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ORIGINAL PAPER

Factors conditioning the formation of European regional convergence clubs

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Abstract Recent findings have indicated the existence of European regional clubs. In the following paper, we examine factors conditioning the distribution of European regional GDPpc by estimating conditioned stochastic kernels, arguably the best method for whole distribution or partial conditionings. We also compute conditioned Markov chains for the conditioning factors detected and their sensitivity to changes in probability. Our results show that a country's fiscal policies to reduce within country inequalities remain the key factor in escaping from backward clubs, together with the integration of women into the labour market. The average number of patents and low-tech manufacturing specialisation indexes are also considered key factors.

JEL Classification O11 · R11

1 Introduction

The literature on economic growth identifies the existence of groups of economies that present homogeneous economic growth patterns and which converge towards a common steady state. These groups have been called convergence clubs. The idea behind their definition is the tendency for such clubs to form around a pole of attraction. Up to this juncture, and strictly regarding the regional European case, empirical evidence has addressed the analysis of European regional intra-distribution dynamics through the estimation of conditional kernel density functions (Quah 1996; López-Bazo et al. 1999; Magrini 2004; Cheshire and Magrini 2005). Their purpose has been the detection of unimodality–multimodality. Multimodality predominates in the European

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regional case which implies the existence of several clubs. However, according to Magrini (1999) and Pittau and Zelli (2006), they evidence a very slow tendency towards unimodality, that is, a catching-up process.

The novelty of the present paper is that we examine the factors which condition the formation of European regional convergence clubs through the estimation of conditioned kernel density functions. Therefore, we carry out a conditional approach. Note that this would allow us to detect the factors that still account for the distribution of Gross Domestic Product in per capita terms (GDPpc). We analyse these conditioning factors at the end of the 1990s for the EU15 regional GDPpc distribution. The static analysis permits the inclusion of a higher number of conditioning factors.

In our opinion, three points of the present paper need to be highlighted. First, as far as we know, this is the first paper conducting a conditional approach to the European regional income levels through the use of the estimation of kernel density functions. Second, this investigation is especially relevant because of European Aid having been readdressed to Eastern regions from the most recent enlargement in 2004. Therefore, some structural factors which could still be conditioning EU15 GDPpc distribution will not be further improved through European regional aid. As a consequence, this would affect the above-mentioned slow regional European catching-up process. Azariadis (2001) claims that premature liberalisation increases the probability of falling into a trap because of the presence of lower levels of productivity. Note that the latter applies for backward EU15 regions. Thus, our empirical investigation needs to be considered as to whether European regional integration has been accompanied by the consolidation of European regional clubs without, perhaps, first correcting certain structural factors. Third and finally, the appearance of clubs in the conditioned GDPpc distribution would forecast a return to the EU GDPpc distribution of a twin-peaked scenario, which was evidenced for the 1970s and 1980s distributions (Pittau and Zelli 2006).

Our results confirm the existence of some factors that still condition the EU15 regional GDPpc distribution. Thus, bimodality is obtained when we condition by the following factors: the average number of patents, female unemployment rate, education polarisation ratio, the high-tech services specialisation index, accessibility time to infrastructure, and within country inequality (regions belonging to each member state). Furthermore, the higher bipolarised distribution is obtained for considering within country disparities. Once these factors have been detected, we proceed to a computation of the effects of changes in probabilities for specific clubs. Within country disparities show the highest expected changes on the conditioned distribution. Thus, the implementation of member state policies remains the key factor to ensure a region escapes from low levels of development.

This present section has been concerned with providing a brief discussion of the purpose of this paper. The rest of the paper is organised as follows. Section 2 introduces these theoretical factors that strengthen the formation of clubs. Meanwhile, Sect. 3 describes the economic data used to proxy these theoretical features. Section 4 discusses the implementation of bivariate kernel density functions that can be usefully employed in undertaking a conditioning approach to GDPpc distribution and show how to compute elasticity changes in a conditioned Markov chains approach. Sect. 5 presents our empirical evidence concerning the factors that underpin the formation of European regional clubs. The final section concludes.

2 Theoretical considerations about conditioning factors

The purpose of this section is to summarise the main theoretical contributions that indicate those factors that could occasion the appearance of clubs and is the main aim of this paper. Based on that, in the next section, we would try to select those economic variables that could be more related to these broad theoretical factors. Obviously, our empirical approach will be conditioned to data availability.

Theoretical approaches adopt either a neoclassical or an endogenous theoretical framework. Within the neoclassical framework, if heterogeneity is permitted across individuals, the dynamics of the Solow growth model can be characterised by multiple steady-state equilibriums. Most neoclassical studies assume that differences in steady state are conditioned by levels of capital, supposing that regions with the same level of capital tend towards the same steady state. Yet, some economies show a persistent deterioration that leads them towards an extreme situation. However, this is only the case when the saving rate is a growing function of the capital–labour ratio; at lower values of this ratio it will be positive. Working within the endogenous growth framework, Azariadis (1996) specifies seven possible situations that might lead to the formation of a growth trap. In this sense, externalities might explain the presence of spatial clusters of regions that share low or high levels of development, a situation that might lead to a poverty trap because of the regions' geographical location (Jalan and Ravallion 1997).

However, this does not apply for the European regions, where development is at a much higher level than that which typically characterises a poverty trap. Notwithstanding, we believe that the possibility should be considered that poorer European regional economies might be trapped within a backward convergence club. Our concern here is that economies at a lower level of development find themselves trapped in a club with no way out. Durlauf (1994) points out that when richer economies achieve a desired degree of stratification, a link between cross-section and intertemporal inequality is then formed.

In this sense, we need to consider a wide-ranging classification of all the reasons that might lead European regional economies to a lower level of development. Factor typology has been presented by the convergence literature as a way of explaining the way in which convergence clubs are constituted. These factors are based on the differentiation in the parameters of production where function can account for lower levels of development. In this sense, a diversification in parameters can lead to multiple growth paths (Chamley 1993; Palivos 1995). Thus, in a study of cross-country data, Desdoigts (1999) notes that clubs emerge endogenously and naturally as homogenous classes on the basis of their economic structure. We believe this could be grouped into a three-level typology: human capital, growth population and technological differences.

