SEMI-PARAMETRIC SPATIAL AUTO-COVARIANCE MODELS OF REGIONAL GROWTH IN EUROPE

Roberto BASILE[*] **et Bernard GRESS**[**]

Abstract - *We propose a semi-parametric spatial auto-covariance specification of the growth model to examine the growth behaviour of European regions in the period 1988-2000. This specification simultaneously takes account of the problems of non-linearities and spatial dependence. We obtain two main results. First, there is a trade-off between the identification of non-linearities and the estimation of the spatial parameters. Second, even when controlling for spatial dependence, there is evidence of strong non-linearity between regional growth and its predictors. In particular, the relation between growth and unemployment is negative but not globally linear: regions with an unemployment rate over a certain threshold appear to be 'locked' within an 'underdevelopment trap' with similar lower growth rates.*

Key-words **-** REGIONAL CONVERGENCE, EUROPE, SPATIAL ECONOMETRICS, MULTIPLE REGIMES, SEMI-PARAMETRIC MODELS.

JEL Classification : O40, O52, R11, C13, C14.

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[*] ISAE, Institute for Studies and Economic Analysis and University of Macerata, Piazza dell'Indipendenza, 4, 00191 Rome (Italy). r.basile@isae.it.

[**] Department of Economics, University of California Riverside, Riverside, California, CA, 92507, USA.

1. INTRODUCTION

The bulk of studies on European regional convergence refer to the basic Barro-Solow regression model (Magrini, 2004). This model explains cross-sectional differences in per-capita GDP growth rates through a set of variables that includes initial per-capita GDP levels and other control variables that 'maintain' constant the steady state of each economy. Here, we claim that this approach can be criticized from at least two different points of view.

First, it does not consider the presence of spatial dependence. As is well known, regional data cannot be regarded as independently generated because of the presence of similarities among neighbouring regions (Anselin, 1988; Anselin and Bera, 1998). As a consequence, the standard estimation procedures employed in many empirical studies can be invalid and lead to serious biases and inefficiencies in the estimates of the convergence rate. Recently, some empirical studies have used the spatial econometric framework for testing regional convergence in Europe (Le Gallo et al., 2003).

Second, most of empirical studies on European regional growth have implicitly assumed that all regions obey a common linear specification, disregarding the possibility of non-linearities (or multiple regimes) in growth behaviour. The issue of multiple regimes has instead been raised in some cross-country growth studies (Durlauf and Johnson, 1995; Liu and Stengos, 1999) that make use of non-parametric or semi-parametric approaches to model the regression function. In these studies, however, spatial dependence did not represent a critical issue. Here, we claim that especially in cross-region studies, multiple regimes and spatial dependence must be simultaneously considered[1].

The aim of this paper is to reconcile these two critical points. Thus, we propose a semi-parametric spatial-covariance model of regional growth behaviour in Europe, which simultaneously takes account of the problems of non-linearities and of spatial dependence. In Section 2, we discuss the two critical points. In Section 3, we propose a new semi-parametric spatial auto-covariance specification of the growth regression model. In Section 4, we report the results of the econometric analysis of regional convergence based on a data set of 161 EU-15 regions for the period 1988-2000. Some conclusions are reported in Section 5.

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[1] Even in cross-country growth studies spatial autocorrelation can be very important, as suggested, for example, by Moreno and Trehan (1997).

2. SPATIAL DEPENDENCE AND MULTIPLE REGIMES IN CONDITIONAL β-CONVERGENCE STUDIES

2.1. Conditional β-convergence

The notion of conditional β-convergence arises from the neoclassical growth model based on the assumptions of (among others) a convex production function with constant return to scale, a closed economic system, and labour market clearing (Barro and Sala-i-Martin, 1995). The basic idea is that the long-run economic growth can be described by a steady state balanced path. In the short run, economies (countries or regions) that have not yet reached their steady state show higher growth than economies closer to the steady state. If steady states are similar between economies, convergence is unconditional; when the steady states differ, convergence becomes conditional upon control variables such as physical and human capital and population growth (Mankiw et al., 1992). The conditional β-convergence hypothesis is therefore tested by simply estimating the following model:

$$(1) \qquad g = \phi X + \varepsilon$$

where g is the per-capita GDP growth rate, X is a vector of variables including the initial per-capita GDP as well as the control variables, ε is a vector of normal i.i.d. error term. The unknown vector of parameters ϕ is generally estimated by OLS. Conditional convergence is said to be favoured by the data if the estimate of the parameter on the initial per-capita GDP is negative and statistically significant.

Here we claim that this approach can be criticized from at least two different points of view: first, the closed-economy hypothesis; and second, the hypothesis of a common linear specification without multiple regimes[2].

2.2. The open-economy assumption and spatial dependence models

While the closed-economy assumption is defensible for countries, it is too strong for regions within a country, where barriers to trade and factor flow are considerably weaker. To understand the implications for convergence of the introduction of the openness hypothesis, we can consider the role of factor mobility, trade relations and technological diffusion. In a nutshell, the speed of

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[2] Other problems with cross-sectional regression analysis, raised by many researchers, but not discussed in the present paper, refer to i) Galton's fallacy; ii) endogeneity problems; iii) unobserved heterogeneity; and iv) temporal instability of the convergence process. In order to control for these problems, alternative approaches, such as panel data methods, time series methods, SUR methods, and the distribution dynamics approach are used (Durlauf and Quah, 1999; Temple, 1999; Islam, 2003).

convergence to the steady-state predicted in the open-economy version of the neoclassical growth model as well as in the technological diffusion models is faster than in the closed-economy version of the neoclassical growth model.

A direct way to empirically test the prediction of a higher speed of convergence once openness is allowed would consist in including interregional flows of labour, capital and technology in the growth regression model. It is quite clear, however, that such kind of direct approach is limited by data availability, especially with regards to capital and technology flows. Some attempts have been made to test the role of migration flows on convergence, but the results of these studies suggest that migration plays a small part in the explanation of convergence (Barro and Sala-i-Martin, 1995).

An indirect way to control for the effects of interregional flows (or spatial interaction effects) on growth and convergence is through spatial dependence models[3]. A first way to take spatial dependence into account is the so-called spatial autoregressive model or SAR (Anselin and Bera, 1998), where a spatial lag of the dependent variable is included on the right hand side of the statistical model. If W is a row-standardized matrix of spatial weights describing the structure and intensity of spatial effects, equation (1) is re-specified as:

$$(2) \qquad g = \phi X + \rho W g + \varepsilon \qquad\qquad \varepsilon \sim N\left(0, \sigma_{\varepsilon}^{2} I\right)$$

where ρ is the parameter associated to the spatially lagged dependent variable Wg that captures the spatial interaction effect indicating the degree to which the growth rate of per-capita GDP in one region is determined by the growth rates of its neighbouring regions, after conditioning on the effect of X. The error term is again assumed normally distributed and independently of X and of Wg, under the assumption that all spatial dependence effects are captured by the lagged term.

An alternative way to incorporate the spatial effects is via the spatial error model or SEM (Anselin and Bera, 1998). This leaves unchanged the systematic component and models the error term in (1) as a Markovian random field, for instance by assuming that:

$$(3) \qquad \varepsilon = \lambda W \varepsilon + u$$

The error term u is assumed to be normally distributed, with mean zero and constant variance (σ^2), independently of X and randomly drawn.

