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SPATIAL GROWTH REGRESSIONS FOR THE CONVERGENCE ANALYSIS OF RENEWABLE ENERGY CONSUMPTION IN EUROPE

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1. Introduction

The issue of energy has become one of the most important topics in implementing sustainable development. Since the current global energy system is largely based on conventional energy, there is a worldwide awareness on the negative environmental impact produced by highly fossil fuel energy consumption. The conventional energy sources are inherently linked to greenhouse gas emissions and to accelerating perturbation of Earth temperature. Global warming is a direct result of air pollution and of rising, in particular, of greenhouse gases. Hence, climate change is deemed an important world environmental challenge, as it has potentially dramatic economic, social and environmental consequences on the quality of life of present and future generations. As the world becomes more sensitive to environmental issues and climate changes, the need to search for renewable, alternative and non polluting sources of energy assumes top priority in many developed countries. An energy resource is often termed renewable when is derived from natural processes and its supply is not affected by the rate of consumption, being replenished constantly. Examples for renewable energy are: solar, wind, geothermal, biomass, hydropower, ocean resources, solid biomass and liquid biofuels. Renewable energy resources can effectively meet energy demand and are environmentally sustainable, as they are clean and green energy sources, with a very huge potential, giving also impulse to economic development, including employment and investment opportunities. These features, as well as the shortcomings of conventional energy, has motivated an increasing number of countries to adopt a renewable energy policy. The concern over remaining fossil fuels reserves, import dependence, security of supply and the alarm about environmental pollution are factors leading the European Union (EU) to be a world leader in renewable energy. The existing EU legislation and all the initiatives aimed at mitigating climate change and improving security have contributed to a decreasing use of fossil fuels. In fact, European data indicate that renewable energy shows a promising prospect. Overall, the European Union now attains 18.4% of its energy requirement through renewable energy sources. According to the Statistics Agency for the European Union (Eurostat), Europe's renewable energy consumption has doubled over the last decade, going from 5% in 1999 to 12.5% in 2010.

The 2009/28/EC Directive on the promotion of the use of energy from renewable sources ("Renewable Energy Directive") sets the objective of reaching at least the 20% of EU's final energy consumption through renewable energy sources by 2020. The Renewable Energy Directive sets for each member State mandatory national target for the overall share of renewable energy sources in gross final energy consumption. The legislative framework, guaranteeing the implementations of these targets, called upon member States to draw up renewable strategies in the form of National Renewable Energy Action Plans.

The share of energy from renewable sources in gross final energy consumption in the EU-27 is showing steady progress towards the 2020 target, albeit the financial and economic crisis. However the EU encompasses a heterogeneous group of nations. The member States present wide variations in resource endowments, in physical infrastructures, in distribution systems, in pricing structures, as well as in many other aspects of energy systems. Accordingly, for a comprehensive analysis of future renewable energy sources developments, it is of crucial importance to determine whether the member States' performance is converging and whether cross-countries differences are declining. It is worth noting that the attention to convergence issues increased especially along with EU enlargement (Halmai and Vasary, 2010) even if the economic and social cohesion is considered the most important objective of EU treaty and the essential condition for a successful EU integration.

The analysis proposed in this paper is designed to provide a statistical examination of share of energy from renewable sources in gross final energy consumption in Europe and the tendency, if any, towards convergence. We make use of the β—convergence methodology (Barro and Sala-i Martin, 1991, 1992) , widely applied in regional growth studies, to examine convergence in renewable energy consumption for EU member States over the period 1995-2010. In the last decade, many studies have shown that β—convergence can effectively be employed to investigate the trends of different socio-economic and environmental indicators (Kerem *et al.*, 2008; Wolszczac-Derlacz, 2009; Liddle, 2009; Gäcther and Theurl, 2011). The β measure of convergence seeks to determine whether a catch-up process takes places, verifying if countries with lower initial level of the variable of interest (in our case European member States with lower performance in the renewable energy consumption) exhibit the fastest growth rates.

This paper examines convergence among EU countries using different spatial growth regression models. A distinctive feature of our study is to recognize the role of space explicitly. We thus discuss several model specifications which are able to take into account both spatial dependence and heterogeneity existing in the data. These models also allow to specify the concepts of global and local β—convergence in a continuous fashion.

The remainder of the paper is structured as follows. In Section 2 we discuss the growth regression models for β—convergence analysis and in Section 3 we provide details on Bayesian inference and computations. In Section 4 we discuss the fit of the models to real data and, finally, in Section 5 we conclude the paper with a discussion.

