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British Regional Growth and Sectoral Trends – Global and Local Spatial Econometric Approaches

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Abstract

This paper looks beneath the surface of British sub-regional aggregate GVA growth over the period 1995-2004, by examining how the differing growth dynamics of the secondary and services sectors have influenced the overall regional growth process. A spatial econometric analysis is undertaken which tests regional secondary, services and aggregate real GVA per capita for absolute and conditional convergence at the NUTS 3 level. Both local and global spatial analysis techniques are utilised in order to gain a detailed insight into the growth process over the period 1995-2004. A number of explanatory factors influencing secondary, services, and aggregate regional economic growth are also identified.

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1. Introduction

The inherently spatial nature of the economic data underpinning regional economic analysis has received increasing levels of attention in recent years with the emergence of an impressive array of spatial econometric techniques. The impact on the regional growth process of core or peripheral location, proximity to natural resources, and spillover effects from neighbouring regions can now be vividly depicted by means of these techniques. One aspect of this spatial data configuration that has started to attract particular attention is that of spatial heterogeneity across regions: if an economic convergence or divergence process is evident in a given region, does this process exhibit contrasting patterns of spatial association across the sub-regions and does the speed of this convergence (or divergence) process vary at a local level? This issue of heterogeneous spatial relationships has seen spatial analysis move from a global perspective with spatially stable parameters to a local one where economic performance can vary from one sub-region to the next. While global spatial analysis techniques acknowledge the importance of location and proximity in the economic development process by controlling for the influence of spatial autocorrelation, they characterise the underlying process as being spatially stable i.e. the same relationship holds across the entire country. However, agglomeration of economic activity and uneven allocation of resources are common features of regional development. Local spatial analysis techniques offer an opportunity to explore the significance of these spatial disparities.

This paper builds upon the work of Henley (2005), Monastiriotis (2006), and Patacchini and Rice (2007) and employs these global and local spatial techniques to shed light on the regional growth process occurring in Britain over the 1995-2004 period. Regional disparities have been synonymous with modern day British economic development and their influence can still be seen in current regional growth trends. In 2005 the gross value added (GVA) per head of population for the UK was £17,700, with London having the highest regional GVA per head of population (£24,100), and the South East following with £20,400.[2] The East of England (£18,900) was the only other region to have a GVA per head of population higher than the national average.[3] Wales had the lowest GVA per head of population at £13,800.[4] That said, there have been signs recently that these disparities may be lessening: in 2005 the North East enjoyed, along with the East Midlands and London, the strongest

[2] Throughout this paper, the term "regions" denotes British NUTS 1 level disaggregation, "counties" denote British NUTS 2 disaggregation, and "sub-regions" denote British NUTS 3 level disaggregation. The term "regional economic growth" is used in a general sense to refer to the field of literature to which this paper belongs.

[3] GVA is defined as follows: Under European System of Accounts 95 (ESA95), the term GVA is used to denote estimates that were previously known as Gross Domestic Product (GDP) at basic prices. Under ESA95 the term GDP denotes GVA plus taxes (less subsidies) on products, i.e. at market prices.

[4] Data available from the Office of National Statistics (ONS) at: http://www.statistics.gov.uk/CCI/nugget.asp?ID=420&Pos=&ColRank=1&Rank=374.

GVA per head growth (4.4 per cent), while the lowest growth rate (3.5 per cent) was experienced in the South East. [5]

This analysis of British regional economic development focuses on NUTS 3 real GVA per capita data spanning from 1995-2004, not just for aggregate British GVA per capita but also for the secondary and services sectors. This approach finds support in the work of Boddy et. al. (2005) who, in their study of productivity differentials based on individual business units, find that "the scale of difference in productivity between particular sectors is very considerable". While the time-span (1995-2004) considered in this paper is dictated by data availability, this decade is nonetheless an important one. It captures a period of time where regional growth in many developed countries has been impacted by the move towards the outsourcing of manufacturing and the absorption of phenomenal technological advances. Britain is no exception to this trend: in 2004 primary, secondary, and services as defined in Section 2, below, accounted for approximately 1%, 22% and 75% of British GVA, while the equivalent shares in 1995 were 2%, 30% and 66%, respectively.[6] This surge in services sector output, accompanied by a falling off of secondary output, justifies a more disaggregated approach to the convergence/divergence debate.

This paper is organised as follows: Section 2 provides a description of the data used in this paper, as well as a brief review of the literature on British regional growth in the years prior to 1995. The spatial dispersion of British real GVA per capita is also discussed, with a set of colour-coded maps provided. A description of how β-convergence analysis has been augmented to include a number of global spatial econometric methods and the local spatial econometric method Geographically Weighted Regression (GWR) is provided in Section 3. The results yielded by these global and local spatial econometric methods in testing for absolute and conditional convergence are reported in Section 4. Conclusions are then presented in Section 5.

2. Data Issues and Background

This paper is primarily focused on NUTS 3 level gross value added (GVA) per capita data. Unadjusted (constrained to headline NUTS2) aggregate GVA by NUTS3 area at current basic prices for the years 1995 to 2004 is available from the Office of National Statistics (www.statistics.gov.uk), as well as being disaggregated for 1) agriculture, hunting and forestry 2) Industry, including energy and construction and 3) service activities, including Financial Intermediation Services Indirectly Measured (FISIM). These three categories are henceforth referred to as "primary", "secondary", and "services", respectively. Estimates of workplace-based GVA allocate income to the region in which commuters

[5] The quantity of real GVA generated by each geographic unit, scaled by that unit's population, is a standard proxy for the productivity in the face of data constraints at high levels of disaggregation. It is not intended to represent income per capita. For a treatment of regional productivity differentials based on individual business units, see Boddy et al (2005).

[6] Calculations based on National Accounts GVA data available from Office of National Statistics, as discussed in Section 2.

work. Per capita estimates can then be constructed using NUTS 3 level population data available from Nomis Labour Market Statistics (www.nomisweb.co.uk). Unfortunately, regional deflators such as the Retail Price Index (RPI) are only available for the UK for the years 2000, 2003, and 2004, and the methodology for this index is still at a formative stage. One could merely use the yearly national deflator for each NUTS 3 region. However, this would be unsatisfactory as it would make no allowance whatsoever for regional price differences – particularly problematic in the British case as secondary, services, and aggregate GVA per capita exhibit clear regional trends, as illustrated in Figures 1-3. In this study, regional deflators for each year have been constructed by weighting the 1995-99 national RPI figure by the 2000 regional RPI weights. Similarly for 2001-2002 regional RPI the 2003 regional RPI figures are used as weights. The basket used to calculate the RPI figures include both consumer goods and services such as household services, personal services, and leisure services.[7] By way of background, it should be noted that studies of British regional growth patterns over the 1977-1995 period, based on National Accounts GDP per capita data for the 62 British counties and New Earnings Survey data, have identified a number of prominent features.[8] Chatterji and Dewhurst (1996) conclude that Regional GDP per capita data yields no evidence of convergence over this time period, though they do identify some sub-periods that exhibit convergence (in periods where the economy as a whole was experiencing slow growth). Bishop and Gripaios (2004) find no signs of convergence over the 1977-1995 period, regardless of whether one uses National Accounts or New Earnings Survey data. A further insight to emerge from this line of research has been the influence of geographic location and spatial factors on British regional growth. Dewhurst (1998) finds evidence of the influence of the fore-mentioned "north-south divide" on British regional growth patterns, while Bishop and Gripaios (2004) also find a significant "north-south divide" effect, which acts to the detriment of the northern areas. More recently a whole range of spatial economic techniques have become available, allowing for a more refined characterisation of the spatial dimension in the regional growth process. When this spatial component is controlled for in convergence analysis, there are signs that not only has Britain not experienced regional convergence in recent decades, but there may even have been a process of divergence in action. Monastiriotis (2006), using wage data from the New Earnings Survey, points to widening aggregate wage disparities throughout the 1980s and 1990s when the issue of spatial dependence is taken into account. Henley (2006) has undertaken a spatial econometric analysis of NUTS 3 level aggregate GVA data for the 1995-2001 period and concludes that British NUTS 3 sub-regions experienced divergence over this time period. The transition from global to local spatial analysis of UK economic activity is evident in the work of Patacchini and Rice (2007). They use local measures of spatial autocorrelation to analyse patterns of spatial association for different indicators of British economic performance. They find that the contributions of occupational composition and productivity vary significantly across local regimes, with a 'winner's circle' of areas

[7] For further details of the composition of the RPI series, see the ONS publication *Economic Trends 615*, February 2005.