Thus, the first reason to take into consideration is that a lower endowment of human capital will promote lower levels of economic activity. In this sense, Azariadis and Drazen (1990) describe such a scenario arising from the existence of threshold effects related to the non-convexity of aggregated production function. Thus, externalities in the technology of human capital accumulation will bring about bifurcations that yield quite different development paths from minor differences in initial conditions. Thus, a relationship can be established between initial conditions and the steady-state performance of aggregated output. Bénabou (1994) states that stratification traps backward economies with lower human capital endowment, while those with a richer endowment continue to grow. In addition, the accumulation of human capital requires certain financing conditions (Barham et al. 1995; Berthelemy and Varoudakis 1996). Cohen (1996) claims that education in poorer economies has not been able to reduce initial knowledge gaps.

The second reason considers lower levels of saving rates and demographic factors. Linking the first reason described above with this second factor, de la Croix (1996) indicates that the lack of financing for the education of future generations and/or the presence of low saving rates increase consumption (what Azariadis terms the "impatience trap") leading the economy into a poverty trap. The situation worsens when these conditions are perpetuated.

Finally, the third factor that might generate lower development levels is R&D endowment and monopolies in technology (Erickson 1994). Although null growth in the capital factor has not occurred in European regions, there are economies with very low growth. Low levels of elasticity usually accompany such a situation. Additionally, the characteristics that condition the market, including size (Rodríguez-Pose 1999—note that the size and the age of a company also affect R&D profits), structure (Baland and Patrick 1996—self-reinforcing effects between technological change and market structure) and technological change (Galor and Ryder 1989; Murphy et al. 1989), are necessary to promote growth. Nevertheless, the absence of adequate social conditions can lead to a loss of ground in the race to introduce technological improvements.

Furthermore, recent literature of what has been called "new economic geography" introduces a new debate because of the fact that similar regions can end up with very different production structures and income levels. See Ottaviano and Puga (1998) for a comprehensive survey. In this sense, Englmann and Walz (1995) and Baldwin et al. (2001) show that increasing returns to scale, the level of trade costs and the spatial dimensions of knowledge spillovers are key factors influencing the formation of a growth trap. Furthermore, simultaneous processes in neighbouring regions should accompany individual regional efforts. Durlauf (1993) affirms that complementarities between activities and companies are necessary in incomplete markets. The basic idea is that a simultaneous and sufficient investment flow addressed to diversified industrial sectors would allow access to externalities (for instance, enhancing the size of the domestic market and promoting infrastructure).

3 European regional data

Taking into account the aim of this paper, that is, to identify the factors that condition the EU15 regional GDPpc distribution which consequence the formation of clubs, we present in this section the available data that can be used for this purpose. We will obtain a static picture of the factors conditioning GDPpc distribution in 1999. The lack of data for certain variables in certain periods means that it is impossible to carry out a dynamic study. In favour of our static approach, findings in the literature demonstrate that persistence is the common trait (López-Bazo et al. 1999; Magrini 1999). The annual data was taken from the EUROSTAT REGIO database GDPpc

Table 1 Definition of the variables

Variable	Definition	Source
GDPpc	Regional Gross Domestic Product in per capita terms and PPP: 1999	REGIO-Database
Population growth	Regional population growth rate for the period 1996–1999	REGIO-Database
Population cohorts rates	Regional ratio between the elderly/youth cohorts: 1999	EUROSTAT
Population density	Regional population density: 1999	REGIO-Database
Human capital	Ratio between high/low human capital endowment levels: 1999	EUROSTAT
R&D	Average European patent applications per million inhabitants: 1998–2000	CRENOS
Sectorial specialisation indexes	Agriculture & Low-tech / High-tech sectorial specialisation levels (either for manufacturing or services)	Cambridge Econometrics Database
Periphericity	Distance to the European core (Luxembourg)	
Country belonging	Dummies assigned to condition of belonging to a member state	
Wages structure	Compensation per employee: 1999	Cambridge Econometrics Database
ICON index	Connectivity to transport terminals by car in minutes weighted by surface	MCRIT
Labour market structure	Female unemployment rates	EUROSTAT

considered in PPA. So, the sample comprised 130 regions combining the NUTS 1 and 2 classifications, which allowed us to achieve a more homogeneous database. NUTS-2 regions were used for Greece, Finland, France, Italy, Portugal, Spain, Sweden, and NUTS-1 regions for Austria, Belgium, Germany, Holland and United Kingdom. We considered Ireland, Denmark and Luxembourg as single regions (NUTS-0).

Hence, we decided to include into our empirical analysis those factors that arise either from neoclassical or endogenous growth models, which have been mainly summarized in the previous section. See Table 1 for the definition of the used variables. Obviously, we have considered proxies restricted to regional data availability. Thus, the underpinning reasons for the considered variables are summarized next.

First, we considered those variables related to regional population characteristics that could affect economic development. In this regard, we included not only population growth (either as a consequence of fertility rates or migration) because of it being a classic factor in neoclassical growth models but also the composition of population by cohorts. The latter factor affects economic development since a high elderly population rate would readdress State economic public policies to welfare policies besides conditioning labour market force. Moreover, the inclusion of population density rates allows us to consider agglomerated economies. Second, we also took into account the regional human capital endowment levels. The reason to consider this factor lies in several arguments: it is a relevant factor in the augmented Solow economic growth model; appears in endogenous economic growth models and; it is also expressed as a conditioning factor for the appearance of regional coalitions (illustrated by Quah 1999). Third, the regional average of patents constitutes a proxy for the effects arisen from R&D levels which express the monopolies in technology. Fourth, we included sectorial specialisation indexes for aggregated sectors based on their technological level. The greater regional specialisation in high-tech sectors allows regions to base their economic development in economic sectors less affected by globalization. Below, we explain in detail in which manner we have constructed these aggregated specialisation indices. Fifth, a core-periphery model is also considered through the use of the distance to the European core (alternatively we used spatial contiguity) as well as regional belonging to a member state which express differences in own-state policy making decisions. Sixth, time cost accessibility to the nearest network allows us to examine the effects arisen from infrastructure endowment levels once European Aid framework has been in operation for 14 years. Finally, two labour market characteristics had been taken into account. Differences in compensation by employee and female unemployment rate would proxy structural labour market features that obviously condition regional economic development level.

