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Income distribution dynamics across European regions: Re-examining the role of space

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ABSTRACT

This paper is aimed at exploring the role played by space on the dynamics of regional per capita income disparities in Europe between 1980 and 2005. To do that, an analysis based on the so-called *distribution dynamics approach* is used as benchmark. Therefore, the external shape of the per capita income distribution and movements within it are examined using both continuous and discrete techniques. This first approach reveals that regional disparities across European regions have decreased over time and, based on the computation of a mobility index, also highlights the existence of a medium mobility degree within the distribution. Subsequently, a *spatially conditioned distribution dynamics approach* is developed to adequately assess the spatial dimension of the convergence process. In this new approach per capita income of each region is doubly conditioned on its per capita income and the per capita income of its neighbours, both in a previous period. Additionally, a novel mobility index on the basis of a spatial Markov chains approach is devised. The results illustrate the importance of geography in explaining regional per capita income evolution; in particular it is shown that poor regions surrounded by rich regions have a much higher probability of escaping the poverty trap than other poor regions.

1. Introduction

Regional convergence has become one of the most heated topics in economic growth literature in the last decades. This is especially so in studies analysing the extent and evolution of European Union (EU) regional disparities (among the many surveys on the issue see, for example, Azomahou et al., 2011; Fingleton, 2003a; Islam, 2003; Magrini, 2004; Meliciani, 2006). Setting aside the academic debate about the relevance of neoclassical, endogenous growth, and new economic geography models to explain convergence/divergence, the main policy reason behind this interest is that a key objective of the EU is "*to reduce the disparities between the levels of development of the different regions and the backwardness of the least favoured regions or islands, including rural areas.*" (EU Treaty, article 158). Hence, mitigating regional disparities, normally measured as differences in regional per capita GDP (income), is a fundamental target of the European regional policy.

In the last decade many methodological advances have been made within this area. Foremost among them is, as indicated by Fingleton, "the growing recognition that space matters and that spatial effects are more readily recognised not simply as nuisance phenomena …, but as being important in their own right as a manifestation or real empirical phenomena with a basis in theory" (Fingleton, 2003b, p. 5). Most papers have dealt with this issue using spatial econometrics within the classical convergence approach centred on the concepts of sigma and beta convergence, specifically by modelling spatial dependence through either spatial autoregressive, cross-regressive and/or spatial error models. The main contribution of this paper is, however, to assess the role played by space on the evolution of regional disparities in Europe by properly including it on the so-called *distribution dynamics approach*, as it overcomes main shortcomings of the classical one (e.g. Fischer and Stumpner, 2008; Magrini, 1999; Magrini, 2009; Quah, 1996a, 1997).[1]

Accordingly, we use as benchmark an aspatial analysis based on the distribution dynamics approach. Indeed, the first part of the paper employs three different but complementary methodological devices to examine the EU regional distribution dynamics. First, univariate density functions are examined to identify the external shape of the distribution and its changes over time. Second, conditional density functions are computed to analyse intra-distribution dynamics, for which a relatively new conditional density estimator suggested by Hyndman et al. (1996) and its new visual tool (the *highest conditional density region plot*) is used. Third, and from a discrete point of view based on the *Markov chains methodology*, intra-distribution dynamics is also examined using the mobility index proposed by Maza et al. (2010).

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[1] As Magrini (2009) indicates, the classical convergence approach "*fails to uncover important features of the dynamics that might characterise the convergence process*".

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After that, the second and main part of the paper aims at examining the role played by space on the dynamics of regional income disparities in Europe. To do that, a *spatially conditioned distribution dynamics approach* is proposed. Concerning the external shape of the distribution, this is done by computing univariate density functions for neighbour-relative per capita income variables. Next, to address the issue of intra-distribution dynamics Hyndmann et al.'s estimator is applied to new conditioned variables: to be precise, per capita income of each region is doubly conditioned on its per capita income and that of its neighbours, both in a previous period. Finally, a *spatial Markov chains methodology* is employed (Le Gallo, 2004; Le Gallo and Chasco, 2008; Monasterio, 2010; Rey, 2001), in which a novel, properly modified version of the aforementioned mobility index is used to quantify the role played by space. In all these three settings the new results are compared to the aspatial ones used as benchmark. This paper departs from an earlier analysis on the role of space on distribution dynamics in two respects: First, in the non-parametric estimation of a doubly conditioned density function in the continuous intra-distribution dynamics analysis by using Hyndmann et al.'s estimator[2]; and, second, in the definition and computation of a new spatial mobility index in the discrete intra-distribution dynamics analysis that allows us to quantify the role of space.

The statistical information used in this paper has been obtained from the Cambridge Econometric Database. Specifically, we examine disparities among 192 EU-15 regions (see the Appendix), most of which correspond to level 2 of the Nomenclature of Territorial Units for Statistics (NUTS), from 1980 to 2005. For brevity's sake, the only variable we employ is per capita income (adjusted for purchasing power parity differences), although the analysis could be directly applied to other relevant variables. We consider relative values, i.e., regional per capita incomes normalised by the European average (EU-15 = 100), as a simple and efficient way to correct for the effects of business cycle and trends in the European average income.

