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Convergence of European regions: a reappraisal

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Abstract

We provide a reappraisal of income convergence across European regions over the period 1990-2005 by using a semiparametric partially linear model to approximate the relationship between the average growth rate of GDP per capita and the initial GDP per capita. Estimation results point out both country heterogeneity and non-linearity in the convergence process. Only low income regions converge while there is little evidence of convergence for higher income regions.

Key words: Convergence; Heterogeneity; Non-linearity; Kernel estimator; European regions

JEL classification: C14; O40; O52

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1 Introduction

The convergence hypothesis according to which poorer economies catch up wealthier ones is considered as a way to differentiate exogenous growth models from endogenous ones. On the one hand, the finding of convergence is generally regarded as evidence of exogenous growth which assumes that persistent growth is primarily driven by exogenous technological process and considers capital accumulation as the source of (conditional) convergence. On the other hand, endogenous growth models emphasize a broad measure of physical and human capital as the main engines of growth, and consider differences in technology levels across economies as the source of convergence or lack thereof. Starting with Baumol (1986), these hypotheses have been extensively tested empirically. Most of the theoretical and empirical works are summarized in, e.g., Barro and Sala-í-Martin (1995), Temple (1999), de la Fuente (1997, 2002), and Islam (2003).

This study aims to provide a reappraisal of the convergence process at the regional level in the European Union. We emphasize the notions of heterogeneity and non-linearity, meaning that the convergence/divergence differs according to initial regional conditions.[1] We estimate the relationship between the average growth rate of GDP per capita and the initial GDP per capita using a semiparametric partially linear model. Country dummies are included in the model to capture the influence of national characteristics on regional growth and to describe differences in the steady-state at the country level. As noticed by Armstrong (1995), when country dummies are included, the convergence coefficient measures the within-country convergence. We also provide a measure to control for regressor endogeneity in order to establish robust estimations.

We use a recent dataset to investigate the convergence between 159 European regions over the 1990-2005 period. This dataset, which includes only population and GDP, is more extensive than datasets previously collected for European regions. Other socio-economic factors that could also be considered are not easily collected at regional level (investment, research and development, communication, human capital, trade, transaction costs, etc.).

The main results that emerge from this study are the following. First, the shape of the nonparametric relationship indicates non-linearity in growth, and suggests that only weak income regions converge. Secondly, we also find that regional convergence does depend on national contexts. Finally, compared to the parametric approximation, test results suggest that the semiparametric model gives a sufficiently accurate description of the data.

The findings of the paper may lead to some policy implications for regional development. Indeed, the European economic integration is traditionally thought of as being beneficial for

[1] This encompasses the usual concept of conditional convergence.

its regions in terms of higher allocation efficiency and increased competition in particular for low income regions. However, there is a risk that economic integration in Europe will be followed by an increase in inequalities between regions. Important efforts were put forth to increase the attractiveness of these regions, in particular by developing public infrastructure. As a result, the question of European integration goes hand in hand with regional convergence policies.[2] In this respect, European structural funds aim to attenuate development disparities between European regions and to correct imbalances which may result from the development of the single market and the single currency. [3] However, the efficiency of these regional policies seems to be mitigated.[4] Our results underline the risk of persistence in inequality mentioned above.

The remainder of the paper is organized as follows. Section 2 presents key concepts and literature background with regard to both the regional convergence and the role of non-linearity and heterogeneity. Section 3 describes the data. The econometric specifications are presented in Section 4. Estimation results are discussed in Section 5. Section 6 concludes the study.

2 Background

Our study is related to many earlier contributions on income convergence. [5] We only point out in this section some salient empirical facts concerning both regional convergence and the role of non-linearity and heterogeneity.

Research over the last decade has considerably improved our understanding of convergence and has raised several conflicting issues as well; see e.g., Bernard and Durlauf (1996) and Caselli et al. (1996). At regional level, Dewhurst and Mutis-Gaitan (1995) use a dataset

[2] See, e.g., Kutan and Yigit (2007) who recognize the beneficial effect ofi ntegration from a long-term perspective.