However, from several variables an important problem may arise: the existence of endogeneity bias. In order to avoid this problem we regressed the possible endogenous variables against income per capita variable. Then, residuals were interpreted as the part of the variable that is not explained by economic conditions. Then, the new variable can be used for conditional income distribution. From the list of variables we considered the next ones as possible endogenous factors: the female regional unemployment rate, the average number of patents or the aggregated sectorial specialisation levels. At this juncture, we should highlight that no significant differences were found in conditioning once possible endogeneity was corrected.

Next, in order to characterise the regions in each club, we computed aggregated sectorial specialisation indexes starting from individual ones. The regional–sectorial concentration coefficient is L_{ij}. From this index, it is possible to know if one sector j is more highly concentrated in region i in comparison with the overall EU value ($L_{ij} > 1$) or, on the contrary, if a small proportion of the Gross Value Added (GVA) of j is located in this region, $L_{ij} < 1$, compared to the EU average. Thus, specialisation patterns are compared to an average value for the EU. The regional–sectorial concentration coefficient is defined as follows where x_{ij} is the GVA in region i in sector j; $x_i.(x_j)$ the total GVA in region i (sector j); x is the total GVA:

$$L_{ij} = \frac{x_{ij}/x_i}{x_j/x} \quad i = 1, \ldots, N; \quad j = 1, \ldots, R \tag{1}$$

These results should allow us to determine whether there is a relationship between regional wealth measured in terms of GDPpc for each of the groups and each sectorial specialisation. The classification sector considered is NACE-CLIO RR17 and the data are drawn from the Cambridge Econometrics Database. All specialisation indexes were also related to their average value. In order to reduce the number of variables belonging to specialisation indexes we computed various average indexes. Thus, the low-tech industrial sector included: Food, beverages and tobacco, Textiles and clothing and Transport equipment; while specialisation in high-tech services was computed by including Transport and Communications and Financial services. Other sectors were aggregated in the alternative technological typologies. That is, the low-tech services sectors are: Wholesale and retail and Hotels and restaurants; meanwhile high-tech manufacturing sectors refer to: Fuels, chemicals, rubber and plastic products and Electronics. In this sense, we have followed the OECD classification of technology and knowledge-intensive sectors. However, in order to consider the effects deriving from increasing returns to scale, we weighted the regional specialisation indexes by means of their relative level of activity.

Finally, we should point out that all variables were expressed in deviations terms to their average value as we did for the GDPpc level. Conducting this study at the regional level does not allow us to consider any further variables.

4 Conditioned stochastic kernels

The theoretical debate points to several factors that might account for the distribution. Yet, we wished to determine whether all the factors account for the whole distribution of the activity. However, we would only obtain an explanation of the average pattern by conducting a regression analysis (traditionally detected by applying β-convergence estimations). Thus, while the representative behaviour is described, we learn little about the entire cross-section distribution.[1] Maasoumi et al. (2006) have described the specific effects of the main conditioning variables on the growth rates of different groups of countries. They claim that there can be little doubt, therefore, that separate models are required to examine such groups. Thus, here we decided to adopt a non-parametric approach which would allow us to detect similar distribution patterns within different groups. See Durlauf and Quay (1999) for a formal definition and a description of some of the properties of stochastic kernels in the study of distribution dynamics. Equation (2) shows the univariate kernel probability density estimator where there are n sample data $\mathrm{GDPpc_i}$ at a point GDPpc, $K(\cdot)$ is a kernel function that must integrate to 1, and h is a parameter called the bandwidth that defines the locale over which the empirical frequency distribution is averaged (smoothing parameter). We used a Gaussian kernel function.

$$\hat{f}(\mathrm{GDPpc}) = \sum_{i=1}^{n} \frac{1}{nh} K\left(\frac{\mathrm{GDPpc} - \mathrm{GDPpc}_i}{h}\right) \tag{2}$$

But, the study of the shape and dynamics of cross-section distributions seems to be merely informative. A conditioning scheme must be undertaken in order to provide an explanation of the shape and mobility detected. Just such a scheme was proposed by Quah (1996), that is, the way in which the set of theoretical factors presented

[1] We also conducted a regression analysis. Our results point to the presence of statistical significance for the following variables: human capital proxy, time cost connectivity to infrastructure, the average number of patents, female unemployment rate, a few sectorial specialisation indices (we included them individually at this stage), compensation per employee and the ratio defining population characteristics.

here in the introduction manifest their conditioning role. By adopting this technique, estimating conditioned stochastic kernels, we should be able to address the issue as to which factors give rise to the formation of clubs. Thus, in order to understand whether a hypothesised set of factors explains a given distribution we can simply ask if the stochastic kernel transforming the unconditional distribution to a conditional one removes these same features. However, the estimation of density functions only informs us about the overall relevance of conditioning, but here we need also to examine the distribution in part. Thus, stochastic conditioned kernels allow us to examine the role of the conditioning factors for each club. The bivariate kernel is defined in Eq. (3). This conditioning approach has been used elsewhere to analyse European unemployment rates (Overman and Puga 2002), Indian GDPpc distribution (Bandyopadhyay 2003) and world distribution of output-per-worker (Beaudry et al. 2002).

$$\hat{f}(\mathrm{GDPpc}/X) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{h_1}\frac{1}{h_2}K\left(\frac{\mathrm{GDPpc}-\mathrm{GDPpc}_i}{h_1}, \frac{x-X_i}{h_2}\right) \tag{3}$$

We conditioned the distributions for each period by considering the GDPpc value expressed normalized with its average level in relation to the value of the variable or factor (X_i) that it conditions, also expressed to its average level. Meanwhile, h_1 and h_2 represented the two bandwidths:

$$f(\mathrm{gdp}_{\mathrm{pc}}/x_i) = f(\mathrm{gdp}_{\mathrm{pc}}, x)/f(x) \tag{4}$$

