E C O N O M I C S   B U L L E T I N

Income distribution dynamics across European regions

Theophile Azomahou
BETA, Universite Louis Pasteur

Jalal El Ouardighi
BETA, Universite Louis Pasteur

Phu Nguyen Van
THEMA

Thi Kim Cuong Pham
BETA, Universite Louis Pasteur

Abstract

We use two datasets to study the convergence process across European regions. Relying on Quah (1966a,1997), we examine the dynamics of income distribution and find evidence of polarization whatever the time horizon considered. Regions whose incomes were close together at an initial period transit subsequently to widely different income levels.

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1 Introduction

Issues on economic convergence have important implications to policy makers with regard to regional development and economic integration in the European Union (EU). Indeed, the European economic integration is generally considered as beneficial for its regions in terms of higher allocation efficiency and increased competition. Moreover, the convergence of the economies is one of the requirements for the new countries eager to integrate the EU. Yet to prevent an increase of inequalities between regions, an important part (0.51% of the GDP of the 15 countries in the European community) of the European structural funds is devoted to regional development; see e.g. European Commission (1996, 1999) for further details. Even if efforts have been made to increase the attractiveness of European regions, inequalities seem persistent. According to Neven and Gouyette (1995), a process of divergence would be even in hand in the European regions. All occurs like if, in less prosperous countries, only the richest regions benefited from the convergence process with the rich countries.

Research over the last decade has considerably improved our understanding on convergence and has also raised several conflicting views. The convergence hypothesis has then induced a huge literature; see e.g., the 1996 *Economic Journal* symposium. Beginning with Baumol (1986), the convergence hypothesis has been extensively tested empirically. Sala-í-Martin (1996) analyses the regional $\beta-$convergence hypothesis on a data of 90 European regions for the 1950-1990 period and find that these regions converge at the 2% rate per year. The author also finds that the cross-regional income dispersion was reduced over time, which is in favour of the $\sigma-$convergence hypothesis.[1] However, as pointed out by Quah (1996, 1997), traditional approaches to convergence hypothesis focus on the average behaviour rather than the dynamics of income distribution. Therefore a particular attention has to be paid to analysing and interpreting convergence empirics which account for the dynamic structure of it, rather than a static average behaviour. According to Quah (1996), $\beta-$convergence or more generally, the coefficients in a cross-section regression is uninformative for a distribution's dynamics. Cross-section regressions can inform only about the average behaviour, not about the behaviour of the entire distribution. Checking for $\sigma-$convergence would not get round this difficulty. Quah (1996, 1997) underlines an 'emerging twin peaks' or polarization in the income distribution in a cross-section of countries. Polarization means that starting from period t, two peaks or modes emerge in the horizon $t+\tau$ income distribution. At the regional level, this method was used by Quah (1996) and Johnson (2000) to study the convergence across the US states over the 1948-1989 period and over the 1929-1993 period, respectively. However, they find no evidence of polarization in the cross-state income distribution. This finding suggests that there is a convergence between the US states over the periods of the study.

In this note, we use the method proposed by Quah (1996, 1997) to examine the convergence process across European regions. This method relies on two approaches : (i) one based on discrete transition probability matrix, and (ii) the other based on conditional density estimation. The latter provides us with a nonparametric approach to convergence empirics that captures the behaviour of the entire income distribution as if it evolves over time. The main empirical result of this study is the emerging of a polarization in the EU. We find that regions whose incomes were close together at an initial period transit subsequently to widely different income levels.

[1] σ-convergence in a cross-section of economies means that the cross-section dispersion of income per capita falls over time whereas β-convergence means that poor economies tend to grow faster than wealthy economies.

2 Data

Two datasets were used in this study. The first sample is the same as in Sala-í-Martin (1996) and Attfield et al. (2000).[2] The data contain series on real GDP per capita (in US \$) in 1950 and 1990 of 90 regions from Germany (11 regions), United Kingdom (11), Italy (20), France (21), The Netherlands (4), Belgium (3), Denmark (3), and Spain (17). More details on this data sample can be found in Sala-í-Martin (1996).