[8] For the purposes of this study, only Great Britain is considered, i.e. Northern Ireland is not included.

in the south and east of England benefiting from both above-average levels of productivity and better-than-average occupational composition, while the low-income regime in the north of England suffers from poor occupational composition. We build upon Patacchini and Rice's (2007) analysis of local spatial autocorrelation by undertaking both global and local spatial regression analyses technique to investigate the presence of convergence and divergence trends in both the secondary and services sector real GVA per capita over the 1995-2004 period.

In order to provide a visual impression of the spatial dispersion of real GVA per capita across British NUTS 3 sub-regions, a set of maps are presented (Figures 1-3). Each map is colour coded, with the light shading denoting 0-100% of median real GVA per capita, medium shading denoting 100-125%, and dark shading denoting over 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 such as the services GVA of London's financial district located in the Inner London West NUTS 3 sub-region.

Figure 1 presents aggregate real GVA per capita for 1995 and 2004. Salient features include the apparent spatial clustering of high GVA per capita in greater London, Manchester, Liverpool, Edinburgh, Glasgow, and Aberdeen (near the North Sea oil fields); a clear expansion of the greater London high-GVA area over the period in question; and the noticeable improvement of the Midlands but no consistent GVA per capita increase in Northern England and Scotland. One might wonder whether these impressions are reflected in the development of the secondary and services sectors over the 1995-2004 period. As illustrated in Figure 2, the secondary industry presents a mixed picture: the North of England NUTS 3 sub-regions appear to have experienced mixed fortunes; a belt of increased GVA per capita is apparent in the Midlands, while the South West and South East exhibit some shuffling of regions between the three categories, but no clear pattern. The services sector (Figure 3) highlights the strength of the high-GVA greater London area, increases in Liverpool and Manchester, but continued sluggishness in Northern England and Scotland. In all it would appear that it is the services industry which drives the expansion of the southern high GVA per capita in the aggregate map. While the secondary sector does appear to be the more dispersed in terms of the highest GVA per capita category; this trend seems to be eclipsed in the aggregate GVA per capita map by the strong services performance. Further descriptive evidence of sub-regional GVA per capita trends can be gleaned from the summary statistics presented in Table 1.

Table 1: Summary Statistics for Secondary and Services real GVA per capita, 1995 and 2004

Secondary Sector GVA per capita (2002 UK£)			Services Sector GVA per capita (2002 UK£)		
	1995	**2004**		**1995**	**2004**
Mean	3,517.29	4,031.72	Mean	6,422.84	11,261.36
Median	3,343.53	3,964.37	Median	5,828.70	9,708.08
Maximum	7,068.65	8,383.50	Maximum	41,398.86	64,654.04
Minimum	1,634.15	1,648.84	Minimum	3,050.08	5,766.21
Std. Dev.	1,162.03	1,168.17	Std. Dev.	3,574.93	6,023.20

The contrast between secondary and services sector GVA per capita developments over the 1995-2004 period is stark. The virtually unchanged mean, median, and standard deviation of secondary GVA per capita over the 10 year period, together with slight increases in the minimum and maximum GVA per capita figures, suggest that any convergence experienced in the secondary sector has not been a buoyant one. Services GVA per capita, on the other hand, bears all the hallmarks of a sector on the move, with its mean and median showing marked increases over the 10 years and its widening standard deviation indicative of the absolute divergence.[9]

[9] Measuring the dispersion of real GVA per capita 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). An alternative way of measuring sigma convergence is to use the coefficient of variation, which is obtained by dividing the standard deviation of the series by the mean of the sample. From Table 1 the coefficient of variation for services appears to fall from 0.56 to 0.53 over the 1995-2004 period. This decrease over time would suggest convergence rather than divergence of real GVA per capita. However, as noted above, the services GVA data contains one notable outlier - the Inner London West financial district - which greatly influences the mean and the standard deviation. Omitting this NUTS 3 region from the coefficient of variation calculation yields figures of 0.29 and 0.34 for 1995 and 2004 respectively and is indicative of a divergence process.

Figure 1: Aggregate Real GVA Per Capita, 1995 (left) and 2004 (right)

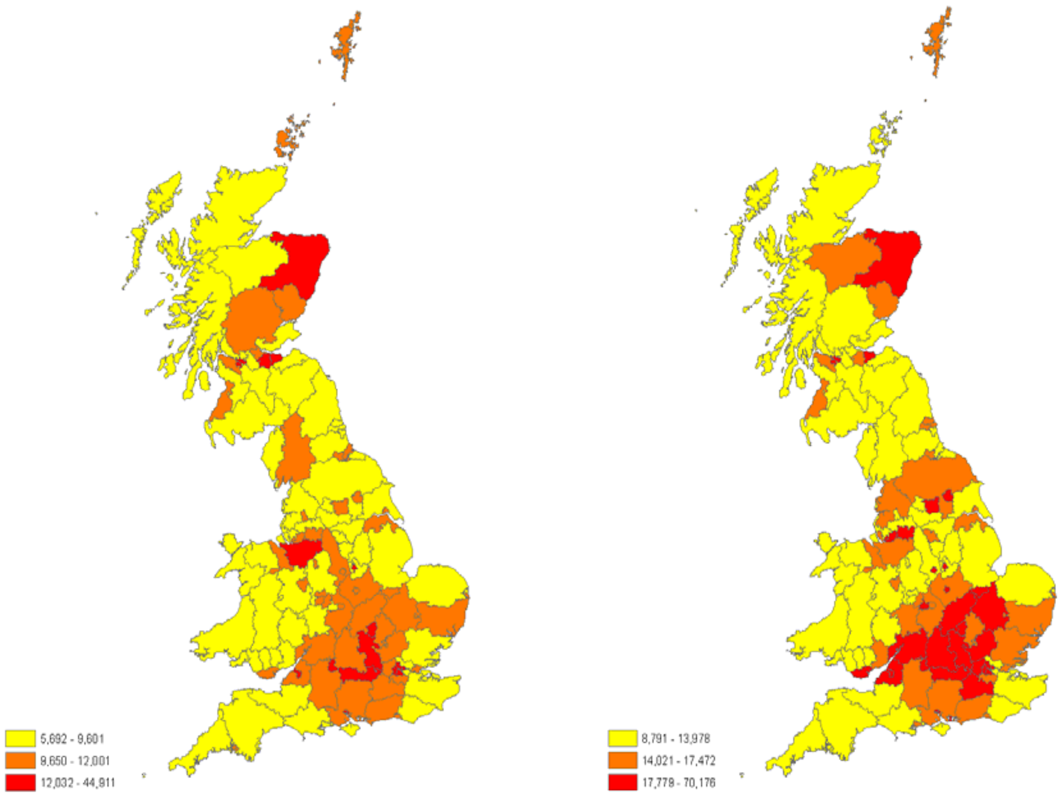


Figure 2: Secondary Sector Real GVA Per Capita, 1995 (left) and 2004 (right)