Stochastic kernels are presented by means of three dimensional diagrams. Our figures include axes defined as the income distribution variable for non-conditioned distribution and the income distribution conditioned by x_i as the conditioned distribution. Conditioned kernels are interpreted as follows. If we detect probability masses running along the diagonal we conclude that the variable used does not contribute to explain the overall GDPpc distribution. The conditioning approach involves testing Eq. (5), whereas regression models only test the expected distribution values (see the hypothesis expressed in 6).

$$H_0 : f(\mathrm{gdp}_{\mathrm{pc}}) = f(\mathrm{gdp}_{\mathrm{pc}}/x) \tag{5}$$

$$H_0\colon E[\mathrm{gdp}_{\mathrm{pc}}] = E[\mathrm{gdp}_{\mathrm{pc}}/x_i] \tag{6}$$

In contrast, a relevant conditioned distribution will be detected when mapping from the unconditional to the conditional distribution we find the probability mass running parallel to the income distribution axis. This, of course, is the desired outcome in order to identify x_i as a conditioning factor. This renders the conditioning factor as one which explains the observed polarisation when the clubs have been detected. This does not rule out the possibility that conditioning relevance might be identified by just a few percentiles' distribution. See Overman and Puga (2002) for a visual interpretation. Then, the selection device of conditioning factors needs to be analysed. For this reason, we made 5,000 bootstrap replications for conditional kernel procedure where sample size was 129. The experiment used two standard normal distributions generated with random uniform distribution values. Our results show that the average density of bivariate kernels results unbiased though at the 5.3% significance level. In spite of this our inference results should be interpreted cautiously.

Our aim, then, is to compare the conditioned and non-conditioned distributions. If they are similar, the whole income per capita distribution will be explained specifically by means of the conditioning factor.[2] In any case, we will also test the hypothesis (5) by means of a Kolmogorov-Smirnov test.

Our next purpose is twofold. First, we compute the number of modes for the conditioned GDPpc distribution with a multimodality test. The detection of multiple modes implies a major alteration on GDPpc distribution because regions become clustered into different clubs. We use the variable bandwidth Gaussian kernel proposed by Silverman (1986) and adapted by Fox (1990). Obviously, this computation is rather more confident than taking a glance at the conditioned distributions. However, the estimated number of modes is very sensitive, as in our case, to reduced sample sizes. Then, multimodality can be detected because of several noisy minor modes. Therefore, we carry out an alternative approach. We estimate Markov chains where the transition matrix contains the overall transitions from the non-conditioned to the conditioned distribution. The best criterion for discretising Markov chain states, as well as identifying the ideal number of states of the chain, needs to be established beforehand. In doing so, the latter allows us to restrict the possible number of modes. A concentration in a concrete state allows the inference that a long-run solution would show convergence towards a common position in the distribution (modality).

Second, once clubs have been detected, we compute the expected change within GDPpc distribution in the Markov chains' ergodic solution (where the probability of belonging to each club is evidenced) [3] once we apply a change in the conditioning factors. Hence, we will detect the real impact on the GDPpc distribution when conditioning factors are altered as a consequence of policy makers' decisions. Then, for instance, we will be able to compute the expected change on GDPpc distribution once regional female unemployment rates are diminished due to labour market reforms. We followed the proposal in Mora (2005). Our final inference purpose was to determine

[2] A particular criticism made against the use of stochastic kernels is the bivariate conditioning that it involves. The use of the bivariate approach impedes the interaction of some of the conditioning factors in the explanation of the whole cross-section distribution. This factor is well captured by means of a regression approach, though for an average representative region. Therefore, we analysed by means of a factor analysis whether the conditioning factors could be grouped so as to capture complementarities. Indeed, factorial analysis examines in which sense and degree the conditioning factors are correlated with each other. However, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy provides a middling value. Thus, it is not recommendable to group the conditioning factors into a single measure. Likewise, another way to detect a complementary relationship is to obtain through the rotated solution of the factor analysis which is the degree of uniqueness of the conditioning variables. The results, again, show that there is no chance to construct a unique factor.

[3] In order to facilitate interpretation of the final results, we should consider five states—low, middle-low, intermediate, middle-high and high—and define them in such a way that each state contains a similar number of regions in the initial values. Here, transition probability estimations were computed by considering maximising likelihood criteria. Finally, the ergodic solutions were obtained from the eigenvector associated with the second eigenvalue of the transition matrix, which is equivalent to the vector in which matrix iteration converges.

the changes in the ergodic solution when a change in transition probabilities occurs. According to Conlisk (1985), the effects of a change in transition probabilities in the ergodic solution of a chain can be quantified.

Let us suppose that there is a gain in the probability of a state's persistence (Δp_{ii}). Clearly, this would bring about a loss in probability in, at least, one state in the chain where economies could transit from i (p_{ij} being $i \neq j$). In line with Conlisk (1985), the effects of a change in transition probabilities in the ergodic solution of a chain (π) can be quantified. Suppose that ϵ is the probability gain in one of the probabilities of the transition matrix (M). To compute the effect of the latter on the ergodic solution, the partial derivate $\partial\pi/\partial\varepsilon$ must first be calculated, and the effect of readjustments in the transitional matrix on the ergodic solution can be estimated. Only these derivatives allow real changes in the ergodic solution to be computed. The effects of the perturbation on the ergodic solution, as well as those on the mean of the first passage matrix, are not characterised in terms of discrete changes, but rather in terms of the direction of change represented by the derivatives, evaluated at ϵ=0 (Conlisk 1985). To compute this, the following sequence must be followed:

$$Z = (I - M + \delta'\beta)^{-1} \quad \text{where } \pi = \beta \cdot Z \tag{7}$$

$$\partial Z/\partial\varepsilon = Z \cdot \mathit{\Gamma} \cdot Z \quad \text{where } \partial M/\partial\varepsilon = \Gamma \tag{8}$$

$$\partial\pi/\partial\varepsilon = b(\partial Z/\partial\varepsilon) \tag{9}$$

in which δ is a vector of ones with size $1 \times n$ (where n is the number of states), β is a vector that satisfies $\beta\delta' \neq 0$, I is the identity matrix, Z is what Conlisk (1985) defines as the "fundamental" matrix (there being a separate matrix for each choice of β) and $\mathit{\Gamma}$ arises out of the changes that are made in the estimated transition matrix. Here, in this application β is selected as the initial probability vector.