[3] The inclusion of spatial dependence in β-convergence models can be justified by other arguments besides controlling for the effects of interregional flows. Generally speaking, spatial autocorrelation can act as a proxy to all the omitted variables (even different from factor migration, technology spill-over, trade and backward and forward linkages) that are correlated over space and catch their effects.

2.3. Multiple regimes in economic growth

The bulk of cross-section growth studies has implicitly assumed that all economies (countries or regions) obey a common linear specification, disregarding the possibility of non-linearities in growth behaviour. Notable exception are Durlauf and Johnson (1995) and Liu and Stengos (1999).

The concept of multiple regimes is often based on endogenous growth models characterized by the possibility of multiple, locally stable, steady-state equilibria as in Azariadis and Drazen (1990)[4]. The basic idea underlying these models is that the level of per-capita GDP to which each economy converges depends on some initial conditions and that, according to these characteristics, some economies converge to one level and others converge to another.

A common specification that is used to test this hypothesis considers a modification of the systematic component in model (1) that takes the form:

$$(4) \quad \begin{array}{lll} g = \phi_1 X + \varepsilon_1 & \text{if} & X < x \\ g = \phi_2 X + \varepsilon_2 & \text{if} & X \geq x \end{array}$$

where x is a threshold that determines whether a region belongs to the first or second regime. The same adjustment can be applied to the systematic component in the (parametric) spatial auto-covariance models.

The hypothesis of linearity has been abandoned in some cross region studies in Europe by assuming the presence of "threshold effects" automatically produced by the membership of each region to one group or another, according to "exogenous" criteria, such as geographical criteria (e.g. Centre versus Periphery) (Basile et al., 2003; Baumont et al., 2003)[5]. However, a problem with multiple regime analysis is that the threshold level cannot be (and must not be) exogenously imposed. Although Basile et al. (2003) and Baumont et al. (2003) use statistical methods to identify the Core and the Periphery, their definitions of regional groups remain 'exogenous' with respect to the growth behaviour.

In order to identify economies whose growth behaviour obeys a common statistical model, we must allow the data to determine the location of the different regimes. Following Liu and Stengos (1999), we argue that a non-parametric specification of the cross-region growth regression function goes a long away in addressing the issue of multiple regimes:

$$(5) \quad g = m(X) + \varepsilon$$

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[4] Multiple and locally steady states can also emerge in neoclassical growth models, as suggested by Galor (1996).

[5] In particular, Baumont *et al.* (2003) use exploratory spatial data analysis.

With this specification we solve the problem of non-linearities, but we still face that of spatial dependence. Thus, our task consists in combining non-parametric estimators with the usual parametric estimators of the spatial parameters. In section 3 we present a semi-parametric extension of the SAR and SEM models which simultaneously accounts for spatial dependence and non-linearities.

3. SEMI-PARAMETRIC SPATIAL AUTO-COVARIANCE MODELS OF GROWTH BEHAVIOUR

Semi-parametric spatial auto-covariance models extend the spatial auto-regression model (SAR) and the spatial error model (SEM) to allow for flexible functional forms in the exogenous variables.

For the semi-parametric spatial autocorrelation model (SP-SAR), an unknown functional form, *m(X)*, replaces the linear form ϕX of the parametric spatial autocorrelation (SAR) model shown in (2):

$$(6) \qquad g = m(X) + \rho W g + \varepsilon \qquad \varepsilon \sim N\left(0, \sigma_\varepsilon^2 I\right)$$

Just as with the parametric spatial model, there are no closed-form solutions for ρ in terms of the observations, and all estimates of these parameters must be obtained by numerical maximization of the log-likelihood function. Anselin (1988, p. 78) derives the (concentrated) log-likelihood function in (7):

$$(7) \qquad \ell(g \mid \rho) = -\frac{N}{2}\ln[2\pi] - \frac{N}{2}\ln\left[\frac{1}{N} g' A' M A g\right] - \frac{N}{2} + \ln[\|A\|]$$

where $A = (I - \rho W)$ and M is the usual 'residual maker matrix', $\left(M = I - X(X'X)^{-1}X'\right)$. Maximizing this is equivalent to minimizing:

$$(8) \qquad \min_{\{\rho\}}\left\{\frac{g'A'MAg}{|A|^{2/N}}\right\}$$

This is also equivalent to (9), where $\hat{\rho}$ can be found from minimizing:

$$(9) \qquad \min_{\{\rho\}}\left\{\frac{e_0'e_0 - 2\rho e_0'e_L + \rho^2 e_L'e_L}{\sum_i \ln(1 - \rho\omega_i)}\right\}$$

which utilizes the residuals from the OLS regressions of g on $X(= e_0)$ and g_L on $X(= e_L)$, where $g_L = Wg$. This time-saving simplification utilizes the eigenvalues of the contiguity matrix, $\omega_i = Eigenvalues[W]$ (see Ord, 1975). In the parametric spatial model, the estimator $\hat{\rho}$ is then substituted into the solution for ϕ to yield $\hat{\phi}$:

$$\begin{aligned} \hat{\phi}_{ML} &= (X'X)^{-1}X'Ag \\ &= (X'X)^{-1}X'g - \rho(X'X)^{-1}X'g_L \\ &= b - \rho b_L \end{aligned} \tag{10}$$

where $b = (X'X)^{-1}X'g$ and $b_L = (X'X)^{-1}X'g_L$.

Estimators for *m(X)* and ρ within the semi-parametric model use a similar procedure, minimizing (9), except using the residuals e_0 and e_L from non-parametric regressions of g on *X*, and g_L on *X*, respectively, and then running a final non-parametric regression of the 'de-spatialized' g values on *X*:

$$g - \hat{\rho}g_L = g^{**} = m(X) + \varepsilon = z\delta^*(X) + \varepsilon \tag{11}$$

where $z_i = \begin{pmatrix} 1 \\ x_i \end{pmatrix}$ and $\delta(x) = \begin{pmatrix} \alpha(x) \\ \beta(x) \end{pmatrix}$. The unknown functional form *m(X)* is then estimated with the non-parametric estimator $z\delta(X)$.

The semi-parametric spatial errors model (SP-SEM) follows a similar approach. The log-likelihood function of the SEM is maximized, using the residuals from the parametric regression of *g* on *X*, as in equation (12):

$$\ell = -\frac{1}{2}\ln|\Omega(\lambda)| - \frac{N}{2}\ln 2\pi\sigma^2 - \frac{(g - X\phi)'\,\Omega(\lambda)^{-1}(g - X\phi)}{2\sigma^2} \tag{12}$$

where the covariance matrix of the errors Ω is a function of the error's spatial parameter λ:

$$E[\varepsilon\varepsilon'] = \sigma^2\left((I_N - \lambda W)(I_N - \lambda W)'\right)^{-1} = \sigma^2\left(AA'\right)^{-1} = \Omega(\lambda)^{-1}$$

where *A* is defined as $I_N - \lambda W$.

