The Spatiality of Productivity across EU Regions

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Abstract

This paper empirically analyses the spatial dispersion of labour productivity, as measured by gross value added per (employee) hour, across European NUTS 2 and NUTS 3 regions over the period 1980-2006. The presence or otherwise of spatial concentrations of labour productivity across NUTS 2 and NUTS 3 regions is assessed, as well as the tendency towards convergence or divergence of labour productivity across European regions over time. It is found that spatial concentrations of labour productivity growth tend to occur across smaller geographic areas such as concentrations of neighbouring NUTS 3 regions, but not across wider NUTS 2 regions or across national boundaries. The analysis also indicates that findings of convergence of labour productivity growth are not robust across NUTS 2 and NUTS 3 spatial scales.

Keywords: Regional Economic Growth, Labour Productivity, Spatial Econometrics

JEL-Classification: R11, R12

1. Introduction

Recent decades have seen a wealth of research emerge documenting the process of economic growth across European Union regions, much of which has aimed to establish the presence (or absence) of convergence in regional growth rates. While the presence of a convergence process in European per capita income in the 1980s has been a prevalent finding of this stream of research, a number of studies have reported a slowdown of convergence thereafter [for example, Neven and Gouyette (1995), Fagerberg and Verspagen (1996), Tondl (1999), Martin (2001), Gardiner et al. (2004), and Pittau (2005)]. It is still disputed whether the convergence process has regained momentum since the 1980s. Methodological differences, as well as differences regarding the geographical unit under consideration, have contributed to emergence of conflicting findings. Geppert and Stephan (2008) point out that while evidence of convergence has forthcoming at a national level, regional disparities within EU member states appear to persist or indeed widen. Geppert and Stephan (2008) posit that these regional disparities are largely due to the persistent strength of agglomeration economies attracting high-income activities to urban areas. What is more, it has been argued that what convergence has occurred across EU regions is most appropriately characterized in terms of regions converging into different clubs [Quah (1996) and Corrado et al.(2005)]. This depiction of neighbouring regions growing at similar speeds serves to emphasize the role of spatial effects in the process of regional growth.

While regional income has been the variable of interest in many of these studies, Enflo and Hjertstrand (2009) note that recent studies have also focused on labor productivity as a driver of regional growth. Gardiner et al. (2004), for example report that the degree of convergence in labor productivity has been disappointingly slow and that much of it seems to have taken place in the boom years of the 1980s.

Labour productivity has been found to exhibit significant and persistent differences across most countries and at different regional definitions [recent examples include Basile (2008), Byrne et al.,(2009), Enflo and Hjertstrand (2009), and Webber(2009)]. However, it is reasonable to question the notion that labour productivity should possess a spatial dimension and to wonder how this spatial aspect might manifest itself. Gardiner et al. (2004) note that both endogenous growth and new economic geography models give strong grounds for expecting productivity to display geographical contiguity, and that such spatial clustering may reflect a range of factors and processes.[1] Contiguous regions may have similar degrees of

[1] As Martin (2001) outlines (in the context of European integration), conventional neoclassical growth theory predicts that a reduction of barriers to trade will lead to an increase in allocative efficiency across regions, and hence in income per capita. Endogenous growth theories incorporate various processes, such as localised collective learning, accumulation of skills, and technological innovation, which are not diminishing in their returns and can contribute to a higher long run growth rate. However, it is also possible for regions to converge to economy-specific steady states due to differences in these various growth processes (conditional convergence) where similar types of regional economies may converge (club convergence). Martin (2001) goes on to note that theories emanating from

access to transport and other modes of communication; they may have similar proximity to major markets; they may share similar socio-institutional set-ups that influence firm performance and entrepreneurship; there may be localised spillovers of knowledge and technology, through inter-firm networking, employee movement and technology sharing, local trading relationships, access to common technology centres, and universities. Contiguous regions may share similar industrial structures and thereby similar responses to common external demand, technology and policy shocks.

Labour productivity in this paper refers to the productive efficiency of a given workforce. In the regional context, labour productivity is the outcome of a variety of regional determinants such as superior technological, social, infrastructural or institutional assets; Gardiner et al. (2004). This paper uses gross value added (GVA) per employee hour at the NUTS 2 and NUTS 3 level to capture regional labour productivity. While this proxy of labour productivity may be somewhat crude, its data availability facilitates the tracking of regional labour productivity over a prolonged period of time. This can be contrasted with more rigorous approaches to measuring regional labour productivity based on spatial variation in earnings, which are confined to a narrow time frame. This is illustrated by Rice et al. (2006), who utilise a measure of regional labour productivity based on regional earnings differentials across 119 British NUTS 3 regions over the period 1998-2001. However, Rice et al's (2006) labour productivity measure exhibits a strong correlation (0.71) with British GVA per employee hour, suggesting that GVA per employee hour has the potential to approximate labour productivity.

This paper aims to (i) present an exploratory spatial analysis of labour productivity in an attempt to ascertain whether a significant spatial component of labour productivity has been present across EU NUTS 2 and NUTS 3 regions over the period 1980-2006, (ii) assess, given the presence or otherwise of this spatial component, the degree of convergence in labor productivity across NUTS 2 and NUTS 3 regions over the period in question, and (iii) ascertain the extent to which spatial productivity spillovers are regionally bounded. The paper precedes as follows : Section 2 provides a description of the data used in this paper. The spatial dispersion of British real GVA per capita is also discussed and illustrated with maps. A description of how β-convergence analysis has been augmented to include a number of global spatial econometric methods is provided in Section 3. The results yielded by these spatial econometric methods are reported in Section 4. Conclusions are then presented in Section 5.

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new economic geography, such as that of Krugman (1991), argue that the reduction of trade barriers leads to divergence, as reductions in transport and transaction costs encourage greater spatial agglomeration and specialization of economic activity.

2. Data Description and Summary Statistics

This paper investigates labour productivity across NUTS 2 and 3 regions in Belgium, France, Germany (excluding regions pertaining to the former East Germany), Ireland, Italy, Holland, Spain, Portugal, and the UK over the period 1980 to 2006. The dataset used in this study has been acquired from *Cambridge Econometrics*. The Eurostat REGIO database is the prime source for the European data produced by Cambridge Econometrics. NUTS 2 and NUTS 3 level employment and constant price Gross Value added (GVA) with 2000 as the base year are used in conjunction with total (national-level) hours worked data available from the University of Groningen's Total Economy database (www.ggdc.net/databases/ted.htm) to construct our measure of regional labour productivity, annual NUTS 2 and NUTS 3 GVA per employee hours worked over the period 1980-2006.[2] The GVA data utilised in this study is not adjusted for purchasing power standards (PPS).

Table 1 provides an overview of average level and growth rates of NUTS 3 labour productivity for the nine EU countries included in this study for 1980-92 and 1992- 2006. Salient characteristics include: (i) in 1980, the highest average levels of labour productivity were observed in Belgium, Germany, and Holland, respectively, and the lowest average levels observed in Spain, Ireland, and Portugal; (ii) in 2006, the highest average NUTS 3 labour productivity is observed in Germany, Ireland, Holland; (iii) 1992-06 average NUTS 3 labour productivity growth rates were uniformly lower than those of 1980-92, with the exception of the UK; (iv) 1992-2006 growth rates were more concentrated than those of 1980-1992.

[2]Cambridge Econometrics produce deflated GVA series for regions by utilising sectoral price deflators from AMECO. Data construction for NUTS 2 and NUTS 3 regions involves deflation, interpolation and summation constraints to ensure consistency across different levels of aggregation. Further details of regarding the *Cambridge Econometrics* data construction are available from:
http://www.camecon.com/Europe/Regional_Local_Cities/KnowledgeBase/Appendices/EuRegM/Data_Construction.aspx.