The second is a new and extensive dataset of 445 European regions observed in 1990 and 1996. It is provided by the Observatory of Sciences and Technology (OST). This dataset contains series on real GDP (measured in European Common Currency (ECU)[3], in 1990 prices) and the level of population for the years 1990 and 1996. For reasons of homogeneity of the regions of the Nomenclature of Territorial Units for Statistics (NUTS)[4], the OST uses regions on level NUTS-0 for Luxembourg (1 region), level NUTS-2 for Germany (38), Austria (9), Belgium (11), Greece (13), Finland (6), The Netherlands (12), Portugal (7) and Sweden (8); and on level NUTS-3 for Denmark (15), France (97), Ireland (8), Italy (103), Spain (52) and United Kingdom (65). To the best of our knowledge, it is the most extensive database available at the regional scale in Europe.[5] Note that our databases include both prosperous regions (for example from West Germany, France, United-Kingdom, Belgium, Luxembourg, Denmark, and The Netherlands) as well as less prosperous regions (from Spain, Portugal, and Greece).

The data present disparities between regions around the European average that are strong. Indeed, the highest level of GDP per capita – in Sweden (in 1990), Belgium-Luxembourg and Denmark (in 1996), is approximately twice the lowest level – in Portugal and Greece. The disparities grow even more marked if one observes the intra-country GDP per capita. The regional range is particularly high in France and Germany, but remains weak in Greece, Sweden and in Portugal. The evolution of GDP per capita between 1990 and 1996 shows a national average growth of 2.35%. The rise is particularly important in the Portuguese, Greek and Irish regions with an average growth rate of about 4%. The Finnish and Swedish regions are characterized by a lowest increase, respectively 0.1% and 0.36% on average. More details on this database can be found in OST (1999).

3 Methodology and empirical results

To study the dynamics of income distribution over time, we compute the transition probability matrix, say, M, from period t to $t+\tau$. Diagonal entries in M traduce the persistence, that is to say, some regions rich at $t+\tau$ had already being rich at time t and similarly, others poor at $t+\tau$ had already been poor at t. Note that we standardize the data $\{x_{t,i}, x_{t+\tau,i}\}_{i=1}^{n}$ by subtracting the sample mean and premultiplying by the inverse of the transpose of the Cholesky factor for the estimated sample covariance matrix to have zero mean and identity covariance matrix. The standardized data, defined in the Cartesian product set $[-2,2] \times [-2,2]$, allow us to analyse the regional income per capita relative to the EU average.

We discretize the set of possible values into intervals at $\{< -1,\ [-1,0),\ [0,1),\ \geq 1\}$, denoted group 1, 2, 3, and 4, respectively. Then, M is a 4×4 matrix with the (j,k) entry

[2] The data is extracted from Eurostat. We are grateful to Attfield et al. (2000) for providing the dataset.

[3] The former European Curency Unit is replaced by the Euro since 1999.

[4] 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).

[5] The list of these 445 regions is available from the authors upon request.

Table 1: Transition probability matrices for the 1950-1990 data (90 regions) and for the 1990-1996 data (445 regions).

		GDP 1990			
# regions	GDP 1950	< -1	$[-1, 0)$	$[0, 1)$	≥ 1
18	< -1	0.222	**0.389**	0.333	0.056
20	$[-1, 0)$	0.050	0.100	**0.550**	0.300
38	$[0, 1)$	0.211	0.289	**0.342**	0.158
14	≥ 1	0.357	**0.429**	0.071	0.143
		GDP 1996			
# regions	GDP 1990	< -1	$[-1, 0)$	$[0, 1)$	≥ 1
59	< -1	0.169	0.305	**0.356**	0.169
141	$[-1, 0)$	0.156	**0.546**	0.255	0.043
194	$[0, 1)$	0.072	**0.485**	0.366	0.077
51	≥ 1	0.020	0.078	**0.647**	0.255

Note: Bold figures represent the highest transition probabilities conditional on starting state.

being the probability that a region in income group j at time t transits to income group k at time $t + \tau$. These probabilities are computed as the empirical frequencies, that is the proportion of regions falling into a given group. Table 1 tabulates matrix M for the first and the second dataset, respectively. The first row (corresponding to group 1 in 1950) in Table 1 shows that 22% of regions in group 1 do not move at all from 1950 to 1990, 39% transit from group 1 to group 2; 33% transit from group 1 to group 3 and only 6%, transit from group 1 to group 4. It follows from this transition matrix that regions in groups 1 and 2 have a higher probability to see their income increased whereas there is a persistence for group 3 and a decrease for group 4. Table 1 also reports transition patterns for the 1990-1996 data sample. We observe that regions in group 1 transit to higher income group, group 2 is persistent, and groups 3 and 4 transit to lower income group. However, two income groups are formed at the arrival period. In light of these results, it seems that a phenomenon of polarization emerges.