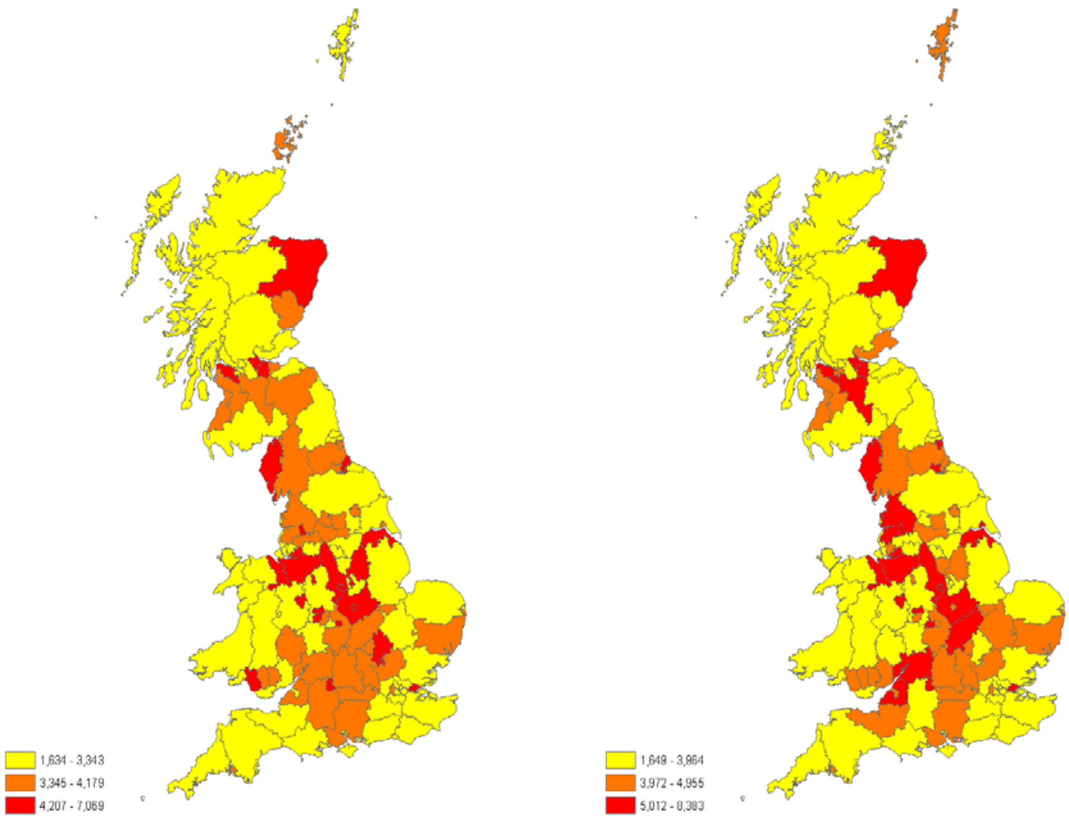
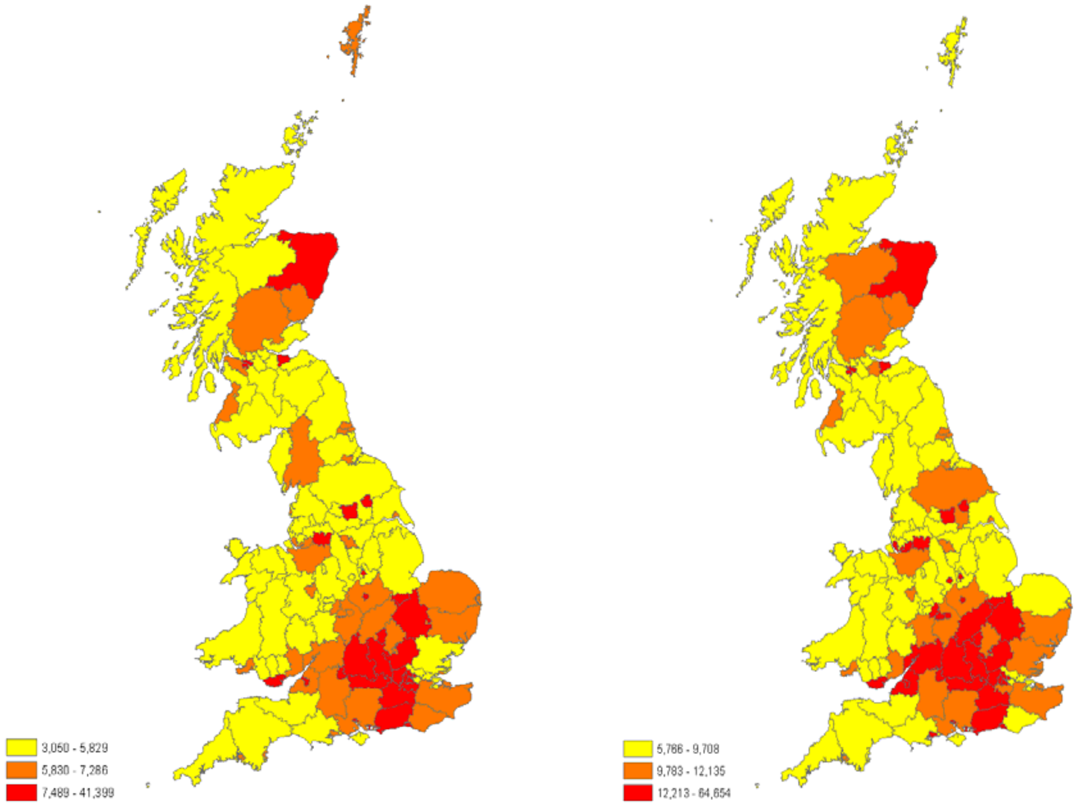


Figure 3: Services Sector Real GVA Per Capita, 1995 (left) and 2004 (right)



In Sections 3 and 4 a number of additional data sources are drawn upon. NUTS 3 level commuter flow data used in the construction of British functional economic areas is available from the Labour Force Survey Data Service (lfs.dataservice@ons.gov.uk). The explanatory variables introduced in the conditional convergence analysis of Section 4 include average primary school pupil-teacher ratio per county and the average A-level pass rate achieved by pupils in each county, both of which are available from the ONS publication *Regional Trends*. The number of businesses registered for Value Added Tax and female employment expressed as a proportion of people aged 16+ are both available from Nomis Labour Market Statistics (www.nomisweb.co.uk). Net capital expenditure data for British sub-regions is available from the ONS series *Regions in Figures*.[10]

3. Regional Convergence and the Spatial Dimension

This section begins with a brief description of how β-convergence analysis, as developed by Baumol (1986), Barro and Sala-I-Martin (1992), and Mankiw et al. (1992), has been augmented to include a number of spatial econometric methods. When considering regional convergence, various empirical approaches have been implemented in the literature: from simple plots of measures of dispersion over time to intra-distributional dynamics using Markov chains applied to GDP per capita. It is β-

[10] *Region in Figures* has now been discontinued. The final edition was Winter 2004/05 (volume 9). It has now been replaced by a new publication, *Regional Snapshot*.

convergence analysis, however, that has lent itself most easily to spatial econometric analysis. This section discusses methods for constructing functional economic areas from administrative regions. The section concludes with an outline of the approach adopted in this paper for allocating British NUTS 3 regions to functional economic regions.

3.1 Global Spatial Econometric Methods and the Modelling of Regional Growth

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 β-convergence. 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:

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

where $\mathbf{y}_t$ 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:

(2) $$E[\varepsilon_t \varepsilon_t'] = \sigma_t^2 I \ .$$

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 steady-state GVA per capita.

