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ABSTRACT

Spatial Determinants of Productivity: Analysis for the Regions of Great Britain*

This Paper uses NUTS3 sub-regional data for Great Britain to analyse the determinants of spatial variations in income and productivity. We decompose the spatial variation of earnings into a productivity effect and an occupational composition effect. For the former (but not the latter) we find a robust relationship with proximity to economic mass, suggesting that doubling the population of working age proximate to an area is associated with a 3.5% increase in productivity in the area. We measure proximity by travel time, and show that effects decline steeply with time, ceasing to be important beyond approximately 80 minutes.

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1: Introduction:

Regional inequalities are a striking and persistent feature of many economies, developed and less developed. This paper investigates the determinants of spatial productivity differences, paying particular attention to the role of proximity to economic mass. Is it the case, as suggested by many theories of economic geography, that proximity to centres of economic activity increases measured productivity?

Our analysis is based on the regions of the Great Britain. The persistence of significant disparities in economic performance across the British regions is well documented, as in the Treasury report "Productivity in the UK: the Regional Dimension" (HMT 2001). Recent data indicates that GDP per capita in London in 2001 is 54% above the average for the UK as a whole, and even higher in Inner London (ONS, 2003). By comparison, GDP per capita in the North East, the poorest of the regions, is just 73% of the national average, falling to as low as 60% of the UK average in certain sub-regions of the North-East. Moreover, these disparities have increased over the period 1995 to 2001 with GDP per head in London and the South East growing relative to that in regions on the periphery - Scotland, the North-East and North West, Wales and the South West. As discussed in the Treasury report, inequalities in income per head derive from many different sources – labour force participation rates, employment rates, skill and occupational composition, and productivity differences. All are correlated, but there may be distinct and separate causal mechanisms driving them.

This paper focuses on income per worker, particularly earnings, and asks two sorts of questions. The first is, to what extent are regional inequalities in income a consequence of variation in the quality of jobs, as distinct from variation in productivity in a given type of job? The second set of questions relates to the determinants of performance across areas. In particular, are differences in performance related to proximity to centres of activity, as hypothesised by many theories of location and spatial clustering? And if so, what is the spatial scale of these effects? How far do they extend?

The first question is addressed by decomposing the average earnings of each area into an occupational composition index and a productivity index. We find that about two-thirds of the spatial variance in earnings is attributable to variations in productivity. The two indices are positively correlated, so that there is a tendency for high productivity areas to benefit also from a larger share of jobs in high-paying occupations. This earnings decomposition is valuable also because of the importance of controlling for occupation and skill levels in assessing regional productivity.[1] Our decomposition provides a primary control, conditioning out the effects on earnings of spatial variation in occupational composition.

We address the second set of questions by econometrically investigating the determinants of spatial variation in measures of economic performance, including the productivity index and the occupational composition index. The investigation is based on arguments from the economic geography literature and the possibility that there are increasing returns to spatial concentration. The increasing returns may derive from knowledge spillovers, thick labour markets, or from pecuniary externalities arising from proximity to customers and suppliers (see for example Fujita and Thisse 2002). The existing literature offers some empirical support for these effects. The survey by Rosenthal and Strange (2004) reports a consensus view (drawn largely from US studies) that the elasticity of city productivity with respect to city size is in the range 0.04 – 0.11. Ciccone and Hall (1996) and Ciccone (2002) find that density of activity has a positive effect on productivity.

We undertake an econometric investigation of these effects across the NUTS3 sub-regions of Great Britain. We find considerable support for the hypothesis that proximity to economic mass raises income, and more specifically average earnings. In order to identify spatial scale, we construct measures of the economic mass within given travel time of each area. Effects appear to be greatest for mass within 40 minutes driving time, tapering off quite sharply thereafter and having no effect beyond approximately 80 minutes. The effects operate through the productivity index, rather than through the occupational composition index. Our best estimate of the elasticity of productivity with respect to economic mass is 0.05, suggesting that doubling mass raises productivity by 3.5%. These results are robust to the inclusion of a range of additional controls, and to the use of alternative estimators to allow for endogeneity and spatial autocorrelation. Moreover, they are not driven entirely by London and the South-East, as we demonstrate by splitting the sample of UK sub-regions into a south-east core that is within 180 minutes driving time of London, and the rest.

The paper is organised as follows. The next section covers data and descriptive issues, and derives the decomposition of earnings into occupational composition effects and productivity effects. The main econometric analysis is reported in section 3, and sections 4 and 5 extend this analysis to include a discussion of endogeneity issues and the presentation of instrumental variable estimates, and to analyse the role of London and the South-East in our results. Section 6 quantifies the effects we have found, and includes a number of

[1] For example, Combes, Duranton and Gobillon (2004) argue that failure to control for the heterogeneity of

counterfactual experiments showing, for example, that a 10% reduction in all travel times in the UK would raise average productivity by 1.12%.

2: Regional income, earnings and productivity

Our analysis is based on data for the subregional NUTS3 spatial units of Great Britain. There are 126 NUTS3 administrative areas in Great Britain but, in order to compile a consistent dataset, a number of these are combined to give a sample of 119 subregional units (that we will term 'areas'). The data series relate to the period 1998 to 2001 and the four years of data are averaged in order to remove some of the year-to-year volatility. Full details of the sample and the data used are provided in the Data Appendix to this paper.

Several different types of income data are available. Estimates of workplace-based gross value-added at the NUTS3 level are calculated according to the income approach by the Office of National Statistics (ONS, 2003). We construct a measure of GVA per hour worked by employees, taking as the denominator an estimate of the total hours worked by employees in the area, derived from data on the numbers of full-time and part-time employees and the average weekly hours worked by each. One drawback of GVA as a measure of income in these quite small areas is that it is sensitive to the spatial allocation of profits and other non-wage income (see ONS 2003 for details). These problems are avoided if we focus on employment income only. Our alternative measure of income is therefore the average hourly earnings of full-time employees in each area and is based on data from the New Earnings Surveys for the relevant years.

Spatial variation in average earnings derives from two sources – differences in the wage rates paid to workers in a given occupation, and differences in the occupational composition of employment. We take as our primary measure of productivity an earnings index which is constructed to control for the occupational composition of employment. These two contributions to the spatial structure of average earnings -- variation in the wage rates paid to workers in a given occupation and variation in the occupational composition of employment – can be separated out as follows. We let w_i^k and l_i^k denote the wage and level of employment in occupation *k* and area *i*. Total employment in area *i* is $L_i = \Sigma_k l_i^k$, and the share of occupation *k* in employment in this area is $\lambda_i^k = l_i^k / L_i$. The average wage of occupation *k* in the economy as a whole (i.e. aggregating across all *i*) is given by

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individual workers can cause large biases in estimates of regional productivity differences.

