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European metropolitan regions: a convergence process?

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Abstract

Regional convergence has become a heated topic in recent decades. Most papers studying this question define regions according to normative criteria, even though this can lead to biased conclusions. In contrast, this article explores the per capita income (PCI) distribution of metropolitan regions defined by a functional criterion, the agglomerated population. Specifically, we examine the external shape and internal movements of the PCI distribution in a sample of 235 European metropolitan regions over the period 1995 to 2006. The results describe a process of income convergence among these regions.

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1. Introduction

The study of regional disparities has become a heated topic in recent decades, especially within the European Union where interest has been fuelled by concerns over the ongoing process of economic integration. Therefore, a great many articles exist on this topic, most of them using, for reasons of data availability, normative/administrative criteria to define regions. However, as indicated by Magrini (1999), the use of this type of regions poses a number of problems that can affect the validity of the results. For this reason, in the present analysis we employ an alternative criterion, specifically a functional one to define European metropolitan regions.

Another important aspect of this paper is its methodology. As shown by Magrini (2009), among others, the classical approach to convergence (beta and sigma convergence) "fails to uncover important features of the dynamics that might characterise the convergence process." Instead we approach the question of regional convergence by examining the dynamics of the distribution itself. First, we estimate univariate density functions to detect changes in the external form of the distribution. Second, we estimate conditional density functions to characterise the internal movements of the population. We do not use the traditional conditional density estimator (e.g. Villaverde, 2006), but a relatively new method with at least two advantages: better statistical properties and more powerful visualisation tools (see Hyndman et al., 1996).

2. Data

As mentioned in the Introduction, the definition of a region should not rely on administrative criteria alone. In fact, there are quite a few different notions of a region among which the functional one -which arises from socio-economic criteria such as size (population or employment), density, and/or the commuting time from peripheral to core areas- stands out.

Accordingly, this study is based on the relative per capita incomes of 235 European Metropolitan regions in the EU-27, expressed in Purchasing Power Standards.[1] The data are derived from EUROSTAT sources (see Dijkstra, 2009), and cover the period between 1995 and 2006.[2] As there is no clear consensus on the definition of a Metropolitan region, we have opted for considering them as the NUTS3 regions (and where necessary, groups of NUTS3 regions) representing urban agglomerations with more than 250,000 inhabitants. The agglomerations are identified using the Urban Audit's Larger Urban Zones, so by definition include the commuter belt around each city.[3] Therefore, these metropolitan regions are not strictly political-administrative bodies.

[1] The entire list of European Metropolitan regions is given in the Appendix. Although the EU has undergone several major changes in its composition, in this paper we consider the same Metropolitan regions for the whole period. Thus, and although our initial sample consisted of 258 Metropolitan regions, insufficient data (fewer than 7 consecutive data) led us to exclude 3 Danish, 3 Spanish, 1 Italian, 1 Dutch, 1 British and 14 Polish regions (23 in total). Note that 13 of the included regions have data series which do not begin in 1995.

[2] Although convergence is a long-run concept, we think a period of 12 years is long enough to refer to the reduction of disparities as convergence and to smooth potential effects of different types of shocks.

[3] A different perception of metropolitan regions can be found, for example, in Krätke, 2007.

3. Convergence? A distribution dynamics approach

We begin by analysing the external shape of the per capita income distribution.[4] Specifically, we estimate univariate density functions for the initial and final years of the sample using a Gaussian kernel with varying bandwidth. A variable bandwidth is appropriate when data are sparse, as is the case in our sample. By varying the bandwidth along the support axis, we can reduce the impact of areas with few observations (potential outliers) on the estimated variance, as well as mitigating the bias due to areas with many observations. Specifically, we employ the adaptive, two-stage kernel density estimator proposed by Abramson (1982):

$$\hat{f}(x) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{h\lambda_i}K\left(\frac{x - x_i}{h\lambda_i}\right) \qquad (1)$$

where K is a Gaussian kernel and $\lambda_i = \sqrt{g / \hat{g}(x_i)}$ are the bandwidth adjustment factors. These factors are defined in terms of a pilot density estimate $\hat{g}(x)$ calculated using the fixed bandwidth h; g is the geometric average of $\hat{g}(x)$ over all i. The value of h is chosen following Silverman's rule of thumb (Silverman, 1986). The results, displayed in Figure 1, allow us to draw the following conclusions:

1. The shape of the distribution changed over the sample period. The probability of a metropolitan region being located near the European average has markedly increased, a clear sign of convergence.
2. The probability masses at relative PCI levels below 0.75 and above 1.4 decreased, another sign of convergence.
3. The distribution presents only one mode in both 1995 and 2006. Its centre is stable and located slightly above the EU-27 average, meaning that metropolitan regions tend to be richer than non-metropolitan regions.