[3] Note that these funds, which amount to a third of the total expenditure, constitute the second largest part of the budget of the European Union after the Common Agricultural Policy.

[4] This is consistent with the findings of Boldrin and Canova (2001, 2003).

[5] Two measures of convergence conceptually different are σ-convergence and β-convergence. The first describes how the distribution of cross-section incomes evolves over time, whereas the second emphasizes the income mobility. β-convergence may be unconditional or conditional on auxiliary variables such as measures of democracy, political stability, industry and agriculture shares in the economy, rates ofi nvestment, technological change, R&D, and human capital, etc. The concept of unconditional β-convergence implies that all the economies have the same level of steady state. On the contrary, conditional β-convergence, for which the growth rate ofi ncome per capita depends on auxiliary variables, allows each economy to converge to its own steady state.

of 63 European regions between 1981 and 1991 and find that the national growth rate has a significant influence on the speed of regional convergence. The authors also show that the results are in favour of the idea of varying growth rates towards a same balanced growth rate instead of the reverse (i.e., several balanced growth rates with the same speed of convergence). Sala-í-Martin (1996) analyses the regional convergence hypothesis by using regional data for the United States (48 states for the 1880-1990 period), Japan (47 prefectures, 1955-1990), Europe (90 regions, 1950-1990), and Canada (10 provinces, 1961-1991). Relying on a parametric specification, the author finds that regions tend to converge at a speed of approximately 2% per year. The result is also in favour of the σ-convergence hypothesis because the interregional distribution of income in all countries has shrunk over time. Baumont et al. (2006) use a sample of 138 European regions over the 1980-1995 period to estimate the spatial spillover effect. Their findings show that the average growth rate of GDP per capita of a given region is positively affected by the average growth rate of its neighboring regions. Garafalo and Yamarik (2002) use a new US dataset covering the 1977-1996 period and confirm the result established by Barro and Sala-í-Martin (1991).

It has been shown that the catching-up of poor regions in Europe is slow, and sometimes even non-existent, since the variation of income amounts to approximately 2% per year; see e.g., Barro and Sala-í-Martin (1991, 1995), Sala-í-Martin (1996), Armstrong (1995) and Neven and Gouyette (1995). However, at this rate, 35 years would be necessary to cut by half the initial inequalities of income per capita. Moreover, Martin (1997) points out that, since the beginning of 1980s, the speed of convergence between European regions decreased and fell to 1.3% between 1978 and 1992. This deceleration could be related to an absence of convergence between poor and rich regions in the same country, whereas convergence between countries continues (see European Commission, 1996). According to Neven and Gouyette (1995), a process of divergence would be in progress between European regions. It would appear that in less prosperous countries, only the richest regions have benefited from a process of convergence with rich countries. Quah (1996b) finds that among the poorest countries in Europe, Spain and Portugal, which have a faster aggregated growth than Greece, experienced a stronger increase in regional inequalities. More generally, this type of evolution supports the idea that an arbitration between global growth and regional equity could exist. Mora et al. (2005) detect a pattern of convergence clubs for the European regions over the period 1985-2000. Ramajo et al. (2008) find that regions in the European Union cohesion-fund countries (Ireland, Greece, Portugal and Spain) converge separately from the rest of regions of the EU.

Common features from these studies are as follows. There is a usual assumption for testing the convergence hypothesis that all countries have a common linear specification. Data used in empirical studies are usually a cross-section or panel. Cross-section studies generally conclude that economies converge slowly with a convergence speed of approximately 2%, sometimes recognized as a "stylized fact". However, the assumption of a common linear specification, inherent in the Solow growth model with a single steady state, is not held in models with multiple steady states as stressed in the theoretical study of Azariadis and Drazen (1990). Furthermore, several authors show that results based on cross-section data are biased because they ignore unobserved national/regional specific effects.

A direct way to overcome this drawback is to include auxiliary variables and country/regional specific effects. In the case of regional data, the choice of auxiliary variables is somewhat limited because of data unavailability. Generally, the distinction of conditional convergence from unconditional convergence consists in testing the specificity common to regions of the same country by incorporating country dummies or variables which reflect the differences in national or local structure. Another way is to use panel data models (see, e.g., Islam, 1995). The convergence speed resulting from these studies appears higher. However, Nerlove (1999) notes that estimation results based on panel data are very sensitive to the estimation method (level or difference regressions, fixed or random effects, etc.).

