterior standard deviation' (square root of the variance of the posterior distribution of the corresponding parameter). All calculations are based on MC^3 sampling using 15 million posterior draws after 5 million burn-in draws.

of income growth in European regions is reflected in the high posterior inclusion probability of the initial income and educational attainment variable. The implied average speed of income convergence and the returns to tertiary education in terms of economic growth are quantitatively comparable to those found in the literature once uncertainty about the parametrization of the spatial autocorrelation term is taken into account (see the results in Crespo Cuaresma and Feldkircher 2013).

In addition, our results indicate that income growth in the last decade was robustly related to the sectoral structure at the regional level. Regions whose employment structure was dominated by the service or manufacturing sector tended to grow on average at higher rates than those with a relatively higher share of employment in the primary sector. The results in Table 2 moreover detects the labor force participation rate variable as an important driver of economic output. Similar to the findings in the previous literature (see, for example, Crespo Cuaresma et al. 2014 or Crespo Cuaresma and Feldkircher 2013), the results suggest that regions with a capital city appear to grow faster on average. The rest of the variables have a low posterior inclusion probability (below the prior expected inclusion probability of 0.5 implied by our binomial-beta prior) and their corresponding parameter estimates have a low level of precision. The mean of the posterior distribution over model size is 5.4, with most of the posterior probability concentrated in models which contain 3 to 8 covariates as explanatory variables. The posterior results for the set of spatial linkage matrices give strong support to contiguity-based spatial weight matrices and in particular to second-order queen contiguity matrix, with a posterior probability of inclusion of more than 99%.

The posterior results for the education equation presented in Table 3 emphasize the importance of income and convergence dynamics as determinants of educational attainment differences across European regions. The contemporaneous level of per capita income, the physical capital investment variable, initial tertiary education attainment, as well as proxies measuring the sectoral structure, infrastructure and the degree of urbanization appear to be very robustly related to the tertiary education attainment shares. The relatively lengthy list of important determinants of tertiary education attainment shares also translates to a higher posterior model size. While the mean of the posterior distribution over model size in the output equation is rather small (5.4), the posterior expected model size in the human capital equation is 9.16. Some evidence of substitutability between physical and human capital can be inferred from the negative posterior mean of the parameter associated to physical capital investment, a variable with relatively high posterior inclusion probability in this equation. The high correlation between the capital city dummy and the infrastructure and output density variables suggests similar effects. Concerning inference on the spatial autocorrelation structure of human capital, the posterior mass appears very concentrated an the 6-nearest neighbour matrix, achieving the highest posterior probability of inclusion of 79%.

4 Income projections under model uncertainty: Human capital and the future of economic growth in Europe

Using the Bayesian model averaging techniques described, we obtain the predictive density of the income per capita and the tertiary education variables for all regions in our sample as a weighted average of model-specific predictive densities as in equations (2.16) and (2.17), where the weights are given by the corresponding posterior model probabilities. Our method allows us to simultaneously project educational attainment and income per capita and iterate the process to obtain paths ranging over long prediction horizons. We provide benchmark projections that can be used for the assessment of future income trends in the continent by keeping all variables constant with the exception of the human capital variable and the level of income, thus calculating model-averaged predictions for all decades up to the year 2100.

4.1 Income and human capital projections

The expected value of the predictive density of income per capita growth, based on the model-averaged conditional expectation of income per capita over the period 2010-2100 is shown in Figure 1, while Figure 2 presents the expected value of the predictive density of the growth rate of tertiary education attainment shares. The income growth projections imply a continuation of the cross-regional income convergence process in the continent over the coming decades. In relative terms, the highest growth rates of income per capita tend to be concentrated in Central and Eastern European economies. This finding carries over to the expected growth rate of tertiary education. For human capital we find a broad pattern of convergence not only for regions located in Central and Eastern Europe but also for regions located in the euro area periphery, most notably Portugal and to some extent Italy and Greece.