In addition to observing changes in the external shape of the given distribution, it is useful to understand the internal changes. To address this issue, we employ an extension of the traditional kernel density estimation popularized by Quah (1996). To be precise, we estimate the so-called *stacked conditional density* (SCD) and *highest conditional density region* (HCDR) plots.[5] As with the density function, to minimize the sensitivity of our estimations to outliers, we use a variable bandwidth calculated following the rules laid out by Bashtannyk and Hyndman (2001). Specifically, we set the bandwidth in the x direction at each point such that the smoothing window always contains 30% of the 1995 data.

The SCD graph, which presents the conditional densities side-by-side in perspective, is mainly an illustrative tool (Figure 2). We will focus our comments on the HCDR plot (Figure 3), which is based on the same conditional probabilities but provides more detailed information on the intra-distributional changes.

The *highest density region* of a sample space is defined as "the smallest region... containing a given probability" (Hyndman et al., 1996). Note that this region need not be continuous. Each

[4] Regional PCI values are normalised to the average per capita income (that is, we take the EU-27 mean to be 1) in order to facilitate comparisons and eliminate the effect of absolute changes over time.
[5] For a revision of this approach, see Maza et al. (2010).

vertical strip in Figure 3 represents the conditional probability density that a region with a given per capita income in 1995 (x-axis) will achieve a different PCI in 2006 (y-axis). The shaded regions of the band represent the highest density regions for probabilities of 25%, 50%, 75% and 90% (in order from darkest to lightest). The bullet (•) marks the mode of each conditional density distribution. The lengths of the shaded regions in Figure 3 confirm that the mobility within each income bracket is relatively high.

The metropolitan regions with the lowest relative PCI in 1995 (i.e., Kaunas, Timisoara, Vilnius and Riga) have come closer to the European average. This is evidenced by their modes, which lie above the main diagonal on the left-hand side of the HDCR plot. Focussing on the greatest concentrations of probability (the bands containing total probabilities of 25% and 50%), we see that for relative PCI values below 0.5, the two darkest areas do not cross the diagonal. This is direct evidence for high mobility, which in turn contributes to the convergence process. The modes of metropolitan regions with above-average PCI are located below the diagonal, again indicating convergence. The highest density bands of metropolitan regions with PCI values above 1.3 the areas do not touch the diagonal, revealing that their relative position has changed for the worse. This is the case, for example, with regions such as Koln, Modena, Bologna and Karlsruhe.

4. Conclusions

As pointed out by Magrini (1999), empirical analyses of regional convergence usually employ available definitions of administrative regions without considering the potential bias created by this choice. To address this issue, we have examined the relative per capita income distribution of European metropolitan regions defined in terms of agglomerated population. In particular, we analyse the internal dynamics and external shape of the distribution between 1995 and 2006.

The shape of the PCI distribution changed significantly during this decade, with a higher concentration of probability around the European average in 2006. In addition, movements within the distribution have been significant, especially for regions near the extremes. That is, many of the poorest regions improved their relative positions over the study period, and many of the richest regions worsened their position. This paper therefore reveals a process of convergence in our sample of European metropolitan regions, in relative contrast with the trend generally detected among conventional administrative regions. The question is whether this is the result of using a different analytical technique or is mostly due to a different definition of region. As there are some papers (see, for example, Maza et al., 2010,[6] and Arbia et al., 2006) that using the same analytical technique as in this one conclude non-convergence for administrative regions, it should be obvious that the main reason for these differences lies in the different concept of region being used. Naturally, this implies that policy-makers should be very cautious when designing and implementing measures to address regional disparities in the EU, in particular when considering the type of regions to which these measures should be focused.