2. GROWTH REGRESSION MODELS FOR β—CONVERGENCE ANALYSIS

Regional economic growth and β—convergence is a topic that has attracted a lot of attention in recent years. Research on this subject has developed in different directions,

but empirical research has predominantly focused on estimating the income convergence speed using cross-sectional data, with a theoretical setting based on the Solow-Swan neoclassical growth model (see, for example Rey and Janikas, 2005; Mathunjwa and Temple, 2007; Barro and Sala-i Martin, 1995). Here, the concept of β—convergence is used to examine the growth and the process of convergence in renewable energy consumption in Europe. To our knowledge, this is the first study conducted along these lines.
The following sections discuss several specifications of growth regression models which are able to take into account both spatial dependence and heterogeneity existing in the data.

2.1. *Global regressions*

Assume that $\tilde{Y}$, denoting the renewable energy consumption, is observed on an irregular lattice $\mathscr{L}$ represented by n countries in Europe. Assume also that the same units of observations in the cross-sectional sample are surveyed more than one time, such that the resulting observations are described as forming a panel or longitudinal data set. Hence, $\tilde{Y}(s_i, t)$, is observed at time points, $t = 0, 1, \ldots, T$ and at each of n countries, s_i.
The assumption of normality of the data is convenient and often reasonable (perhaps after transformation). Thus, we say that $\tilde{Y}$ follows a matrix normal distribution $N_{nT}(\mu, \Sigma, \mathbf{\Omega})$, where μ is a parameterized mean, Σ is an (n, n) spatial covariance matrix and $\mathbf{\Omega}$ a (T, T) temporal covariance matrix. We assume that we can use explanatory terms, $X_j(s_i, t)$, $j = 1, \ldots, q$, in the mean to include specific effects of some economic variables. Furthermore, since for the same units of observations the number of repeated measurements is limited in time, we assume that $\mathbf{\Omega}$ is an identity matrix. Hence, we avoid the modelling of any possible temporal correlation structure underlying the data.
The methodology used to measure β-convergence generally involves estimating a growth equation in the following form

$$\ln\left(\frac{\tilde{y}(s_i, t)}{\tilde{y}(s_i, t-1)}\right) = \alpha + \beta \ln \tilde{y}(s_i, t) + \boldsymbol{X}(s_i, t)'\boldsymbol{\eta} + u(s_i, t)$$

or equivalently

$$y(s_i, t) = \boldsymbol{Z}(s_i, t)'\boldsymbol{\gamma} + u(s_i, t) \tag{1}$$

with $y(s_i, t) = \Delta \ln \tilde{y}(s_i, t)$, where Δ is the difference operator, $Z(s_i, t) = \left[1 \ \ln \tilde{y}(s_i, t)\ X(s_i, t)\right]$, and $\boldsymbol{\gamma} = \left[\alpha\ \beta\ \boldsymbol{\eta}'\right]'$.
In equation (1), $y(s_i, t)$ is the growth rate of electricity consumption from renewable sources (henceforth denoted ECRS) in country i at time t, $\boldsymbol{X}(s_i, t)$ includes all other factors supposedly affecting the growth rate, $\boldsymbol{\gamma}$ is a vector of parameters to be estimated, and $u(s_i, t)$ are zero mean and uncorrelated normally distributed error terms. Hence, $Cov\left[u(s_i, t), u(s_j, t)\right] = 0$, $\forall\ i \neq j$, so that $\Sigma = \sigma_u^2 \mathbf{I}_n$.
Conditional convergence is found whenever β is negative, thus implying that, after controlling for other factors, countries with low initial consumption levels grow on average faster than others having relatively higher levels. If the value of $\boldsymbol{\eta}$ is restricted to zero, it is simplistically assumed that the countries are structurally similar, characterised

by the same steady-state and differing only in their initial conditions. In this case, the β—convergence is said to be "absolute".
Recent contributions introduce a spatial dimension into the formulation of the problem (see, for instance, Arbia, 2006). A key property of many economic data at regional level is that observations at nearby sites tend to be similar to one another. In fact, there is strong evidence (see, for example, Fischer and Stirböck, 2006; Niebuhr, 2001) that spatial spillovers have a significant influence on economic growth and therefore observations from regional growth datasets cannot be regarded as independently generated, even after controlling for region-specific determinants. Thus, the proximity and numerous linkages between neighbouring regions imply that regional economic variables are likely to be interdependent which conflicts with the assumptions under which equation (1), hereafter denoted as model M1, can be validly estimated. There are indeed reasons to believe that the omission of the spatial structure from the analysis of the regional β—convergence process is likely to produce biased results.
Most empirical studies in the spatial econometrics literature model spatial spillovers in the framework of simultaneous autoregressive (SAR) specifications (Arbia, 2006) conditional on a given spatial contiguity matrix, $\mathbf{W}$, which specifies the spatial interactions among the countries. Here, to account for spatial dependence, we assume that the n—vector, $\mathbf{u}(t)=\left[u(s_1,t),\ldots,u(s_n,t)\right]'$, is a zero mean conditional autoregressive (CAR) process (Cressie, 1993) with covariance matrix $\Sigma=\sigma_u^2\left(\mathbf{I}-\rho\mathbf{W}\right)^{-1}$, where ρ is the spatial interaction parameter and $\mathbf{W}$ is symmetric with elements equal to 1 for neighbouring countries and 0 otherwise. In the following, the specification of equation (1) with a CAR structure in the error terms will be referred to as model M2.