The paper is structured as follows: the next section applies the distribution dynamics approach to an aspatial set up. The third section extends the same approach to a spatial setup in order to highlight the role played by space. The final section provides some concluding remarks.

2. Distribution dynamics: An aspatial approach

To briefly illustrate the extent and evolution of per capita income differences across the European regions, we initially examine the ratio between the weighted average per capita incomes of the 25% richest and 25% poorest regions. For the sample period, this ratio is equal to 2.26 and strongly decreases between 1980 (4.30) and 2005 (1.92). Additionally, the regions with the highest and lowest per capita income are roughly the same in both 1980 and 2005. These preliminary results suggest the existence of remarkable disparities and relative rank stability among the European regions, as well as an intense convergence process. The analysis in the following paragraphs explores in greater depth these and other characteristics of the regional per capita income distribution in the EU-15.

2.1. External shape

A common approach for examining the external shape of a distribution and its changes over time is to compute a non-parametric kernel density. A key choice when estimating these functions is the selection of a proper smoothing parameter or bandwidth, to put less weight on observations that are further from the point being evaluated. To this end, we use a Gaussian kernel with optimal bandwidth according to Silverman's (1986) rule-of-thumb. We use a fixed (rather than a variable) bandwidth because the problem of data sparseness is not very relevant.[3] The kernel density estimate of a series Y (i.e., relative per capita income) at a point y is given by:

$$f(y) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{y-Y_i}{h}\right) \tag{1}$$

where n is the number of observations (regions) i, $K(\bullet)$ is the Gaussian kernel function, and h denotes the bandwidth parameter.

Fig. 1 shows the European regional per capita income distribution for the initial and final years of the sample period. Significant shifts are seen in the external shape. The probability mass is much more concentrated around the mean in 2005 than in 1980, and the main mode has clearly moved to the right. In order to locate the position of the modes we apply the proposal of Salgado-Ugarte et al. (1997),[4] which shows that the main modes in 1980 and 2005 are located at 74.4% and 92.8%, respectively, of the European average. The distribution also displays a second mode in 1980 (134.6%) and two minor modes in 2005 (153.1 and 185.6%). The long tails at the lower and upper distribution ends that existed in 1980 have disappeared in 2005. Therefore, the conclusion is that the distribution has experienced a clear convergence process.

2.2. Intra-distribution dynamics: A continuous version

Intra-distribution dynamics analysis can be performed from a continuous or a discrete perspective (for a recent reference see Maza et al., 2010). One of the most common continuous approaches involves the calculation of stochastic kernels (see Durlauf and Quah, 1999; Quah, 1997; and Rosenblat, 1969). This approach consists of the estimation of the conditional density of a variable Z (the relative per capita income in the period $t+s$) given a variable X (the relative per capita income in the period t). Therefore, the stochastic kernel approach estimates the probability of jumping from one per capita income level in year t to another in year $t+s$.

On the basis of the standard kernel estimator, Hyndman et al. (1996) proposed an alternative conditional density estimator with better statistical properties. This estimator is given by:

$$\hat{f}^*_\tau\left(z|x\right) = \frac{1}{b}\sum_{i=1}^{n} w_i(x) K\left(\frac{||z-Z^*_i(x)||_z}{b}\right), \tag{2}$$

where

$$w_i(x) = K\left(\frac{||x-X_i||_x}{a}\right) / \sum_{j=1}^{n} K\left(\frac{||x-X_j||_x}{a}\right) \tag{3}$$

and a and b are smoothing or bandwidth parameters on the two spaces. Unlike the standard stochastic kernel approach, $Z^*_i(x) = e_i + \hat{r}(x) - \hat{l}(x)$, where $\hat{r}(x)$ is the estimator of the conditional mean function $r(x) = E[Z|X = x], e_i = z_i - \hat{r}(x_i)$, and $\hat{l}(x)$ is the mean of the estimated conditional density of $e|X = x$.

Although it can be proved that if $\hat{r}(x) = \sum_{i=1}^{n} w_i(x) Z_i$, then $\hat{f}^*_\tau(z|x)$ is equivalent to the traditional kernel estimator, in any case the mean function $\hat{f}^*_\tau(z|x)$ has better bias properties than it, as well as a smaller integrated mean square error.

Hyndman et al. (1996) also proposed two new ways to visualise the conditional density: the *stacked conditional density* (SCD) and the *highest conditional density region* (HCDR) plots. The SCD plot arranges densities side by side in a perspective graph. The HCDR

[2] This same approach, but using a standard kernel estimator instead of Hyndmann et al.'s one, has been developed by Magrini (2004).

[3] We replicated the estimation by using an adaptive kernel density estimator (Abramson, 1982) to minimize the sensitivity of our estimates to the presence of potential outliers. The results were roughly the same.

[4] Alternative modality tests can be seen in Silverman (1981) and Hall and York (2001).