Figure 3 depicts the projected average growth rate of income per capita in the period 2010-2100 against the (log) income per capita in 2010 for all NUTS-2 regions included in the analysis. The same type of convergence plot over the projection period is shown in Figure 4 for the share of the labour force with tertiary education. The convergence trends observed in the available sample are projected to continue over the coming decades, with two clearly discernible clusters of income growth across European regions depicted in Figure 3. These patterns imply that income convergence in Europe is expected to be mainly driven by between-country dynamics as opposed to within-country convergence. Such a development constitutes a continuation of the relative income developments observed over the last decades in Europe in terms of closing the gap in within-country versus between-country income differentials (see for example the results in Crespo Cuaresma et al. 2014). Figure 4 provides ample evidence for predicted convergence in terms of human capital. Regions that experienced high rates of tertiary education attainment in 2010 tend to grow slower as compared to regions with relatively low rates of tertiary education attainment. Under the assumption that a policy-maker is able to control the rate of human capital accumulation prevailing in some region, the findings suggest that if the initial stock of human capital is low, policy-makers tend to invest in education at a rate above average, producing the convergence pattern shown in Figure 4.

To quantify the output growth premium emanating from increasing human capital levels across regions we produce projections based on a so-called no-change scenario. This scenario assumes that tertiary education levels remain at their 2010 levels, implying that convergence is entirely driven by initial income dynamics. Figure 5 presents the differences of growth

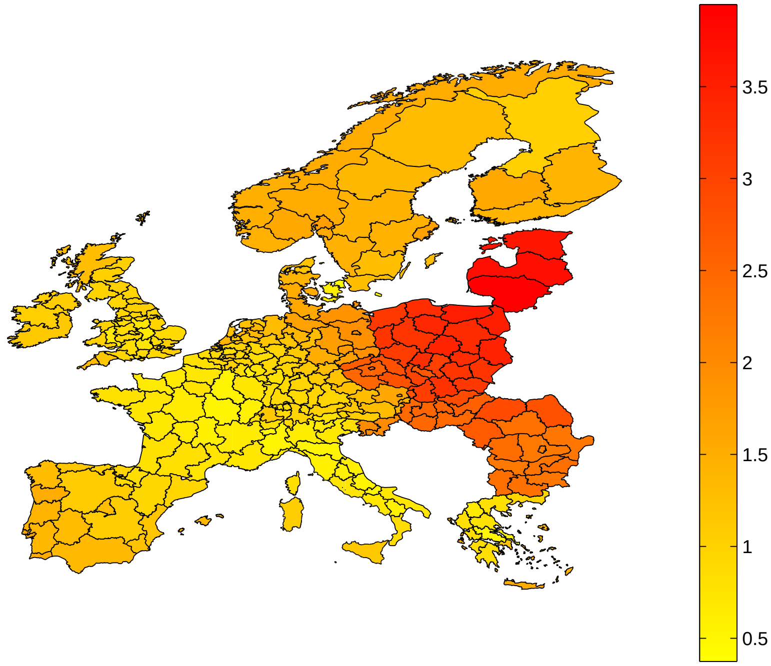

Figure 1: Projected average annual growth of GVA per capita (2010 to 2100)