Differences in the fundamentals of regional economies introduce the possibility of spatial heterogeneity. This means that the relationship represented by (1) might not be stable over space which implies that the true value of its coefficients varies in space (referred to as structural instability). A theoretical motivation for heterogeneity can be found in endogenous growth theory (Azariadis and Drazen, 1990) as well as the neoclassical model with heterogenous structure (Galor, 1996). Spatial heterogeneity is related to the concept of convergence clubs, which accounts for the possibility of multiple, locally stable, steady-state equilibrium to which economies with similar fundamentals converge (Durlauf and Johnson, 1995). Econometric methods that attempt to directly accommodate heterogeneity offer alternative approaches to the problem of estimation and inference.
Partitioning the cross-sectional sample into regimes based on ECRS levels is one approach to modelling heterogeneity. Thus, mixture models provide a natural way to deal with the heterogeneity in data that may come from two or more sub-populations.
Finite mixtures of multiple regression models and their statistical inference are discussed in detail in Frühwirth-Schnatter (2006) and in this section we will briefly review the regression modelling based on normal errors. A finite mixture regression model assumes that a set of G regression models characterized by the parameters $\left(\gamma_1,\sigma^2_{u1}\right),\cdots,\left(\gamma_G,\sigma^2_{uG}\right)$ exists, and that for each observation pair $\left(y(s_i,t),\mathbf{Z}(s_i,t)\right)$ a hidden random indicator R_i chooses one among these models to generate $y(s_i,t)$

$$y(s_i,t)=\mathbf{Z}(s_i,t)'\gamma_{R_i}+u(s_i,t),\quad u(s_i,t)\sim N(0,\sigma^2_{u,R_i}). \tag{2}$$

The parameters $(\gamma_j, \sigma^2_{uj})$'s, $j = 1, \ldots, G$, that need to be estimated from the data, vary among a set of G possible values with probabilities $p_1, \ldots, p_G$, with the constraint $\sum p_j = 1$. In other words, assuming a normal distribution on the perturbation u, the conditional distribution of $y(\cdot)$ given $\mathbf{Z}(\cdot)$ is a mixture of normal distributions

$$y(\cdot)|\mathbf{Z}(\cdot) \sim p_1 N\big(\mathbf{Z}(\cdot)'\gamma_1, \sigma^2_{u1}\big) + \cdots + p_G N\big(\mathbf{Z}(\cdot)'\gamma_G, \sigma^2_{uG}\big).$$

Equation (2) will be denoted henceforth as model M3.

A different approach to modelling heterogeneity relies on separate models estimated using a sub-sample of the data based on observations nearby each observation. These models are often based on the estimated parameters to detect systematic variation in the relationship being examined over space. For this reason, we propose a locally linear regression model described in the next section. This model, denoted as M4, is capable of producing inferences regarding our concept of local convergence.

2.2. *Local regressions*

The motivation for using local regressions is that if spatial dependence arises due to inadequately modeled spatial heterogeneity, these models can potentially eliminate this problem. McMillen and McDonald (1997) introduced a form of spatial non-parametric locally linear weighted regression (LWR) which Brundson *et al.* (1996) term geographically weighted regression. In the following we extend the LWR approach by discussing a Bayesian model which accommodates spatial autocorrelation with the introduction of a CAR prior on site-specific regression coefficients (see Section 3.1 for further details).

Let $\mathbf{y}_i = \big[y(s_i, 1), \ldots, y(s_i, T)\big]'$ and $\mathbf{Y} = \big[\mathbf{y}'_1, \ldots, \mathbf{y}'_n\big]'$ be the $(T, 1)$ site specific and $(nT, 1)$ complete response vectors, respectively. Also, let $\mathbf{Z}_i = \big[\mathbf{Z}(s_i, 1); \ldots; \mathbf{Z}(s_i, T)\big]$, and $\mathbf{Z} = \big[\mathbf{Z}_1; \ldots; \mathbf{Z}_n\big]$, be the $(T, q+2)$ site specific and $(nT, q+2)$ complete regression matrices, respectively. Finally, let $\mathbf{U} = \big[\mathbf{u}'_1, \ldots, \mathbf{u}'_n\big]'$ be the $(nT, 1)$ vector of error terms.