Two other lines of research have emerged from the literature. The first one analyses the distribution dynamics of economies. Quah (1996a,c,d, 1997) finds evidence of polarization and stratification in the growth process. Bianchi (1997) states that the determinants of the steady state vary across economies. Consequently, the σ-convergence hypothesis has the advantage of examining the evolution over time of the entire income distribution in a cross-section of countries. From nonparametric multimodality tests of σ-convergence in a cross-section of 119 countries between 1970 and 1989, it becomes apparent that there is a stratification in the convergence process. Likewise, using parametric panel data models (102 countries between 1960 and 1989), Lee et al. (1997) show that estimates of β-convergence traditionally defined in the literature are subject to substantial biases in a stochastic Solow growth model. They also show that steady-state growth rates differ significantly across countries. This growth heterogeneity is a major determinant of the dispersion in cross-country income.

The second line of research involves the investigation of heterogeneity and non-linearity in the growth process (see, e.g., Durlauf and Johnson, 1995; Liu and Stengos, 1999; Durlauf, 2000, 2001; and Durlauf et al., 2001).[6] These studies generally find the existence of non-linearity and heterogeneity at the country level. In particular, Durlauf and Johnson (1995) use a sample of 96 countries between 1960 and 1985 and regression tree techniques. They reject the linear model in favour of a multiple regime alternative in which different economies

[6]See also Phillips and Sul (2007) for a survey.

obey different linear models when grouped according to initial conditions. Moreover, Liu and Stengos (1999) question the single linear regime. They employ a semiparametric additive partially linear model on a data of 86 countries between 1960 and 1990 and find the existence of heterogeneity or non-linearity in the relationship between initial output and schooling level, and growth rate. These results confirm the presence of multiple growth regimes which is also corroborated by Huang (2005). By using the framework of distribution dynamics and a threshold regression model, Fiaschi and Lavezzi (2007) show that income growth is nonlinear. Hereafter we provide a reappraisal of income convergence by focusing on heterogeneity and non-linearity at the regional level.

3 Econometric specification

We propose a semiparametric partially linear model to investigate the convergence process on European regions over the 1990-2005 period. The model is given by

$$g_i = m\left(x_{0,i}\right) + Z_i'\gamma + \varepsilon_i, \qquad i = 1, \cdots, n. \tag{1}$$

We assume for the moment that ε_i is an independent random error with $E\left(\varepsilon_i | x_{0,i}, Z_i\right) = 0$ and $V\left(\varepsilon_i | x_{0,i}, Z_i\right) = \sigma^2\left(x_{0,i}, Z_i\right)$; g_i is the average growth rate of region i over the period of study; $x_{0,i}$ is the logarithm of GDP per capita in 1990; $m\left(.\right)$ is an unspecified function of $x_{0,i}$ that may be nonlinear; Z_i is a $K \times 1$ vector of other variables that enter linearly in (1). We specify Z as a set of country dummies, which account for country heterogeneity or differences in the steady state. This heterogeneity may be related to represent economic determinants and other factors (legislation, various subsidies for regional development purposes, etc.) that are common to a group of regions of the same country.

We implement the procedure proposed by Robinson (1988) sketched as follows to estimate (1). Taking the expectation of (1) with respect to $x_{0,i}$ yields

$$E\left(g_i | x_{0,i}\right) = m\left(x_{0,i}\right) + E\left(Z_i | x_{0,i}\right)' \gamma + E\left(\varepsilon_i | x_{0,i}\right). \tag{2}$$

Then, taking the difference between (1) and (2), we obtain

$$g_i - E\left(g_i | x_{i,0}\right) = \left[Z_i - E\left(Z_i | x_{i,0}\right)\right]' \gamma + \varepsilon_i - E\left(\varepsilon_i | x_{0,i}\right). \tag{3}$$