Table 1: Average NUTS 3 Labour Productivity for selected EU countries (1980-2006)

	Average level			Growth (%)		Standard Deviation		
	1980	*1992*	*2006*	*1980-92*	*1992-06*	*1980*	*1992*	*2006*
Belgium	21.48	28.44	33.26	2.18%	1.05%	3.22	3.64	3.85
France	18.71	26.41	33.10	2.70%	1.50%	3.44	3.65	5.08
Germany	20.73	28.80	35.12	2.69%	1.33%	5.41	3.99	4.75
Ireland	10.82	19.05	34.01	4.43%	3.76%	2.38	2.77	8.14
Italy	17.54	21.69	24.65	1.68%	0.87%	2.89	2.75	2.51
Holland	20.40	27.21	33.83	2.46%	1.44%	7.98	4.00	5.22
Portugal	5.32	8.64	10.22	3.92%	1.04%	1.81	2.10	3.23
Spain	12.95	18.06	20.41	2.61%	0.86%	2.37	2.59	1.84
UK	15.71	19.82	28.17	2.11%	2.30%	5.31	3.58	6.29

Source : Cambridge Econometrics

Table 1 also presents the standard deviation of average NUTS 3 labour productivity in 1980, 1992, and 2006. This provides an initial impression of whether or not the labour productivity of NUTS 3 regions has become more concentrated or dispersed over the period in question. Measuring the dispersion between regions based on the standard deviation of the cross-section series is referred to as "sigma convergence"; see Barro and Sala-I-Martin (1992). From Table 1 it appears that the NUTS 3 regions of Belgium, France, Ireland, and Portugal have become more dispersed over the 1980-2006 period, in terms of labour productivity. NUTS 3 regions in Germany, Holland, and the UK appear to have become more concentrated by 1992 but have subsequently experienced dispersion. In order to provide a visual impression of the spatial dispersion of labour productivity across European NUTS 3 regions, a set of maps are presented (Figures 1-2). The shading in Figure 1, labour productivity in 1980 and 2006, represents <50%, 50-100, 100-125%, and >125% of median real GVA per capita. Each sub-region is shown relative to the median rather than the mean to mitigate the impact of outliers. The shading in Figure 2, labour productivity growth in 1980-92 and 1992-06, denotes growth of <0%, 0-3%, 3-6%, and >6%.

Figure 1: NUTS 3 labour productivity (GVA per employee hour), 1980 (left), 2006 (right)

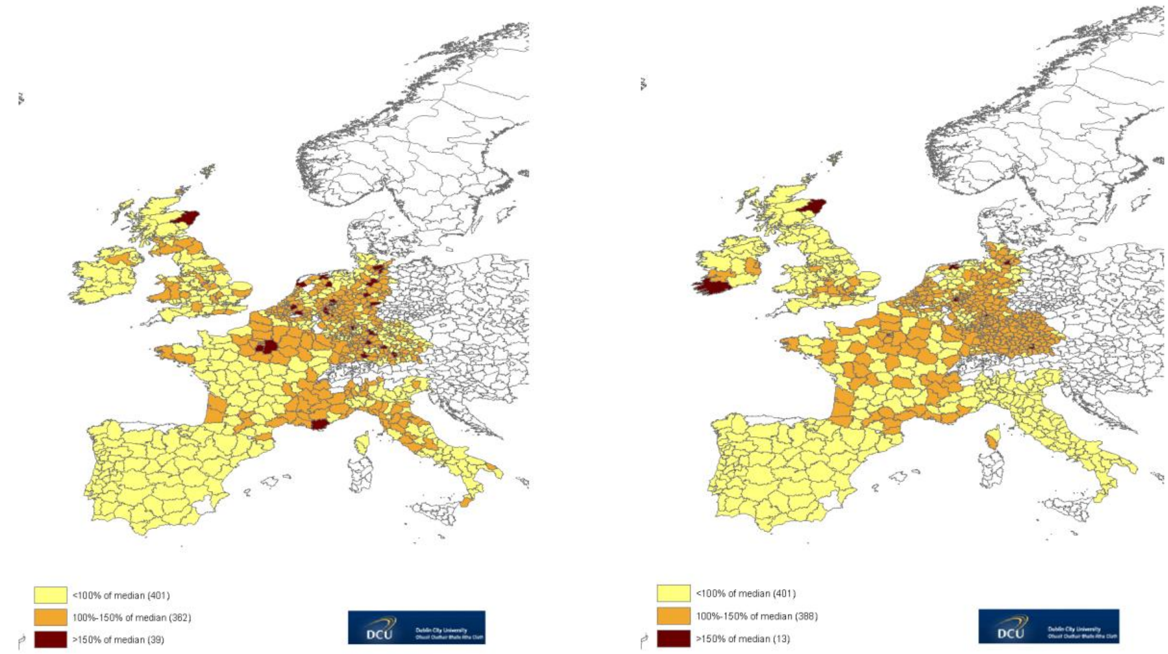
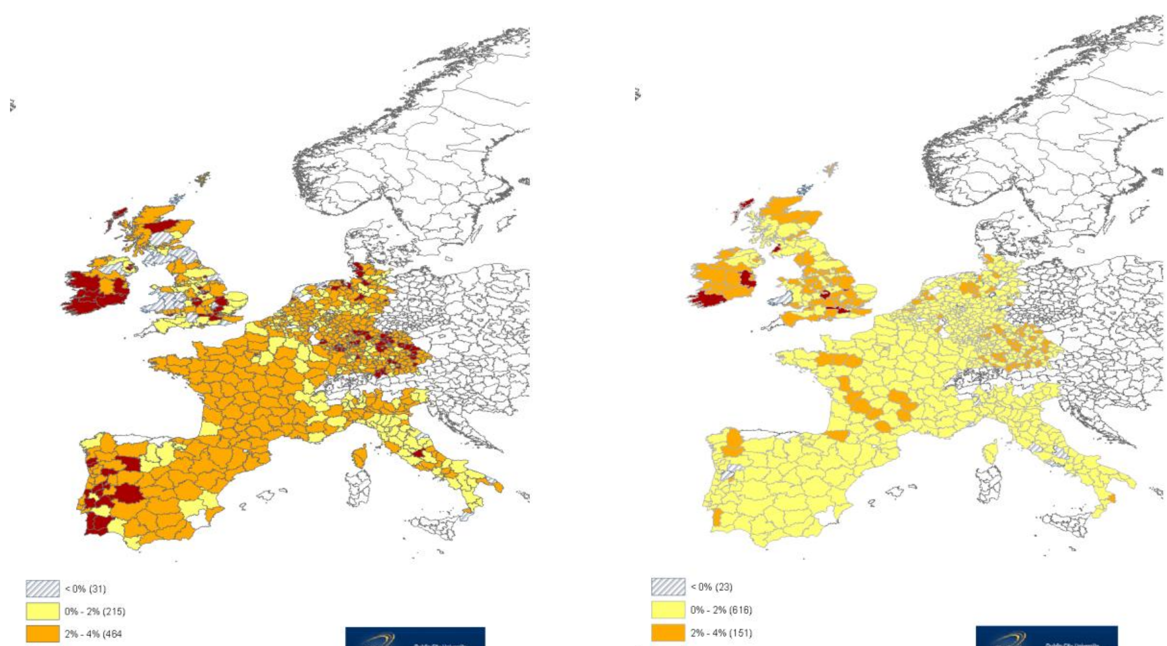


Figure 2: NUTS 3 growth of labour productivity (GVA per employee hour), 1980-92 (left) and 1992-2006 (right)

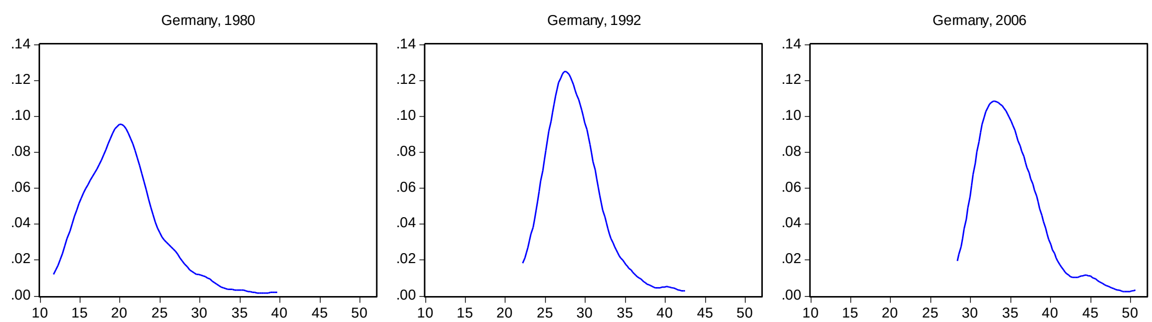


The maps presented in Figures 1 and 2 illustrate the spatial patterns that exist in the geographic dispersion of levels of labour productivity across EU NUTS 3 regions. The maps also indicate that labour productivity growth rates have become more homogenous across NUTS 3 regions over time. This pattern is also apparent in the NUTS 2 maps presented in the appendix (Figures A1-A2). However, these maps are limited in that they divide the underlying data in four discrete categories. To address this shortcoming, kernel density estimates are presented in Figure 3. Kernel density estimation is a non-parametric technique that allows us visualise the evolution of the entire cross-sectional distribution of NUTS 3 regions in a continuous form. The kernel estimator for the density function $f(x)$ at point x is