5 Empirical evidence

Before conditioning GDPpc distribution, we show the shape of the non-conditioned distribution in 1999 (see Fig. 1) where the variable has been normalised to its average level. Our results are in line with previous findings (López-Bazo et al. 1999; Magrini 1999; Pittau and Zelli 2006). Thus, it seems that poorer regions tended to catch-up to the middle group (although the mode is below the average position). At the same time, the right tail which corresponds to the richer European regions show a higher mass of probability than in the left tail and in the extreme position of the distribution, an exclusive club seems to be evidenced. However, the Silverman multimodality test indicates the existence of a unique mode.

Figure 2 shows the results of the conditioned kernels for the entire distribution. Our results show that the variables differ on several matters. Anyway, for all conditioning factors the conditioned distributions are not more equally distributed than the non-conditioned one. We have confirmed this result by means of a Kolmogorov–Smirnov test. Figure 2 shows that there appear to be differences in the number of clubs (peaks), some of which do not condition, while others have a partial effect on the distribution.

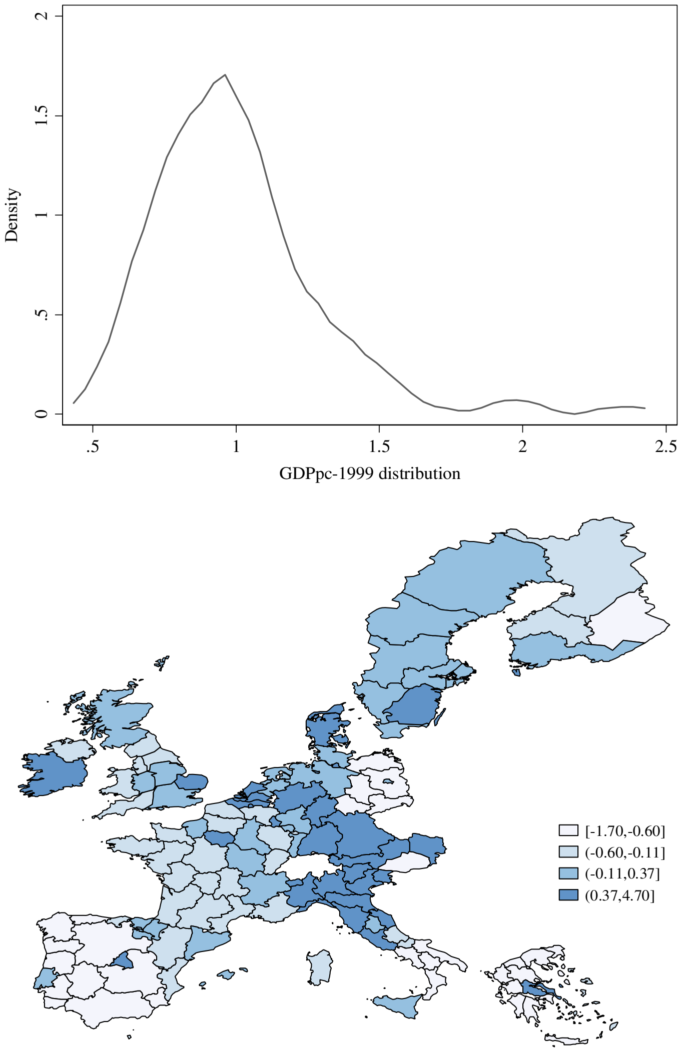

Fig. 1 Non-conditioned GDPpc distribution (1999)

Based on our conditioned bivariate kernels we need to consider the number of peaks and determine whether the conditioning is actually working.

Although some figures could be clear, then, we proceed to compute a multimodality test (Silverman 1986) in order to obtain which is the statistically significant number of modes for the conditioned GDPpc distributions. Our results show that one peak was obtained for the following conditioning variables in the conditioned distributions: agriculture specialisation index, the ratio of elderly population to the number of young members, low-tech manufacturing index, compensation per employee, growth in population and distances to core and the low-tech services specialisation index. In contrast, two or more clubs are obtained for: average number of patents, female