We can estimate γ by Ordinary Least Squares, denoted as $\hat{\gamma}$. Then, an estimator of $m\left(x_{0,i}\right)$ is given by

$$E\left[\left(g_i - Z_i'\hat{\gamma}\right) | x_{0,i}\right] = \hat{m}\left(x_{0,i}\right). \tag{4}$$

In relations (3) and (4), $E\left(Z_i | x_{0,i}\right)$, $E\left(g_i | x_{0,i}\right)$, and $\hat{m}\left(x_{0,i}\right)$ are estimated nonparametrically by the kernel method. We use both the local constant kernel estimator (known also as the Nadaraya-Watson estimator) and local linear kernel estimators. Moreover, this method requires the choice of a kernel function and a smoothing parameter. For our calculations, we use the Gaussian function and several choices of smoothing parameter (the rule of thumb, and the cross-validation method (see Silverman, 1986, Pagan and Ullah, 1999). As the results given by these two estimators are very similar, we only discuss the results based on the Nadaraya-Watson method. It should be also noted that the semiparametric specification (1) mixes continuous ($x_{0,i}$) and discrete (Z_i) regressors. Thanks to Bierens (1987), we know that when the regressors in (1) are a mix of continuous and discrete, if we apply the kernel method as if all regressors were continuous, we still get consistent estimates. The only thing we should be careful about is the convergence rate and the asymptotic distribution of the estimator of $E\left(Z_i|x_{0,i}\right)$.

We also use a competing specification which accounts for the endogeneity of x_0. Statistically, it corresponds to assumptions $E\left(\varepsilon_i|Z_i\right) = 0$ and $E\left(\epsilon_i|x_{0,i}\right) \neq 0$. This model can be estimated by the approach of Newey et al. (1999). Let us assume that there exists a set of instruments W_i such that $E\left(\varepsilon_i|W_i\right) = 0$ and

$$x_{0,i} = W_i'\eta + \nu_i \tag{5}$$

where $E\left(\nu_i|W_i\right) = 0$. Following Newey et al. (1999), we also assume that $E\left(\varepsilon_i|W_i, \nu_i\right) = \rho\nu_i$, which implies that $\varepsilon_i = \rho\nu_i + \zeta_i$. Hence, the model becomes

$$g_i = m\left(x_{0,i}\right) + Z_i'\gamma + \rho\nu_i + \zeta_i, \tag{6}$$

where ζ_i is the new error term. Estimation of this model is similar to that of the model without endogeneity as previously described but now with an additional linear component. As ν_i is not observed, it will be replaced by the residuals computed from the ordinary least squares regression of (5).

4 Data description

The data are built on the Eurostat-Regio database. They contain regional GDP and population over the period 1990-2005, measured in PPS (Purchasing Power Standard) at 1990 price levels. For reasons of homogeneity of the regions of the Nomenclature of Territorial Units for Statistics (NUTS), we use regions at level NUTS-2 for all countries.[7] The resulting database provides us with 159 European regions. The database includes both prosperous regions (for example from West Germany, France, United Kingdom and Belgium), as well as less prosperous regions (from Spain, Portugal, and Greece).

[7] The nomenclature in European regions is a hierarchical classification established by EUROSTAT. This classification starts from country level information (NUTS-0) to community level (NUTS-5).

Table 1 presents the descriptive statistics on GDP per capita for each country. We observe that disparities between regions around the European average are strong. Indeed, the highest level of GDP per capita - in Germany (in 1990), is approximately twice the lowest level - in Greece and Portugal.

Table 1: Descriptive statistics.

		GDP per capita (PPS 1990 prices)			Dispersion of GDP [(a)]		
Country	Number of regions	1990 [(b)]	2005 [(b)]	Growth rate (%) [(c)]	1990	2005	Growth rate (%) [(d)]
Belgium	11	14781	25922	3.77	0.233	0.219	-0.42
Germany	30	17115	28429	3.34	0.189	0.220	1.02
Spain	17	11347	22532	4.61	0.201	0.168	-1.23
France	22	14419	23492	3.26	0.150	0.141	-0.44
Greece	13	8240	17851	5.15	0.168	0.165	-0.12
Italy	20	14596	23636	3.23	0.269	0.259	-0.25
The Netherlands	12	14416	26796	4.11	0.134	0.165	1.39
Portugal	5	8776	17529	4.62	0.194	0.183	-0.42
United Kingdom	29	13521	24253	3.97	0.105	0.149	2.37
all	159	13803	24247	3.84	0.273	0.226	-1.25