$\overline{w}^k = \Sigma_i l_i^k w_i^k / \Sigma_i l_i^k$, while $\overline{\lambda}^k = \Sigma_i l_i^k / \Sigma_i L_i$ is the share of occupation k in total employment for the economy as a whole. It follows that average earnings in area i, e_i, may be decomposed as follows:

$$e_i \equiv \Sigma_k w_i^k \lambda_i^k = \Sigma_k w_i^k \overline{\lambda}^k + \Sigma_k \overline{w}^k \lambda_i^k + \Sigma_k (w_i^k - \overline{w}^k)(\lambda_i^k - \overline{\lambda}^k) - \Sigma_k \overline{w}^k \overline{\lambda}^k. \tag{1}$$

The first term on the right-hand side of (1) is the average level of earnings at location i conditional on the occupational composition being the same as for the economy as a whole; it will be denoted $q_i = \Sigma_k w_i^k \overline{\lambda}^k$. Since q_i measures the spatial variation in wages while controlling for occupational structure it reflects spatial differences in productivity, and we will refer to it as the productivity index. The second term on the right-hand side picks up the composition effects and will be denoted $c_i = \Sigma_k \overline{w}^k \lambda_i^k$. It measures the average level of earnings of area i given its specific occupational composition but assuming that the wage rate for each occupation is equal to the UK average in that occupation. Remaining terms measure the covariance in earnings and composition across occupations in area i, and will be referred to as r_i.

Using sub-regional data on earnings by occupation from the New Earnings Survey and on the occupational composition of employment taken from the Labour Force Survey, we compute the productivity index and the occupational composition index as specified above for each of the NUTS3 areas. In theory, each of these indices can be computed at varying levels of occupational disaggregation. In practise, the availability of reliable sub-regional data on occupational composition means that the occupational composition index, c_i, can be computed only at the level of the 9 major occupational groups. However, to construct the productivity index, q_i, it is possible to disaggregate further to the level of 38 minor occupational groups.

Table 1 gives summary statistics for each of these measures and the relationship between them. The numbers in brackets are the same statistics with Inner London (East and West) excluded from the sample. Correlation coefficients between each of the variables are reported in the lower part of the table. As expected, GVA per hour worked (denoted g_i) and average hourly earnings are positively correlated with each other, and with the composition index and the productivity index. Moreover the composition index and the productivity index are positively correlated. This indicates that relatively high productivity and a good occupational composition tend to go hand in hand, although the correlation coefficient, at around 0.66, is not that high. We also note that the sample properties of the productivity index do not vary significantly with the level of occupational disaggregation. As we would expect, the more disaggregated index (i.e. the one computed for 38 distinct occupational categories) displays a little less spatial variation. However, the two indices are very highly correlated (0.987) and their relationship with the other variables appears very similar.

The relationships between the series are illustrated in figure 1. Figure 1a shows the plot of average hourly earnings, e_i, against GVA per hour worked, g_i, with both series expressed relative to their mean value. Clearly there is a high correlation between g_i and e_i (0.76, table 1), but with some major outliers, most notably the two Inner London areas where earnings are particularly high relative to GVA per hour worked. It is interesting to note that, in general, areas with a high ratio of earnings to GVA per hour worked tend to be metropolitan areas, including for example Solihull and East Merseyside, and also Brighton and Hove and Liverpool.

Table 1: Summary Statistics for 119 NUTS 3 Administrative Areas.

(Bracketed term: excluding Inner London – East and West)

	GVA per (employee) hour worked g_i	Average hourly Earnings e_i	Composition Index, c_i (9 major groups)	Productivity index, q_i (9 major groups	Productivity index, q_i (38 groups)
Mean (£)	18.66 (18.58)	9.82 (9.71)	10.17 (10.15)	9.93 (9.86)	9.57 (9.51)
Variance	3.71 (3.28)	1.66 (0.97)	0.22 (0.19)	0.76 (0.47)	0.62 (0.40)
Coefficient of variation	0.1032 (0.0974)	0.1314 (0.1016)	0.0460 (0.0420)	0.0878 (0.0697)	0.0823 (0.0667)
Minimum	14.79	7.79	9.12	8.47	8.31
Maximum	25.20 (24.18)	17.54 (13.16)	12.03 (11.35)	14.53 (11.90)	13.52 (11.45)
Correlation coefficients					
GVA, g_i	1.00	0.7610 (0.7414)	0.6695 (0.6148)	0.7207 (0.6812)	0.7217 (0.6798)
Earnings, e_i		1.00	0.8202 (0.8077)	0.9638 (0.9450)	0.9569 (0.9387)
Composition index, c_i			1.00	0.6573 (0.5801)	0.6767 (0.6077)
Productivity index, q_i (9)				1.00	0.9875 (0.9807)

More important for our analysis is the decomposition of earnings into the productivity index and the composition effect. Figure 1b plots the productivity index against average hourly earnings. Recall that the productivity index, q_i, is equal to the average level of earnings in area *i* conditional on the employment shares of each occupation being the same as for Great Britain as a whole. If all the spatial variation in average earnings derived from productivity differences then equalising the occupational composition of the areas would have no effect on average earnings. If this were the case, the plot would lie along the 45-degree line in Figure 2 and the simple regression of productivity on average earnings would have a coefficient of unity. At the other extreme, if the spatial variation in average earnings is derived entirely from occupational composition with no differences in productivity then equalising occupational composition would equalise average earnings across the NUTS 3 areas, and the plot in Figure 2 would be a horizontal line. The slope coefficient of the simple linear regression line fitted to the plot in Figure 1b measures the contribution of the productivity index to the variance in earnings, and is equal to 0.6 (0.62 without Inner London East and West).[2] In other words variance in productivity accounts for some 60% of the variance in earnings. The gap between the 45^{o} line and the productivity index is the composition index plus covariance for each area ($c_i + r_i$) and these account for around one third of the spatial variation in earnings.

In conclusion, this section indicates that it is possible to separate the spatial variation of earnings into a productivity effect and a composition effect, with the former being quantitatively more important. Of course, the separation is not perfect – jobs within an occupation are far from homogeneous, even at the level of 38 occupations. Theory suggests that the determinants of productivity and of occupational structure are quite different, and we will see this come through in the econometric analysis of the next section.

3. Explaining regional disparities:

3.1. Conceptual framework

We start by outlining a theoretical framework within which interactions between the different aspects of regional inequality can be placed, and which points to the relationships that we will estimate econometrically. We do not set out a formal model (for which the reader can see Rice and Venables 2003), instead describing the ingredients informally (although rigorously).

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[2] Given the decomposition, $e_i = q_i + c_i + r_i$, the slope coefficient of the simple regression of the productivity index (q_i) on earnings (e_i) is equal to $[\text{var}(q_i)+\text{cov}(q_i, c_i + r_i)]/\text{var}(e_i)$ i.e. the share of the variance of q_i plus its covariance in the total variance of e_i.