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

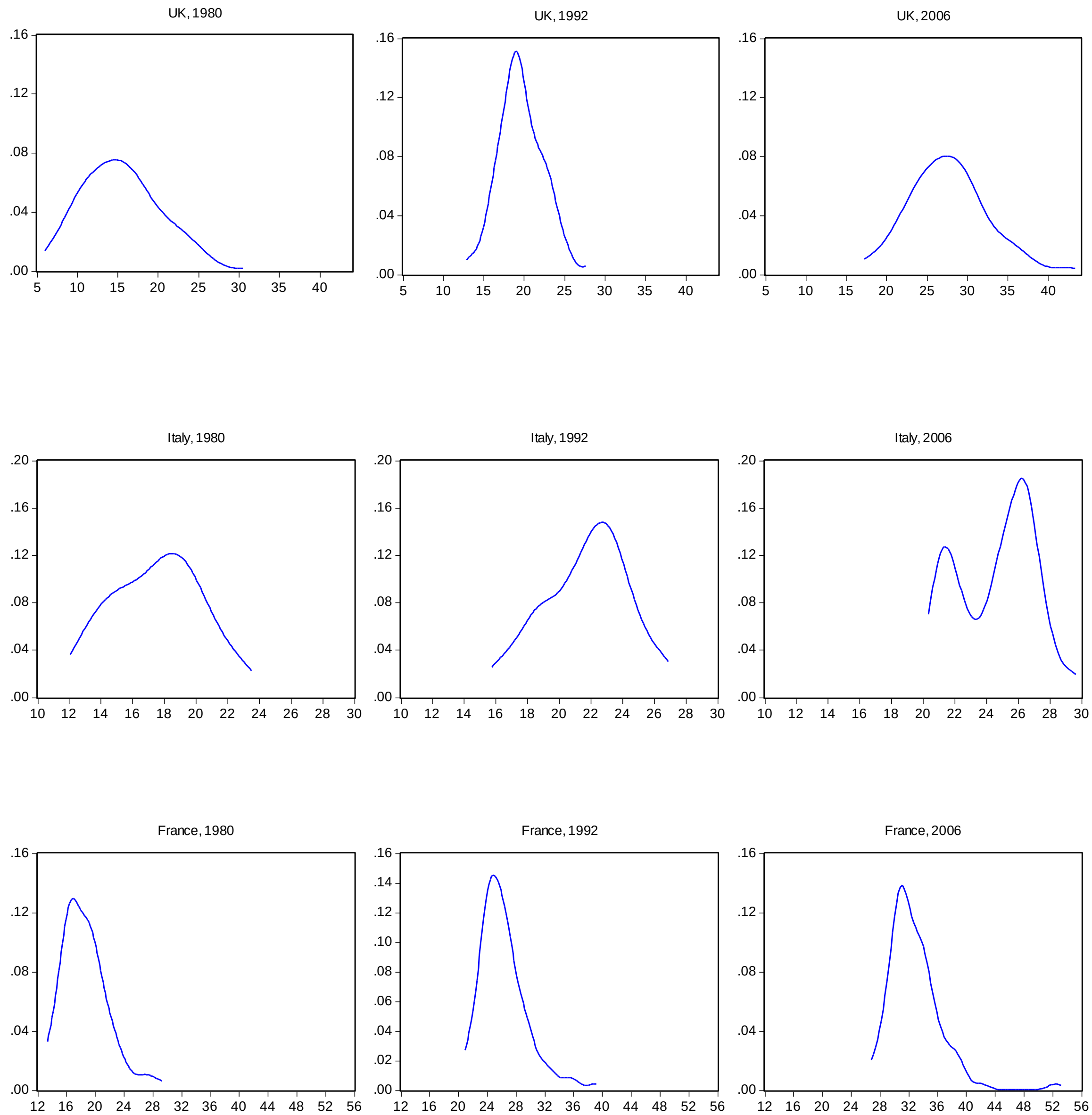
where $x = x_1, x_2, \ldots, x_n$, is an independent and identically distributed sample of random variables from a probability density $f(x)$ and $K(\cdot)$ is the standard normal kernel with window width h. The window width essentially controls the degree to which the data are smoothed to produce the kernel estimate. The larger the value of h, the smoother is the resulting kernel distribution. Figure 3 presents kernel density estimates for Germany, UK, France, and Italy, as these countries have the largest number of NUTS 3 regions.[3] The two-stage direct plug-in bandwidth selection method of Sheather and Jones (1991) is employed, which has been shown to perform quite well for many density types by Park and Turlach (1992) and Wand and Jones (1995).

Figure 3: Kernel Density Estimates for NUTS 3 regions of four European countries



[3] The kernel density estimations presented are based on the following number of NUTS 3 regions: Germany, excluding East Germany (326), France (96), Italy (87), and UK (130). Comparative figures for the other five European countries in this study are Belgium (40), Ireland (6), Netherlands (38), Portugal (27), and Spain (43).Details on omitted NUTS 3 regions are provided in Section 4.

Figure 3 (contd): Kernel Density Estimates for NUTS 3 regions of four European countries



The kernel density estimates presented in Figure 3 illustrate differences in the distribution, and evolution over time, of labour productivity across the NUTS 3 regions of the four countries. In each of the countries, the distribution of NUTS 3 regions' labour productivity all appear to move to the right of the graphs over time, which indicates an increase in average labour productivity over time. In France distributions appear to be relatively concentrated , while Italy and UK appear to be more dispersed. The question of convergence hinges on whether the distributions become more or less concentration over time, and visual impressions provided by the kernel density estimators are assessed more rigorously in

Section 4. From Figure 3 it is clear that the distributions of UK, Germany, France become more skewed to the right over time, driven primarily by the presence of extreme high growth regions (such as the London financial district) in the distributions. It is also apparent that Italy changes from a unimodal to a bimodal density over time, and that there are also hints of this in the German distribution. This tendency to move towards a bi-modal density is indicative of a divergence of NUTS 3 region labour productivity over time and the polarisation of regions into convergence clubs; Quah (1996).[4] This idea of regional polarisation of growth rates is addressed in more detail in Section 4 by means of the concept of *local convergence*.

3. Spatial data analysis and labour productivity

We now assess the spatial dimension of labour productivity across EU regions over the 1980-2006 period. The first step is to statistically test for the presence of spatial autocorrelation in labour productivity across EU regions. In order to investigate this, the well-known diagnostic for global spatial autocorrelation, Moran's I statistic, is utilised. Once the presence (or absence) of spatial autocorrelation has been established, the issue of convergence across sub-regions is then considered in Section 4.

The global Moran's i statistic for spatial autocorrelation yields a test statistic which can be defined as follows:

(2)
$$I_t = \left(\frac{n}{s}\right) \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\, y_{it}\ \ y_{jt}}{\sum_{i=1}^{n}\sum_{j=1}^{n} y_{it}^{2}}$$

where w_{ij} represents the elements of the spatial weighting matrix W, n and s denote the total number of sub-regions and the summation of w_{ij} respectively. The results of this diagnostic test for spatial autocorrelation on NUTS 2 and 3 labour productivity and employment density in 1980,1992, and 2006 are reported in Table 2. The test has been carried out using a fixed distance spatial weighting matrix, where w_{ij} denotes the row standardized reciprocal distance between sub-regions i and j within a fixed threshold. For regions beyond this threshold, $w_{ij} = 0$. The fixed distance threshold for NUTS 3 labour productivity has been selected using multi-distance spatial cluster analysis (Ripley's k-function). Ripley's k-function is a descriptive statistic used for detecting deviations from spatial homogeneity by comparing, over different geographic intervals, the mean and variance of the spatial distribution of the actual data with those generated by a homogenous Poisson process; Dixon(2002). The fixed distance

[4] A number of statistical techniques have been developed for testing whether the estimated distributions are unimodal or multimodal. Among them are the Timm (2002) bimodality index, the Silverman (1981, 1986) multimodality test, and the nonparametric test of density time invariance using the test statistic of Li (1996). See Colavecchio et al. (2009) for a detailed discussion of these multimodality tests.

threshold is chosen as the distance within which deviations from spatial homogeneity are observed to highest. Applying Ripley's k-function to German, French, Spanish, Italian, and UK NUTS 3 labour productivity yields threshold distance of 90km, 145km, 240km, 81km, and 140km respectively.[5] With these in mind, a threshold of 200km is utilized in the NUTS 3 level analysis that follows. For the NUTS 2 level analysis, this threshold is increased to 250km to ensure that all NUTS 2 regions have at least one neighbour. As this spatial weight specification is intuitive and derived from the underlying data, it used in the regression analysis undertaken in the following sub-section.