Notes. [(a)] For each country, figures are averages computed on values of GDP per capita of its regions. [(b)] Annual growth rate of GDP per capita over the 1990-2005 period. [(c)] The figures reported are the standard deviation ofl og(GDP per capita) . [(d)] Annual growth rate of the dispersion of GDP per capita over the 1990-2005 period.

The evolution of GDP per capita between 1990 and 2005 shows an average growth rate of 3.84%. Growth is particularly important in Greek, Portuguese and Spanish regions. In contrast, Italian and French regions are characterized by the lowest growth, 3.23% and 3.26% on average respectively. To illustrate the concept of σ-convergence, we also report in Table 1 the standard deviations of GDP per capita (in logarithm) in 1990 and 2005. On the one hand, we note that the dispersion of GDP per capita tends to be reduced over time, with a decrease of 1.25% on average. The reduction of inequalities is particularly strong between the Spanish regions (-1.23%). On the other hand, we observe an increase in the dispersion of the GDP per capita between the regions in the United Kingdom (2.37%), in the Netherlands (1.39%) and in Germany (1.02%). These findings suggest the presence of some country heterogeneity.

The same patterns can be revealed in Figure 1 which displays two almost uni-modal distributions of regional GDP per capita in 1990 and 2005. These distributions contain a non negligible upper tail corresponding to high income regions. They also describe a global increase of income over time. However, income per capita in 2005 has a lower mode and a higher dispersion than that of income per capita in 1990.

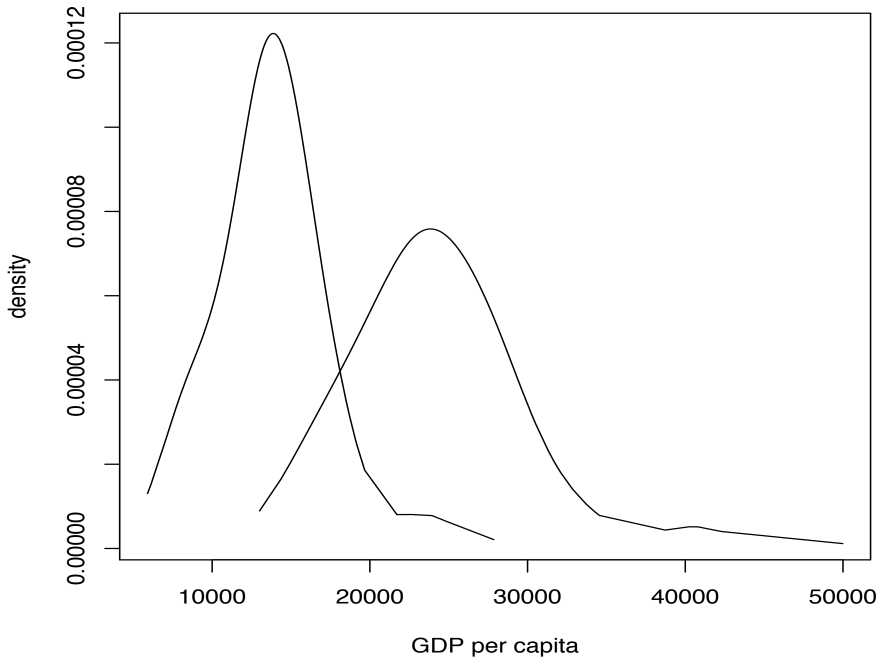

Figure 1: Kernel estimation of the distribution of GDP per capita in 1990 (left) and 2005 (right).