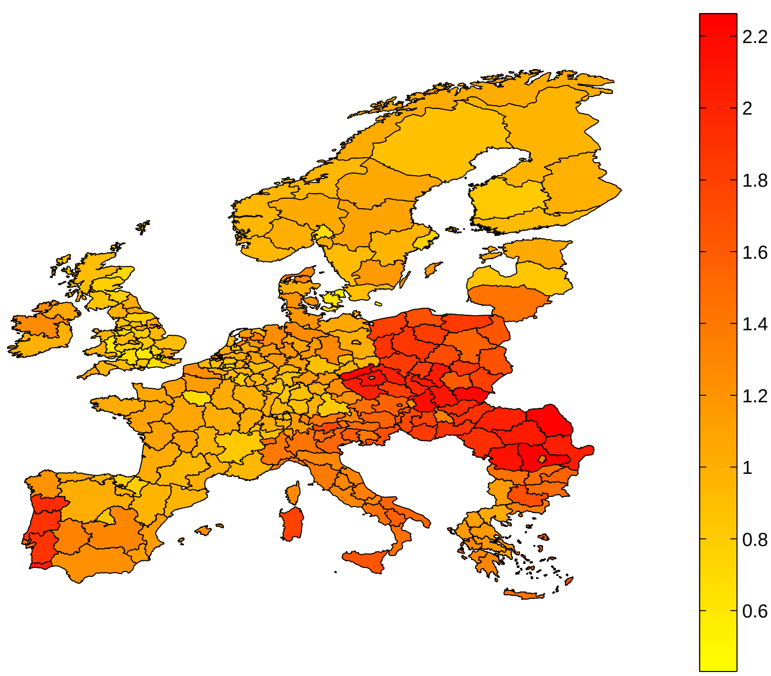

Figure 2: Projected average annual growth of tertiary education attainment shares (2010 to 2100)

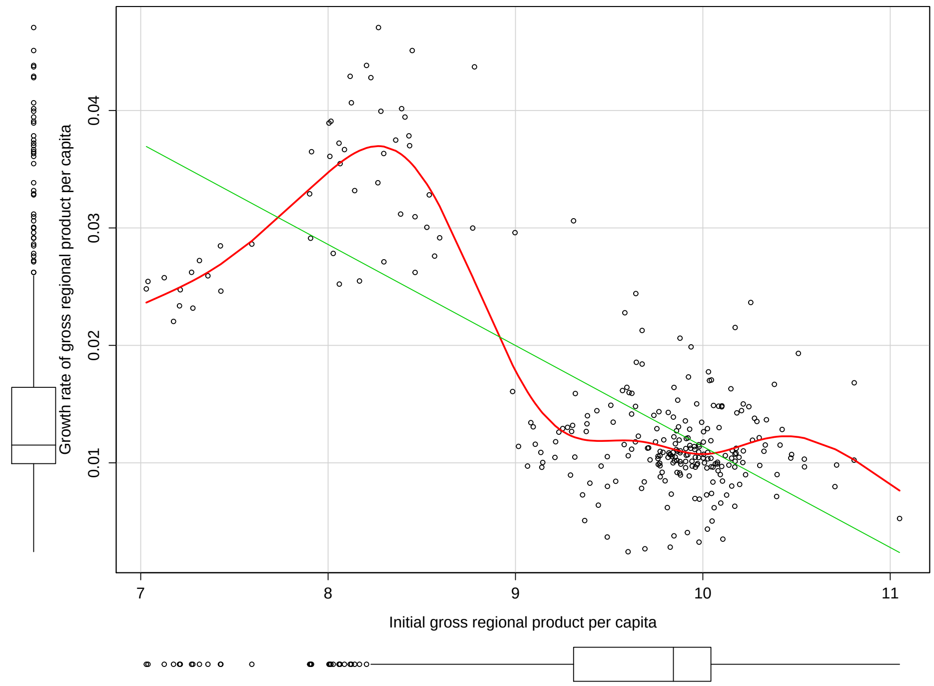

Figure 3: Projected average annual growth of GVA per capita (2010 to 2100) against log-level of GVA per capita, 2010