In the SP-SEM, however, residuals from the local-linear, non-parametric regression of g on *X* are used, weighted with a local estimator of the covariance matrix, which provides equation (13):

$$(13) \quad \ell(\lambda, \sigma^2, \delta) = -\frac{1}{2}\ln\left|\Omega^*\right| - \frac{N}{2}\ln 2\pi\sigma^2 - \frac{1}{2\sigma^2}(g - Z\delta(x))'\,\Omega^{*-1}(g - Z\delta(x))$$

where we will now use the non-parametric conditional-mean estimator:

$$g_i = z_i\delta(x) + \varepsilon_i$$

where: $z_i = [1 \quad x_i]$ and $\delta(x) = \begin{pmatrix} \alpha(x) \\ \beta(x) \end{pmatrix}$

or, in matrix notation: $g = Z\delta(x) + \varepsilon$. To get the Local-Linear GLS estimator for δ, we minimize:

$$(g - Z\delta(x))'\,\Omega^{*-1}(g - Z\delta(x)) = \varepsilon'\Omega^{*-1}\varepsilon$$

with respect to *δ(ξ)* which gives us:

$$\hat{\delta}_{GLS}(x) = \left(Z'\Omega^{*-1}Z\right)^{-1} Z'\Omega^{*-1}g$$

where $\Omega*-1$ is the local covariance matrix is the global covariance matrix, weighted for closer values according to the kernel function:

$$\Omega^{*-1} \equiv \sqrt{K(x)}\Omega^{-1}\sqrt{K(x)}$$

and where *K(x)* is the diagonal matrix of local weights $k\left(\frac{x_i - x}{h}\right)$.

This is the local (linear) GLS (LLGLS) estimator as in Henderson and Ullah (2004). For more details, see also Gress (2004). Estimation of λ is performed numerically from a concentrated form of (13) which is used, in turn, to create $\hat{\Omega}$ and thus $\hat{\delta}_{GLS}(x)$.

4. EMPIRICAL RESULTS

4.1. Data and variables

Our empirical analysis is based on the dataset compiled by Cambridge Econometrics on total value added (computed at 1995 prices and converted in the PPP of the same year), population, employment and physical capital investments and on data collected by Eurostat-Regio on unemployment rates and on levels of education for the European NUTS-2 regions. The data set consists of 161 regions[6].

The dependent variable is the growth rate of the per-capita value added of the region (g), while the predictors introduced are: 1) ln(Y/L), initial per-capita gross value added (GVA); 2) ln(sk), average proportion of real physical investments to real value added; 3) ln(sh), average percentage of working age population that is in secondary school (data available only for the period 1993-1997); 4) n, average growth rate of the population; 5) u, average unemployment rate; and 6) ln(agr), percentage of workers employed in agriculture. All of the variables are scaled to the EU-15 average. The model is estimated for the period 1988-2000, which covers the first two programming periods of EU Structural Funds.

Variables 1)-4) are those included in the Mankiw et al. (1992) specification of the growth regression, which is derived from a human capital-augmented version of the neoclassical growth model. This model predicts that the average growth rate of per-capita income is a positive function of human and physical capital and a negative function of population change and of the initial level of per-capita value-added.

The inclusion of the unemployment rate, u, on the right hand side of the model is suggested by some recent endogenous growth models which relax the assumption of labour market clearing underlying the neoclassical growth model, while maintaining the prediction of conditional β-convergence[7]. In particular, some authors explore the possible effects of unemployment upon human capital accumulation, and thus on economic growth (see, e.g., Aghion and Howitt, 1994; Podrecca, 1998; Mauro and Carmeci, 2003). Higher employment (lower unemployment) implies higher human capital accumulation if this comes mainly through learning-by-doing on the job (Mauro and Carmeci, 2003). In the aggregate, unemployment can influence negatively the accumulation of human capital in the economy by preventing the work experience from being acquired. In steady-state the growth rate is a positive function of the efficiency of the scholastic system and of the employment rate. Hence, economies with higher equilibrium unemployment rates exhibit lower long-run growth rates.

Finally, we include the share of agricultural employment in total employment, ln(agr), as explanatory variable in the regression equation, in order to

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[6] For various reasons, we have excluded some NUTS-2 regions from the dataset. Specifically, for the region of Bruxelles our dataset indicates *extremely* low levels of agricultural employment. Other regions, namely Berlin, Luxemburg, Ireland, Sterea Ellada and Flevoland resulted to be strong outliers in growth behaviour.

[7] The assumption of labour market clearing underlying the neoclassical growth model appears too strong if we think about the huge labour market imperfections and the huge regional unemployment disparities in Europe.

control for the effect of the regional economic structure. Indeed, the income dynamics may be influenced by the structural changes generating labour force shifts from low-productivity sectors (agriculture) to high-productivity sectors (industry and services) (Paci and Pigliaru, 1999).

4.2. A trade-off between the smoothness of the estimated function and the estimation of the spatial parameter

Of central importance to the estimation of semi-parametric models is the choice of the smoothing parameter or window width. Usually the window-width is chosen among three ways: as a function of the variance of the data, minimizing the asymptotic integrated mean-squared error of the data, or minimizing the out-of-sample mean-squared error via cross-validation methods. Cross-validation techniques are considered most robust and in the spirit of non-parametrics as they make no assumptions on underlying distributions. However it is most difficult to apply in a spatial context. In addition to being computationally expensive due to the high dimensions of models we are running, with the addition of spatial data, out-of-sample estimation of mean squared errors (for example) has potential theoretical issues as the structure of the spatial contiguity matrix must change whenever any observation is dropped. Furthermore, for the SP-SAR model, there are three separate cross-validations that must be performed, the first for g on X to determine e_0, the second for g_L on X, determining e_L, and a third cross-validation for the de-spatialized regression of g** on X, as in equation (11), estimating the fits and slopes of the final model. Likewise, the SP-SEM model also has three regressions of which each would require a separate cross-validation. However, as the method we use to estimate the spatial parameter in our SP-SEM does not maximize the likelihood function directly, there are no such regressions to be run for it.

Table 1: Alternative Optimal Window-Widths

Variable	Silverman Rule-of-Thumb	Sheather-Jones	Cross-Validated (SP-SAR)		
			h*1	h*2	h*3
ln(Y/L)	0.178	0.072	0.32	0.29	0.16
ln(sk)	0.151	0.018	0.09	0.17	0.10
N	0.421	0.155	0.92	0.97	1.00
ln(sh)	0.108	0.052	0.11	0.07	0.10
ln(agr)	0.694	0.323	0.94	1.62	0.50
U	0.323	0.114	0.67	0.83	0.50

Table (1) shows the optimal window-widths as calculated by these three alternate methods. The Silverman 'Rule-of-Thumb' is based on Silverman (1986) which assumes that the underlying conditional distribution is Normal. The Sheather-Jones (1991) method minimizes AMISE ('asymptotic mean integrated square error') with non-parametric estimates of the (conditional) density, also assuming a Normal underlying distribution. It is evident that the values determined by the Sheather-Jones method are of the order of half the magnitude of those determined by the Silverman Rule-of-Thumb. The cross-validated values are generally larger than the Silverman values, implying greater linearity, except for the variable ln(*sk*) where it is smaller.

In fact, for both the SP-SEM and the SP-SAR models, the results from the unit scaling of the Silverman window-widths are over-fit, and we feel that a scaling of the Silverman window-widths by a factor between 2 or 3 gives the most reasonable results in both cases. We base this conclusion on a number of considerations. Firstly, the unit scaling yields an R^2 of 0.904 for the SP-SEM and 0.915 for the SP-SAR model. Fits of this magnitude should be suspected of being over-fit. Secondly, the residuals from both regressions become much more *normally* distributed, with lower levels of skewness and lower Jarque-Bera statistics, when the scaling of the window-widths is between 2 and 3. Finally, the estimates of the spatial autocorrelation parameters become more stable around these values, while the estimates of the conditional means and slopes still retain a good degree of flexibility, suggesting that the regressions are not yet entirely linear and still able to capture some of the underlying non-linear functional forms.