Table 2: NUTS 2 Moran's *I* Global Spatial Autocorrelation Statistic

	Global Moran's *I* statistic			
	1980	2006	1980-92	1992-06
NUTS 2 Labour Productivity	0.582***	0.573***	0.056	0.471***
NUTS 3 Labour Productivity	0.597***	0.792***	0.127***	0.305***

Note: Significance at ***1%, **5%, and *10% level.

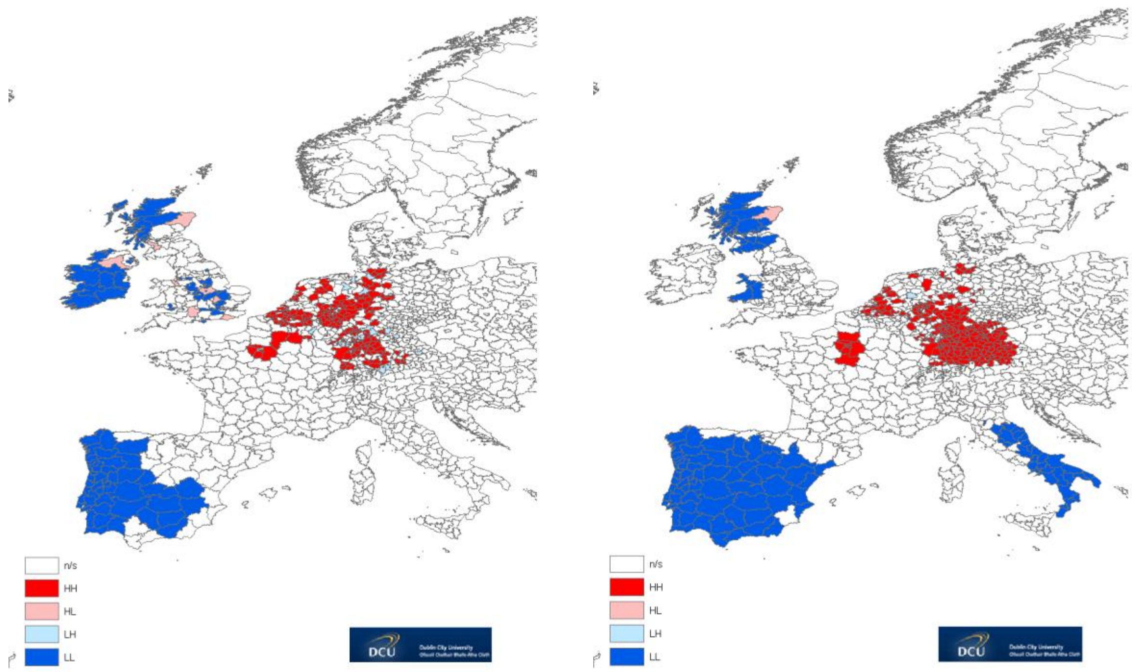
Table 2 indicates that labour productivity has exhibited spatial autocorrelation both in levels and growth rates across NUTS 3 regions from 1980 to 2006. However, at the NUTS 2 level labour productivity growth has only displayed statistically significant spatial autocorrelation in the period 1992-2006. However, in order to gain a fuller understanding of the spatial patterns inherent in the NUTS 2 and NUTS 3 labour productivity data, we calculate local Moran's *i* statistics. NUTS 3 local Moran's i maps are presented in Figures 4 and 5 below, while the NUTS 2 equivalents are provided in Appendix 1 (Figures A3 and A4). Unlike its global counterpart, the local Moran's *i* statistic describes the association between the value of the variable at a given location and that of its neighbours, and between the value within the neighbourhood set and that for the sample as a whole; Patacchini and Rice (2006). The local Moran's *i* maps presented in Figures 4 and 5 show the NUTS3 regions for which the local statistics are significant at the 0.05 level.[6] The four shaded categories of the local Moran's *i* maps correspond to the four types of

[5] This regionally bounded nature of labour productivity spillovers is reminiscent of Niebuhr (2001), who finds for 71 West German NUTS 3 regions over the period 1976-96 that the half distance of spatial income per capita spillovers is no more than 50 km.

[6] Ord and Getis (1995) have shown that the local statistics for any pair of locations, i and j, are correlated whenever their neighbourhood sets contain common elements Given this, Ord and Getis suggest using a Bonferroni bounds procedure to assess significance such that for an overall significance level of α, the individual significance level for each observation is taken as α /n, where n is the number of observations in the sample. However, Patacchini and Rice (2007) note that in practice, for any given location the number of other locations in the sample with correlated local statistics is likely to be considerably smaller than n, and so this procedure is expected to be overly conservative. For the illustration purposes Figures 4 and 5 are based on the overall significance level of 0.05.

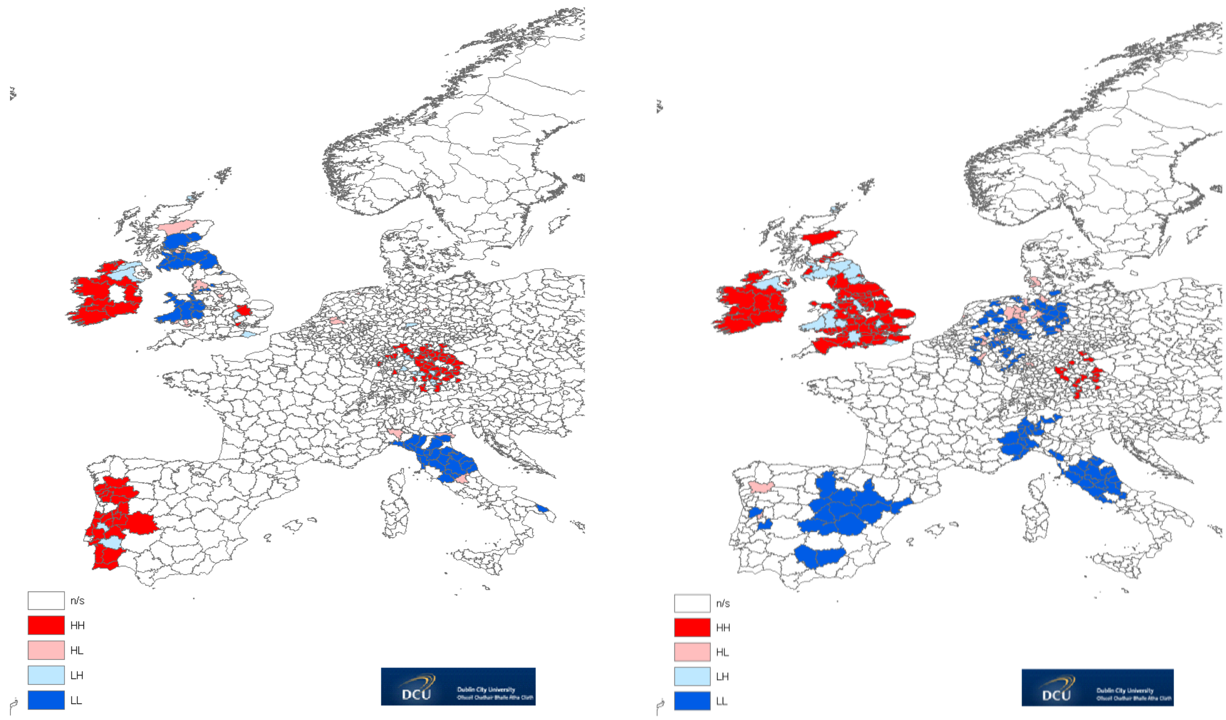
local spatial association between a location and its neighbours: HH (upper right), contains areas with a high value surrounded by areas with high values; HL (lower right) consists of high value areas with relatively low value neighbours; LL (lower left) consists of low value areas surrounded by other areas with low values; and LH (upper left) contains low value areas with high value neighbours.