Suppose that there are many different spatial units ('areas'), each of which contains workers of different skill or occupational types. There are at least as many activities (eg production sectors) with tradable output as there are different skill/occupation types. Firms in these activities operate under perfect competition and constant internal returns to scale and face the same price of capital everywhere. They choose where to produce and, at equilibrium, price equals unit cost in all activities in all areas. Labour productivity is however area specific (for reasons to be discussed below), and these productivity variations apply equally to all skills/occupations. The productivity variations may be a physical productivity difference or a value effect, as would be the case if, for example, in one area all output prices were higher or all non-labour input prices lower.

Given these assumptions, two things follow. The first is that any spatial variations in labour productivity will be equal to spatial variations in wages. The mobility of production activities bids up wages in high productivity areas so that labour captures all the benefit; furthermore, under our assumptions spatial wage differences are proportionately the same for all skill/occupation types. Second, no production activities have an incentive to move, as all earn zero profits in all areas. The production structure of each spatial unit is either determined directly by the skill/occupation mix of the labour force (if there are as many skill/occupation types as production activities) or is indeterminate.[3]

Now, add to this the possibility that labour can move between areas. This will bid up land and property prices in high productivity and high wage areas until the real income of a particular skill/occupation type is the same everywhere. There is therefore an equilibrium in which firms and workers are fully mobile, and the ultimate beneficiaries of spatial productivity differences are property owners. The equilibrium has two properties. First, the skill/occupation mix of each location is indeterminate (the model does not say exactly what sort of labour moves to bid up land prices), as is the structure of production. Second, (and crucially for our purposes) the nominal wages of each type of worker vary across areas, and these variations are equal to the productivity differences between areas. We will therefore use such variations in wages as our measure of productivity.

The assumptions that we have outlined give the benchmark case. Relaxing them adds more detail but does not change the main conclusion. For example, spatial productivity differences may be greater for some types of workers or for some activities than others, in which case the model would also provide a theory of regional specialisation. We do not

[3] These are standard results from higher dimensional trade theory.

pursue this further, instead focusing just on the equilibrium spatial variation of income and productivity.

With this structure in mind, there are two research tasks. The first is dividing the observed spatial variation in average income per worker between variation in the occupational composition of areas and variation in the wages (earnings) of workers of a particular type. This we did in the preceding section, giving our measure of productivity. The second is to model productivity differences across areas. Our hypothesis is that increasing returns cause labour productivity to be high in regions that have, in some sense, proximity to a large economic mass. Three main sorts of mechanisms have been put forward (see Fujita and Thisse 2002 for a survey). One is technological externalities; firms learn from co-presence with other firms in related activities, so innovating and implementing new technologies efficiently. A second is that thick labour markets work more efficiently, by having lower search costs and generating improved labour market matching. The third main mechanism is simply that, in the presence of transport costs, firms gain from having good access both to their customers and to suppliers of intermediate goods and services. Notice that while the first of these mechanisms raises the physical productivity of a worker of a given type in a given job, the other two do not. Market access effects mean simply that firms seek to locate where they can save on trade and transport costs.

We do not seek to identify each of these effects separately, but merely their combined effect by estimating a relationship with general form

$$y_i = f(x_i)m(\Sigma_h p_h a_{hi}) . \qquad (2)$$

The dependent variable, y_i, will be alternative measures of per worker income and productivity. Independent variables include a set of controls for each area, x_i, and spatial mass effects. p_h is a measure of the economic mass of each area, a_{hi} is a measure of the interaction between area h and area i, and the function $m(.)$ captures the combined spatial mass effects. For theoretical derivation of particular forms of this equation, see Fujita et al (1999) or Redding and Venables (2004).

The next section estimates several different forms of this relationship, and establishes our main results. However we note that the location of 'economic mass' may itself be endogenous; in section 4 we discuss this further and present results estimated using instrumental variables.

3.2: Explaining regional productivity: economic mass by time bands.

Our measure of the economic mass of each area, p_h, is its population of working age. It is central to our approach that we capture proximity effects in a rich and flexible way, allowing not only for own area effects, but also for inter-area effects (the interaction terms, a_{hi}). This is important both because NUTS3 areas are relatively small with boundaries determined by administrative rather than economic considerations, and because we wish to understand the spatial scale over which economic mass effects occur.

We need a concept of proximity between NUTS3 regions, and measure this by driving time between the economic centres of these regions. Driving times are more economically relevant than other measures of proximity, such as distance or contiguity, and produce slightly better results than do estimates based on geographical distance. We then form driving-time bands around each area. Thus, for each NUTS3 area, we construct a series of proximity bands and measure population of working age within each proximity band. So, for example, we measure the population of working age within 40 minutes driving time of area *i*; within 40-80 minutes driving time of area *i*, and so on. We construct these bands under two alternative models of the distribution of population within each NUTS3 area. Broadly speaking the first model assumes that the population of each NUTS3 area is massed at the economic centre of the area, so lies entirely within a single proximity band. The alternative approach assumes that the population is evenly distributed across the area, so may be divided between several proximity bands ('smoothed population'). Details of the procedure for identifying the centres of areas, the estimation of travel times between centres, and the distribution of population within each area are provided in the Appendix.

With this structure, the estimating equation becomes

$$\ln y_i = \beta_0 + \sum_b \alpha_b p_{bi} + \sum_j \beta_j x_{ji} + \varepsilon_i \tag{3}$$

where p_{bi} denotes the population of working age within the proximity band *b* of area *i*. In writing equation (2) in this way we have assumed a particular functional form, and allow the data to identify the weights a_b for each proximity band.

In Table 2 we report the results obtained with three proximity bands; up to 40 minutes, 40 to 80 minutes and 80 to 120 minutes, and with both 'mass point' (table 2a) and smoothed population (table 2b). Additional controls are included to allow for other area specific characteristics that may have affect outcomes. Variation in the education levels of the local workforce is controlled for by including the proportion of the economically active population with specified levels of qualifications. The preliminary analysis identified six distinct educational levels ranging from no formal qualifications up to degree level qualifications. These were aggregated into three groups to obtain a more parsimonious and statistically robust specification. The three groups are: first degree or higher (level 4 or above); intermediate levels qualifications (levels 1, 2 and 3) and no formal educational qualifications (unqualified or trade qualifications only). The intermediate qualification level is taken to be the reference group. In addition, a set of dummy variables for the 10 NUTS1 regions are included to capture any unobserved region-specific fixed effects.

This basic model is estimated taking as the dependent variable each of the income measures; GVA per hour worked, g_i, and average earnings, e_i; the occupational composition index, c_i, and the productivity index, q_i. The OLS parameter estimates for the model with and without the regional dummies are reported in the first two columns of each of the block in table 2. In the third column we report the results obtained with the inclusion of a spatially lagged dependent variable as an additional explanatory variable. This is to allow for the possibility of spatial dependence in the data that is not fully captured by the population bands. In this case, the model is estimated by maximum likelihood methods, rather than OLS, to take account of the correlation between the spatially lagged dependent variable and the error term.