Equations (1) and (2) can be augmented to capture interactions across space, a refinement which reflects more accurately the realities of the growth process across regions. As Henley (2006) notes, this spatial dimension can exert its influence on regional growth through numerous channels: adjustment costs and barriers to labour and capital mobility, spatial patterns in technological diffusion, the ability of regions to pursue independent regional growth policies, and the extent to which neighbouring regions interact and benefit from spillover effects. Any analysis which ignores the influence of spatial location on the growth process runs the risk of producing biased results. Following from Anselin (1988), spatial dependence has been incorporated into the β-convergence specification in two ways: it can be included as an explanatory variable in the specification or it can be modelled as operating through the error process.[11] The former, known as a Spatial Autoregressive Model (SAR), depicts a region's growth as being directly affected by growth in neighbouring regions. This direct spatial effect is independent of the exogenous variables and is captured by including a spatial autoregressive parameter, ρ, and a spatial weight matrix, *W*, in the specification:

$$(3) \qquad \ln\left(\frac{y_{i,t+k}}{y_{i,t}}\right) = \alpha + (1-e^{-\lambda k})\ln(y_{i,t}) + \rho W \ln\left(\frac{y_{i,t+k}}{y_{i,t}}\right) + \varepsilon_{i,t}$$

In equation (3), the growth of a given region is influenced by the growth rate of adjacent regions. This "spatial lag" approach can also be utilised where a region's growth rate is though to be influenced by the initial income level of adjacent regions, a specification which Rey and Montouri (1999) refer to as a spatial cross-regressive model:

$$(4) \qquad \ln\left(\frac{y_{i,t+k}}{y_{i,t}}\right) = \alpha + (1-e^{-\lambda k})\ln(y_{i,t}) + \tau W \ln(y_{i,t}) + \varepsilon_{i,t} \cdot$$

It may be the case that, rather being directly affected by the growth rate of its neighbours, a region's growth rate may be influenced by a complex set of random, unexpected shocks transmitted across space. Such unexpected shocks take the form of spillovers associated with technology or consumer tastes. In this Spatial Error Model (SEM) case, the spatial influence does not enter the systematic component of the specification. Instead, it is captured in an error term which contains a spatial error coefficient, ζ, and an idiosyncratic component, *u*, where $u \sim N(0,\sigma^2 I)$.

$$(5) \qquad \ln\left(\frac{y_{i,t+k}}{y_{i,t}}\right) = \alpha + (1-e^{-\lambda k})\ln(y_{i,t}) + \varepsilon_{i,t} \qquad \text{where} \quad \varepsilon_{i,t} = \zeta W \varepsilon_{i,t} + u_{i,t}$$

Section 4 reports results for cross-sectional growth equation regressions which test for absolute and conditional convergence using the SAR and SEM specifications.

3.2 Local Spatial Econometric Methods

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). Therefore it may be desirable to utilise an econometric technique which takes account of the possibility of spatial heterogeneity in speeds of

[11] For more detailed treatment of spatial autoregressive and spatial error models, see Bernat (1996), Rey and Montouri (1999), and Fingleton and Lopez-Bazo (2006).

convergence across regions. One such technique is geographically weighted regression (GWR), a technique for exploratory spatial data analysis developed by Brunsdon, Charlton, and Fotheringham (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. The standard OLS regression specification of (1) above can be rewritten as follows to incorporate parameters that vary locally:

$$\text{(6)} \qquad \ln\left(\frac{y_{i,t+k}}{y_{i,t}}\right) = \alpha_i + \sum \beta_i \ln(y_{i,t}) + \varepsilon_{i,t}$$

where, as discussed above, $\beta_i = \left(1 - e^{-\lambda_i k}\right)$. 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).[12]

$$\text{(7)} \qquad w_{ij} = e^{-0.5.(d_{ij}/b)^2}$$

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 regions near to region *i* having a greater influence as they are multiplied by region *i*'s weighting matrix, $\mathbf{W}_i$:

$$\text{(8)} \qquad \hat{\beta}_i = \left(X' \cdot W_i \cdot X\right)^{-1} \cdot X' \cdot W_i \cdot Y$$

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.

[12] While a Gaussian kernel has been used in the GWR specifications presented in the forthcoming sections, running the regressions with a bi-square (adaptive) kernel yields a similar set of results. Bi-square results are available from the author on request.

According to Brunsdon et al. (1999 p.497), 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 (Congdon, 2003; 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. As these local correlation correction techniques are still being developed, the degree of local correlation is assessed in this paper by comparing the local correlations of the explanatory variables. 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.

4. Spatial Analysis of β-convergence

The focus now turns to establishing the empirics of regional growth and β-convergence across British sub-regions, in the presence of possible spatial dependence. The first step is to statistically test for the presence of spatial autocorrelation in sub-regional secondary, services and aggregate real GVA per capita data. From Figures 1-3 it appears that clear spatial patterns exist in the geographic dispersion of secondary, services and aggregate real GVA per capita across British sub-regions. In order to confirm this, the well-known diagnostic for global spatial autocorrelation, Moran's *I* statistic, is utilised. Once the presence of spatial autocorrelation has been established, the issue of convergence across sub-regions is then considered. As outlined in Section 3, the cross-sectional growth equations which test the hypotheses of absolute conditional convergence are easily augmented to incorporate spatial autoregressive (SAR) components and spatial error (SEM) components, as well as being easily captured in the local GWR specification. What is more, the inclusion of a set of explanatory variables in the conditional convergence growth equation allows one to identify those factors which may explain the trends observed in British sub-regional growth over the 1995-2004 period.

4.1. Diagnostic Test for Global Spatial Autocorrelation

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

(9)
$$I_t = \left(\frac{n}{s}\right)\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} y_{it} y_{jt}}{\sum_{i=1}^{n}\sum_{j=1}^{n} y_{ij} y_{jt}}$$

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 secondary, services and aggregate log real GVA per capita for 1995 and 2004, as well as for real GVA per capita growth over the 1995-2004 period, are reported in Table 2. The test has been carried out using two different types of spatial weighting matrix: i) a binary contiguity matrix, where w_{ij} = 1 if sub-regions are geographically adjacent, and w_{ij} = 0; ii) an inverse distance spatial weighting matrix, where w_{ij} denotes the row standardised reciprocal distance between sub-regions *i* and *j*.

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

	Secondary		Services		Aggregate	
	Binary *W*	Distance *W*	Binary *W*	Distance *W*	Binary *W*	Distance *W*
Log real GVA per capita 1995	0.115**	0.079***	0.200**	0.179***	0.114**	0.102***
Log real GVA per capita 2004	0.156**	0.097**	0.238***	0.207***	0.197**	0.176***
GVA per capita Growth 1995-2004	0.017	-0.017	0.198***	0.108***	0.123**	0.093***

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

It is clear from Table 2 that secondary, services, and aggregate real GVA per capita do indeed exhibit strong spatial autocorrelation across sub-regions in both 1995 and 2004, the start- and end-point of the dataset used in this paper. However, when one considers growth rates over the 1995-2004 period, it is just services and aggregate GVA per capita growth that exhibit spatial autocorrelation, which suggests that aggregate GVA growth spatial autocorrelation over the 1995-2004 period has been influenced by that of the services sector. These findings appear to be robust to the type of spatial weighting matrix used in the Moran's *I* statistic.

4.2. Global Analysis of Absolute β-convergence

Table 3 below presents spatial autoregressive (SAR) and spatial error and (SEM) cross-sectional regressions of secondary, services, and aggregate GVA per capita growth on initial, 1995, log GVA per capita *($lnGVA_{1995}$)* – as outlined in Section 3. This is the standard test for absolute β-convergence (augmented to capture two distinct types of spatial influence), where a negative significant coefficient on initial log GVA per capita indicates convergence and a positive significant coefficient indicates divergence. GVA per capita data for 125 of the 128 NUT 3 sub-regions are used in the specifications in Table 3.[13] In keeping with the notation of Section 3, ρ and τ represent the spatial autocorrelation coefficient and spatial error coefficient, respectively. The spatial weighting matrix used in throughout this section is the row standardised inverse distance matrix.[14]

Table 3: Absolute Convergence Regressions for British NUTS 3 Sub-regions, 1995-2004

Dependent variable: Average GVA Growth per Capita (1995-2004)						
	Spatial Autoregressive Model (SAR)			**Spatial Error Model (SEM)**		
	Secondary	Services	Aggregate	Secondary	Services	Aggregate
Constant	0.202	-0.005	-0.035	0.185	0.013	-0.009
	(0.037)***	(0.027)	(0.037)	(0.035)***	(0.025)	(0.037)
$\ln GVA_{1995}$	-0.022	0.005	0.006	-0.021	0.005	0.006
	(0.0.7)***	(0.003)*	(0.004)	(0.004)***	(0.03)*	(0.004)
ρ (SAR)	-0.524	0.314	0.433			
	(0.313)*	(0.253)	(0.225)*			
τ (SEM)				-0.553	0.313	0.423
				(0.332)*	(0.257)	(0.229)*
R^2	0.20	0.05	0.07	0.19	0.05	0.06
Log Likelihood	339.138	399.38	388.02	338.75	399.24	387.64
Number of Obs	125	125	125	125	125	125

Note: Standard errors are given in parenthesis. Significance at ***1%, **5%, and *10% level

With regard to regional growth convergence, a number of finding emerge from Table 3. First, it is clear that there is no absolute convergence in aggregate real GVA per capita growth over the 1995-2004 period. Second, services sector GVA per capita growth does not show signs of convergence. It actually appears be experiencing a process of divergence. Finally, secondary sector GVA per capita growth exhibits strong convergence, with an estimated annual speed of convergence of ranging from 2.3-2.8%. This, as suggested in Section 2, may reflect a process of sub-regional secondary GVA per capita being sucked towards the average, due to the sector's near- stagnant growth performance over the 1995-2004 period. As for the competing spatial specifications, both yield similar findings in terms of R^2 values and log-likelihood values.