This last point relates to the trade-off between the smoothness of the estimated function and the estimation of the spatial parameter. As the estimated function is forced to be smoother (with a larger window-width) the estimated spatial parameter becomes larger as it 'absorbs' the non-linearity of the true function (see Tables 2 and 3). As the unit scaling of the Silverman window-widths was already felt to be seriously over-fit, it can immediately be concluded that the Sheather-Jones optimal window-widths, at less than half the size of the Silverman values, are far too small to be seriously considered.

Table 2: SP-SAR – smoothness vs. spatial dependence (p-values in parenthesis)

	H* = c × hSilverman = c × {0.178, 0.151, 0.421, 0.694, 0.323, 0.108}					
	C					
	0.5	1.0	1.5	2.0	2.5	3.0
$\hat{\rho}$	0.293 (0.000)	0.373 (0.000)	0.301 (0.000)	0.264 (0.000)	0.2615 (0.000)	0.278 (0.000)
σ^2	0.002 (0.000)	0.054 (0.000)	0.112 (0.000)	0.152 (0.000)	0.183 (0.000)	0.207 (0.000)
R^2	0.996	0.900	0.794	0.723	0.666	0.622
$R^2_{Adjusted}$	0.996	0.897	0.788	0.714	0.655	0.610
Log-Likelihood	82.670	-172.724	-230.056	-253.562	-268.609	-278.669
Normality (Jarque-Bera)	5465.0	183.679	45.309	12.776	3.410	0.958
Moran I-Statistic	4.513	1.400	0.780	0.851	0.891	0.892

Table 3: SP-SEM: smoothness vs. spatial dependence (p-values in parenthesis)

	H* = c × hSilverman = c × {0.178, 0.151, 0.421, 0.694, 0.323, 0.108}					
	C					
	0.5	1.0	1.5	2.0	2.5	3.0
$\hat{\lambda}$	0.005 (0.382)	0.134 (0.178)	0.210 (0.034)	0.2490 (0.010)	0.282 (0.003)	0.3170 (0.001)
σ^2	0.002 (0.000)	0.060 (0.000)	0.119 (0.000)	0.147 (0.000)	0.183 (0.000)	0.204 (0.000)
R^2	0.996	0.889	0.778	0.721	0.647	0.596
$R^2_{Adjusted}$	0.996	0.884	0.770	0.711	0.633	0.600
Log-Likelihood	262.7	0.551	-53.545	-74.953	-88.671	-98.058
Normality (Jarque-Bera)	5560.8	161.7	26.852	9.702	1.386	0.055
Moran I-Statistic	5.320	4.232	4.157	4.336	4.798	5.248

Both of the semi-parametric models exhibit smaller estimates of the spatial correlation parameters than their parametric counterparts. While the SEM model estimates the spatial error autocorrelation to be 0.38, the SP-SEM model yields an estimated autocorrelation of only 0.27 (at the chosen window-width scaling of 2.5). Likewise, the spatial autoregressive model estimates the spatial autoregressive parameter to be 0.38, whereas the SP-SAR model returns an estimate of 0.26 at the chosen scaling. Again, we hypothesize that this is due to a 'spill-over' between the non-linearity of the underlying functions and the estimation of the spatial parameters. By forcing the data to conform to the parametric form, the residual non-linearities are assumed into the spatial parameter. Thus we feel that the estimates of the spatial parameters in the semi-parametric models are more reliable than their parametric counterparts.

4.3. Estimation of the conditional means: loess fits

Because the SP-SEM and SP-SAR models are estimating a flexible hypersurface in 7 dimensions for the conditional means of the regression, it is only possible to visualize a projection of this surface in 2- or 3- dimensions. Doing such a projection, however, collapses the remaining dimensions, forcing whatever curvature there may be to appear as random fluctuations. So, while the surface estimated is in fact smooth in 7 dimensions, it appears noisy and random when only a few dimensions of it are shown at a time. To facilitate an easier visual analysis of our results, therefore, we estimated additive semi-parametric models, which provide 2-dimension plots for each explicative variable.

For some variables, namely ln(*agr*), ln(*sk*) and *n*, the relationship between them and growth rates appeared graphically to be approximately linear and a F-test suggested that the null hypothesis of linearity could not be rejected. Thus, we took the shares of agriculture employment, the average proportion of real physical investments to real value added, and the growth rate of population entering the model linearly, whereas we allowed the education level, ln(*sh*), the unemployment rate, u, and the initial level of per capita GVA, ln(*Y*/*L*), to make up the nonlinear components of the models, except in the case of the SP-SEM where ln(*Y*/*L*) entered the model linearly.

We used the local regression techniques to estimate the nonlinear functions. Specifically, we used the loess locally weighted regression smoother (Cleveland and Devlin, 1988), which is a particular specification of the local polynomial regression model. The loess uses a nearest-neighbour bandwidth selection which allows the value of h to change as a function of *X*. A parameter, called span, allows identifying the k nearest neighbours of *X*, i.e. the *k* elements *Xi* closest to *X*. Thus, the span defines the size of the neighbourhood in terms of a proportion of the sample size: i.e. $k \approx span \times n$. As with fixed bandwidth selection, as the span parameter gets large, the local fit approaches a global parametric fit. Another advantage of loess estimator is that it incorporates robustness in the fitting procedure, to down-weight outlying observations. This is implemented by the use of bisquare weights in an iterative smoothing procedure[8].

When the variable enter the model non-parametrically, the loess regression is always specified as a 1-degree polynomial with the span ranging from 0.4 to 0.75 (each local neighbourhood contains 40-75% of the observations), except for *m*(ln(*sk*)) for which a span equal to 1 has been chosen. The choice of the polynomial degree and of the span is always based on the distribution of the error term. The two parameters are chosen at the level indicated by an orthogonal deviance of residuals with respect to the fitted values (Hastie and Tibshirani, 1990).

These estimates are presented graphically in Figures 1-7 in the Annex, both for the SP-SEM and the SP-SAR models[9], alongside 95% point-wise confidence bands, $\hat{m}(X) \pm 2\hat{\sigma}[\hat{m}(X)]$. The vertical axis reports the scale of per-capita growth rates; the horizontal axis reports the scale of each independent variable.

[8] Local linear regression estimates previously discussed were based on a fixed bandwidth selection: the value of *h* is constant for each point *x* in the design space. A constant bandwidth was employed in order to easily show the important trade-off between smoothness and spatial dependence.

[9] The estimated spatial dependence parameter for the *SP-SAR* and *SP-SEM* are respectively equal to 0.26 and 0.28.

It is immediately apparent that both semi-parametric models yield strikingly similar estimations of the conditional means, with some exceptions. Moreover, it seems clear that the flexible functional form reveals a good deal more information about the structure of the economic relationship than do their parametric brothers.

The SP-SAR graphical output in Figure 1 allows us to identify non-linearities between the initial levels of per-capita GVA, ln(Y/L), and subsequent regional growth rates. Figure 1 suggests that European regions do not converge to a common 'conditional' steady state. According to this figure, we could say that there are at least three growth regimes or convergence clubs. There is convergence first amongst 'poor' regions, i.e. those with a level of per-capita GVA lower than 75% of the European average (i.e. lower than -0.3 in log terms); second amongst regions with a level of per-capita GVA between 90% and 110% of the European average (i.e. between -0.1 and 0.1 in log terms); and finally amongst 'rich' regions with a level of per-capita GVA higher than 135% of the European average (i.e. higher than 0.3 in log terms).