Figure 4: Local moran's *i* – NUTS 3 labour productivity, 1980 (left) and 2006 (right)



However, the Bonferroni procedure is utilised in the local geographically weighted regression (GWR) analysis in Section 4.

Figure 5: Local moran's *I* – NUTS 3 labour productivity growth, 1980-92 (left) and 1992-06 (right)



The local Moran's *i* statistics illustrated by in the labour productivity maps (Figure 4) identify a number of clear areas of spatial correlation: central and southern Germany (HH), the Netherlands (HH), Paris and it surrounding regions (HH), Ireland (LL in 1980), Spain (LL in 1980 and, to a lesser extent, in 2006), Portugal (LL), and Southern Italy (LL in 2006). While the HH concentrations appear to be relatively stable throughout the time period, the LL concentrations display more flux over the 1980-2006 time period.[7] The growth of labour productivity (Figure 5) appears to contain fewer concentrations than labour productivity levels (Figure 4). The most noticeable HH growth concentrations consist of peripheral regions (Ireland and Portugal) and Southern England, with smaller HH concentrations apparent in southern Germany and the Netherlands (in 1992-2006). The most noticeable LL concentrations in 1980-1992 appear in Northern Italy and peripheral regions in the UK, and in 1992-2006 the centre and northwestern corner of Italy, central Spain, as well as some regions in the northern Germany and the Netherlands. The NUTS 2 maps (Figures A3 and A4 of the appendix) replicate the pattern of relatively lower labour productivity levels and growth rates residing in Spain and Portugal, but also point to a very sparse set of HH concentrations. High levels of labour productivity appear to be associated with the top

[7] A further issue with local measures of autocorrelation statistics is that they are affected by the presence of global spatial association, and hence inference based on the normal approximation (as is the case in Figures 4 and 5 above) is likely to be hindered; Anselin(1995). See Patacchini and Rice (2006) for a detailed discussion of limitations associated with local autocorrelation statistics.

tier urban centres of northwestern Europe, with high growth rates prominent in Ireland, southern England and Scotland.

4. Local Spatial Econometric Methods and the Modelling of Regional Convergence

While a variety of distinct convergence concepts have emanated from the economic growth literature, one form of convergence which has received particular attention over the last two decades has been that of neoclassical β-convergence, as developed by Baumol (1986), Barro and Sala-I-Martin (1992), and Mankiw et al. (1992). This form of convergence occurs when poor regions grow faster than richer regions, resulting in a catching-up process where the poor regions close the economic gap that exists between their richer counterparts. The now-standard specification of β-convergence can be expressed in vector form as follows:

(3) $$\ln\left(\frac{y_{t+k}}{y_t}\right) = \alpha + (1 - e^{-\lambda k})\ln(y_t) + \varepsilon_t$$

where $\boldsymbol{y}_t$ denotes the vector of per capita income of each state *i* in year *t*; α represents the intercept term, and $(1\text{-}e^{-\lambda k})$ is the convergence coefficient, which is usually reparametrized as $\beta = (1\text{-}e^{-\lambda k})$. The β coefficient is then estimated using Ordinary Least Squares (OLS), and the speed of convergence, λ, can then be calculated. A negative estimate for β indicates that growth rates of per capita income over the *k* years is negatively correlated with initial incomes – a finding which is interpreted as a support for the hypothesis of convergence. It is assumed that the error terms from different regions are independent:

(4) $$E\left[\varepsilon_t \varepsilon_t'\right] = \sigma_t^2 I \, .$$

This unconditional β-convergence specification can then be augmented, as per Barro and Sala-I-Martin (1992), to include a range of control variables (such as differences in human capital accumulation, infrastructure disparities, industrial structure, as well as dummy variables reflecting different regional characteristics) which may capture differences in the paths of the steady-state regional growth.

The models of convergence presented in equations (3) and (4) can easily be augmented to capture interactions across space. This spatial dimension has most commonly been introduced a spatial autoregressive term (SAR) or a spatial error term (SEM) into the convergence specification; Anselin (1995). These spatial models then test for *global convergence*, in that they assume that a homoscedastic spatial relationship holds across the entire geographic area under consideration. However, as Eckey et al.

(2007) note, the influence between the dependant variable and a set of independent variables often differs across regions (spatial non-stationarity). Similarities in legal and social institutions, as well as culture and language may create spatial local uniformity in economic structures, leading to spatial locality in rates of convergence, i.e *local convergence*; Ertur et al. (2007). Therefore it may be desirable to utilise an econometric technique which takes account of the possibility of spatial heterogeneity in speeds of convergence across regions. One such technique is geographically weighted regression (GWR), a technique for exploratory spatial data analysis developed by Fotheringham, Brunsdon, and Charlton, (see, for example Brunsdon et al. (1996, 1998), Fotheringham et al. (1998, 2002). GWR permits parameter estimates to vary locally as the parameters are estimated separately at each observed location.[8] The standard OLS regression specification of (3) above can be rewritten as follows to incorporate parameters that vary locally:

(5) $$\ln\left(\frac{y_{i,t+k}}{y_{i,t}}\right) = \alpha_i + \sum \beta_i \ln(y_{i,t}) + \varepsilon_{i,t}$$

where, as discussed above, $\beta_i = (- e^{-\lambda_i k})$. In the calibration, observations are weighted according to their proximity to region *i*. As the distance between two regions becomes smaller, the weight becomes greater. The Euclidian distance between to regions (d_{ij}) is used to calculate a Gaussian weighting function. At the observed point, *i*, the weighting of the data point will be unity and the weighting of the other data will decrease according to a Gaussian curve as the distance between *i* and *j* increases, so that for a data far away from *i* the weighting will fall close to zero, effectively excluding these observations from the estimation of parameters for location *i*; Fotheringham et al. (2002).[9]

(6) $$w_{ij} = e^{-0.5.(d_{ij}/b)^2}$$

Similar to kernel regression estimation, it is the bandwidth, *b*, that determines the extent to which the distances are weighted. A greater bandwidth increases the smoothing across the regions, giving regions i and j a relatively larger (smaller) weighting if they are far from (close to) each other. The bandwidth is computed by minimising the Akaike information criteria. In the GWR setting, the parameter estimate for β_i can then be estimated by weighted least squares, with the values of the independent variables from

[8] Other techniques developed for testing for local convergence include spatial local autoregressive estimation (SALE) proposed by Pace and LeSage (2004) its bayesian counterpart presented in Eurfur et al. (2007).
[9] A bi-square adaptive Gaussian kernel has been used in the GWR specifications presented in the forthcoming sections.

regions near to region *i* having a greater influence as they are multiplied by region *i*'s weighting matrix, W_i:

$$\hat{\beta}_i = \left(X' \cdot W_i \cdot X\right)^{-1} \cdot X' \cdot W_i \cdot Y \tag{7}$$

where X is the matrix form of the independent variable $\ln(y_{i,t})$ and Y is the matrix form of the $\ln\left(\frac{y_{i,t+k}}{y_{i,t}}\right)$ dependant variable.

According to Brunsdon et al. (1998), the GWR estimation of separate parameters for every region gives it an advantage over global spatial error (SEM) and spatial lag (SAR) models as spatial dependence in the error term can be caused by a missing spatial-varying relationship.