Nevertheless, the transition matrix M is a discretized version of the dynamics of income distribution. We now investigate the polarization underlined above in a continuous income space. Following the notations in Johnson (2000), assume that the cross-region income distribution (in logarithm) at time t can be described by a density function $\varphi_t(x_t)$, where x_t denotes the income at period t.

As in general the income distribution evolves over time, we assume that the density prevailing at period $t+\tau$, for $\tau > 0$, is $\varphi_{t+\tau}(x_{t+\tau})$. We suppose that the process describing the evolution of the distribution is time-invariant and first-order, then the relationship between the two distributions can be summarized as

$$\varphi_{t+\tau}(x_{t+\tau}) = \int_0^\infty f_\tau(x_{t+\tau}|x_t)\,\varphi_t(x_t)\,\mathrm{d}x_t, \tag{1}$$

where $f_\tau(x_{t+\tau}|x_t)$ denotes the conditional density of $x_{t+\tau}$, τ periods latter. Compared to the above discrete approach, $f_\tau(x_{t+\tau}|x_t)$ represents the continuous analogue of the transition matrix. Let us denote $g_\tau(\mathbf{x})$ by the joint density, where $\mathbf{x} = [x_t, x_{t+\tau}]$. We estimate $g_\tau(\mathbf{x})$ as

$$g_{\tau}(\mathbf{x}) = \frac{1}{nh^2} \sum_{i=1}^{n} K\left(\frac{1}{h}(\mathbf{x} - \mathbf{x}_i)\right), \tag{2}$$

where $K(.)$ is a kernel function, and h is the bandwidth or smoothing parameter. We use a bivariate Gaussian kernel, $K(\mathbf{x}) = \frac{1}{2\pi}\exp\left(-\frac{1}{2}\mathbf{x}'\mathbf{x}\right)$ and the optimal bandwidth, see e.g., Silverman (1986).[6] We estimate $f_{\tau}(x_{t+\tau}|x_t)$ by $g_{\tau}(\mathbf{x})/g_t(x_t)$, where $g_t(x_t)$ is the marginal density of x_t, which is obtained by integrating $g_{\tau}(\mathbf{x})$ over $x_{t+\tau}$. We calculate the kernel density estimates from the standardized data on a grid of evaluation points defined on the Cartesian product set $[-2, 2] \times [-2, 2]$.[7]

Figure 1 and 2 display the surface plot of the joint distribution of log of real GDP per capita for 1950 and 1990 for the first sample, and for 1990 and 1996 for the second sample, respectively. The two graphs show an almost uni-modal distribution with a probability mass concentrated around the sample mean values. This means that the two samples contain a high proportion of middle-income regions.

Figures 3, 4 and Figures 5, 6 display the surface plot of the estimates of $f_{\tau}(x_{t+\tau}|x_t)$ and the corresponding contour plots for the two samples, respectively. The conditional density estimates (Figures 3 and 5) show how the cross-sectional distribution at t evolves into $t+\tau$. The results for the two samples show a similar bi-modal distribution (a peak corresponding to weak income in $t+\tau$, 1990 for the first sample and 1996 for the second sample, and another corresponding to high income in $t+\tau$). However in the 1990-1996 sample, the bi-modal pattern is clearly marked and the peak corresponding to high income in 1996 is higher.

Contour plot in Figures 4 and 6 makes this clear. They show a peak below the 45° line and a peak above the 45° line. For example, in the second sample, the contour peak values are located around 0.3, which is equivalent to a value of GDP per capita of 13,448 ECUs (approximately the mean of the EU).[8] Then, for each sample, we observe different behaviours for regions having approximately the same income. In the first sample, a part of low income regions tends to have decreasing income over the 41-years horizon whereas the other tends to have increasing income. In other words, some of the low income regions tend to grow quickly whereas the others do not. We observe a similar dynamic pattern in the second sample (note that now we have 7-years horizon).