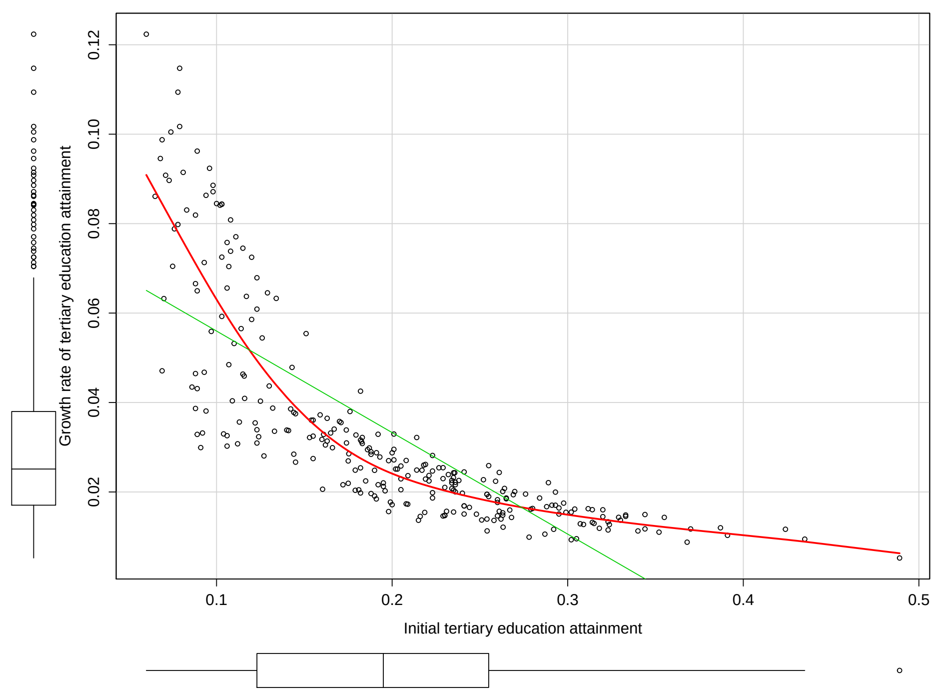

Figure 4: Projected average annual growth of tertiary education attainment shares (2010 to 2100) against tertiary education attainment share, 2010

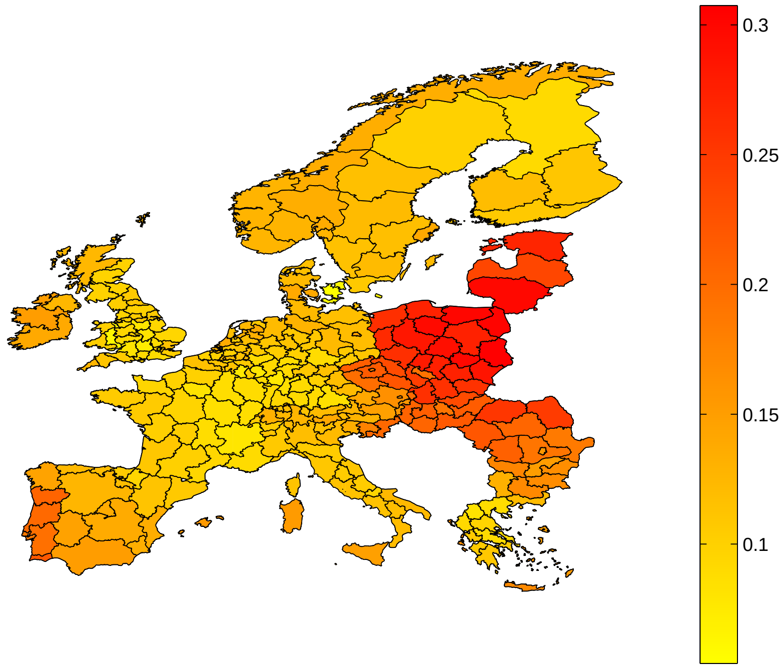

Figure 5: Projected average annual growth difference between the benchmark scenario and a hypothetical no-change scenario (2010 to 2100)

rates between both scenarios. For regions in Central and Eastern Europe the output growth premium is between 0.25 and 0.30%. Regions in Portugal, Greece and southern Italy also grow faster by around 0.20%. Our findings thus suggest that convergence in terms of income per capita is significantly affected by increases in human capital in each respective regions, where the growth premium is especially pronounced in regions with low initial income and human capital endowments.