[13] In order to ensure consistenecy with the expanatory variables included in Table 4, the NUTS 3 sub-regions of East and West Cumbria have been amalgamated into one region: Cumbria. Similarly, East Derbyshire and South and West Derbyshire have been combined to form Derbyshire, while North and South Nottinghamshire have been combined to form Nottinghamshire.

[14] The regression specifications of Table 3 have also been run using the binary contiguity spatial weighting matrix. The results are qualitatively similar to those reported in Table 3 and are available from the author on request. Higher R^2 values and lower log-likelihood values suggest that the specifications using inverse distance spatial weighting matrix are superior to those using the binary contiguity weighting matrix.

4.3. Global Analysis of Conditional β-convergence

The cross-sectional specifications used to test for absolute convergence are now augmented with a set of explanatory variables, which may capture differences in the paths of steady-state GVA per capita. The explanatory variables introduced to the analysis address a number of key features which have emerged from the literature as being influential in the economic growth process. Foremost amongst these are initial education levels and human capital formation, which are necessary to raise productivity.[15] Regarding human capital, this paper follows the approach of Henley (2005) which includes two variables, each capturing distinct aspects of human capital accumulation process: (i) the county average primary school pupil-teacher ratio (*Pupil_Teacher*) and (ii) the average A-level pass rate (*grades*) achieved by pupils in each county. It is this exam which enables pupils to enter university. As 1995 data is unavailable for both of these variables, data dating from 1993 is used instead. As these variables are unavailable at sub-regional level, the data for each county is applied to the sub-region residing in that county. As discussed in Section 2, location and geographic proximity have been identified as key drivers of the British regional growth process – a feature which has been typified by the oft-cited "north-south divide". In order to capture this, a set of dummy variables for the eleven NUTS 1 regions has been constructed. Furthermore, the rural/urban orientation of each sub-region is captured through the inclusion of a variable representing each sub-region's 1995 agricultural real GVA as a proportion of aggregate real GVA *(Agri)*. However, *Agri* is not included in the services GVA specifications as it exhibits strong negative correlation with the dependent variable.[16] Data on the capital stock residing in each sub-region at the start of the 1995-2004 period is unavailable. That said, data on the number of businesses registered for Value Added Tax (VAT) is available and is disaggregated for secondary and services sectors. A similar approach is taken by Hart and McGuinness (2003), where the stock of enterprises is used as a proxy for capital utilization. These variables are expressed in per capita terms with respect to their relevant sub-region and included in the conditional convergence specifications *(No. of Businesses)*. In order to control for capital investment, net capital expenditure as a proportion of aggregate real GVA for each sub-region *(Capital Expenditure)* in 1997, deflated as described in Section 2, is also included in the specifications.[17] A further control variables, females in employment in 1995 expressed as a proportion of people aged 16+ (*Fem Emp'ment*) is included in order capture differences in local labour market conditions (such as the tightness of the labour market) at the beginning of the 1995-2004 period. This is in keeping with Perugini and Signorelli (2004) who also use female employment as a proxy for labour market performance. From a methodological perspective, one weakness of cross-region regressions is that of reverse causality and endogeneity. With the exception of *Capital Expenditure*, all the explanatory

[15] See Mankiw et al. (1992) and Barro and Sala-I-Martin (1995, pp. 420-445) for a detailed discussion regarding the inclusion of control and environmental variables in conditional convergence regressions.

[16] As *Agri* does not exhibit a strong correlation with Total GVA per capita growth, it is included in the Total GVA per capita growth regressions.

[17] Capital expenditure data for the 11 NUTS 3 regions of Wales was unavailable for 1997. As a proxy, the capital expenditure per worker figure for the NUTS 1 region, Wales, is weighted by the real GVA of NUTS 3 region.

variables used in the conditional convergence specifications refer to 1995 or earlier – and thereby not susceptible to such reverse causality. *Capital Expenditure* is assumed to be weakly exogenous, and instrumental variable techniques have not been applied to it. As in Sub-section 4.2, ρ and τ represent the spatial autocorrelation coefficient and spatial error coefficient, respectively, and the spatial weighting matrix used is the binary contiguity matrix. Table 4 reports results for 125 NUTS 3 level sub-regions.

Similar to the absolute convergence case, the results reported in Table 4 clearly show that there is no evidence of convergence of aggregate real GVA growth per capita over the 1995-2004 period. In the case of the services sector, across the specifications there appears to be support for the hypothesis that the services sector has experienced divergence over the 1995-period. A further feature that the conditional convergence results have in common with their absolute counterparts is the clear secondary sector convergence, but this time with the estimated annual speed of convergence residing within a 3.0-4.0% range. In all, these finding along with those of the absolute convergence specifications point to a situation where aggregate real GVA per capita growth has been influenced by the conflicting tendencies towards divergence and convergence emanating from the services and secondary sectors, respectively.

Table 4: Conditional Convergence Regressions for British NUTS 3 Sub-regions, 1995-2004

Dependent variable: Average GVA Growth per Capita (1995-2004)						
	Spatial Autoregressive Model (SAR)			**Spatial Error Model (SEM)**		
	Secondary	Services	Aggregate	Secondary	Services	Aggregate
constant	0.177	-0.009	0.008	0.172	-0.033	0.009
	(0.045)***	(0.035)	(0.042)	(0.040)***	(0.031)	(0.040)
$\ln GVA_{1995}$	-0.029	0.011	0.003	-0.030	0.010	0.002
	(0.005)***	(0.003)***	(0.004)	(0.005)***	(0.003)***	(0.004)
Grades	0.0002	0.0001	0.0001	0.0003	0.0003	0.0001
	(0.001)	(0.0004)	(0.0004)	(0.0006)	(0.0004)	(0.0004)
Pupil_Teacher	0.002	0.0004	0.001	0.001	0.0001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Agri	-0.047	-	-0.00002	-0.046	-	-0.183
	(0.114)	-	(0.00001)***	(0.110)	-	(0.084)**
No. of Businesses	0.286	-0.396	0.015	0.280	-0.334	0.015
	(0.903)	(0.169)**	(0.092)	(0.900)	(0.171)**	0.092
Capital Expenditure	0.179	0.099	0.029	0.178	0.095	0.018
	(0.165)	(0.099)	(0.112)	(0.165)	(0.10)	(0.114)
Female Emp'ment	0.002	0.0002	0.000	0.002	0.0002	0.000
	(0.001)**	(0.0004)	(0.001)	(0.0006)**	(0.0004)	(0.001)
NE	0.001	-0.011	-0.015	0.001	-0.008	-0.014
	(0.008)	(0.005)**	(0.006)***	(0.001)	(0.004)*	(0.005)***
NW	-0.009	-0.004	-0.009	-0.007	-0.002	-0.009
	(0.006)	(0.004)	(0.005)**	(0.006)	(0.004)	(0.004)**
YH	0.003	-0.003	-0.007	0.006	-0.002	-0.006
	(0.007)	(0.004)	(0.005)	(0.006)	(0.004)	(0.004)
EM	0.008	0.005	-0.002	0.012	0.006	-0.001
	(0.007)	(0.004)	(0.005)	(0.007)*	(0.004)	(0.005)
WM	0.001	0.001	-0.008	0.004	0.003	-0.007
	(0.006)	(0.004)	(0.004)*	(0.006)	(0.004)	(0.004)*
EE	-0.0003	0.001	-0.004	0.000	0.0004	-0.003
	(0.006)	(0.004)	(0.006)	(0.006)	(0.004)	(0.004)
L	-0.006	-0.005	-0.004	-0.005	-0.006	-0.003
	(0.008)	(0.006)	(0.006)	(0.009)	(0.008)	(0.006)
SW	0.005	-0.001	-0.003	0.005	-0.001	-0.002
	(0.006)	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)
W	-0.008	-0.0004	-0.013	-0.001	-0.007	-0.012
	(0.007)	(0.004)	(0.005)***	(0.001)	(0.006)	(0.005)***
S	0.004	-0.008	-0.010	0.004	0.0034	-0.009
	(0.007)	(0.004)*	(0.005)*	(0.005)	(0.005)	(0.004)**
ρ (SAR)	-0.585	-0.631	-0.171			
	(0.276)**	(0.297)**	(0.324)			
τ (SEM)				-0.849	-0.734	-0.204
				(0.257)***	(0.295)**	(0.340)
R^2	0.34	0.21	0.20	0.36	0.21	0.20
Log Likelihood	351.48	410.26	398.06	351.96	410.03	397.73
Number of Obs	125	125	125	125	125	125