[6] It is convenient to notice that, although Maza et al.'s paper (2010) analyses two periods, the one directly comparable to the sample period employed here tend to conclude in the existence of non-convergence or, at least, rather weak convergence.

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Appendix: List of metropolitan regions

Belgium: Bruxelles/Brussel, Antwerpen, Gent, Charleroi, Liège; **Bulgaria:** Sofia, Plovdiv, Varna; **Czech Republic:** Praha, Brno, Ostrava, Plzen; **Denmark:** Odense; **Germany:** Berlin, Hamburg, München, Köln, Frankfurt am Main, Stuttgart, Leipzig, Dresden, Düsseldorf, Bremen, Hannover, Nürnberg, Wuppertal, Bielefeld, Halle an der Saale, Magdeburg, Wiesbaden, Göttingen, Darmstadt, Freiburg im Breisgau, Regensburg, Schwerin, Erfurt, Augsburg, Bonn, Karlsruhe, Mönchengladbach, Mainz, Ruhrgebiet, Kiel, Saarbrücken, Koblenz, Mannheim, Münster, Chemnitz, Braunschweig, Aachen, Lübeck, Rostock, Kassel, Osnabrück, Oldenburg, Heidelberg, Paderborn, Würzburg, Wolfsburg, Bremerhaven, Heilbronn, Ulm, Pforzheim, Ingolstadt, Reutlingen, Cottbus, Siegen, Hildesheim; **Estonia:** Tallinn; **Ireland:** Dublin, Cork; **Greece:** Athina, Thessaloniki; **Spain:** Madrid, Barcelona, Valencia, Sevilla, Zaragoza, Málaga, Murcia, Valladolid, Oviedo, Pamplona/Iruña, Santander, Bilbao, Córdoba, Alicante/Alacant, Vigo, Granada, Coruña (A), Donostia-San Sebastián, Cádiz; **France:** Paris, Lyon, Toulouse, Strasbourg, Bordeaux, Nantes, Lille, Montpellier, Saint-Etienne, Rennes, Amiens, Rouen, Nancy, Metz, Reims, Orléans, Dijon, Clermont-Ferrand, Caen, Grenoble, Toulon, Tours, Angers, Brest, Le Mans, Avignon, Mulhouse, Marseille, Nice, Lens – Liévin; **Italy:** Roma, Milano, Napoli, Torino, Palermo, Genova, Firenze, Bari, Bologna, Catania, Venezia, Verona, Pescara, Caserta, Taranto, Padova, Brescia, Modena, Salerno, Prato, Parma, Reggio nell Emilia, Bergamo, Latina, Vicenza; **Cyprus:** Lefkosia; **Latvia:** Riga; **Lithuania:** Vilnius, Kaunas; **Luxembourg:** Luxembourg; **Hungary:** Budapest, Miskolc, Debrecen; **Malta:** Valletta; **Netherlands:** s' Gravenhage, Amsterdam, Rotterdam, Utrecht, Eindhoven, Tilburg, Groningen, Enschede, Heerlen, Breda, Haarlem, Dordrecht, Leiden; **Austria:** Wien, Graz, Linz, Salzburg, Innsbruck; **Poland:** Lódz, Kraków, Wroclaw, Poznan, Gdansk, Olsztyn, Czestochowa, Bielsko-Biala; **Portugal:** Lisboa, Porto; **Romania:** Bucuresti, Cluj-Napoca, Timisoara, Craiova, Constanta, Iasi, Galati, Brasov; **Slovenia:** Ljubljana, Maribor; **Slovakia:** Bratislava, Košice; **Finland:** Helsinki, Tampere, Turku; **Sweden:** Stockholm, Göteborg, Malmö; **United Kingdom:** London, Birmingham, Glasgow, Liverpool, Edinburgh, Manchester, Cardiff, Sheffield, Bristol, Belfast, Newcastle upon Tyne, Leicester, Exeter, Wrexham, Portsmouth, Worcester, Coventry, Kingston-upon-Hull, Stoke-on-Trent, Nottingham, Bradford-Leeds, Sunderland, Brighton and Hove, Plymouth, Swansea, Derby, Southampton, Northampton, Luton, Swindon, Stockton-on-Tees, Bournemouth, Norwich.