However GWR is not without its pitfalls, of which Wheeler (2009) provides a thorough treatment. Wheeler (2009) notes that empirical research and simulation studies have demonstrated that local correlation in explanatory variables can lead to estimated regression coefficients in GWR that are strongly correlated and, hence, problematic for inference on relationships between variables. The standard error calculations in GWR are only approximate due to reuse of the data for estimation at multiple locations (Lesage, 2004) and due to using the data to estimate both the kernel bandwidth and the regression coefficients (Wheeler and Calder, 2007). In addition, local collinearity can increase variances of estimated regression coefficients in the general regression setting (Neter et al, 1996). Techniques for correcting local correlation are currently being developed. Wheeler (2007) implements a ridge regression technique which reduce collinearity effects by penalizing the size of regression coefficients and Wheeler (2009) has developed a penalized form of GWR, called the “geographically weighted lasso” (GWL), which shrinks the least significant variable coefficients to zero. An issue related to inference of the regression coefficients is that of multiple testing in GWR, where tests of coefficient significance are carried out at many locations using the same data (Wheeler, 2007; Fotheringham et al., 2002). Following Ord and Getis (1995) a Bonferroni correction procedure is used to adjust the significance level of individual tests to achieve an overall significance level, where the overall significance level is adjusted by dividing by the number of observations in the sample (i.e the number of multiple tests) to get the individual significance level for each observation.

5. Local Spatial Regression Results

The geographically weighted regression technique (GWR), as presented in Section 4, is now utilised to undertake a local analysis of β-convergence of labour productivity across European NUTS 2 and NUTS 3 regions over the periods 1980-92 and 1992-2006. The GWR procedure is used to estimate the local parameter values of cross-sectional regressions of labour productivity growth on initial logged labour productivity *(lnLP)* and one further explanatory variable, the percentage of services employment (*Serv*) in each NUTS 2 and NUTS 3 region in the initial year of the relevant time period**.** The inclusion of this latter variable is in keeping with the concept of conditional convergence, as discussed in Section 4, and intended to control varying regional characteristics arising from industrial structure. Local convergence speeds based on the $lnLP_{1980}$ *and* $lnLP_{1992}$ parameter estimates that are significant at the bonferroni bounds discussed in Section 4 are presented for NUTS2 and NUTS 3 scales via colour-coded maps in Figures 6 and 7 below.[10] Tables 3 and 4 present the minimum, lower quartile, median, upper quartile, and maximum values of the set of local parameter value estimates and local R^2. The focus on local convergence in this study has been motivated on the grounds that the influence between the dependant variable and a set of independent variables often differs across regions. Following Fotheringham et al. (2002), a Monte Carlo based significance test for spatial variability of parameters is employed in order to assess the stability of the GWR parameter estimates. Results of this test are presented in Table 5.

[10]As the dependent variable is defined as average real GVA per capita growth, the speed of convergence, θ, is calculated as θ = log (1-βk)/k, where k denotes the number of years in the time period. The individual one-tailed critical t-values associated with the Bonferroni bounds (calculated as α /n) are +/- 3.5 for NUTS 2 regions and +/3.75 for NUTS 3 regions. Given that Bonferroni bounds are regarded as being very conservative, in Figures * we use critical t-values of 2.5 and 3.3 for NUTS 2 and NUTS 3 regions, respectively.

Figure 6: NUTS 3 labour productivity convergence speeds based on statistical significance at Bonferroni bounds,1980 (left), 2006 (right)

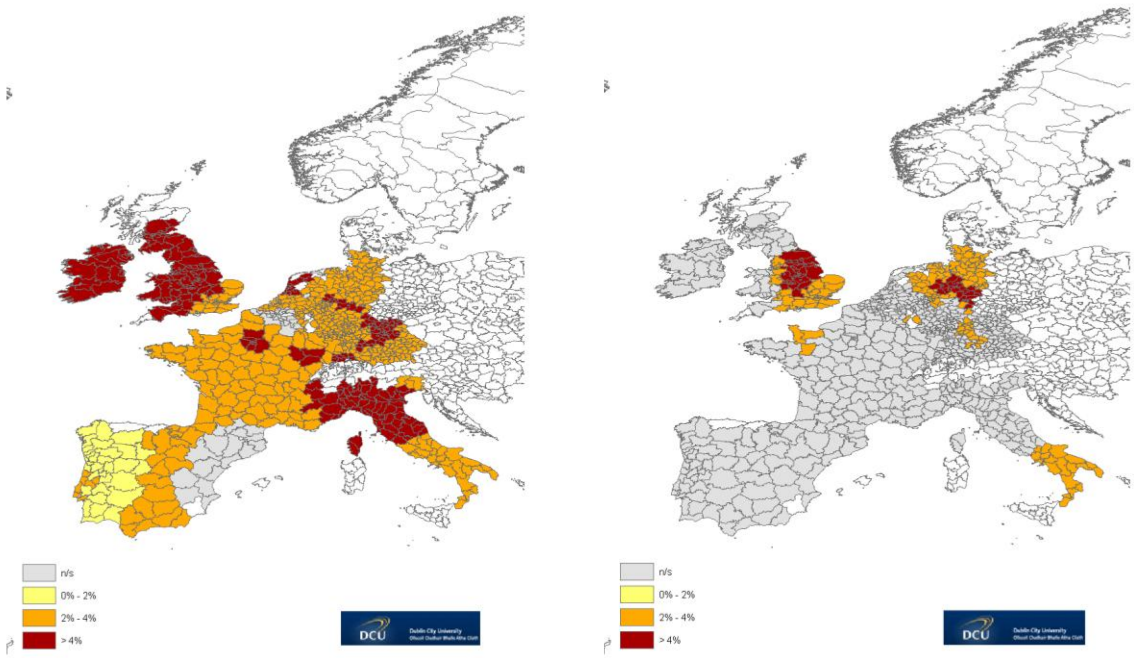


Figure 7: NUTS 2 labour labour productivity convergence speeds based on statistical significance at Bonferroni bounds,1980 (left), 2006 (right)

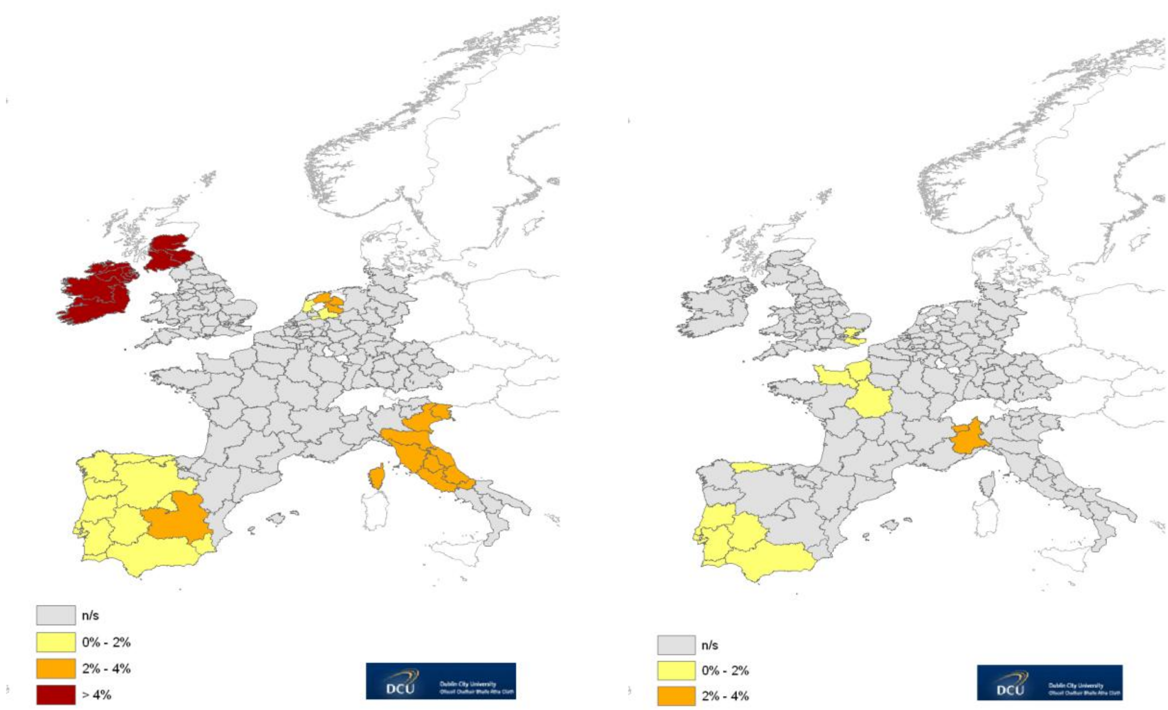


Table 3: NUTS 3 local GWR parameter estimates, 1980-1992 and 1992-2006[11]

Dependent variable: Labour Productivity Growth					
	Min	**Lower Quartile**	**Median**	**Upper Quartile**	**Max**
1980-92					
constant	0.046	0.123	0.157	0.184	0.244
$lnLP_{1980}$	-0.085	-0.057	-0.045	-0.037	-0.005
$Serv_{1980}$	-0.060	-0.008	0.004	0.019	0.080
R^2	0.23	0.69	0.82	0.97	0.97
1992-06					
constant	-0.042	0.053	0.088	0.127	0.260
$lnLP_{1992}$	-0.081	-0.036	-0.024	-0.011	0.022
$Serv_{1992}$	-0.058	-0.016	-0.005	0.008	0.090
R^2	0.08	0.35	0.43	0.86	0.86

Note: Total number of observations 788; average number of nearest neighbours for GWR regression: 42 in 1980-92 and 52 in 1992-2006. Figure* illustrates significance of local parameters.