To account for heterogeneity, we produce estimates using the following locally linear regression model

$$\mathbf{A}_i\mathbf{Y} = \mathbf{A}_i Z\gamma_i + \mathbf{A}_i\mathbf{U}, \qquad i = 1, \ldots, n \tag{3}$$

where $\mathbf{A}_i$ is a (K, nT) indicator matrix which selects the neighbors of observation i. For each country i, model M4 thus results in a regression model based only on the response and explanatory variables corresponding to the sub-sample of the K—nearest neighbours. We also note that equation (3) produces locally linear estimates that can vary systematically as the sub-sample size increases towards the global estimates one would achieve using the entire sample. Hence, the model allows a systematic assessment of the mapping between the locally linear estimates accommodating heterogeneity in steady states and convergence speeds and estimates based on the global sample reflecting homogeneity.

3. Inference and computations

Full probabilistic inference for the model parameters is facilitated by adapting standard Markov chain Monte Carlo (MCMC) algorithms for regression linear models to our model formulations.

3.1. Prior specification

For the general regression model the inferential difficulties are not particular to a specific prior modeling, but rather appear as a generic issue. We have thus chosen for our application standard conjugate priors, that is, independent normal priors on the regression coefficients γ, and inverse gamma priors on the variances σ_u^2. An exception is model M2 which requires a prior specification for the spatial parameter ρ. Following Sain and Cressie (2007), we specify its prior to be proportional to $\exp\left\{-\rho^2/\varsigma^2\right\}$, where the prior parameter ς is specified by choosing small values, since the prior for ρ is concentrated around zero.

For model M3, we define a Dirichlet prior on the weight vector $(p_1, \ldots, p_G)$, setting $D_G(1, \ldots, 1)$. Furthermore, when the degree of heterogeneity in the data is unknown, it is unreasonable to postulate a fixed number G of components in the mixtures, and G must be estimated as well. From a Bayesian point of view, this implies using a prior distribution on G. While this complex estimation problem has been addressed for standard mixtures through reversible jump techniques (Richardson and Green, 1997), we opt for the alternative proposed by Stephens (2000) based on birth-and-death processes. Both approaches are equally valid on theoretical grounds (since they both satisfy the required detailed balance conditions) and our choice is based solely on practical considerations. The birth-and-death process avoids the specification of well-calibrated moves, such as the splits-and-merges of Richardson and Green (1997) and the corresponding computation of the Jacobians of the one-to-one transforms, plus it allows for easier changes of both prior distributions and parameterization. In this study, the estimation of the number of components in the mixtures is obtained by choosing a Poisson, $P(\lambda)$, distribution as a prior distribution on G and, for simplicity's sake, for this prior we have chosen $\lambda = 2$ which favouring a small number of components.

The specification of the priors concludes with model M4. In this case, since we have site-specific regression parameters, a spatial CAR prior on $\gamma_i, i = 1, \ldots, n$ is also considered in the model parametrization.

3.2. Posterior inference

Posterior inference for the model regression parameters is facilitated by the use of Gibbs sampler algorithms. In general, the full conditional distributions are "standard" multivariate Gaussian or Gamma distributions. Exceptions are for the spatial parameter ρ, which is sampled using a Metropolis-Hastings step, G and p_i for which we refer to Frühwirth-Schnatter (2006) and Hurn *et al.* (2003).

3.3. Model Comparison: the Deviance Information Criterion

When different plausible models can be envisaged, model comparison represents an important inferential issue. Several Bayesian selection methods have been developed for comparing different models and, for a discussion, see for example Banerjee *et al.* (2004). Here, we consider the Deviance Information Criterion (DIC, Spiegelhalter *et al.* (2002))

which represents a generalization of the AIC based on the posterior distribution of the deviance, $\mathscr{D}(\Theta) = -2\log L(\Theta \mid y)$, where Θ is a parameter vector containing all unknowns in a model and $L(\Theta \mid y)$ the corresponding likelihood. Hence, the DIC is defined as

$$DIC = \overline{\mathscr{D}} + p_{\mathscr{D}} = 2\overline{\mathscr{D}} - \mathscr{D}(\overline{\Theta}),$$

where $\overline{\mathscr{D}}$ defines the posterior expectation of the deviance, $\overline{\mathscr{D}} = E_{\Theta|y}(\mathscr{D})$, and $p_{\mathscr{D}}$ is the effective number of parameters, $p_{\mathscr{D}} = \overline{\mathscr{D}} - \mathscr{D}(\overline{\Theta})$ and here $\overline{\Theta}$ represents the posterior mean of the parameters.