If we compare the results for the two alternative measures of area income, g_i, and e_i, we find that the specification using earnings e_i as the dependent variable is the better determined, although in both cases there is evidence of a significant positive effect of economic mass as measured by population on income. Focusing on this equation, earnings increase with the population of working age up to a distance of some 80 minutes travel time from the centre of the sub-region. The quantitative impact of population declines with distance, with the coefficients on the 40 to 80 minutes band significantly smaller than that for the 0 to 40 minute band. Beyond 80 minutes the population effects are statistically insignificant.

The next question to be addressed is whether the relationship between earnings and economic mass comes about through the productivity component, the occupational composition component, or both. In this respect, the results are quite unambiguous. We find no evidence of a significant effect from population to occupational composition, particularly once we control for region-specific effects. By contrast, the relationship between population and productivity is strong and well determined. Productivity increases with population within 80 minutes travel time, and the magnitude of effects are significantly greater the closer is population, i.e. for the 0 to 40 minute band than for the 40 to 80 minute band. As one would expect the magnitude of the population effects is sensitive to the measurement of population and the effects tend to fall off more sharply with distance when population is smoothed across space (table 2b) rather than concentrated at a mass point (table 2a).

Turning to the other variables in the regression equation, the qualification controls are statistically significant in all cases. As one would expect, a higher proportion of the population qualified to first degree or higher is associated with a higher level of income in the area as measured by GVA per hour worked and by average hourly earnings; while the reverse is true for the proportion of unqualified workers. If it were possible to control perfectly for occupational composition in the construction of the productivity index then one might expect that the impact of qualifications on earnings would come only through the composition index, and not at all through productivity. While this is not so, it is the case that education levels, and in particular the proportion of population with degree level qualifications, has a much weaker effect on productivity than on average earnings and on occupational composition.

Along with the parameter estimates and their associated z-values, we report the values of diagnostic tests for possible misspecification of the spatial structure of the data. The first is a test for a spatial process in the error term of the model and the second test is for an omitted spatially lagged dependent variable.[4] In each case, the null hypothesis of no spatial dependence is tested against an alternative of spatial dependence within a specified proximity. Proximity is measured in terms of estimated driving times and the tests are computed for values of 30, 60, 90 and 120 minutes, with the highest values obtained in each case reported in the table. Both tests are valid only under the assumption of normality and so we report also the value of the Jacques-Bera test statistic for normality of the errors.

The diagnostic statistics show no evidence of a spatial process in the error term of the model once regional dummies are included in the specification. There is, however, evidence of an omitted spatial lag in the model for GVA per hour worked, and, to a lesser degree in the equations for average hourly earnings and the productivity index. A comparison of the OLS estimates in column 2 with the ML estimates in column 3 shows that the inclusion of the spatially lagged dependent variables has little effect on the other parameter estimates. In

[4] For details of the structure of the spatial test statistics see Anselin (1992), pp173-179.

Table 2a: Time bands: population at mass point

	Ln(GVA per employee hour worked, g_i)			Ln(Average hourly earnings, e_i)			Ln(Occupational composition index, c_i)			Ln(Productivity index, q_i)		
	OLS	OLS	ML	OLS	OLS	ML	OLS	OLS	ML	OLS	OLS	ML
Population of working age within 40 mins travel time	-0.0238 (-1.57)	0.0017 (0.10)	0.0004 (0.02)	0.0341 (2.34)	0.0420 (3.29)	0.0441 (4.02)	-0.0018 (-0.50)	-0.0019 (-0.45)	-0.0019 (-0.43)	0.0302 (2.87)	0.0348 (3.65)	0.0367 (4.10)
…………within 40-80 mins travel time	0.0163 (3.15)	0.0176 (3.55)	0.0173 (4.05)	0.0227 (7.53)	0.0206 (6.34)	0.0217 (7.30)	0.0032 (2.41)	0.0016 (1.24)	0.0016 (1.38)	0.0175 (6.08)	0.0159 (6.14)	0.0167 (6.93)
…………within 80-120 mins travel time	-0.0014 (-0.49)	0.0005 (0.16)	0.0002 (0.05)	0.0012 (0.63)	0.0006 (0.18)	0.0009 (0.37)	0.0014 (1.72)	-0.0002 (-0.23)	-0.0002 (-0.24)	0.0004 (0.22)	0.0013 (0.49)	0.0015 (0.74)
Propn of econ active with degree level qualifications)	0.1196 (2.65)	0.1126 (2.26)	0.1237 (2.64)	0.1886 (6.70)	0.1971 (6.41)	0.1966 (6.24)	0.1109 (9.53)	0.1416 (8.99)	0.1417 (10.84)	0.0928 (3.69)	0.0751 (3.11)	0.0749 (2.92)
Propn of econ active with no formal educ qualifications)	-0.2013 (-3.82)	-0.1438 (-2.20)	-0.1255 (-1.84)	-0.1961 (-5.32)	-0.1748 (-3.48)	-0.1721 (-3.74)	-0.0853 (-5.59)	-0.0471 (-2.07)	-0.0469 (-2.46)	-0.1002 (-3.01)	-0.1011 (-2.76)	-0.0985 (-2.63)
Regional dummies	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Spatial lag of dependent var.			0.0421 (1.87)			-0.0211 (-1.76)			0.0004 (0.06)			-0.0176 (-1.79)
R-squared	0.4824	0.5871	0.5988	0.8286	0.8613	0.8648	0.8040	0.8468	0.8468	0.7413	0.7896	0.7978
Normality	0.3934 (0.82)	1.7148 (0.42)		1.9056 (0.39)	2.8753 (0.24)		2.3933 (0.30)	0.6180 (0.73)		2.3933 (0.30)	3.1254 (0.21)	
LM (spatial error)	2.2264 (0.14)	3.4780 (0.06)	1.1973 (0.27)	19.35 (0.00)	0.7270 (0.39)	1.0181 (0.31)	10.31 (0.00)	1.2957 (0.26)	1.1814 (0.67)	22.88 (0.00)	0.5452 (0.46)	0.6697 (0.41)
LM (spatial lag)	3.5197 (0.06)	3.7554 (0.06)	-	0.5260 (0.47)	2.7736 (0.10)	-	2.4134 (0.12)	0.0058 (0.94)		0.1506 (0.70)	2.97 (0.09)	

Notes: The OLS parameter estimates are reported with the values of the z statistic computed using Hubert-White robust standard errors in parentheses.
The values of the following diagnostic test statistics are reported along with the associated probability level in parentheses:
Normality: Jarque-Bera test for non-normal errors, distributed as χ^2 with 2 degrees of freedom.
LM(spatial error): robust version of the Lagrange multiplier test for spatial autoregressive or spatial moving average errors, distributed as χ^2 with 1 degree of freedom.
LM(spatial lag): robust version of the Lagrange multiplier test for spatial lag dependent variable, distributed as χ^2 with 1 degree of freedom.
The test statistics for spatial autocorrelation are computed with spatial weight matrices W={w_{ij}} where w_{ij}=1 if the estimated driving time between area i and area j is less than d minutes and w_{ij}=0 otherwise for values of d = 60, 90 and 120. The reported value for the test statistics is the highest of the three alternatives.
ML indicates maximum likelihood estimates.