Table 4: NUTS 2 local GWR parameter estimates, 1980-1992 and 1992-2006

Dependent variable: Dependent variable: Labour Productivity Growth					
	Min	**Lower Quartile**	**Median**	**Upper Quartile**	**Max**
1980-92					
constant	-0.045	0.062	0.079	0.100	0.239
$lnLP_{1980}$	-0.074	-0.026	-0.020	-0.016	0.032
$Serv_{1980}$	-0.09	-0.009	0.011	0.027	0.082
R^2	0.12	0.59	0.72	0.98	0.98
1992-06					
constant	-0.043	0.003	0.018	0.038	0.108
$lnLP_{1992}$	-0.028	-0.009	-0.006	-0.001	0.015
$Serv_{1992}$	-0.028	-0.004	0.020	0.042	0.069
R^2	0.26	0.33	0.43	0.74	0.74

Note: Total number of observations 153; nearest neighbours for GWR regression: 21in 1980-92 and 61 in 1992-2006. Figure* illustrates significance of local parameters.

[11] As noted in Section 1, the EU countries analysed in this study are Belgium, France, Germany (excluding regions pertaining to the former East Germany), Ireland, Italy, Holland, Spain, Portugal, and the UK For the purposed of the GWR analysis the following observations are omitted: NUTS 3: Tenerife and Gran Canaria (Spain); Oost-Groningen (NL), Delfzijl en omgeving (NL) and Overig Groningen (NL); Isle of Wight, Isle of Angelsey Lochaber, Skye Eileann Siar, Shetlands , Inverness Caithness and Aberdeen (all UK); NUTS 2: North Eastern Scotland; Highlands and Islands (UK); Groningen (NL). As has become standard in empirical studies of EU regional growth, NUTS 2 and NUTS3 regions associated with Groningen and Aberdeen are omitted due to over-shore natural resources.

Table 5: Test for Spatial Variability of Parameters

	NUTS 3 GWR parameters	NUTS 2 GWR parameters
	p-value	*p-value*
1980-92		
constant	0.001***	0.050*
$\ln LP_{1980}$	0.001***	0.160
$Serv_{1980}$	0.420	0.410
1992-06		
constant	0.001***	0.001***
$\ln LP_{1992}$	0.001***	0.020*
$Serv_{1992}$	0.001***	0.001***

Note: Significance at ***0.1%, **1%, and *5% level.

The most notable feature of the local convergence maps at NUTS 3 level (Figure 6) is the contrast between the widespread occurrence of local convergence over the period 1980-1992 and the absence of widespread local convergence over the period 1992-2006. Local convergence can be observed amongst regions across France, southern and central Germany, Netherlands, the north of Italy, Ireland and the UK in the 1980-1992 period. However, only the East of England, Northern Germany, and southern Italy exhibit local convergence over the 1992-2006 period. This weakening of local regional convergence trends in the latter time period is also reflected in the narrower range of estimated *lnLP* coefficients and local R^2 values for the 1992-2006 period than for the earlier period (Table 3). The uneven spatial pattern of NUTS 3 local regional convergence is indicative of the spatial variability of the *lnLP* parameter motivated the choice of the local GWR specification. This is confirmed in Table 5, where the spatial stationarity of the $lnLP_{1980}$ and $lnLP_{1992}$ parameter estimates is rejected at a 0.1% level of statistical significance.

The local convergence maps at NUTS 3 level (Figure 7) over the periods 1980-1992 and 1992-2006 reveal an even starker absence of regional convergence across EU regions in the latter period than in the NUTS3 case. While the GWR results for the 1980-1992 period echoes the NUTS 3 findings in the dame period in revealing local convergence amongst NUTS 2 regions in Ireland, Scotland, Northern Italy, Spain, Portugal, and a number of regions in the Netherlands, the 1992-2006 counterpart only points to a few regions (such as the south of the Iberian peninsula, and north of France, and north west corner of Italy) as experiencing local convergence. This absence of local convergence is also reflected in the narrower range of estimated *lnLP* coefficients and local R^2 values for the 1992-2006 period compared with the earlier period (Table 4). As in the NUTS 3 case, the test for spatial variability yields interesting results: while the spatial stationarity of $lnLP_{1980}$ estimated parameters is rejected at the 0.01% level, the spatial stationarity of the $lnLP_{1992}$ parameter estimates is only rejected at a 2% significance level. This relatively less robust finding for the $lnLP_{1992}$ parameter estimates would seem to reflect the lack of local convergence observed in Figure 7.

5. Conclusions

This paper analyses empirically the spatiality of European NUTS 2 and NUTS 3 level labour productivity over the period 1980-2006. Key findings to emerge from this study can be summarised as follows:

(i) As illustrated by the spatial autocorrelation analysis of Section 2, spatial concentrations of labour productivity growth tend to occur across relatively smaller areas such as NUTS 3 regions, but not across wider NUTS 2 regions or across national boundaries. Furthermore, the kernel density estimates for Germany, UK, France, and Italy illustrate that distinct national patterns exist in the way in which the distribution of NUTS 3 regions' labour productivity evolves over time, with regional polarisation and skewed distributions more prominent in some countries than in others.

(ii) The results from GWR analysis presented in Section 4 yield a number of clear insights into the spatiality of labour productivity growth across European regions with the 1980-92 and 1992-06 periods. First, there appears to be a marked change from the situation of widespread NUTS 3 level local convergence over the 1980-92 period to a more sclerotic local convergence pattern observed over the period 1992-2006. What is more, at the NUTS 2 level there appears to be an absence of any meaningful local convergence over the period 1992-2006. Second, at NUTS 3 level established top-tier urban centres such as London, Paris, Hamburg, and Munich (in the earlier period) appear as prominent centres of observed local convergence of labour productivity. This is at odds with the conventional non-local "catch-up" stories inherent in neoclassical growth theory, in which low productivity peripheral regions would be expected to close the gap that exists between them and more productive regions across a wide geographical area.

(iii) Results indicative of labour productivity growth convergence over the period 1992-2006 convergence do not appear to be robust across NUTS 2 and NUTS 3 spatial scales. While local labour productivity growth convergence can be observed at both scales for the 1980-92 period, NUTS 3 level analysis yields a faster rate convergence.

This paper points to a spatiality of labour productivity that is characterised by localized, regionally bounded concentrations of productive efficiency. While this paper aims to establish to stylized facts of the spatiality of labour productivity rather than the underlying causes, it is conceivable that employment density and industry agglomeration forces such as local inter-firm networking, employee movement and technology spillovers, as well as commuter flows into highly productive growth centres, facilitate the spreading out (i.e. convergance) of spatial concentrations of labour productivity across pockets of neighbouring NUTS 3 regions, while labour productivity levels do not necessarily become more even across NUTS 2 regions or national boundaries. What is more, the analysis of this paper indicates that this tendency has become more pronounced in recent years.