Computing DIC via MCMC is almost trivial. In fact, it is easily calculated from an MCMC output by taking the sample mean of the simulated values of $\mathscr{D}(\Theta)$, minus the plug-in estimate of the deviance using the sample means of the simulated values of Θ.

4. β-CONVERGENCE ANALYSIS OF EUROPEAN COUNTRIES

The data used in this study refer to an annual panel data set obtained from Eurostat's databases which covers a period of fifteen years (1995-2010). The study considers 25 of the 27 EU member States for which comparable indicators are available. Cyprus and Malta have thus been excluded from the list. The EU countries included in the analysis are: Belgium, Bulgaria, Czech Republic, Denmark, Germany, Estonia, Ireland, Greece, Spain, France, Italy, Latvia, Lithuania, Luxembourg, Hungary, Netherlands, Austria, Poland, Portugal, Romania, Slovenia, Slovakia, Finland, Sweden, United Kingdom. However, together with these States we also consider: Norway, Switzerland and Croatia.

β—convergence models are estimated in the pursuit of identifying the tendency towards convergence of renewable energy source consumption among European countries. The variable of interest is represented by the annual growth rate of the indicator measuring the contribution of electricity produced from renewable energy sources to national electricity. This structural variable, developed for measuring the contribution to the 2020 objectives on renewable sources for the EU 27, is calculated as the ratio between the electricity produced from renewable energy sources and the gross national electricity consumption for a given calendar year. Electricity produced from renewable energy sources comprises the electricity generation from hydro plants, wind, solar, geothermal and electricity from biomass/wastes. Gross national electricity production includes the total gross national electricity generation from all fuels (including auto-production) plus electricity imports, minus exports.

Some explanatory variables are also included in the model as proxies for different steady states. This favours a conditional convergence analyses which, unlike the absolute β—convergence approach, accepts the idea that the steady-state of the countries could be different. Both from theoretical and empirical perspectives, the following set of covariates are considered: the energy intensity of economy, the per capita GDP measured in purchasing power standards and the total population. All these explanatory variables are included in the model as growth rates. The energy intensity of economy is defined as the ratio between the gross inland consumption of energy and the gross domestic product (GDP). It measures the energy consumption of an economy and its overall energy efficiency. It is supposed to negatively affect a country's growth in renewable energy source path. A full explanation of the explanatory variables is given in Table 1.

TABLE 1
Description of explanatory variables.

Variable name	Variable description
Energy intensity of the economy	This indicator is the ratio between the gross inland consumption of energy and the GDP for a given calendar year. It measures the energy consumption of an economy and its overall energy efficiency.
GPD in purchasing power standards	GDP per capita in PPS is expressed in relation to the European Union (EU-27) average set equal to 100. PPS eliminates the differences in price levels between countries allowing meaningful volume comparisons of GDP between countries.
Total population	The inhabitants of a given area on 1 January of the year in question (or, in some cases, on 31 December of the previous year). The population is based on data from the most recent census adjusted by the components of population change produced since the last census, or based on population registers.

Before discussing the results from the estimated convergence models, it is useful to note that considering the 28 countries, the share of energy from renewable energy sources in gross final energy consumption has increased from 12.93% in 1995 to 19.94% in 2010. In 2010 the highest share is observed in Norway (89.96%), followed by Austria (61.41%) Switzerland (54.81%) and Sweden (54.48%). On the opposite end of the spectrum we find Luxembourg (3.09%), United Kingdom (6.71%), Belgium (6.79%) and Poland (6.97%). Looking at the national mandatory targets (Directive 2009/28/EC) for share of energy from renewable source, we also find that some countries, such as Romania, Estonia and Sweden, are very close to accomplish their 2020 national targets. Conversely, United Kingdom, Ireland, Netherlands and France are 10 percentage points below their fixed goals. In 2010 the Italian share of energy from renewable sources is around 10%. Since the planned target for 2020 is 17% in final energy consumption, it follows that Italy is about 7 percentage points below the target.

In Figure 1 and 2 we show quantile maps of the variables, $\ln \tilde{y}(s_i, 1995)$ and $\ln\left(\frac{\tilde{y}(s_i,2010)}{\tilde{y}(s_i,1995)}\right)$, for the 28 countries. Especially the map at 1995 shows that observations at nearby sites tend to be very similar; a comparison of the two maps also shows that in accordance with the neoclassical growth theory, the lower is the ECRS at time 1995, the higher tends to be its variation over the observational period.