These exemplary predicted income paths present a benchmark scenario which can be used to downscale national income projections such as those used to inform integrated assessment models for climate change simulations (see for example Crespo Cuaresma 2015). The focus on human capital dynamics as a driving force of income growth provides a suitable framework to combine the methods presented here with other population projections by age, sex and level of education such as those used in the context of the scenarios used recently by the Intergovernmental Panel for Climate Change in their fifth assessment report (see KC and Lutz 2015). Our contribution offers thus a tool to expand the analysis provided by this input to integrated assessment models to subnational units using a robust and internally coherent methodological framework.

4.2 Robustness checks

As a robustness check, we also performed an alternative model averaging exercise based on (non-filtered) spatial autoregressive (SAR) model specifications as shown in equations (2.1) and (2.2). For this robustness exercise, we used standard g-priors for the slope coefficients, an inverse Gamma prior for σ^2 and a uniform prior defined over (-1,1) for the spatial autoregressive parameter ρ. Due to the computational costs of numerical integration in this setting, we used a reduced set of spatial linkage matrices, restricted to ten different nearest neighbour structures. Applying BMA to our data with the set of models spanned by the SAR specifications reinforces the results previously presented. Income convergence and human capital investment appear as robust drivers of economic growth, with parameters which are well estimated in terms of the ratio of posterior mean to posterior standard deviation. The share of employment in market services and two spatially lagged variables (income per-capita and tertiary education) appear robustly and positively related to regional economic growth, while the old-age dependency ratio is also a robust covariate, in this case with a negative partial correlation with income growth. Given that the application in this study is related to long-term projection horizons, we rely on predictions based on spatially filtered specifications estimated using the cross-section for the full period 2001-2010 for the projection exercise.[5]

To assess the robustness of our predictions, we carried out several checks changing the in-sample information. First, we investigated whether the recent financial crisis has an significant impact on the outcome of our income growth projections. Using the period from 2000 to 2007 as an estimation sample (and thus effectively excluding the information on the crisis), the results obtained are qualitatively unchanged, implying that our projections are robust with respect to the exclusion of (large) short-term business cycle fluctuations. In terms of quantitative differences, neglecting information on the crisis only implies slightly higher growth rates of income per capita for the regions in our sample.

5 Conclusions

We present a framework to obtain projections of income per capita developments at the regional level in European countries. The projections build on recent development in Bayesian modelling and explicitly allow for uncertainty over the importance of different growth determinants and the specification of spatial spillovers. We circumvent possible endogeneity issues by jointly modelling output and human capital in a system of equations. Using a sample spanning the period from 2000 to 2010, we asses the potential contribution of future educational attainment to economic growth and income convergence among European regions over the next decades.

Our results highlight the importance of income convergence dynamics and human capital as driving forces for income growth in the continent, being consistent with the bulk of the literature on growth determinants. Based on these estimates we design a simple projection exercise based on Bayesian averaging of predictive densities. We simultaneously project income and human capital, while keeping all other covariates at their 2010 levels. To disentangle the growth premium caused by increases in human capital we also construct a hypothetical no-change scenario, where everything is held constant except for initial income. Our benchmark scenario shows significant income convergence effects leading to a further

[5]For comparison, we also obtained income projections using SAR models. These are qualitatively and quantitatively very similar to the projected income paths presented in the following and are available from the authors upon request.

narrowing of the income differences between poor and rich regions in Europe over the coming decades, fuelled by human capital investment. The relative return of improving educational attainment levels in terms if economic growth appears particularly large in peripheral European economies. Our results provide a new perspective on the possible importance human capital has for *future* economic growth. While our empirical contribution emphasizes the growth enhancing effect of human capital, it is worth noting that the scenario outlined above serves as a mere illustration of what is possible within our modelling framework. Richer scenarios that do not only assume that human capital is changing over time, but a set of other quantities under control of the policy maker, can be constructed in a straightforward fashion.

The set of econometric methods presented in this paper can serve as a basic framework to obtain income projections and be expanded in a straightforward manner to include alternative spatial structures, interaction terms or parameter heterogeneity across regions. It is worth noting that the proposed framework is linear and thus fails to account for temporal parameter heterogeneity. Thus a possible avenue of further research would be to extend the existing approach to allow for non-linearities over time.

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