Note: Standard errors are given in parenthesis. Significance at ***1%, **5%, and *10% level. The NUTS 1 level regional dummy variables included are North East (NE), North West (NW), Yorkshire and the Humber (YH), East Midlands (EM), West Midlands (WM), East England (EE), London (L), South West (SW), Wales (W), and Scotland (S). South East is the base region.

The conditional convergence regressions also provide some insights into the factors which have driven these growth trends over the 1995-2004 period. Reflecting its lack of convergence in Tables 3 and 4, aggregate real GVA growth per capita appears to have been negatively associated with sub-regions whose GVA contains a relatively large agricultural content (as indicated by the *Agri* variable) and peripheral location (such as the North East, North West, Wales, and Scotland).

The explanatory variables in the services sector regressions also reflect the divergence trends evident in Tables 3 and 4. The Scotland and North East NUTS 1 region dummies turn out to be significant, displaying a negative relationship with services GVA growth. In the NUTS 3 level regression of Table 7, the spatial autocorrelation coefficient spatial error terms are both negatively significant, suggesting that bordering a NUTS 3 sub-region which enjoys strong services GVA growth does not enhance one's own prospects of services sector growth. In the secondary sector, the significant positive *Fem Emp'ment* coefficient indicates that the local labour market conditions prevailing in 1995 clearly influenced growth prospects over the 1995-2004 period.

Two problems often emerge in studies utilising highly disaggregated regional data: (i) neglect of the impact of commuter flows and (ii) the administrative delineation of regions may not reflect self-contained economic areas. In the British context, Fingleton (2003) has found that commuting exerts a significant effect on wages and productivity in central cities. Curran (2009) constructs a set of functional economic areas for Britain, where the 128 NUTS 3 regions are aggregated together using a method based on commuter flow data, in the spirit of Coombes (1986). These functional economic areas serve as a robustness check for results emanating from the econometric analysis carried out on the NUTS 3 level data. The results presented in Tables 3-4 above are very much in line with those emanating from growth regressions based the functional economic areas, as undertaken by Curran (2009).

4.4. Local Analysis of Conditional β-convergence

The geographically weighted regression technique (GWR), as presented in sub-section 3.2, is now utilised to undertake a local analysis of conditional β-convergence on the British NUTS 3 1995-2004 real GVA per capita data. The GWR procedure is used to estimate the local parameter values of cross-sectional regressions of secondary and services GVA per capita growth on initial secondary and services log GVA per capita *($lnGVA_{1995}$)* and the set of explanatory variables described above. Unlike the global SAR and SEM specifications, the GWR regression specification does not include regional dummy variables. The variable *Agri* is also omitted from the GWR specification. Tables 5 and 6 below present the minimum, lower quartile, median, upper quartile, and maximum values of the set of local parameter value estimates and R^2. For comparison, the global SAR and SEM estimates from Table 4 are also are also presented. Significance levels for the global SAR and SEM estimates are indicated in Tables 5 and 6, while significance levels for the variables we are most interested in (secondary and services $lnGVA_{1995}$) are presented via colour-coded maps in Figures 4 and 5 below.

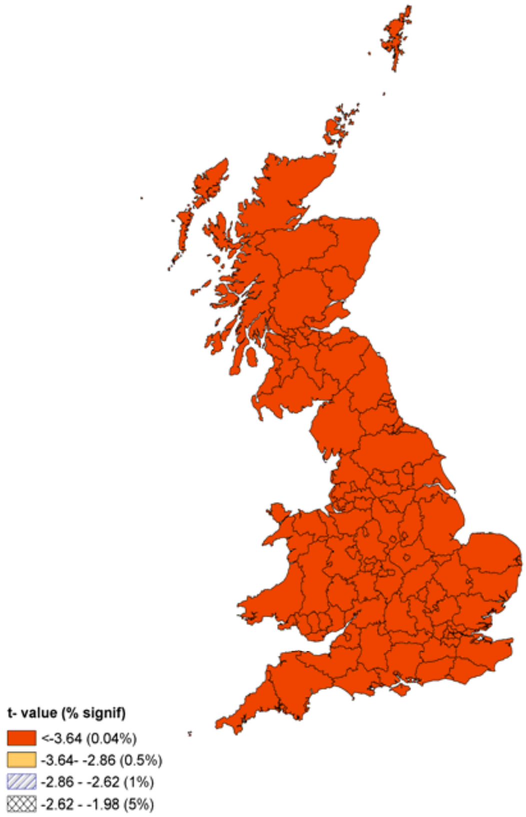
Table 5: Secondary Sector local GWR and global SAR and SEM estimates

Dependent variable: Average Secondary GVA Growth per Capita (1995-2004)							
	Min	**Lower Quartile**	**Median**	**Upper Quartile**	**Max**	**Global SAR**	**Global SEM**
constant	0.132	0.137	0.142	0.149	0.195	0.177***	0.172***
$\ln GVA_{1995}$	-0.029	-0.026	-0.026	-0.026	-0.026	-0.029***	-0.030***
Grades	-0.0002	-0.0002	-0.0001	-0.0001	-0.0001	0.0002	0.0003
Pupil_Teacher	0.001	0.001	0.002	0.002	0.002	0.002	0.001
No. of Businesses	0.036	0.052	0.075	0.098	0.189	0.286	0.280
Capital Expenditure	0.042	0.052	0.058	0.065	0.089	0.179	0.178
Female Emp'ment	0.002	0.002	0.002	0.002	0.002	0.002**	0.001**
R^2	0.23	0.23	0.24	0.24	0.26	0.34	0.36

Note: Significance indicated for global parameters only. Figure 4 illustrates significance of local parameters. Significance of global parameters denoted as follows: ***1%, **5%, and *10% level. SAR and SEM global parameter estimates are extracted from Table 4 above.

In Table 5 it is useful to compare the local GWR parameter estimates with those which were significant in the global SAR and SEM specifications (ie: *constant, $\ln GVA_{1995}$*, and *Female Emp'ment*). It is clear from such a comparison that the range of local GWR parameter estimates lie very close to the global SAR and SEM estimates. The test for spatial variability of parameters based on a Monte Carlo significance test on the local estimates fails to reject the hypothesis of spatial stationarity. An inspection of the statistical significance of the local parameter estimates of $\ln GVA_{1995}$ is presented in Figure 4. It can also be seen from Table 5 that the range of local R^2 values, while lower than their global counterparts due to differences in the specifications, are in line the global R^2 values. However, the caveats regarding local correlation and local statistical inference discussed in subsection 3.2 should be borne in mind

Figure 4: Local *t*-statistics for secondary real GVA per capita, 1995-2004



Note: Negative t-statistics (left) reflect negative regression parameter estimates.