For each fitted model, the MCMC algorithm is run for $50,000$ iterations. Posterior inference is based on the last $40,000$ draws using every 10th member of the chain to avoid autocorrelation within the sampled values. Several MCMC *diagnostics* could be used to test the convergence of the chains (see, for example, Geweke, 1992; Gilks *et al.*, 1996; Spiegelhalter *et al.*, 2002; Jones *et al.*, 2006). In our case, convergence of the chains of the model is monitored visually through trace plots as well as using the R-statistic of Gelman (1996) on four chains starting from very different values. A comparison of the different fitted models is performed through the Deviance Information Criterion (DIC)

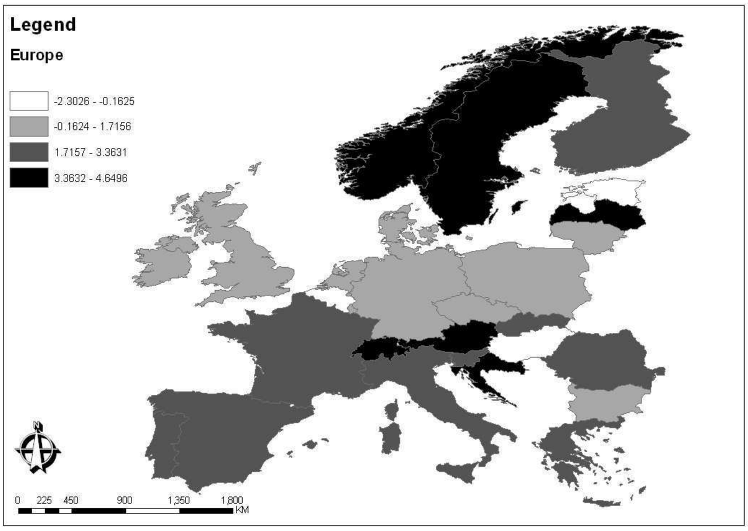

Figure 1 – Quantile maps of the 28 European countries: spatial distribution of $\ln \tilde{y}(s_i, 1995)$.

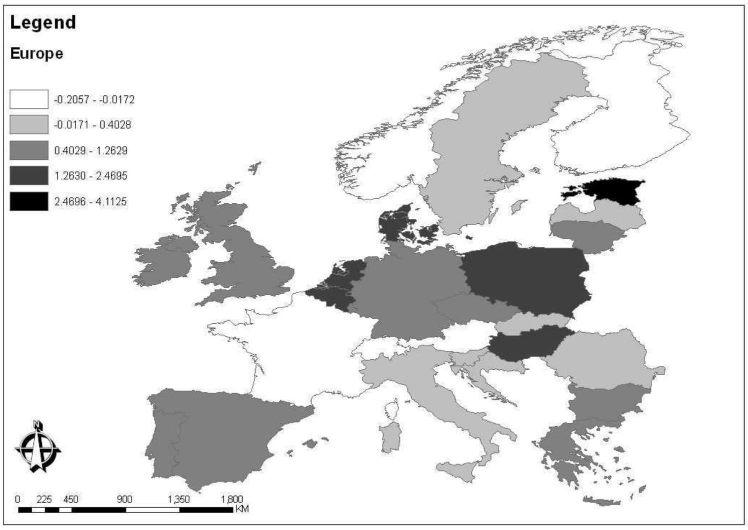

Figure 2 – Quantile maps of the 28 European countries: spatial distribution of $\ln\left(\frac{\tilde{y}(s_i, 2010)}{\tilde{y}(s_i, 1995)}\right)$.

TABLE 2
Posterior summary of the regression parameters of models M1 and M2. In brackets we show the 2.5 *and* 97.5 *percentiles used for defining the* 95% *credible interval limits.*

Models	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\eta}_1$	$\hat{\eta}_2$	$\hat{\eta}_3$
M1	0.176	-0.042	-0.865	-1.432	-1.219
	(0.134, 0.218)	(-0.055, -0.029)	(-1.327, -0.404)	(-1.979, -0.868)	(-2.206, 0.725)
M2	0.188	-0.039	-0.755	-1.352	-1.185
	(0.133, 0.215)	(-0.056, -0.028)	(-1.327, -0.404)	(-1.975, -0.865)	(-2.205, 0.726)

as described in Section 3.3.

For all the estimated models, the 95% credibility intervals suggest that, apart from the parameter linked to the total population, all other parameters can be considered as non-zero. All the β's are statistically significant and, consistently with the convergence hypothesis, they are negative suggesting that the growth rate of ECRS over the years is negatively correlated with its initial volume. The posterior mean of β also indicates the rate at which countries approach their steady-state and hence the speed of convergence. Based on this value, the *half-life*, which is the time span necessary for current disparities to be halved, can be computed as $t = \ln(2)/\beta$.