5 Estimation results

Table 2 reports estimation results of the models with and without controlling for endogeneity of the regional GDP per capita in 1990 (x_0). For the model with endogeneity of x_0, we use the national GDP per capita in 1990 (computed from regional GDP per capita) as an instrument for x_0.[8] Moreover, for comparison purposes, we also include estimation results for the standard parametric model often used in the convergence literature, where all parameters enter linearly:

$$g_i = \delta x_{0,i} + Z_i' \gamma + \varepsilon_i. \tag{7}$$

Figures 2 and 3 present the estimated function $\hat{m}_h(x_0)$ with the corresponding 95% pointwise confidence interval for models with and without endogeneity, respectively. We

[8] It would be interesting in a further study to address this issue by using information on other variables if their availability allows it.

also plot the parametric counterpart, $\hat{\delta}x_0$. The difference between the parametric and the semiparametric models is salient. We observe that an important part of the parametric curve lies outside the nonparametric confidence interval in both cases. This is especially noticeable in Figure 3.

Table 2: Parametric and semiparametric estimations of convergence process in European regions.

	(1)		(2)		(3)	
Variable	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Intercept	0.0447**	3.662	–	–	–	–
log(initial GDP)$^{(a)}$	-0.0022	-1.709	–	–	–	–
Belgium	-.0011	-1.059	-0.0014	-1.362	-0.0009	-0.951
Germany	-0.0033**	-4.07	-0.0038**	-4.729	-0.0003**	-3.701
Greece	0.0059**	5.117	0.0039*	3.13	0.0024*	2.334
Spain	0.0034**	3.676	0.0029*	3.169	0.0023**	2.615
France	-0.0041**	-4.992	-0.0042**	-5.263	-0.0036**	-4.563
Italy	-0.0044**	-5.131	-0.0048**	-5.806	-0.0045**	-5.378
The Netherlands	0.0009	0.915	0.0008	0.871	0.0001	1.154
Portugal	0.0029	1.926	0.0012	0.795	0.0000	-0.062
ρ	–	–	–	–	0.0034**	5.101
# observations	159		159		159	

Notes. Specification: (1) parametric model, (2) semiparametric model, (3) semiparametric model with endogeneity of x_0. The dependent variable is the average growth rate of GDP per capita. $^{(a)}$ ln(initial GDP) is the logarithmic value of GDP per capita in 1990. Estimations are performed on a sample of 159 European regions for the period 1990-2005.. * significance at the 5% level. ** significance at the 1% level.

To compare the parametric and the semiparametric models without the endogeneity of x_0 (the two specifications are nested), we use the test statistic proposed by Li and Wang (1998) (see the Appendix for more details). The null hypothesis corresponds to the parametric specification, and the alternative is the semiparametric one. The test is one-sided and its statistic asymptotically follows a standard normal distribution. Li and Wang (1998) find that the normal approximation does not perform well for small or moderate samples and suggest the use of a bootstrap. Our sample size is 159 which might be thought of as being moderate. We use both the asymptotic version and the bootstrap version of the test. The computed value of the test statistic is $J_n = 2.832$, much higher than the asymptotic normal value 1.645 and also higher than the corresponding bootstrap critical values $J_n = 1.419$ at the 5% level leading to the reject of the null of the associated parametric specification. We can conclude that the semiparametric model without the endogeneity of x_0 provides a better approximation of the data than the parametric one. Now, in order to determine the most suitable fit for the data among the two nested semiparametric models (models with and without controlling for endogeneity of x_0), we use the simple t test for the null hypothesis $\rho = 0$. As shown in Table 2, ρ is significant at the 1% level, favouring the choice of the model with endogeneity of x_0.