The choice of significance levels illustrated in Figure 4 above is influenced by the Bonferroni correction procedure discussed in subsection 3.2. In this correction procedure 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. In this particular study with a sample of 125 observations, an overall significance level of 5% implies an individual significance level for each observation of 0.04%. However, as Fotheringham et al. (2002, p.165) describe individual significance levels derived in this way as highly conservative, they are taken here as a higher bound and significance levels 5%, 1%, and 0.5% are also illustrated in Figure 4. Using the significance levels as per the Bonferroni correction procedure, it is clear from Figure 4 that the secondary sector $lnGVA_{1995}$ GWR parameter estimates yields parameters statistically significant at the Bonferonni level across all the British NUTS 3 regions. Such a strong result is in keeping with the clear convergence trend identified in the global secondary sector SAR and SEM regressions undertaken in subsection 4.3.

Table 6: Services Sector GWR and global SAR and SEM estimates

Dependent variable: Average Services GVA Growth per Capita (1995-2004)							
	Min	**Lower Quartile**	**Median**	**Upper Quartile**	**Max**	**Global SAR**	**Global SEM**
constant	-0.071	-0.065	-0.059	-0.051	0.002	-0.009	-0.033
$lnGVA_{1995}$	0.005	0.010	0.011	0.011	0.012	0.011***	0.010***
Grades	0.000	0.000	0.000	0.001	0.001	0.0001	0.0003
Pupil_Teacher	0.0005	0.0008	0.0008	0.0008	0.0009	0.0004	0.0001
No. of Businesses	-0.490	-0.456	-0.414	-0.364	-0.097	-0.396**	-0.334**
Capital Expenditure	0.059	0.062	0.064	0.068	0.082	0.099	0.095
Female Emp'ment	-0.0002	0.0003	0.0003	0.0004	0.0004	0.0002	0.0002
R^2	0.12	0.16	0.17	0.17	0.17	0.21	0.21

Note: Significance indicated for global parameters only. Figure 5 illustrates significance of local parameters. Significance of global parameters denoted as follows: ***1%, **5%, and *10% level.

When the services sector local GWR parameter estimates for $lnGVA_{1995}$ are compared with those which were significant in the global SAR and SEM specifications, they appear to be in the same order of magnitude (Table 6). As with the global SAR and SEM parameter estimates, the entire range of local GWR estimates are positive.[18] This indicates that it is a divergence rather than a convergence process that is occurring in the services sector. However, of particular interest at this point is the spatial stationarity of the services sector local GWR parameter estimates for the services sector $lnGVA_{1995}$. A constant theme running through this analysis thus far has been the spatial concentration of the services sector in the south of England and the role of this spatial concentration in driving the divergence process identified in previous sections. 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.

Table 7: Test for Spatial Variability of Parameters

	Secondary GWR parameters	**Services GWR parameters**
	p-value	*p-value*
constant	0.17	0.01***
$lnGVA_{1995}$	0.73	0.04**
Grades	0.89	0.77
Pupil_Teacher	0.07*	0.48
No. of Businesses	0.93	0.02**
Capital Expenditure	0.91	0.92
Female Emp'ment	0.39	0.13

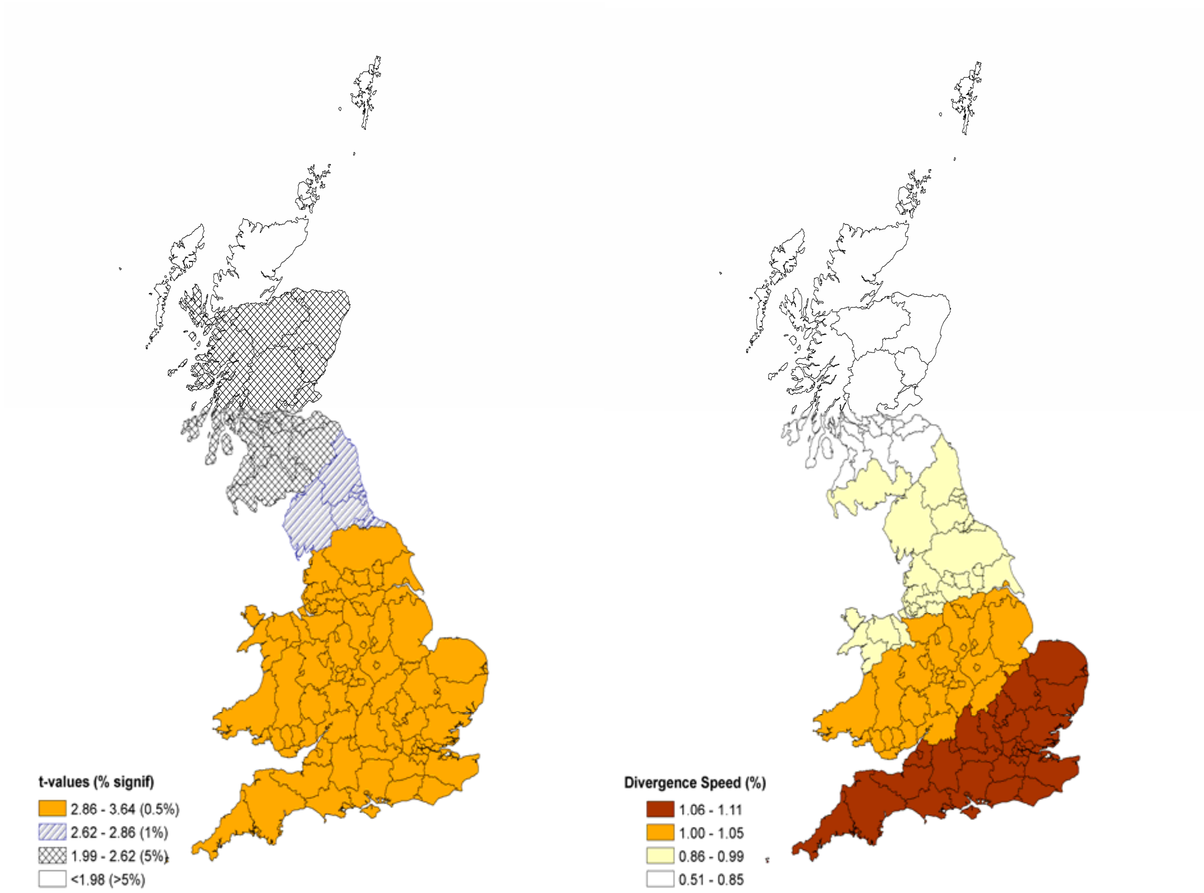
Note: Significance at ***1%, **5%, and *10% level

The results of the test, given in Table 7, reject the hypothesis of spatial stationarity of services sector $lnGVA_{1995}$ GWR parameter estimates, while failing to reject the hypothesis of spatial stationarity of

[18] Regarding issue of local correlation discussed in subsection 3.2, the only explanatory variables to exhibit a noticeable level of correlation were $lnGVA_{1995}$ and no. of businesses (a mean correlation coefficient of 0.56 across the 125 local regressions).

secondary sector $lnGVA_{1995}$ GWR parameter estimates. This result points to spatial variability of the services $lnGVA_{1995}$ GWR parameter estimates and, by extension, spatial variability in the services sector speed of divergence. As anticipated above, the secondary sector GWR parameter estimates do not exhibit spatial variability.

Figure 5: Local *t*-statistics (left) and divergence speeds (right) for services real GVA per capita, 1995-2004



Note: Colour-coded categories for divergence speeds (right) derived using Natural Breaks (Jenks) classification. All the divergence speeds shaded non-white correspond to significance levels of 0.5% or 1%.

The colour-coded maps of statistical significance of the services sector local parameter estimates of $lnGVA_{1995}$ (Figure 5, left) do not exhibit the robust results seen in the secondary sector case. None of the NUTS regions exhibit significance at the Bonferroni level (0.04%). However, there is a large number of British NUTS 3 regions which enjoy a level of significance of 0.5%, all located in the southern and midland areas. This pattern is in keeping with the services sector spatial variability of the local $lnGVA_{1995}$ parameter estimates identified in Table 7 above. The divergence speeds associated (calculated as per subsection 4.2 above) with the local $lnGVA_{1995}$ parameter estimates are illustrated in Figure 5 (right). Again, the spatial variability of the local $lnGVA_{1995}$ parameters is reflected in the differing speeds of divergence, which appear to be at their highest in the greater London, South East, and South regions and decrease as one moves further north. This moves us beyond the SAR and SEM regression models' finding of services sector global divergence as it takes account of the differences in the speeds at which divergence of services activity plays out "on the ground". In this way, local services sector divergence patterns can be identified and a more layered insights into the divergence process can be attained.