However, when the SP-SEM is applied, the fit for ln(Y/L) becomes linear, thus revealing that European regions do follow a global convergence path, i.e. all regions converge to the same steady state. As is well known, the spatial error model can be interpreted in terms of random shocks diffusion. In the presence of significant spatial error dependence, the random shocks to a specific region are propagated throughout the Union. The introduction of a positive shock to the error for a specific region has obviously the largest relative impact (in terms of growth rate) on this region. However, there is also a spatial propagation of this shock to the other regions. The magnitude of the shock spill-over dampens as the focus moves away from the immediate neighbouring regions (Le Gallo et al., 2003). Evidently, this diffusion process also helps to relax, rather than to exacerbate, the multiple-regime structure of the convergence process in Europe.

The relation between per-capita GVA growth rates and unemployment rates (u) is negative: higher labour quality (lower unemployment) induces higher growth rates, while lower labour quality (higher unemployment) induces lower growth rates (Figure 2). The decreasing path, however, is far from being globally linear. As the unemployment rate increases, the per-capita GVA growth rate initially drops steeply, before nearly levelling out at higher levels of unemployment. Thus, above a certain threshold, European regions show similar lower per-capita growth rates. We can say that, over a certain rate of unemployment, regions appear to be 'locked' in an 'underdevelopment trap', regardless of whether they have 10%, 20% or 30% unemployment rates (respectively, 1.0, 2.0 and 3.0 in the figure).

The effect of the secondary school enrolment ratio (ln(sh)) on per-capita GVA growth rates is far from being 'monotonic'. Figure 3 clearly shows that there is a positive relationship between the two variables until the level of education exceeds a certain threshold. But, once this threshold is exceeded, there is a negative effect of education on growth.

The per-capita GVA growth rate declines 'linearly' with the share of agriculture employment (ln(*agr*)) in both semi-parametric models (Figure 4). Thus, the existence of a structural effect on GVA growth rates seems substantially confirmed by the estimates.

The relationship between per-capita GVA growth rates and physical capital investments (ln(*sk*)) is also linear and positive, both in SP-SAR and in SP-SEM model fitting, as one may expect from theory (Figure 5). Finally, Figure 6 graphically shows the lack of any relation between per-capita GVA growth and population growth rates (*n*).

Figures 2 and 3 have clearly shown that the secondary school enrolment ratio and the unemployment rate have both a significant and opposite effects on growth. As discussed above, these two variables capture different forms of accumulation of human capital. Indeed, human capital may be accumulated through both schooling investments and work experience. Thus, higher unemployment rates imply lower human capital accumulation when this comes through learning-by-doing on the job (Mauro and Carmeci, 2003). Now, we propose an alternative specification of the semi-parametric regression model with a local linear fit over the combination of ln(*sh*) and *u*. This specification allows us to assess whether each variable matters, or whether only one of them is important. The graphical output is reported in a 3-dimensional perspective plot with the two initial conditions on the two horizontal axes and the smoothed impact on growth plotted on the vertical axis (Figure 7). We can clearly see that our model predicts higher growth rates for regions with a rate of unemployment lower than the EU average, whatever the level of schooling investment. In particular, when relatively low levels of formal education are accompanied by relatively low level of unemployment, the estimated growth rate is above the EU average.

5. CONCLUSIONS

In this paper we have addressed the issue of the most appropriate regression model to describe and interpret the experience of regional growth and convergence in the EU over the 1988-2000 period, which embraces the two first programming periods of European Structural Funds. In particular, we have claimed that the traditional linear approach to the analysis of conditional convergence cannot automatically be applied at the regional scale in Europe, since it does not take into account the presence of spatial dependence and of non-linearity (or multiple regimes) in the growth behaviour. Thus, we have proposed a semi-parametric spatial auto-covariance growth model which simultaneously takes account of the problems of non-linearities and spatial dependence.

First, the econometric results suggest that there is a trade-off between the identification of non-linearities (i.e. the choice of the window-width) and the estimation of the spatial parameters. With a larger window-width the estimated spatial parameter becomes larger as it 'absorbs' the non-linearity of the true function. This also implies that the semi-parametric models always exhibit smaller estimates of the spatial correlation parameters than their parametric counterparts: by forcing the data to conform to the parametric form, the residual non-linearities are assumed into the spatial parameter. Thus we feel that the estimates of the spatial parameters in the semi-parametric models are more reliable than their parametric counterparts.

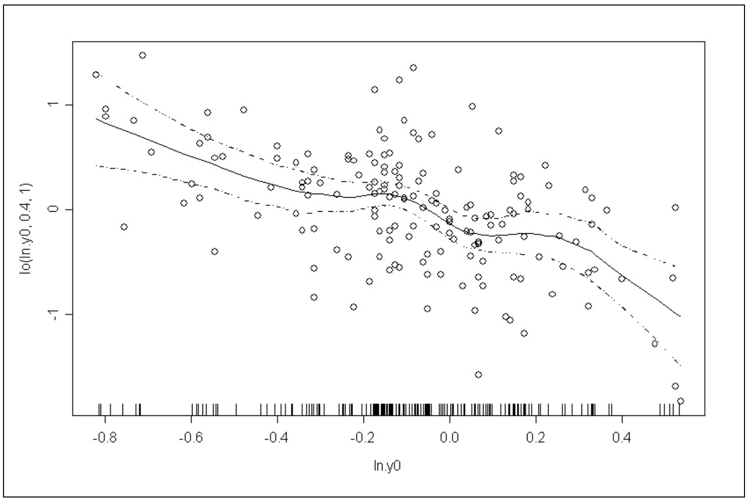
Secondly, the results of these semi-parametric spatial auto-covariance models confirm that assuming a common regime (or linear) approach is misleading: non-linearities are important in regional growth in Europe even when the spatial dependence is controlled for. In particular, our data reveal the existence of a non-linear negative relationship between growth and initial conditions in the case of the semi-parametric spatial autocorrelation model (SP-SAR). This means that European regions do not converge to a common 'conditional' steady state: there are in different growth regimes or convergence clubs. When the growth model is estimated through the semi-parametric spatial error model (SP-SEM) the relation between initial per-capita value added levels and the subsequent growth rates become linear.

There are also important non-linear effects of the two variables that capture the process of human capital accumulation (the secondary school enrolment ratio and the unemployment rate) on growth rates. In particular, lower unemployment rates (higher human capital accumulation when this comes through learning-by-doing on the job) induce higher growth rates, while higher unemployment rates (lower human capital accumulation) induce lower growth rates. However, above a certain threshold in the unemployment rate, European regions appear to be 'locked' within an 'underdevelopment path', showing similar lower per-capita value-added growth rates, whatever the level of schooling investment. This evidence suggests that only a combined policy aimed both at increasing the education level and at reducing the unemployment rate in backward regions can foster human capital formation in Europe and eventually boost these regions out of an underdevelopment trap.