Table 2b: Time bands: smoothed population												
	Ln(GVA per (employee) hour worked, g_i)			Ln(Average hourly earnings, e_i)			Ln(Occupational composition index, c_i)			Ln(Productivity index, q_i)		
	OLS	OLS	ML	OLS	OLS	ML	OLS	OLS	ML	OLS	OLS	ML
Population of working age within 40 mins travel time	-0.0175 (-1.14)	0.0069 (0.37)	0.0047 (0.28)	0.0425 (2.61)	0.0512 (3.68)	0.0539 (4.60)	-0.0023 (-0.61)	-0.0040 (-0.79)	-0.0040 (-0.85)	0.0366 (3.52)	0.0433 (3.95)	0.0457 (4.85)
………….within 40-80 mins travel time	0.0177 (2.65)	0.0177 (3.00)	0.0176 (3.49)	0.0184 (4.25)	0.0149 (3.68)	0.0161 (4.58)	0.0032 (2.06)	0.0014 (0.77)	0.0014 (1.00)	0.0145 (4.56)	0.0119 (4.03)	0.0128 (4.53)
………….within 80-120 mins travel time	-0.0019 (-0.61)	0.0006 (0.16)	0.0002 (0.06)	0.0025 (1.15)	0.0037 (1.22)	0.0039 (1.42)	0.0016 (2.00)	0.0006 (0.51)	0.0006 (0.55)	0.0015 (0.54)	0.0030 (1.15)	0.0032 (1.44)
Ln(% of econ active with degree level qualifications	0.1197 (2.72)	0.1151 (2.32)	0.1262 (2.65)	0.1921 (6.31)	0.1946 (5.86)	0.1947 (6.03)	0.1118 (9.44)	0.1401 (8.44)	0.1401 (10.72)	0.0954 (3.83)	0.0744 (2.91)	0.0746 (2.88)
Ln(% of econ active with no formal educ qualifications	-0.1984 (-3.43)	-0.1386 (-2.08)	-0.1205 (-1.75)	-0.1966 (-4.45)	-0.1728 (-3.39)	-0.1695 (-3.63)	-0.0838 (-5.28)	-0.0473 (-1.30)	-0.0473 (-2.50)	-0.1013 (-3.15)	-0.0987 (-2.75)	-0.0957 (-2.55)
Regional dummies	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Spatial lag of dependent var.			0.0420 (1.85)			-0.0220 (-1.80)			-0.0000 (-0.01)			-0.0187 (-1.89)
R-squared	0.4722	0.5820	0.5936	0.8210	0.8567	0.8605	0.7972	0.8247	0.8470	0.7351	0.7917	0.7950
Normality	0.5203 (0.77)	1.7528 (0.42)		1.7039 (0.43)	1.6665 (0.43)		1.3638 (0.51)	0.8345 (0.66)		1.7736 (0.41)	1.4385 (0.49)	
LM (spatial error)	2.4784 (0.12)	3.2618 (0.07)	1.1583 (0.28)	19.76 (0.00)	0.9977 (0.32)	1.3527 (0.24)	8.5468 (0.00)	0.9755 (0.32)	0.9754 (0.32)	24.20 (0.00)	1.3015 (0.25)	1.5394 (0.21)
LM (spatial lag)	3.5480 (0.06)	3.6866 (0.05)	-	1.3685 (0.24)	2.8564 (0.09)	-	0.0309 (0.86)	0.0006 (0.98)	-	2.4304 (0.11)	3.2261 (0.07)	-

particular, the parameter estimates on the successive population bands in the earnings and productivity equations are robust to this particular form of misspecification; increasing marginally in value and statistical significance with the inclusion of the spatially-lagged dependent variable.

3.3 Explaining regional productivity: spatial decay.

Table 2 (a and b) indicate that the effect of economic mass on earnings falls away sharply with travel time. It is possible to examine this relationship further by taking a finer cut on the width of the time bands and Table A1 in the Appendix presents results obtained with smoothed population and bands of 30 minutes and 20 minutes width. The results are qualitatively similar to those in Table 2, confirming that the impact of population on average hourly earnings and on productivity declines with distance. For the 30 minute bands, the coefficients on productivity decline monotonically with time. However, as we move to finer band-widths, the individual coefficients on the population variables become less well determined. This is due to the degree of multicollinearity among the population variables increasing as the width of the bands is reduced.

An alternative approach is to impose restrictions on the weights attached to successive population bands prior to estimation. Referring back to equation (2), we specify a functional form relating the weights a_{hi} to time travelled, along with functional forms for *m*(.) and *f*(.). For example,

$$\ln y_i = \beta_0 + \alpha \ln\left[\sum_b p_{bi} \exp(-\theta(t_b - 30)/30)\right] + \sum_j \beta_j x_{ji} + \varepsilon_i \qquad (4)$$

where p_{bi} is population of working age within travel time band with outer edge t_b minutes of NUTS3 area *i* and $\exp(-\theta(t_b - 30)/30)$ is the weight attached to this population band. Travel time bands are computed for population within 30 minutes and then at 10 minute intervals, so t_b = {30, 40, 50…. 120}. The functional form assumes that weights decline exponentially with slope coefficient θ indicating the relative weight attached to successive population bands in the mass index. (Results with weights declining linearly rather than exponentially are given in appendix table A2). The parameter α measures the elasticity with respect to the mass index as a whole. The parameters, α and θ, together with the β_j for the additional controls, are estimated using non-linear least squares. Table 3 reports results obtained for this specification both with regional dummies (lower panel) and without (upper panel) . We use smoothed population estimates but the results obtained with mass point population estimates are quantitatively very similar, in particular the estimates of α are close in all cases.