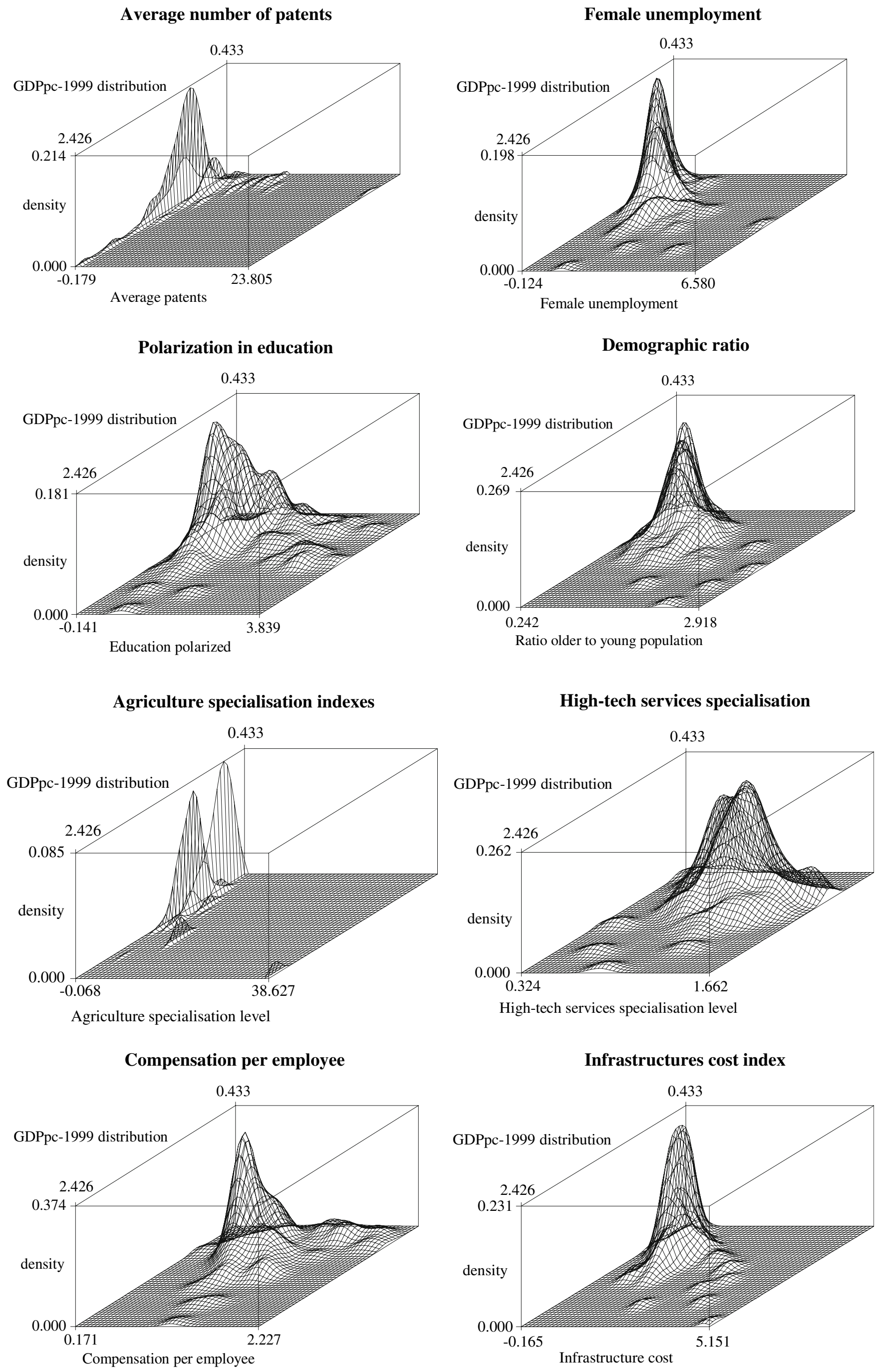

Fig. 2 Conditioned GDPpc distribution (1999)

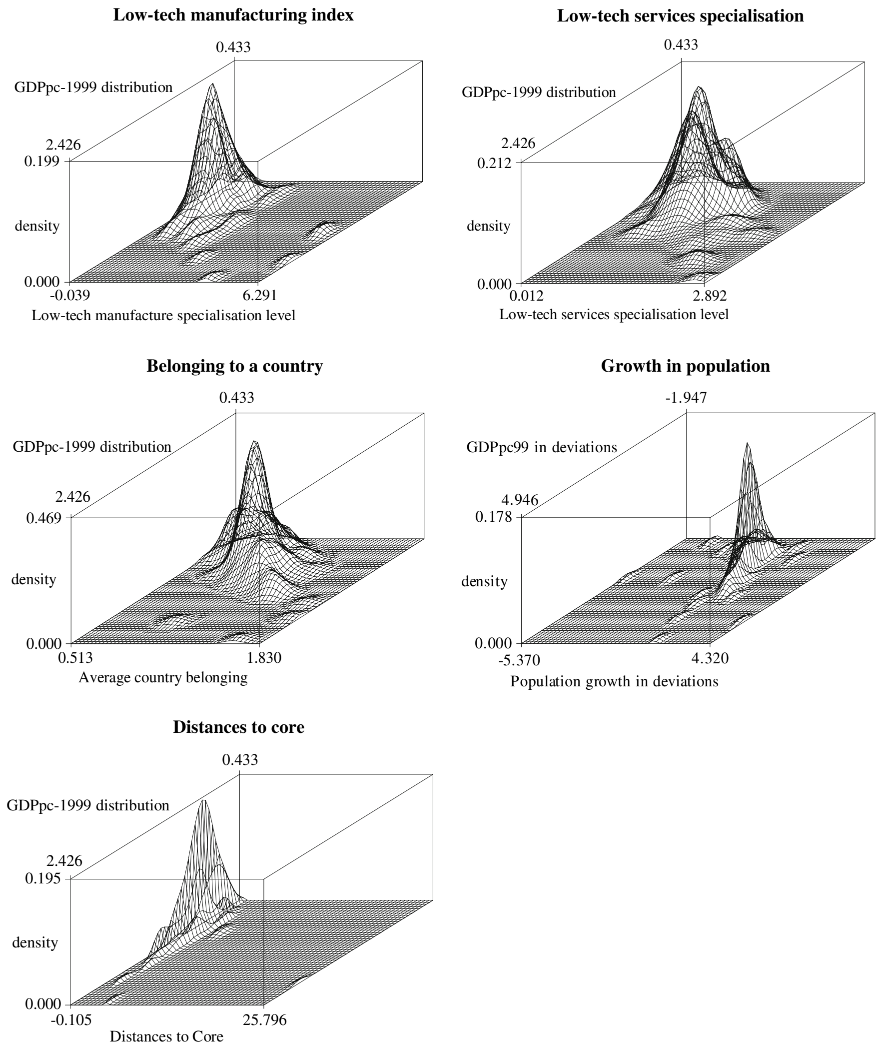

Fig. 2 continued

unemployment, education polarisation, high-tech services specialisation index, and the infrastructure cost index and within country inequality (region belonging to each member state). Notwithstanding, we should remark the sensitiveness of these multi-modality test results to noisy upper modes. For that reason, results are not clear for a few unimodality results. Thus, as mentioned above, we carry out a Markov chain's approach. In doing so, we restrict the number of modes. Ergodic probabilities show us the tendency of the distribution to concentrate on a unique or fewer modes.