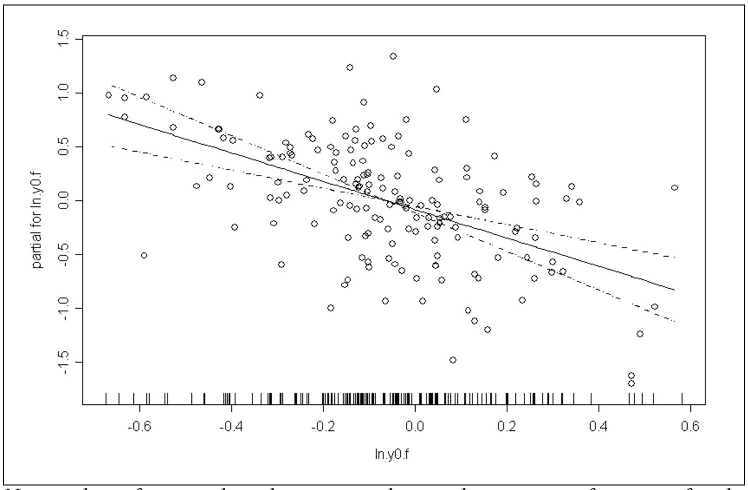
ANNEX

Figure 1: Semi-parametric Spatial auto-covariance models. Loess fits. GDP growth versus ln(Y/L)

Fit SP-SAR; ρ=0.26; span=0.4; polynomial degree=1



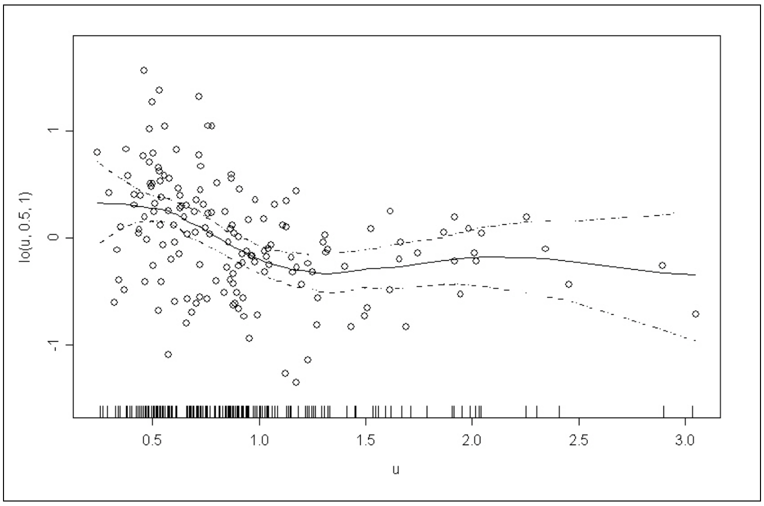
Fit SP-SEM; λ=0.28. Linear specification



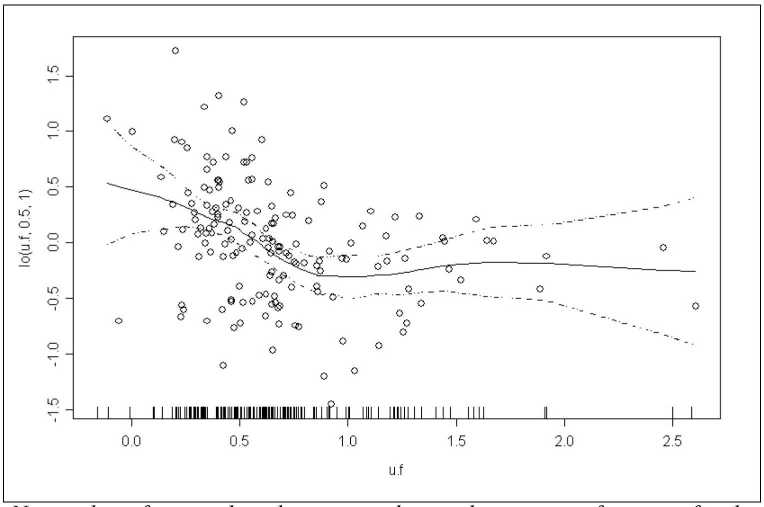
Notes: these figures plots the estimated partial-regression functions for the additive SP-SAR and SP-SEM regressions of per-capita income growth on the initial level of per-capita income. The points in the graphs represent "partial residuals" for each predictor. The broken lines give pointwise 95% confidence bands.

Figure 2: Semi-parametric Spatial auto-covariance models. Loess fits. GDP growth versus u

Fit SP-SAR; ρ=0.26; span=0.5; polynomial degree=1



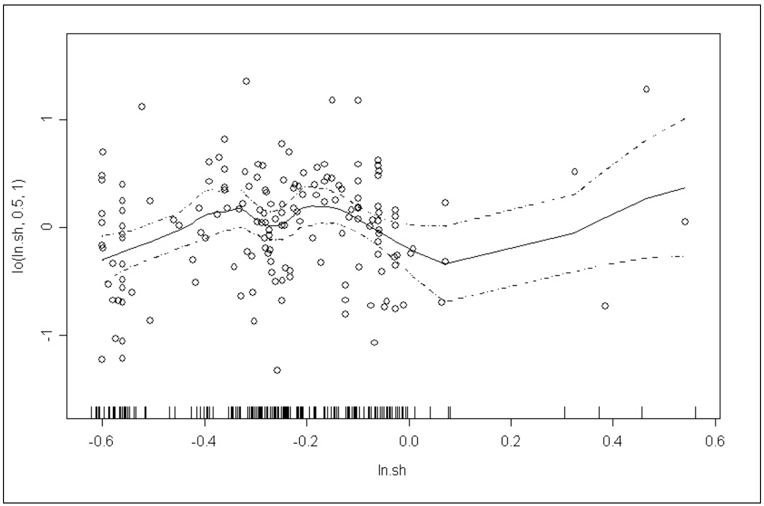
Fit SP-SEM; λ=0.28; span=0.5; polynomial degree=1



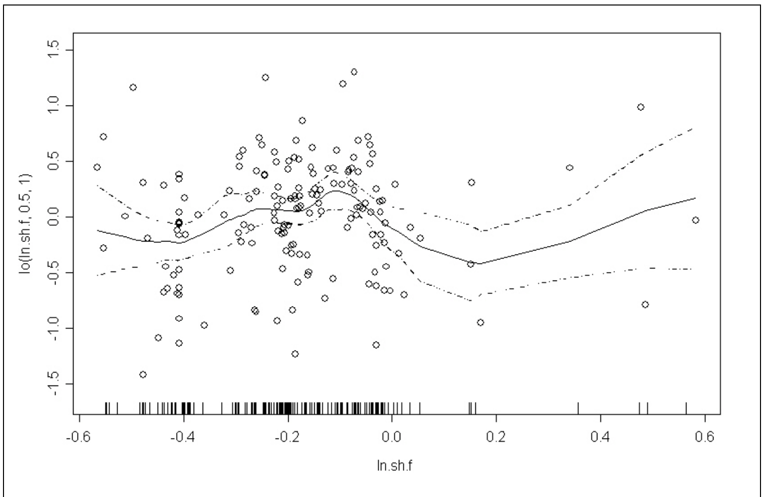
Notes: these figures plots the estimated partial-regression functions for the additive SP-SAR and SP-SEM regressions of per-capita income growth on the unemployment rate. The points in the graphs represent "partial residuals" for each predictor. The broken lines give pointwise 95% confidence bands.