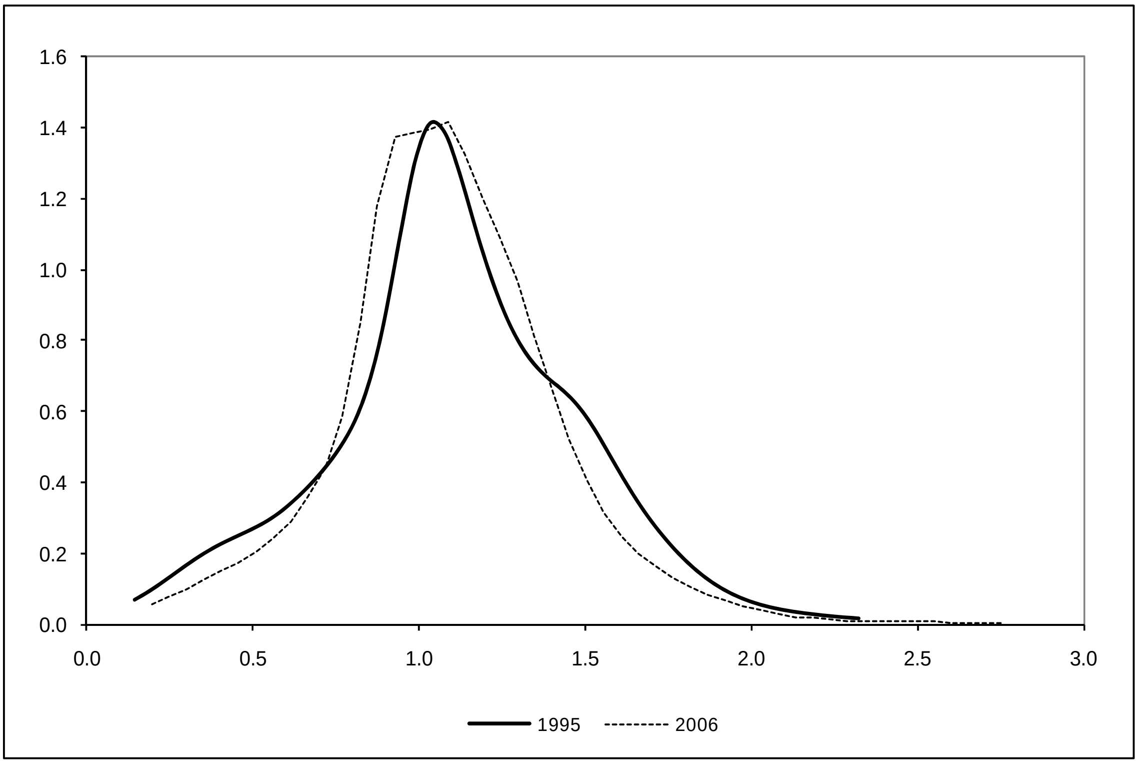

Fig. 1. PCI probability density functions (EU-27=1) in 1995 and 2006. The plots are calculated non-parametrically using the two-stage kernel density estimator proposed by Abramson (1982).