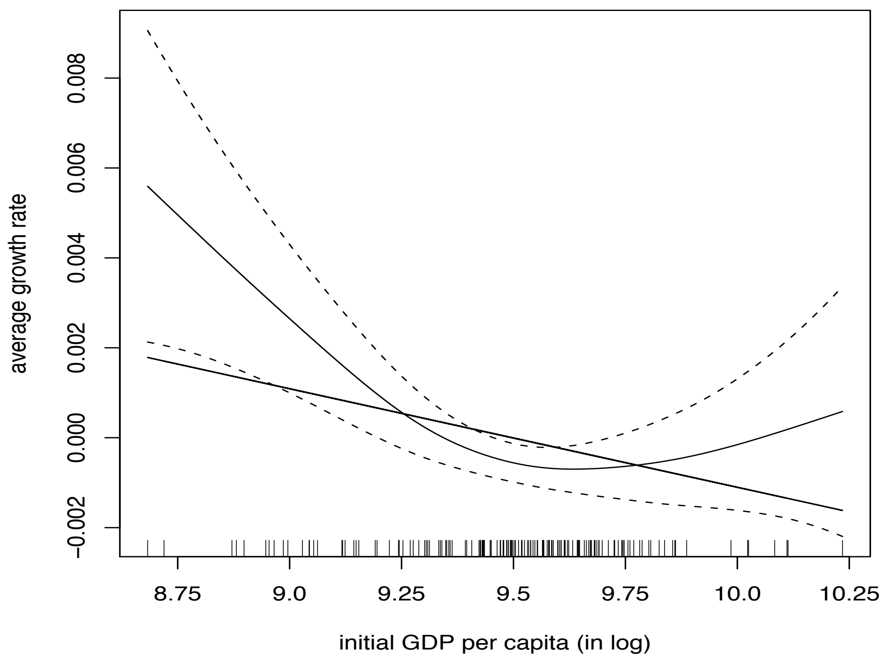

Figure 2: Nonparametric estimation of $m(x_0)$ without accounting for endogeneity of x_0, where x_0 is log of regional GDP per capita in 1990. The solid curve represents the estimate $\hat{m}_h(x_0)$, the two dash curves correspond to the 95% pointwise confidence interval. The solid line corresponds to the parametric estimate $\hat{\delta}x_0$.

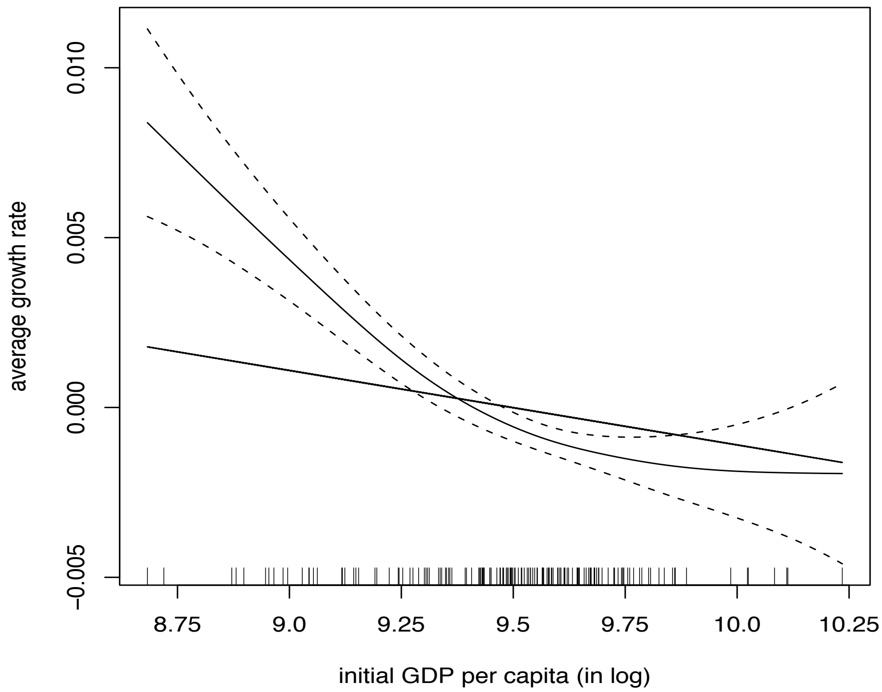

Figure 3: Nonparametric estimation of $m(x_0)$ accounting for endogeneity of x_0, where x_0 is log of regional GDP per capita in 1990. The solid curve represents the estimate $\hat{m}_h(x_0)$, the two dash curves correspond to the 95% pointwise confidence interval. The solid line corresponds to the parametric estimate $\hat{\delta}x_0$.

The results show an evidence of convergence for low income regions (with income approximately lower than 13400 PPS) while there is no clear convergence for higher income regions. Furthermore, the convergence process for low income regions is non-linear. There are also country effects as several country dummies are statistically significant. This suggests that national economic performance has significant impact on regional growth and then regional convergence process.