Hence, adopting a conditional Markov chain approach, we find that the more conditioning variables present the lowest eigenvalues (persistence index). Our approach considered five states assuming an equal number of regions within each state. A lower

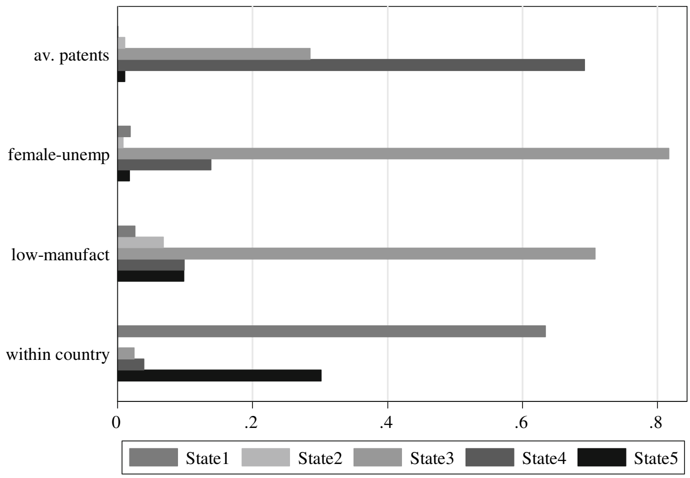

Fig. 3 Markov chains ergodic distributions (5 states)

eigenvalue denotes minor coincidences between the conditioned and non-conditioned distributions, which causes the distribution to become polarized into clubs. Ergodic distributions reveal a polarized picture coinciding with the results from our conditioned kernel approach. However, these ergodic probabilities are more informative. We can specify better the detected number of clubs for each of the conditioning factors rather than computing the multimodality test. Absorbing states are found for some of the conditioning variables, which impede any further comments on these variables (the ratio of elderly population to the number of young members, the low-tech services specialisation index and the infrastructure cost index). However, in the case of those ergodic Markov chain results plotted in Fig. 3 we can see that bipolarization exists for conditioning based on female unemployment and the average number of patents (Markov chain results are available upon request). In contrast, low-tech manufacturing specialisation splits the distribution into more than two clubs (the higher tail is equally distributed among the fourth and fifth chain' states). Meanwhile, the education polarisation appeared showing two extreme tails with a significant probability mass. Notwithstanding, the higher bipolarised distribution was obtained for considering within country disparities. The latter is in accordance with the increasing EU internal country disparities.

However, we should question whether these clubs are persistent, albeit that economic policies do affect ergodic distributions. Thus, a sensitivity measure for Markov chains was computed in order to observe changes in the ergodic distributions when small changes occurred in each state in the transition matrix (we assume increases of over 0.1 for each state and decreases of a half for contiguous states). Figure 4a, 4b illustrates the changes in ergodic distribution. Thus, changes in the lower contiguous state cause the situation of the regions to worsen, while the changes in the higher contiguous state are indicative of improved conditions. Our calculations showed that major changes, so a higher concentration on one peak, were observed derived by: changes in education polarization, changes in population growth rates and reducing

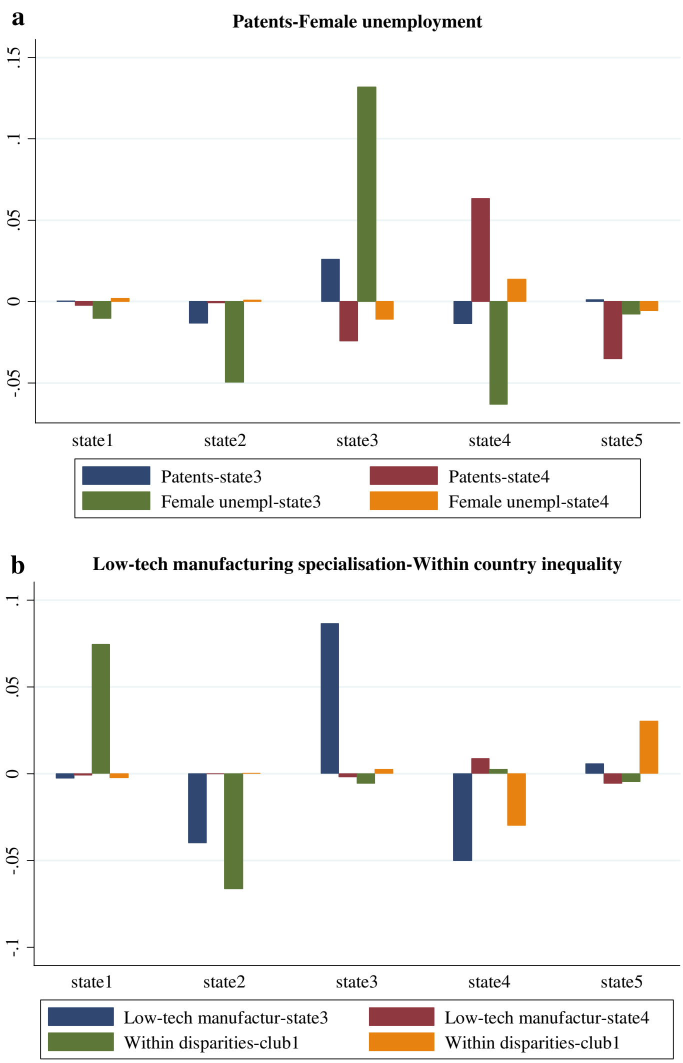

Fig. 4 Changes in ergodic distributions: $\Delta p_{ij} = 0.1$ for polarized states: **a** Patents-Female unemployment; **b** Low-tech manufacturing specialisation-Within country inequality

female unemployment rates. Minor changes were computed for improving average number of patents and increasing low-tech manufacturing specialisation indexes. Regarding within country disparities (see Fig. 4b), the lower club showed higher changes in ergodic distribution, therefore enforcing this situation. Thus, the implementation of member state policies addressed to the reduction of within-country regional inequality remains the key factor to ensure a region escapes from low levels of development. In this regard, further research needs to be done in order to explain why intra-country disparities still remain although between-country gap has been reduced.