Estimation results from models M1 and M2 are shown in Table 2. For model M1 we have, $\hat{\beta} = -0.042$, which suggests a *half-life* of 16.5 years. Estimating model M2, which allows for the modelling of the spatial correlation in the error terms, gives $\hat{\rho} = 0.086$ (0.015, 0.112) (95% credible interval limits in brackets) and $\hat{\beta} = -0.039$ which implies a *half-life* of almost 18 years. As expected, the convergence speed estimates for models which do not include spatial effects appear to be higher than in cases where spatial spillovers are explicitly modeled.

In Table 3 we also show estimation results from model M3 which provides the possibility of modelling spatial heterogeneity. The analysis suggests the presence of two ($G = 2$) components in the mixtures with probabilities $p_1 = 0.385$ and $p_2 = 0.615$. The estimation of a larger number of groups is characterised by numerical problems and leads to an unstable computational procedure. For the first group, consisting of 8 EU countries (Bulgaria, Estonia, Greece, Hungary, Ireland, Lithuania, Portugal and Spain), we have $\hat{\beta}_1 = -0.051$ which implies a *half-life* of 13.5 years. The estimated group membership probabilities associated to each country are also very close to one. Apart from Luxembourg and Czech Republic, for which the estimated group membership probabilities are, respectively, 0.57 and 0.52, the group membership probabilities of all other countries belonging to the second group are also large and, in general, greater than 0.92. For this second group, we have $\hat{\beta}_2 = -0.033$ which implies a much slower convergence rate. Note that this is a distinct feature of the Italian energy sector given that Italy belongs to this second group.

Comparing the models M1-M3, we have found that M3 performs best in terms of fitting providing the smallest values for the deviance (-298.20) and DIC (-284.33). The values of the DIC are bigger for M1 (-160.11) and M2 (-187.64), and suggest that model M2,

TABLE 3
Posterior summary of the regression parameters of model M3. In brackets we show the 2.5 *and* 97.5 *percentiles used for defining the* 95% *credible interval limits.*

	Model M3					
Groups	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\eta}_1$	$\hat{\eta}_2$	$\hat{\eta}_3$	p_i
I	0.225 (0.135, 0.322)	-0.051 (-0.084, -0.020)	-1.281 (-2.535, -0.058)	-2.209 (-3.482, -0.972)	-3.006 (-7.476, 1.651)	0.385 (0.165, 0.524)
II	0.128 (0.085, 0.172)	-0.033 (-0.047, -0.020)	-0.725 (-1.135, -0.333)	-0.851 (-1.385, - 0.309)	1.654 (-1.743, 5.024)	0.615 (0.476, 0.834)

which allows for the introduction of the spatial interaction parameter ρ, can provide a slightly better fit.
Along with a global convergence coefficient, site-specific estimates of the β's, which represent the contribution of the single countries to the convergence process, can also be obtained through model M4. Notice that since the model choice criteria based on the deviance imply the use of the same data for all the models considered, model M4 is not compared with the others through the Deviance Information Criterion. Instead, the DIC is used here as a criterion to choose the number, K, of nearest neighbors to be used in the parametrization of model M4.
Assuming heteroscedastic errors in equation (3), the DIC criterion suggests that $K = 6$ provides an adequate amount of sample data on which to base estimates of the model parameters. For this choice, the estimated local parameters vary between -0.058 and -0.023. All the estimated β's are consistent with the convergence hypotheses. They are all negative and thus, none of them suggests divergence of a country from surrounding areas.
A spatial map of their estimated values, shown in Figure 3, suggests that there is a group of countries which tend to behave differently from the others. In average, the convergence parameter β of these countries is close to -0.048 and, quite interesting, most of them belong to the first cluster identified by the mixed regression model M3 discussed above.

5. DISCUSSION

The topic of convergence is at the heart of a wide-ranging debate in the growth literature. As a consequence, the empirical literature on convergence is large and rapidly expanding. However, the studies in regional convergence have not followed a uniform path. Several distinct types of convergence have been suggested in literature, each being analysed with different methods. The form of convergence we have considered in this paper has been referred to as β-convergence. The Solow-Swan model has extensively been used to test this form of convergence and to include spatial effects in the analysis, CAR models have been used here to extend the basic formulation. On the other hand, the temporal sparsity of the data has prevented an easy modelling of any temporal correlation structure underlying the data. The modeling of such temporal correlation will be a topic for future work.
We have found that the estimated speed of convergence is rather low when absolute