Figure 3: Semi-parametric Spatial auto-covariance models. Loess fits. GDP growth versus ln(sh)

Fit SP-SAR; ρ=0.26; span=0.5; polynomial degree=1



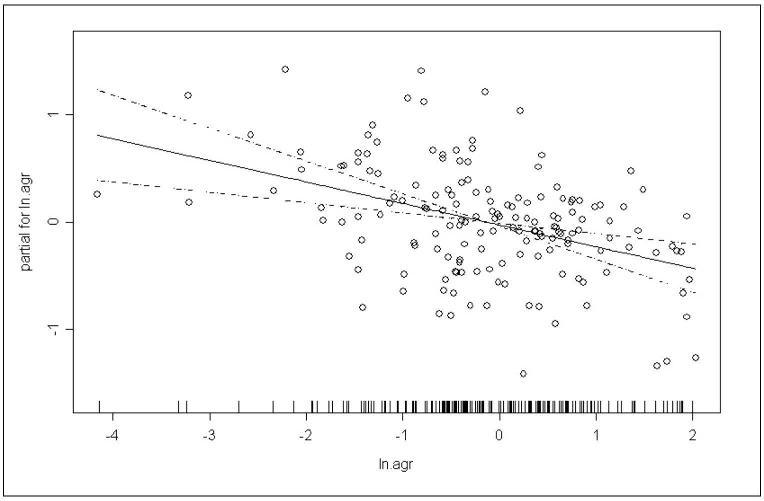
Fit SP-SEM; λ=0.28; span=0.5; polynomial degree=1



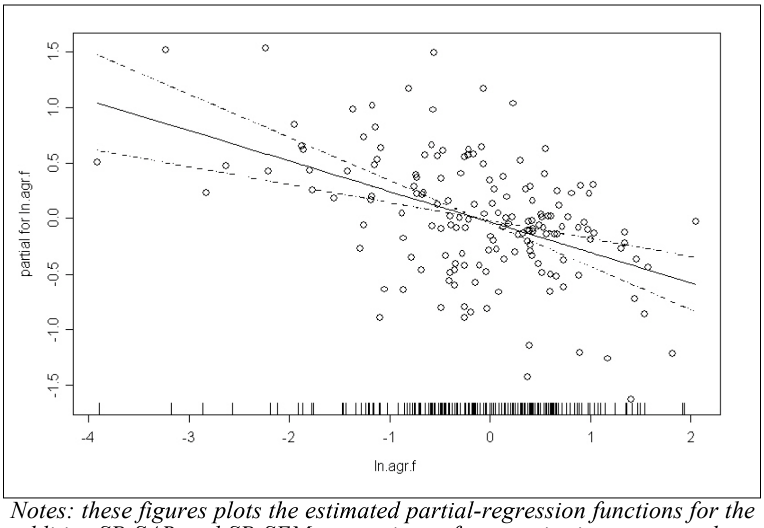
Notes: these figures plots the estimated partial-regression functions for the additive SP-SAR and SP-SEM regressions of per-capita income growth on levels of education. The points in the graphs represent "partial residuals" for each predictor. The broken lines give pointwise 95% confidence bands.

Figure 4: Semi-parametric Spatial auto-covariance models. Loess fits. GDP growth versus ln(agr)

Fit SP-SAR; ρ=0.26. Linear specification



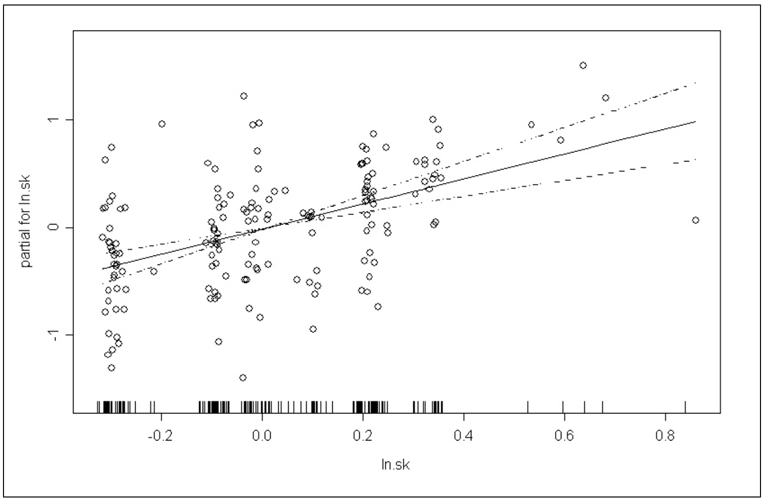
Fit SP-SEM; λ=0.28. Linear specification



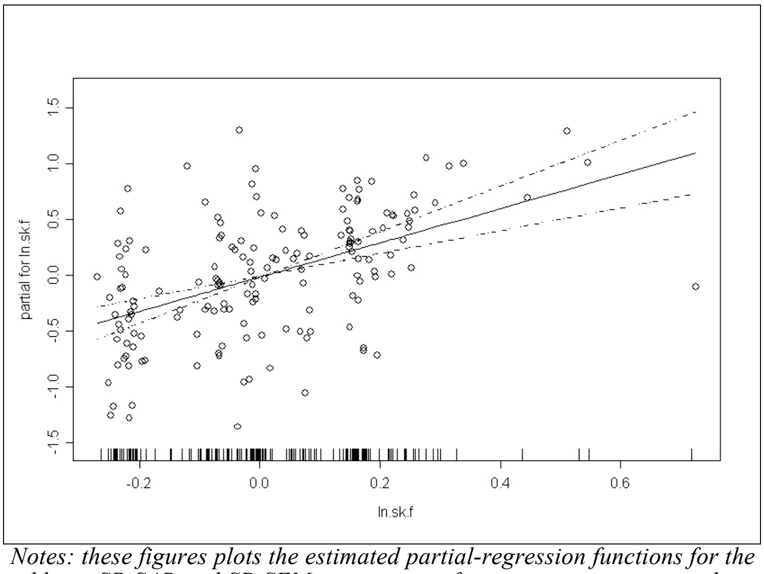
Notes: these figures plots the estimated partial-regression functions for the additive SP-SAR and SP-SEM regressions of per-capita income growth on the share of agriculture employment. The points in the graphs represent "partial residuals" for each predictor. The broken lines give pointwise 95% confidence bands.

Figure 5: Semi-parametric Spatial auto-covariance models. Loess fits. GDP growth versus ln(sk)

Fit SP-SAR; ρ=0.26. Linear specification



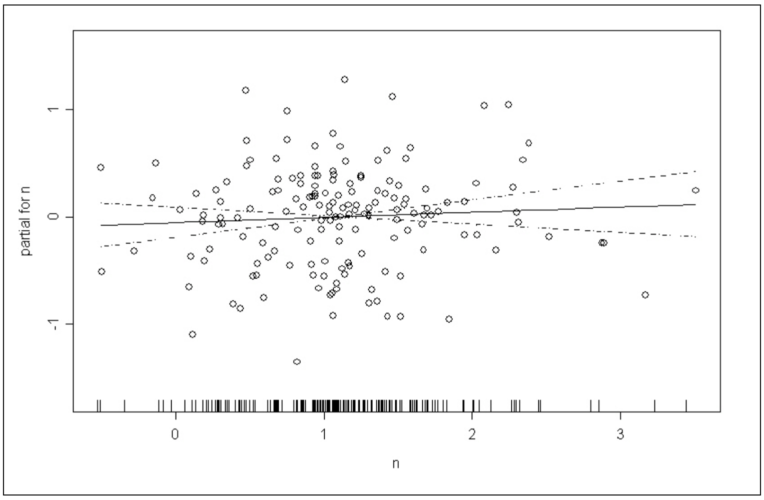
Fit SP-SEM; λ=0.28. Linear specification