6 Main conclusion

Here, the European regional distribution of GDPpc has been conditioned and evidence has been provided for the existence of clubs among these regions. Higher bipolarisation has been detected when considering within country disparities. Notwithstanding, income distribution differences would seem to be due to a range of complementary factors. Our results point to a process of bipolarisation from conditioning based on female unemployment rate, low-tech manufacturing specialisation and the average number of patents. After computing changes in ergodic probabilities using a conditioned Markov chain approach, the factors of belonging to a member state, female unemployment rate, low-tech services specialisation and population growth have been detected as the most relevant for modifying a polarised regional structure. However, results should be taken cautiously since specific economic policies improving some of these conditioning factors could present externalities on the others. Indeed, this is the main advantage derived once we use a regression methodology. Thus, acting in one direction, maybe would have consequences greater than expected from our estimated probabilities.

Thus, our findings involve State government investment actions. In this regard, Jalan and Ravallion (1997) state that the growth perspectives of poorer zones depend on the government's capability to invert the tendency to under-invest. Our results point to stress on some conditioning factors: specific industrial sectors (low-tech manufacturing was one of the conditioning factors that split the European regional GDPpc distribution into clubs), policies addressed to improve female participation employment rates or to introduce R&D improvements. Note that these policies could be complementary and generate further effects than those predicted through our findings.

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References

Azariadis C, Drazen A (1990) Threshold externalities in economic development. Quart J Econ 105:501–526
Azariadis C (1996) The economics of poverty traps. Part 1 complete markets. J Econ Growth 1:449–486
Azariadis C (2001) The theory of poverty traps: what have we learned? In: Bowles S, Durlauf SN, Hoff K (eds) Poverty Traps, pp 17–40. Princeton University Press, Princeton
Baland J-M, Francois P (1996) Innovation, monopolies and the poverty trap. J Develop Econ 49:151–178
Baldwin R, Martin P, Ottaviano G (2001) Global income divergence, trade and industrialisation: the geography of growth take-offs. J Econ Growth 6:5–37
Bandyopadhyay S (2003) Some dynamics and explanations of unequal growth across Indian states. Discussion Paper No. 77, World Institute for Development Economics Research
Barham V, Boadway R, Marchand M, Pestieau P (1995) Education and the poverty trap. Eur Econ Rev 39:1257–1275
Beaudry P, Collard F, Green DA (2002) Decomposing the twin-peaks in the world distribution of output-per-worker. Working Paper No. 9240, National Bureau of Economic Research
Bénabou R (1994) Human capital, inequality, and growth: a local perspective. Eur Econ Rev 38:817–826
Berthelemy J-C, Varoudakis A (1996) Economic growth, convergence clubs, and the role of financial development. Oxford Econ Pap 48:300–328

Cohen D (1996) Test of the convergence hypothesis: some further results. J Econ Growth 1:351–361
Chamley C (1993) Externalities and dynamics in models of learning by doing. Int Econ Rev 34(3):583–609
Cheshire P, Magrini S (2005) Analyzing growth distribution dynamics: isolating divergence factors. Paper presented at the 45th European regional Science Association Congress, Amsterdam
Conlisk J (1985) Comparative statics for Markov chains. J Econ Dynam Control 9:139–151
Desdoigts A (1999) Patterns of economic development. J Econ Growth 4:305–330
de la Croix D (1996) Economic development and convergence clubs: the role of inherited tastes and human capital. Discussion Paper No. 9624, Institut de Recherches Economiques et Sociales (IRES), Université catholique de Louvain.
Durlauf SN (1993) Nonergodic economic growth. Rev Econ Stud 60(2):349–66
Durlauf SN (1994) Spillovers, stratification and inequality. Eur Econ Rev 38:836–845
Durlauf SN, Quay DT (1999) The new empirics of economic growth. In: Taylor JB, Woodford M (eds) Handbook of macroeconomics. North-Holland, Amsterdam pp 231–304
Englmann F-C, Walz U (1995) Industrial centers and regional growth in the presence of local inputs. J Reg Sci 35(1):3–27
Erickson RA (1994) Technology, industrial restructuring, and regional development. Growth and Change 25:353–379
Fox J (1990) Describing univariate distributions in Modern methods of data analysis. In: Fox J, Long JS (eds) Sage, Newbury Park, pp 58–125
Galor O, Ryder HE (1989) Existence uniqueness and stability of equilibrium in a overlapping model with productive capital. J Econ Theory 49:360–375
Jalan J, Ravallion M (2002) Geographic poverty traps? A micro model of consumption growth in rural China. J Appl Econ 17(4):329–346
López-Bazo E, Vayá E, Mora T, Suriñach J (1999) Regional dynamics and convergence in the European Union. Ann Reg Sci 33(3):343–370
Maasoumi E, Racine J, Stengos T (2006) Growth and convergence: a profile of distribution dynamics and mobility. J Econ 136(2):483–508
Magrini S (1999) The evolution of income disparities among the regions of the European Union. Reg Sci Urban Econ 29(2):257–281
Magrini S (2004) Regional (di)convergence. In: Henderson JV, Thisse JF (eds) Handbook of regional and urban economics. Cities and geography (Handbooks in economics), vol 4. Amsterdam, Elsevier
Mora T (2005) Elasticities of ergodic solutions in the Markov chains approach to economic growth convergence. Pap Regi Sci 84(1):121–126
Murphy KM, Shleifer A, Vishny R (1989) Industrialization and the big push. J Polit Econ 97(5):1103–1026
Ottaviano GIP, Puga D (1998) Agglomeration in the global economy: a survey of the 'new economic geography'. World Econ 21(6):707–731
Overman HG, Puga D (2002) Unemployment clusters across European regions and countries. Econ Policy 34:115–147
Palivos T (1995) Endogenous fertility, multiple growth paths, and economic convergence. J Econ Dynam Control 19:1489–1510
Pittau MG, Zelli R (2006) Empirical evidence of income dynamics across EU regions. J Appl Econ 21:605–628
Quah DT (1996) Regional convergence clusters across Europe. Eur Econ Rev 40:951–958
Rodríguez-Pose A (1999) Innovation prone and innovation averse societies: the passage from R&D to economic performance in Europe. Growth and Change 30:75–105
Silverman BW (1986) Density estimation for statistics and data analysis. Chapman& Hall/CRC, New York