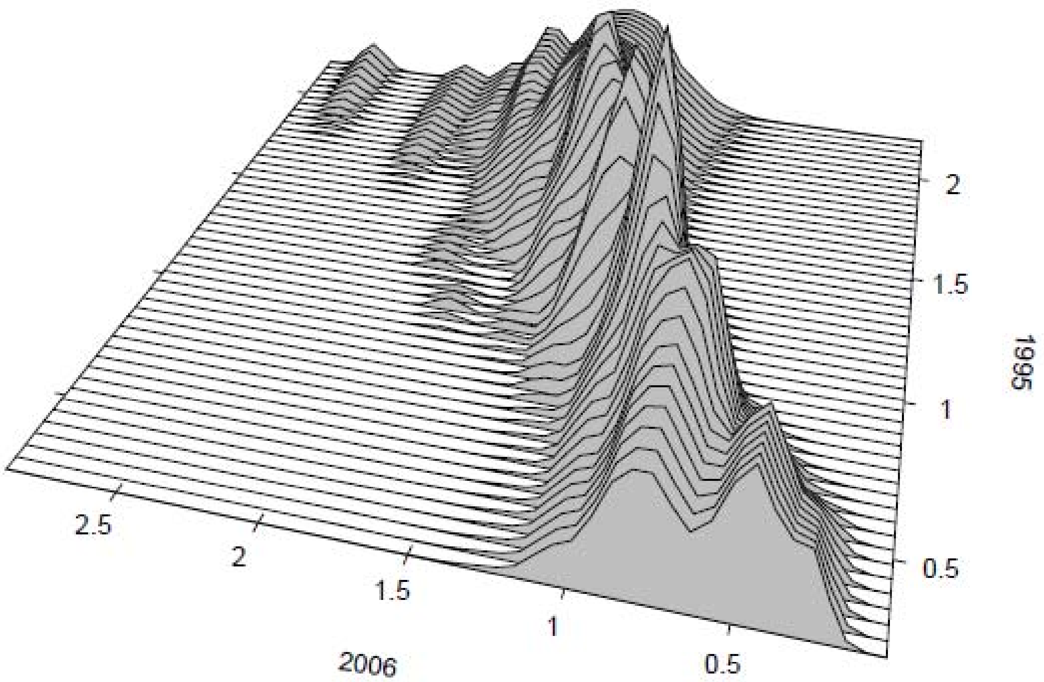

Fig. 2. Intra-distribution dynamics: the stacked density plot (EU-27=1). Conditional probability densities of transition between 1995 and 2006 income levels. The curves are obtained using a Gaussian product kernel density estimator, with a variable bandwidth based on the rule suggested by Bashtannyk and Hyndman (2001). The stacked conditional density plot was estimated at 50 points.

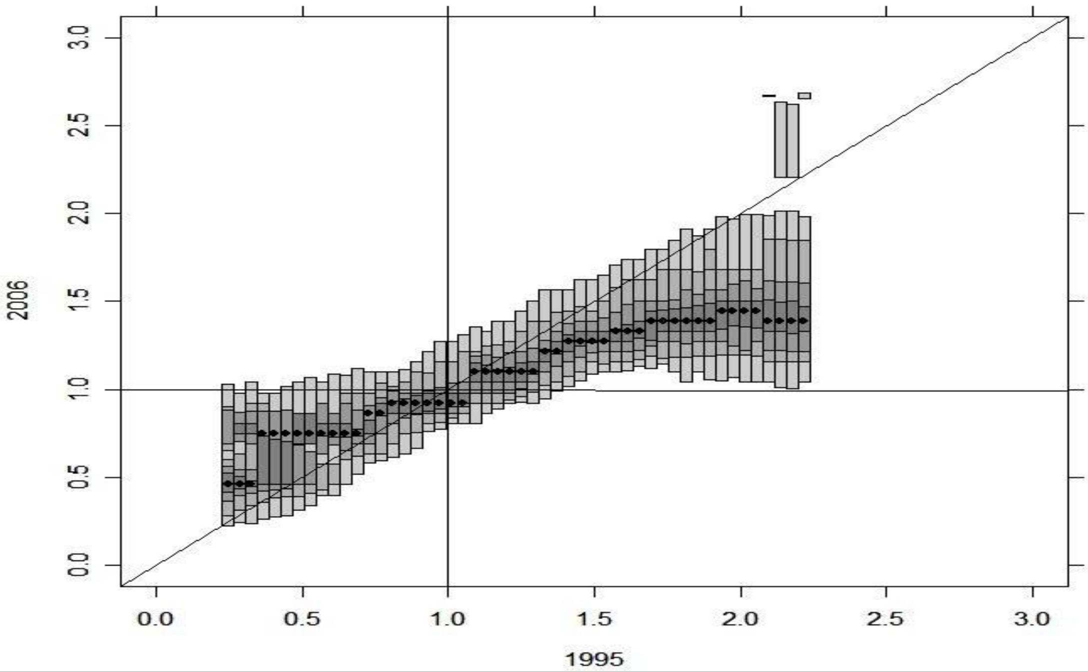

Fig. 3. Intra-distribution dynamics: highest density region (HDR) plot (EU-27=1). From darkest to lightest, the shaded bands are the smallest possible regions containing 25%, 50%, 75% and 90% of the total conditional probability. The bullets indicate distribution modes. This plot is based on the conditional density functions estimated in Figure 2.