5. Conclusions

This paper aims to address the following question: how should the process of British regional economic growth over the decade 1995-2004 be characterised? Disaggregating British real GVA per capita into its secondary and services components indicates it is not appropriate to characterize the development process experienced in this time period as a convergence process. Nor do the findings of this paper support the findings of certain previous literature that neither a convergence or divergence process can be discerned from the available data. It would appear that trends exhibited by aggregate real GVA per capita mask the contrasting fortunes of the secondary and services industry. While the secondary industry appears to have stagnated and its growth rate has experienced a convergent compression to the mean, the services industry has surged ahead in over the 1995-2004 period – a development that has manifested itself in a process of divergence where the South East and Greater London regions continue to pull away from the chasing pack. It should be borne in mind that the services industry is known to be a heterogeneous one. One would expect that this fore-mentioned divergence process has been driven by the more sophisticated sub-sectors of the services industry.

While global spatial regression techniques acknowledge the importance of location and proximity in the economic development process by controlling for the influence of spatial autocorrelation, they characterise the underlying process as being spatially stable i.e. the same relationship holds across the entire country. Even a cursory glance at the spatial dispersion of British services sector real GVA per capita over the 1995-2004 period suggests that such a characterisation is unlikely to reflect actual services sector development. What is more, the growing contribution of services sector GVA to the aggregate GVA suggests that this issue is not confined to the services sector development process. In this paper the spatial analysis technique known as Geographically Weighted Regression (GWR) is applied in order to make the transition from global analysis to local analysis. While the global spatial analysis techniques utilised in this paper provides valuable information about the secondary and services convergence and divergence processes at a national level, GWR offers the opportunity to get a more nuanced view of these processes as it allows us to identify regional differences in convergence and divergence trends. The main findings of this paper concerning real GVA per capita secondary sector convergence and services sector divergence across British NUTS 3 regions over the 1995-2004 period are evident from both global and local spatial analysis. Once these trends are established at a global level, the local spatial analysis techniques then provide additional insights as how these trends play out locally. In this way, employing global and local spatial analysis in a complementary fashion has facilitated a more detailed characterisation of the British economic development process over time.

References

Anselin L. (1988) *Spatial Econometrics: Methods and Models*, Kluwert Academic.

Barro R. J. (1991) Economic Growth in a Cross-Section of Countries, *Quarterly Journal of Economics* 105, 407-443.

Baumol WJ (1986) Productivity Growth, Convergence, and Welfare: What the Long-run Data Show, *American Economic Review* 76: 1072-1085.

Bernat A. (1996) Does Manufacturing Matter? A Spatial Econometric View of Kaldor's Laws, *Journal of Regional Science* 36: 463-477.

Bishop P. and P. Gripaios (2004), Earnings Biases and Convergence in the UK: A County Level Analysis, *Applied Economics Letters* 11(1), 33-37.

Bishop P. and P. Gripaios (2006) Earnings Convergence in GB Counties: A Distribution Dynamics Approach, *Applied Economics Letters* 13, 29-33.

Boddy M., Hudson, J., Plumridge A., and D. Webber (2005) Regional Productivity Differentials: Explaining the Gap, No 515, Discussion Papers from University of the West of England, School of Economics.

Brunsdon, C., Fotheringham, A. S. and M. E. Charlton (1996) Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity, *Geographical Analysis* , 28, 281-298.

Brunsdon, C., Fotheringham, A. S. and M. E. Charlton (1998) Spatial Nonstationarity and Autoregressive models, *Environment and Planning A*, 30, 957-973.

Chatterji, M. and J. H. L Dewhurst (1996) Convergence Clubs and Relative Economic Performance in Great Britain: 1977–1991, *Regional Studies*, 30, 1996, pp. 31–40.

Colavecchio, R., Curran D., and M.Funke (2009) Drifting Together or Falling Apart? The Empirics of Regional Economic Growth in Post-Unification Germany, *Applied Economics* (forthcoming).

Congdon P. (2003) Modelling Spatially Varying Impacts of Socioeconomic Predictors on Mortality Outcomes, *Journal of Geographical Systems* 5 161 - 184

Curran D. (2009) "British Regional Economic Growth: A Spatial Econometric Approach", *European Journal of Spatial Development*, Refereed Paper No. 37.

Dewhurst J. (1998) Convergence and Divergence in Regional Household Incomes per Head in the United Kingdom, 1984-93, *Applied Economics* 30, 31-35.

Eckey, H-F., Kosfeld, R., and M. Türck, (2007) Regional Convergence in Germany: a Geographically Weighted Regression Approach, *Spatial Economic Analysis*,2:1,45-64

Fingleton B.(2003) Increasing returns: evidence from local wage rates in Great Britain
Oxford Economic Papers.55: 716-739

Fingleton B. and E. Lopez-Bazo (2006) Empirical Growth Models with Spatial Effects, *Papers in Regional Economic Science* 85(2)

Fotheringham, A. S., Brunsdon, C. and M. E. Charlton, (2002) *Geographically Weighted Regression. The Analysis of Spatial Varying Relationships*, Chichester, Wiley.

Fotheringham, A. S., Charlton, M. E. and C. Brunsdon, (1998) Geographically Weighted Regression: A Natural Evolution of the Expansion Method for Spatial Data Analysis, *Environment and Planning* , 30, 1905-1927.

Hart M. and S. McGuinness (2003) Small Firm Growth in the UK Regions 1994-1997: Towards an Explanatory Framework, *Regional Studies* 37(2): 109-122

Henley, A. (2005) On Regional Growth Convergence in Great Britain, *Regional Studies* 39, 1245-1260

LeSage J. P. (2004) A Family of Geographically Weighted Regression Models" *Advances in Spatial Econometrics, Methodology, Tools and Applications* Eds L Anselin, R J G M Florax, S J Rey (Springer Verlag, Berlin) pp 241 - 264

Mankiw G, Romer D. and D. Weil (1992) A Contribution to the Empirics of Economic Growth, *Quarterly Journal of Economics* 107: 407-437.

Monastiriotis, V. (2006) Sub-regional Disparities in Britain: Convergence, Asymmetries and Spatial Dependence, Research Papers in Environmental and Spatial Analysis No. 12, European Institute, London School of Economics.

Neter J., Kutner M. H., Nachtsheim C. J., and W. Wasserman (1996) *Applied Linear Regression Models*, Irwin, Chicago.

Ord J. K. and A. Getis (1995) Local spatial autocorrelation statistics; distributional issues and an application, *Geographical Analysis* 27, 286–305.

Patacchini, E. and P. Rice (2007) Geography and Economic Performance: Exploratory Spatial Data Analysis for Great Britain, *Regional Studies*, 41:4,489-508

Perugini,C. and M. Signorelli (2004) Employment Performance and Convergence in the European Countries and Regions, *The European Journal of Comparative Economics* Vol. 1, n. 2, 2004, pp. 243-278.

Rey S. and B. Montouri (1999) U.S. Regional Income Convergence: A spatial Econometric Perspective, *Regional Studies* 33: 143-156.

Wheeler D. (2007) Diagnostic Tools and a Remedial Method for Collinearity in Geographically Weighted Regression, *Environment and Planning A* 39(10)

Wheeler, D., and Calder C. (2007) An Assessment of Coefficient Accuracy in Linear Regression Models with Spatially Varying Coefficients, *Journal of Geographical Systems* 9(2) 145 - 166

Wheeler D. (2009) Simultaneous Coefficient Penalization and Model Selection in Geographically Weighted Regression: The Geographically Weighted Lasso, *Environment and Planning A* 41 pp 722-742