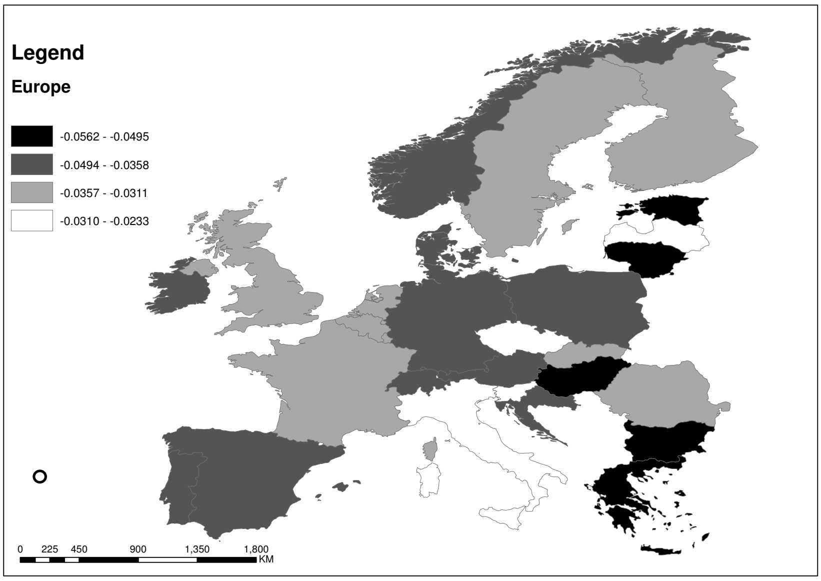

Figure 3 – Map of the site-specific convergence parameters, β_i, for the 28 European countries.

convergence models are used and higher when using conditional convergence models. The inclusion of spatial effects is in general highly relevant and tends to reduce the estimated speed of the global convergence process, while highlighting that the speed of convergence is higher for countries with low ECRS levels.

To account for spatial heterogeneity, local linear regression models as well as mixture regression models were considered in the analysis. Depending on the degree of heterogeneity among possible subpopulations, the data can display a unimodal, bimodal or even a multimodal distribution. When the membership of subpopulations is unknown, these types of data are typically analyzed by a mixture model with a finite number of component distributions. In our case we have shown that mixture regression models provide a flexible parametric framework for statistical modelling and analysis of ECRS levels. The construction, prior modelling, estimation and evaluation of mixture distributions in a Bayesian paradigm is well documented in literature and for known results we have referred to Frühwirth-Schnatter (2006), Hurn *et al.* (2003), Stephens (2000) and Marin and Robert (2007).

Local linear regression models often rely on the estimated parameters to detect systematic variation in the relationship being examined over space. One advantage of this model is that a mapping of the parameter estimates allows for an examination of the sensitivity of inferences with regard to the choice of the sub-sample size. Examining the sequence of estimates for varying sub-sample sizes and check whether inferences would differ as the sub-sample size varies represents an important issue for these type of models. Results from our model M4 suggest that the convergence parameter β can vary substantially among countries. Estimates from the model based on four and five nearest neighbors are nearly identical to those reported here based on the six nearest neighbors.

These results are also supported by the use of the DIC that does not change dramatically for K equal to 4, 5 and 6. However, we have noticed that estimation results change substantially by using a first-order contiguity matrix. The choice of the neighbourhood structure thus remains an important issue for this kind of models. To this purpose, connections to graphical models (Whittaker, 1990) could provide useful insight into modeling and parameter estimation, including the uncertainty over the nature of $\mathbf{W}$ (Crespo Cuaresma and Feldkircher, 2013). This topic is currently being considered for future research.
The local linear regression model has highlighted a group of countries for which the speed of convergence is quite high. It is interesting to note that most of these countries characterize one of the two clusters estimated by the mixture regression model M3.
Finally, we conclude by noticing that, in general, does not exist a consensus theoretical framework to guide empirical works on growth, and existing models do not completely specify the variables of primary interest as well as those that should be held constant while conducting statistical inference. Thus, it was beyond the scope of this paper to discuss the possible fundamental factors of variation in the ECRS growth. However, data limitations remain a serious problem in the European context. Reliable data allowing consistent regional comparisons are scarce. Hence, not surprisingly, the results obtained with the β-convergence strongly depend on the specification adopted (absolute or conditional convergence, variables included as covariates, incorporation of spatial effects) and on the observations (period and countries considered). It is therefore difficult to draw a single general conclusion from the vast panel of existing studies.

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SUMMARY

Spatial Growth Regressions for the convergence analysis of renewable energy consumption in Europe

In recent years there has been an increasing awareness on problems related to the economic growth and on the conditions under which some socio-economic variables measured on European countries tend to converge over time towards a common level. This paper is concerned with the use of energy from renewable sources and considers the extent to which EU countries meet the binding commitment to reach a fifth of energy consumption from renewable sources by 2020. By discussing empirical results on the economic growth pattern of 28 countries in the period 1995-2010, we make use of several spatial growth regression models. We show that the proposed models are able to capture the complexity of the phenomenon including the possibility of estimating site-specific convergence parameters and the identification of convergence clubs.