Table 3: Spatial decay

$$\ln y_i = \beta_0 + \alpha \ln\left[\sum_b p_{bi} \exp(-\theta(t_b - 30)/30)\right] + \sum_k \beta_j x_{ji} + \varepsilon_i$$

p_{bi} : population of working age (ths) within travel time band (t_b - 10, t_b) of NUTS3 area i; for ($30 \le t_b \le 120$)

	Ln(GVA per employee hour worked, g_i)	Ln(Average hourly earnings, e_i)	Ln(Occupational composition index, c_i)	Ln(Productivity index, q_i)
α	0.0152 (1.64)	0.0571 (8.07)	0.0080 (2.52)	0.0462 (8.19)
θ	0.5437 (0.42)	1.2784 (3.75)	-0.9546 (-0.84)	1.5138 (3.96)
Ln (% of econ active with degree level qualifications)	0.1042 (2.35)	0.1889 (5.79)	0.1145 (9.48)	0.0938 (3.64)
Ln (% of econ active with no formal educ. Qualifications)	-0.2261 (-3.93)	-0.2359 (-5.54)	-0.0855 (-5.53)	-0.1301 (-3.87)
R-squared	0.4280	0.7644	0.7929	0.6624

α	0.0300 (2.66)	0.0482 (6.02)	0.0025 (0.86)	0.0410 (6.45)
θ	0.8166 (0.98)	1.4110 (3.02)	-0.6869 (-0.21)	1.5078 (3.31)
Ln (% of econ active with degree level qualifications)	0.1154 (2.21)	0.2100 (5.57)	0.1404 (10.14)	0.0876 (2.92)
Ln (% of econ active with no formal educ. qualifications)	-0.1308 (-1.68)	-0.1546 (-2.74)	-0.0464 (-2.55)	-0.0818 (-1.83)
Regional dummies	Yes	Yes	Yes	Yes
R-squared	0.5496	0.8274	0.8244	0.7512

These results confirm a number of our earlier findings. As before, the relationship with economic mass is better determined with average hourly earnings than with a GVA-based measure of income. That said, the estimated elasticity of GVA per hour worked with respect to economic mass is positive and statistically significant when regional dummies are included - so economic mass matters – although the estimate of θ is not well determined. For average hourly earnings, the estimated elasticity with respect to the mass index is 0.048 (0.057 without regional dummies).

Most importantly, we find that the effects of economic mass on income come about through productivity as measured by the earnings index, rather than through occupational composition. Looking at the case with regional dummies, for the index of occupational composition the estimates of α (the elasticity with respect to the mass index) are not significantly different from zero, and the estimate of θ is not well-determined either. By contrast, the estimated elasticity of the earnings index with respect to economic mass is 0.041 (0.046 without regional dummies) and is very well-determined. Similarly, the estimate of θ indicates that effects decline with distance, and is well-determined.

4. Instrumental variable estimates

An alternative hypothesis is that spatial variation in income and productivity may arise as a result of exogenously determined spatial characteristics that are not directly observable. Areas with good characteristics have high income and productivity, and also attract population. If this is the case then the population variables will be correlated with the error term in the model, and as a result parameter estimates are biased and inconsistent. As is standard, we address this possible problem by employing an instrumental variable estimator. Our instruments are based on the population of the NUTS 3 area in 1851 as reported in the 1851 Census.[5] Given the 1851 population figures, we compute the population within given proximity bands in a manner analogous to that used for current population and use these as instruments. The validity of these instruments rests on the assumption that the exogenous factors that influenced the pattern of settlement in the mid-nineteenth century are unrelated to income and productivity at the end of the twentieth century, apart from their effect through present-day population.

The instrumental variable estimates for the basic specification with three population bands are reported in table 4, together with those for the non-linear spatial decay model. In both cases, the results are based on the 'smoothed' population estimates. Once again, we observe that the alternative estimation method has little impact on the overall pattern of results, either qualitatively or quantitatively. Moreover, these results are robust to variations in the instrument set to include alternative measures of 1851 population bands and geographical-based measures such as distance (in kilometres) from London. Further, in cases

[5] The correlation coefficient between the 1851 population and the current population of working age across the NUTS3 regions is 0.69.

with over-identifying restrictions on the instrument set, the restrictions are not rejected by the data.

Table 4: Instrumental Variable estimates

	Ln(GVA per (employee) hour worked, g_i)	Ln(Average hourly earnings, e_i)	Ln(Occupational composition index, c_i)	Ln(Productivity index, q_i)
Population of working age within 40 mins travel time	0.0020 (0.11)	0.0627 (3.51)	-0.0029 (-0.66)	0.0476 (3.64)
…………within 40-80 mins travel time	0.0167 (3.22)	0.0116 (2.78)	0.0013 (0.84)	0.0099 (3.27)
…………within 80-120 mins travel time	0.0017 (0.58)	0.0039 (1.30)	0.0006 (0.57)	0.0033 (1.32)
Ln(% of ec. active with degree level qualifications	0.1127 (2.41)	0.1923 (6.23)	0.1400 (9.77)	0.0730 (3.12)
Ln(% of ec. active with no formal educ. qualifications	-0.1412 (-2.27)	-0.1738 (-3.90)	-0.0470 (-2.28)	-0.1001 (-3.08)
Regional dummies	Yes	Yes	Yes	Yes
R-squared*	0.5813	0.8549	0.8469	0.7878

Instruments: 1851 population in the area within 40 mins travel time; within 80 mins travel time; within 120 mins travel time; Ln(% of economically active population with degree level qualifications); Ln(% of economically active population with no formal educational qualifications); regional dummies.

$$\ln y_i = \beta_0 + \alpha \ln\left[\sum_b p_{bi} \exp(-\theta(t_b - 30)/30)\right] + \sum_j \beta_j x_{ji} + \varepsilon_i$$

α	0.0409 (3.35)	0.0596 (6.94)	0.0033 (0.98)	0.0495 (7.25)
θ	0.6304 (0.80)	1.3214 (2.79)	-0.6030 (-0.03)	1.4348 (3.04)
Ln(% of econ active with degree level qualifications)	0.1160 (2.36)	0.2120 (5.96)	0.1407 (10.82)	0.0892 (3.15)
Ln (% of econ active with no formal educ. qualifications)	-0.1169 (-1.58)	-0.1380 (-2.58)	-0.0450 (-2.31)	-0.0694 (-1.63)
Regional dummies	Yes	Yes	Yes	Yes
R-squared*	0.5454	0.8241	0.8449	0.7491

Instruments: 1851 population in the area within each travel time band t_b between 30 and 120 minutes; Ln(% of economically active population with degree level qualifications); Ln(% of economically active population with no formal educational qualifications); regional dummies.
* Note: the R-squared statistic is not bounded in [0,1]

The IV estimates confirm the main findings from earlier tables. In general, the IV estimates of the elasticity with respect to economic mass in table 4 are somewhat larger than their LS counterparts in Tables 2b and 3. For example, the IV estimate of α (the elasticity with respect to economic mass in the spatial decay model) for the productivity index is 0.0495, as compared with the NLS estimate is 0.0410. By contrast, the IV estimate of θ, the rate of decay, is smaller than its NLS counterpart; 1.43 as compared with 1.51.

We take the estimate of $\alpha = 0.0495$ as our benchmark estimate of the elasticity of productivity with respect to economic mass, and we use it in section 5 to assess the quantitative importance of these productivity effects. But before doing this we investigate further the robustness of our results, in particular assessing the possibility that effects are all due to London.