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Appendix

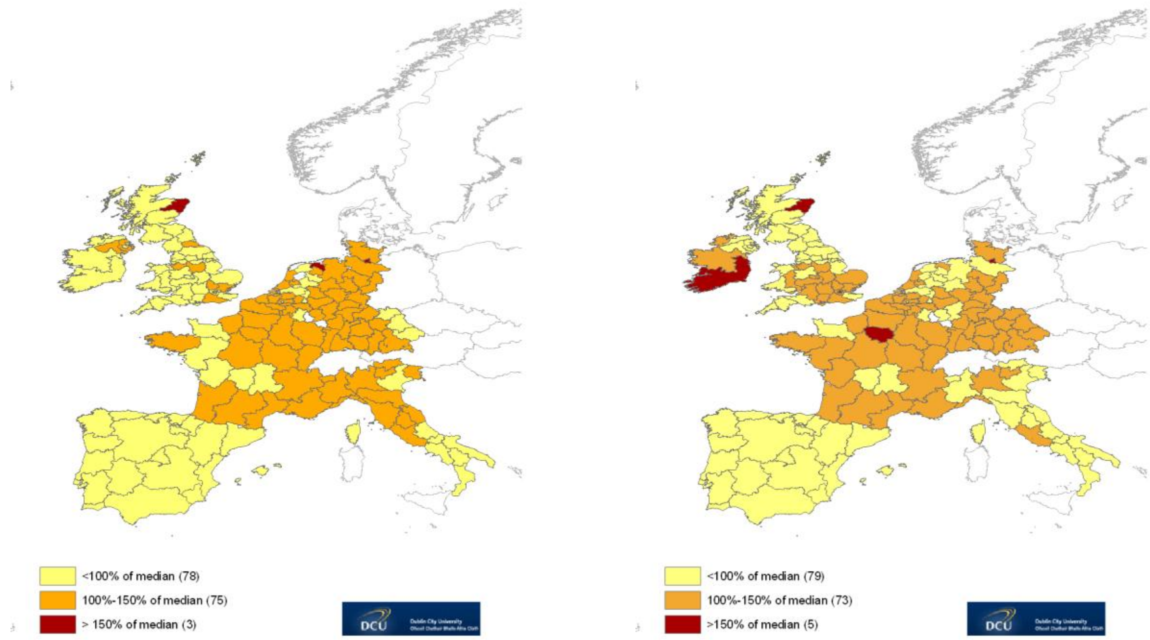

Figure A1: NUTS 2 labour productivity (GVA per employee hour), 1980 (left), 2006 (right)

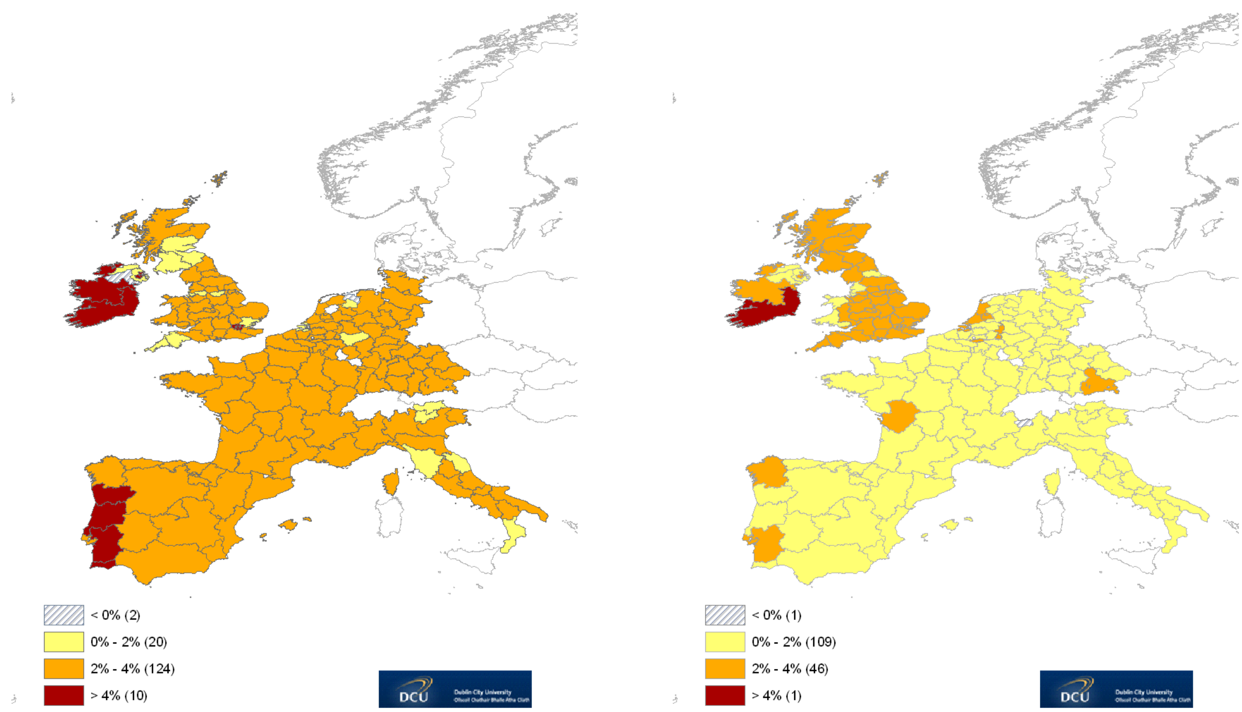

Figure A2: NUTS 2 labour productivity growth (GVA per employee hour), 1980-92 (left), 1992-06 (right)

Figure A3: Local moran's *i* – NUTS 2 labour productivity, 1980 (left) and 2006 (right)

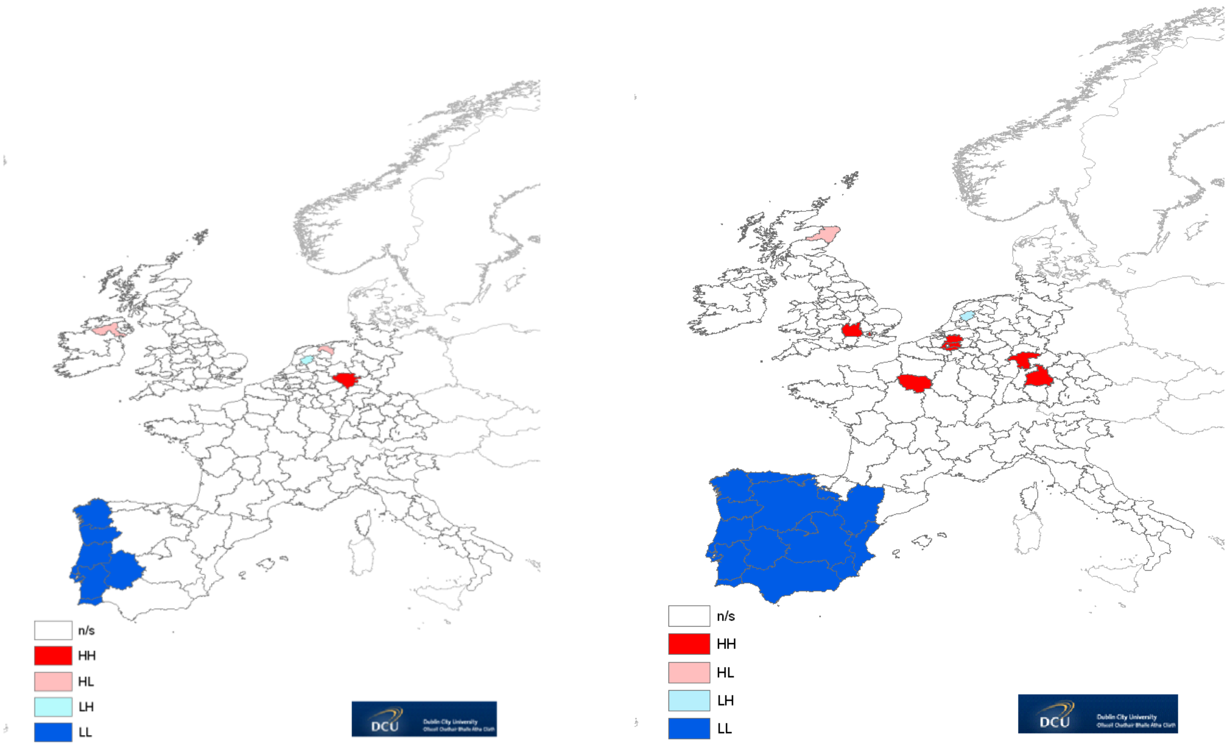

Figure A4: Local moran's *i* – NUTS 2 labour productivity growth, 1980 (left) and 2006 (right)