These figures do exhibit some "peaks" which appear different from that observed by (Quah, 1997, Fig. 5.1) in a cross-country data and by (Johnson, 2000, Fig.1) in the case of the US states. Indeed, Quah (1997) find a polarization. However, the peaks are located on the main diagonal. The peaks in Johnson (2000) suggest that there is a convergence between the US states. Our estimate does not imply the same behaviour in the long-run. The key message from Figures 4 and 6 is that regions whose incomes were close together at an initial period transit subsequently to widely different income levels.

[6] In calculating the optimal bandwidth, we need the value of the integral, over 2-dimensional real space, of the squared kernel function. The value of this integral equals 0.0796. Note that other bandwidth selection methods might be implemented, such as cross-validation, etc.

[7] All computations in this paper are performed in Gauss.

[8] Recall that data (in log) were standardized before estimation. Then, to retrieve the value for 1990, 13,448 ECUs, we compute $\exp(a\sigma^2+m)$, with $a = 0.3$ (standardized income), $\sigma^2 = 0.0833$ (variance of unstandardized income), $m = 2.5738$ (mean of unstandardized income).

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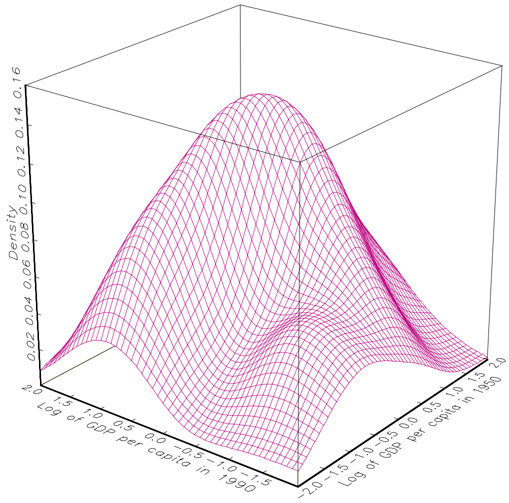

Figure 1: Surface plot of the joint distribution of log-real GDP per capita in 1950 and 1990, $g(\mathbf{x})$ where $\mathbf{x} = [x_{50}, x_{90}]$, using a bivariate Gaussian kernel and the optimal bandwidth, $h = 0.473$.

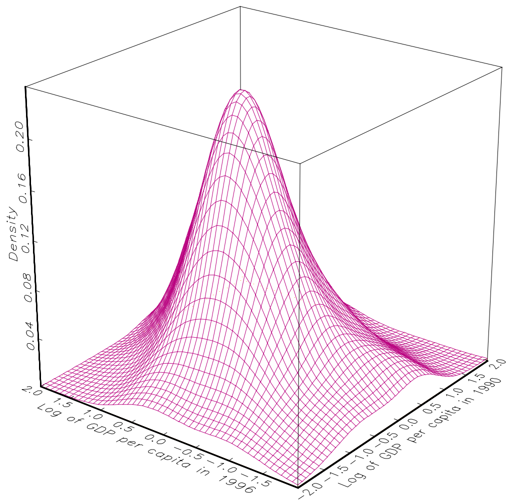

Figure 2: Surface plot of the joint distribution of log-real GDP per capita in 1990 and 1996, $g(\mathbf{x})$ where $\mathbf{x} = [x_{90}, x_{96}]$, using a bivariate Gaussian kernel and the optimal bandwidth, $h = 0.362$.

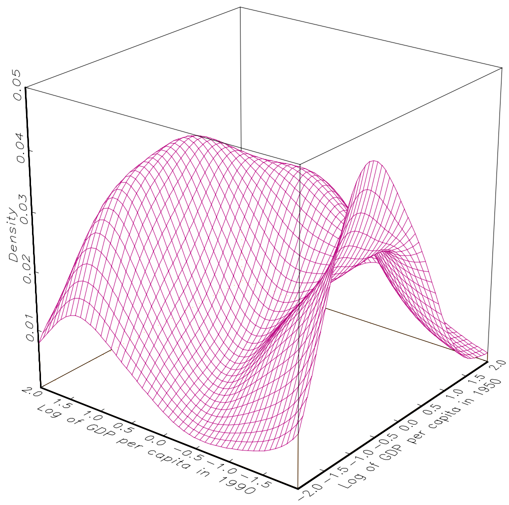

Figure 3: Surface plot of the conditional density of log-real GDP per capita in 1990 conditional on that in 1950, $f(x_{90}|x_{50})$, using a bivariate Gaussian kernel and the optimal bandwidth, $h = 0.473$.