5: London and the South-East.

We have already seen that our results are robust to specification of functional form, and to the choice of estimator. The question remains however: how much of what we have found emanates from London? There are conceptually two distinct issues. First, does the presence of London shape the productivity even of areas far away from London? And second, do the observations for London and the South East of England as a whole drive all the results we have found?

To investigate the first issue, we add an additional control variable that measures the travel time between the sample point and Central London. In general, in the absence of the economic mass variables, the travel time to London variable is negative and statistically significant. However, with the inclusion of the economic mass variables, this is no longer the case (see appendix table A3). This is the case for both the specification of equation (3) and the spatial decay model in equation (4), and is robust to the use of the IV, rather than the LS, estimator.

The second issue is the extent to which the results relating economic mass and productivity are driven by the observations from London and the South East corner of England. This area of the UK is ranked highly both in terms of economic mass and the outcome measures and it is possible that the regression results reported above are reflecting a specifically London area phenomenon rather than a more general economic relationship. We have seen, in section 2, the extent to which Inner London observations are outliers in the data. To investigate the role of London we re-estimate the model with central London and its neighbours excluded from the sample. For this exercise, the London neighbourhood set is defined in terms of travel time from central London, starting at 60 minutes travel time and increasing to 180 minutes. At 180 minutes travel time from central London, the sample is split into two equal size groups - a south-east 'core' and a 'periphery'. At this distance the 'core' is made up of Greater London, the South-East and East of England regions and extends into the Midlands as far north as Birmingham and Derby, and to the south west to include Dorset, Somerset and into South Wales as far as Cardiff.

Table 5 reports the estimates of the parameters α and θ of the spatial decay model (4) as the sample is varied, with the estimates for the full sample given in the final column for comparison. It should be noted that for this particular robustness exercise, regional dummies are not included as additional controls, and so adjustment to the changing sample can only come about through the parameters of interest. In interpreting the results, it is important to bear in mind that as we vary the sample, two effects are operating. The first is simply that observations for London and its immediate neighbours are excluded. The second is that as observations for areas surrounding London are dropped from the sample so the weight attached to London's population in the index of economic mass declines exponentially, until beyond 120 minutes, London's population no longer contributes to the economic mass for any area in the sample.

Looking across the columns of Table 5, we see that the parameter estimates are relatively stable and their statistical significance remains robust. The final three columns of Table 5 allow us to compare the results for the two equal size samples of the South-east 'core' and the periphery, together with the entire sample. It is indeed the case that the relationship between economic mass and productivity is stronger for the South-East core. However, among the set of disparate areas that make up the 'periphery', there is still evidence of a statistically significant relationship between productivity as measured by the earnings index and economic mass. Thus, comparing the non-linear IV estimates, the elasticity with respect to economic mass is 0.038 in the case of the periphery as compared with 0.065 for the South-East core. While these two values are significantly different from each other, neither is significantly different from the value of the elasticity for the entire sample (0.052). The rate at which economic mass effects decline with travel time (the θ parameter) does not appear to differ significantly between the two sub-samples.

Table 5: Productivity index, regional sub-samples							
Excluding NUTS3 areas that are within specified travel time of Central London						Including only areas within 180 minutes travel time of Central London	Full sample
	60 mins	90 mins	120 mins	150 mins	180 mins		
Number of observations	111	100	87	72	59	60	119
NLS							
α	0.0384 (7.16)	0.0334 (6.39)	0.0285 (5.58)	0.0331 (6.03)	0.0372 (6.40)	0.0614 (6.01)	0.0462 (8.19)
θ	1.1525 (3.23)	1.2998 (2.97)	1.5181 (2.49)	2.360 (2.43)	1.9077 (2.69)	1.4944 (3.31)	1.5138 (3.96)
Non-linear IV							
α	0.0416 (7.39)	0.0340 (6.31)	0.0345 (6.33)	0.0348 (6.38)	0.0378 (6.46)	0.0653 (6.46)	0.0520 (8.58)
θ	0.8703 (2.48)	0.7802 (1.95)	0.8141 (2.02)	0.8713 (2.14)	1.3075 (2.66)	1.6779 (3.29)	1.5395 (3.70)

Instruments: 1851 population in the area within each travel time band (% of economically active population with degree level qualifications, % of economically active population with no formal educational qualifications). Education controls as in previous tables. No regional dummies.

6. Quantification: how large are the effects?

Having established that proximity to economic mass has statistically significant productivity effects, we now turn to its quantitative importance. We base our discussion around the non-linear instrumental variable estimates with regional dummies (table 4, lower panel), although similar effects come from the separate time bands.

First, how important is proximity in the relationship? We take as the central estimate of θ a value of 1.43 (table 4, lower panel). This means that moving a mass of population 30 minutes further away reduces its impact on productivity by three-quarters ($\exp(1.43) \approx 4$). Thus, an extra 400,000 persons of working age between 90-100 minutes away have the same impact on productivity as an extra 100,000 persons 60-70 minutes away, or an extra 25,000 persons 30-40 minutes away. A linear (rather than exponential) specification of the time weights is reported in appendix table A1. In this case, an extra 100,000 workers 60-70 minutes away has the same effect as an extra 40,000 workers 30-40 minutes away, and effects go to zero beyond 80 minutes. These are both quite steep rates of spatial decay, but are consistent with industry level studies in the literature, for example Rosenthal and Strange (2003).

The coefficient α is the elasticity of productivity with respect to distance-weighted spatial mass and its estimated value is 0.0495 (table 4, lower panel). Quantitatively, an elasticity of 0.05 means that doubling the spatial mass that an area accesses increases its productivity by 3.5% (= $2^{0.05}$ - 1). This estimate is at the lower end of the range of estimates typically found in the literature. This is reviewed by Rosenthal and Strange (2004) who report a consensus view that 'doubling city size seems to increase productivity by an amount that ranges from roughly 3-8%'.

An alternative approach to assessing the quantitative importance of economic mass in determining productivity is to consider how much spatial variation in UK productivity is attributable to variation in economic mass and how much to variation in other factors. Table 6 provides a decomposition of the variance of the predicted values of the (log) productivity index into the various sources based on the IV estimates of the non-linear spatial decay model (Table 4, lower half).[6] Looking at the sample as a whole, some 34% of the variance in predicted (log) productivity is directly attributable to variance in economic mass, as compared with the 46% that is due to variance in the levels of qualification and the region-specific factors, and 20% that is accounted for by the positive covariance between the two sets of variables. With the two Inner London areas excluded from the sample, the contribution due to the variance in economic mass alone increases to 40%, with a corresponding reduction in the contribution due to the covariance term. More significantly, the effects of economic mass appear to be more influential in determining spatial variation in productivity among areas outside of the upper ranges of the productivity distribution. Thus with areas in the upper quartile of the productivity distribution excluded from the computation, variance deriving from economic mass is equivalent to more than two-thirds of the total variance, offset to some extent by negative covariance with the other observable factors.