6 Concluding remarks

The aim of this study was to take advantage of a new dataset to reexamine the growth process between European regions, relying on a semiparametric framework. Our major findings can be summarized as follows:

(i) There are non-linearity and heterogeneity in the convergence/divergence process. We find that only weak income regions converge, but the convergence is not uniform.

(ii) Compared to parametric approximations, test results indicate that semiparametric models perform better.

Relying on our findings, some comments regarding the efficiency of regional policy are in order. Previous studies suggest that, from 1950 to 1990, a convergence process took place in Europe. On average, regions that had a lower initial income per capita had a higher growth rate than others. However, our estimates based on a rather different period (1990-2005) suggest that only weak income regions converge and that there is no evidence of convergence for high income regions.

As the semiparametric specification adopted in our study takes account of regional and country heterogeneities, each region has its own steady state which depends on both regional and national factors (captured by regional income and country dummy). Thus, the result that only weak income regions converge implies a certain skepticism because these regions may be held in a "poverty trap". Moreover, we think that the non-convergence of higher income regions means that they may have already achieved their own steady states. Regional policies should take this into account in order to improve economic integration within European regions in particular for the new countries that have joined the European Union.

It would be promising in further studies to integrate recent findings in geography economics – which insist on the phenomenon of local spillovers in the spirit of Krugman (1991) and Krugman and Venables (1995) on the one hand, and on the spatial heterogeneity and spatial spillovers underlined by Baumont et al. (2006), Ramajo et al. (2008), Pfaffermayr (2009), and Arbia et al. (2010), among others, on the other hand.

7 Appendix: Testing parametric vs. semiparametric specification

The test statistic proposed by Li and Wang (1998) is

$$I_n = \frac{1}{n^2 h} \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} U_{in} U_{jn} K_{ij},$$

where $U_{in} = g_i - x_{0,i}\hat{\delta} - Z_i'\hat{\gamma}$ is the residual from the *mixed* regression, $\hat{\gamma}$ is the semiparametric $\sqrt{n}$-consistent estimator based on the alternative model and $\hat{\delta}$ is the OLS estimator of δ based on the null hypothesis which consists of the parametric model. Under H_0, $J_n := nh^{1/2} I_n / \sqrt{\hat{\Omega}} \to N(0,1)$ in distribution, as $n \to \infty$, where

$$\hat{\Omega} = \left(1/n^2 h\right)^{-1} \sum_{i}^{n} \sum_{j \neq i}^{n} U_{in}^2 U_{jn}^2 K_{ij}^2$$

is a consistent estimator of $\Omega = 2\left[\int K^2(v)\,\mathrm{d}v\right] \times E\left\{f_{x_0}(x_0)\left[E\left(\sigma^2(x_0, Z)\,|x_0\right)\right]^2\right\}$, with $f_{x_0}(x_0)$ being the density of x_0; $\sigma^2(x_0, Z) = E\left(U^2 | x_0, Z\right)$. Under H_1, Prob$[J_n > B_n] \to 1$ as $n \to \infty$, where B_n is any nonstochastic bounded sequence. It should be noted that the test is one-sided. In practice, H_0 is rejected if $J_n > c_\kappa$ at the significance level κ, where c_κ is the upper κth percentile from the standard normal distribution. It should be also noted that $\hat{\gamma}$ as well as $\hat{\delta}$ do not affect the limiting distribution of J_n under the null. Li and Wang (1998) examine the finite sample performance of the test. They find that the normal approximation does not work well for small or moderate samples and suggest the use of bootstrap for computing the critical value.

In our application, we have 159 regions, which can be considered as a moderate sample. Therefore, we also use the wild bootstrap method, as described above, to compute the bootstrap critical value of the test statistic. This bootstrap version of the test provides very accurate estimated size. It results in a B bootstrap distribution of the test statistic, J_n^*. We will reject the null if $J_n > J_{n,\kappa}^*$, where $J_{n,\kappa}^*$ is the bootstrap critical value corresponding to the significance level κ.

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