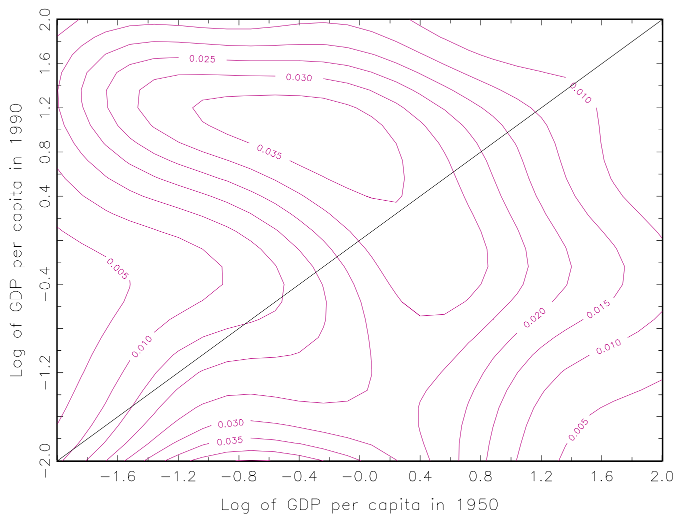

Figure 4: Contour plot of the conditional distribution $f(x_{90}|x_{50})$, where x_{90} and x_{50} are log-GDP per capita in 1990 and 1950, respectively. The straight line denotes the 45° diagonal.

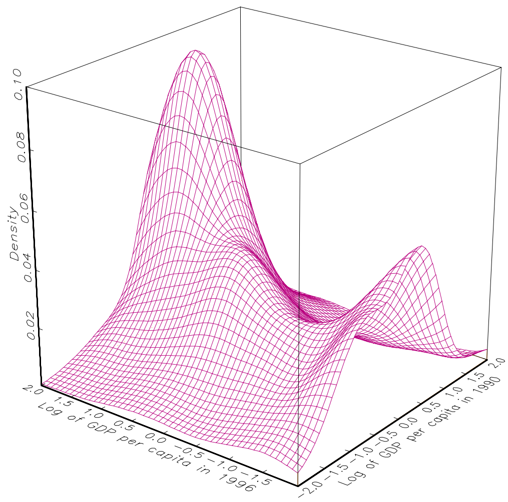

Figure 5: Surface plot of the conditional density estimate of $f(x_{96}|x_{90})$ using a bivariate Gaussian kernel with the optimal bandwidth $h = 0.36$, x_{96} and x_{90} are log-GDP per capita in 1996 and 1990, respectively.

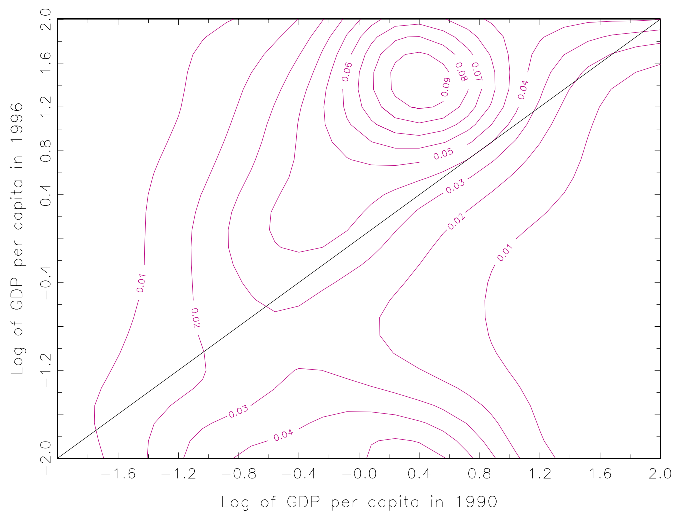

Figure 6: Contour plot of the conditional density estimate of $f(x_{96}|x_{90})$, where x_{96} and x_{90} are log-GDP per capita in 1996 and 1990, respectively. The straight line denotes the 45° diagonal.