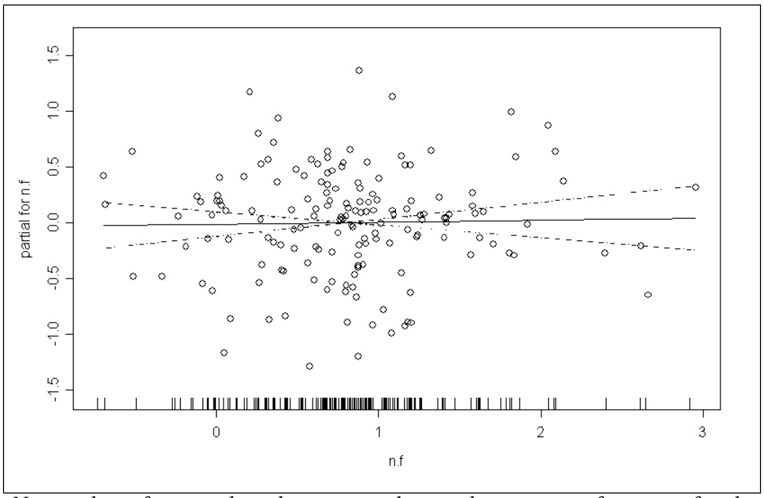
Notes: these figures plots the estimated partial-regression functions for the additive SP-SAR and SP-SEM regressions of per-capita income growth on physical capital investments. The points in the graphs represent "partial residuals" for each predictor. The broken lines give pointwise 95% confidence bands.

Figure 6: Semi-parametric Spatial auto-covariance models. Loess fits. GDP growth versus n

Fit SP-SAR; ρ=0.26. Linear specification



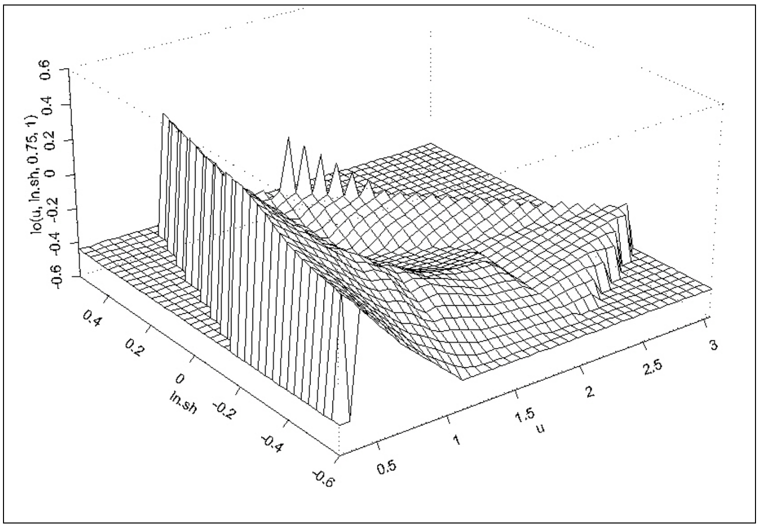
Fit SP-SEM; λ=0.28. Linear specification



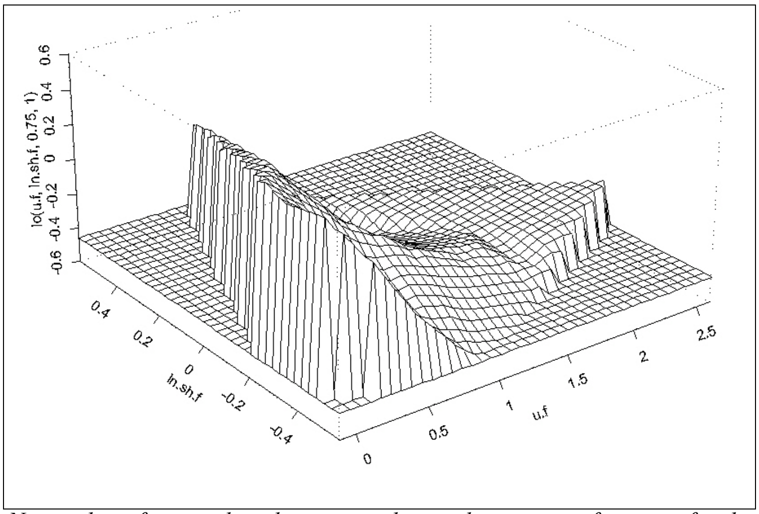
Notes: these figures plots the estimated partial-regression functions for the additive SP-SAR and SP-SEM regressions of per-capita income growth on population growth rates. The points in the graphs represent "partial residuals" for each predictor. The broken lines give pointwise 95% confidence bands.

Figure 7: Semi-parametric Spatial auto-covariance models. Loess fits. GDP growth versus the interaction between ln(sh) and u

Fit SP-SAR; ρ=0.26; span=0.75; polynomial degree=1



Fit SP-SEM; λ=0.28; span=0.75; polynomial degree=1



Notes: these figures plots the estimated partial-regression functions for the additive SP-SAR and SP-SEM regressions of per-capita income growth on the interaction between levels of education and unemployment rates.

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MODÉLISATION SEMI-PARAMÉTRIQUE DE L'AUTOVARIANCE SPATIALE APPLIQUÉE A LA CROISSANCE RÉGIONALE EN EUROPE

Résumé - *Nous proposons une spécification spatiale et semi-paramétrique de l'autocovariance dans un modèle de croissance afin d'examiner la dynamique des régions européennes durant la période 1988-2000. Cette spécification prend en compte simultanément les problèmes de non-linéarité et de dépendance spatiale. Nous obtenons deux résultats principaux. Premièrement, un arbitrage entre l'identification de la non-linéarité et l'estimation des paramètres spatiaux est nécessaire. Deuxièmement, même si la dépendance spatiale est contrôlée, il existe une forte non-linéarité entre la croissance régionale et ses prédicteurs. En particulier, la relation entre la croissance et le chômage est négative mais globalement non-linéaire : les régions associées à un taux de chômage supérieur à une certaine valeur critique apparaissent bloquées dans une trappe de sous-développement avec des taux de croissance similaires et faibles.*

MODELIZACIÓN SEMI PARAMÉTRICA DE LA AUTOVARIANTE ESPACIAL APLICADA AL CRECIMIENTO REGIONAL EN EUROPA

Resumen - *Proponemos una especificación espacial y semi-paramétrica de la autocovariante en un modelo de crecimiento para examinar la dinámica de las regiones europeas durante el périodo 1988-2000. Esta especificación toma en cuenta a la vez los problemas de que no es lineal y los de dependencia espacial. Obtenemos dos resultados. El primero es que es necesario un arbitraje entre la identificación de lo que no es lineal y la estimación de los parametros espaciales. El segundo es que, aunque sea controlada la dependencia espacial, existe, la relacion entre el crecimiento regional y sus predicadores no es nada lineal. En particular, la relación entre el crecimiento y el paro es negativa pero globalmente no es lineal. Las regiones que tienen una tasa de paro superior a un cierto valor crítico aparecen como bloqueadas en una situacion de subdesarrollo con tasas de crecimiento parecidas y bajas.*