[6] Given the spatial decay model (4), the predicted (log) productivity index for area *i* may be decomposed as follows: $\hat{\ln} q_i = \ln \tilde{q}_i + \sum_j \hat{\beta}_j (x_{ji} - \bar{x}_j)$ where $\ln \tilde{q}_i$ is the 'equalised qualifications' predicted values obtained by using the parameter estimates to predicted productivity in each area conditional on the values for the qualification variables and the regional specific dummies being equal to the UK average value in each case. It follows that $\mathrm{var}(\hat{\ln} q_i) = \mathrm{var}(\ln \tilde{q}_i) + \mathrm{var}(\sum_j \hat{\beta}_j x_{ji}) + 2\,\mathrm{cov}(\ln \tilde{q}_i, \sum_j \hat{\beta}_j x_{ji})$

Table 6: Decomposition of the spatial variation in productivity				
		% of variance in predicted (log) productivity attributable to		
	Variance in predicted (log) productivity	Variance in economic mass	Variance in other observables (qualifications + region specific factors	Covariance between economic mass and other observables
Entire sample	0.0048015	33.83	45.89	20.28
Inner London excluded	0.0030807	40.01	45.90	14.09
Upper quartile of productivity distribution excluded	0.0021026	68.20	48.12	-16.32

A final indicator of the quantitative importance of the mass effects comes from considering the following experiment. Suppose that all journey times in the UK were cut by 10%. How much does productivity increase, holding the qualifications and location of the labour force constant? Answers to this question are given in Table 7, based on predictions from the IV estimates of the spatial decay model, (Table 4; lower half). We see an overall UK productivity gain of 1.12%. If we base our predictions on the NLS estimates of the model (Table 3, lower half), we obtain a somewhat lower estimate of 0.92%. This number is of course an induced productivity gain, additional to any effects that would be included in a standard cost-benefit analysis of a transport improvement. It does not include direct cost and time-savings. We have not experimented with reducing travel time on particular routes or in particular regions, but the results of the UK wide experiment are generated for each NUTS3 sub-region. In Table 7 we report, in addition to the UK average, the average results for each NUTS1 region, and the minimum and maximum values in each of these areas. In very low density areas speeding up transport has essentially no induced productivity effect, hence the low minimum values for Scotland and the South West. The highest value is for Peterborough (a 2.22% productivity increase), gaining from improved access both to the London area and to the Midlands.

Table 7: % productivity gain from 10% reduction in all driving times			
	Average	Minimum	maximum
UK average	1.12 (0.92)		
North East	0.81 (0.67)	0.53 (0.43)	1.04 (0.87)
North West	1.10 (0.91)	0.88 (0.70)	1.44 (1.21)
Yorks-Humberside	1.25 (1.03)	1.07 (0.89)	1.45 (1.12)
East Midlands	1.33 (1.09)	0.69 (0.54)	1.66 (1.37)
West Midlands	1.30 (1.07)	0.88 (0.71)	1.73 (1.42)
East	1.35 (1.11)	0.32 (0.24)	2.22 (1.81)
London	0.90 (0.75)	0.73 (0.61)	1.08 (0.91)
South East	1.31 (1.08)	0.99 (0.80)	1.66 (1.39)
South West	1.08 (0.88)	0.31 (0.26)	1.62 (1.27)
Wales	1.09 (0.88)	0.48 (0.36)	1.57 (1.27)
Scotland	0.80 (0.66)	0.00 (0.00)	1.55 (1.13)

7: Conclusions.

Three main conclusions follow from our analysis.

The first is that a robust and quantitatively important determinant of variations in productivity between NUTS3 regions of Great Britain is the proximity of each area to 'economic mass' – the presence of a large population of working age within 80 minutes or less driving time. Our estimate of the elasticity of productivity with respect to economic mass is consistent with (although at the lower end of) the estimates produced for other countries using other techniques, and consistent with mechanisms put forward in theoretical literature on geographical economics.

Second, our productivity measure is based on a decomposition of earnings into a productivity effect and an occupational composition effect. The occupational composition index captures the extent to which an area's employment is in occupations that are (in terms of the average for GB as a whole) more or less well paid. The occupational composition index is positively correlated with productivity, so regions with high productivity also tend to have good employment structures. However, we find no evidence of a systematic relationship between occupational composition and proximity to economic mass. This finding is consistent also with the theory we outlined which offers predictions about productivity but – in its simplest form – not about the spatial structure of occupations.

Third, the magnitude of the productivity effects we find suggest that doubling the ‘economic mass’ to which an area has access raises its productivity by 3.5%. This seems modest, but its impact is important as there are large variations in areas’ access to economic mass. Moreover, a closer examination of the contribution of economic mass to explaining spatial variations in productivity suggests that economic mass is particularly influential in areas in the lower half of the productivity distribution. More than two thirds of the productivity variation between these areas is due to variation in their access to economic mass. We undertake some counterfactual experiments to assess the likely gains from transport improvements. For example, a 10% reduction in average journey times throughout the Great Britain would raise productivity by 1.12%, and nearly twice this amount for areas whose access to large population mass is increased the most.

Appendix 1: Decompositions:

w_i^k and l_i^k are wage and employment in occupation *k* and area *i*

Total employment in area *i*, $L_i = \Sigma_k l_i^k$.

Share of occupation *k* in employment in area *i*, $\lambda_i^k = l_i^k / L_i$.

Proportion of entire population in occupation *k*, $\overline{\lambda}^k = \Sigma_i l_i^k / \Sigma_i L_i$.

Average wage in occupation *k*, $\overline{w}^k = \Sigma_i l_i^k w_i^k / \Sigma_i l_i^k$, so $\overline{w}^k \overline{\lambda}^k = \Sigma_i l_i^k w_i^k / \Sigma_i L_i$

Average wage in area *i* $e_i = \Sigma_k l_i^k w_i^k / \Sigma_k l_i^k = \Sigma_k \lambda_i^k w_i^k$

Decomposition, for each area *i:*

$e_i = \Sigma_k w_i^k \lambda_i^k = \Sigma_k w_i^k \overline{\lambda}^k + \Sigma_k \overline{w}^k \lambda_i^k + \Sigma_k (w_i^k - \overline{w}^k)(\lambda_i^k - \overline{\lambda}^k) - \Sigma_k \overline{w}^k \overline{\lambda}^k$

or, $e_i = q_i + c_i + r_i$.

Appendix 2: Data appendix:

All data is at the level of the 126 NUTS 3 areas of Great Britain. To achieve a consistent data set the following NUTS 3 areas are aggregated: East Cumbria and West Cumbria; South and West Derbyshire and East Derbyshire; North Nottinghamshire and South Nottinghamshire; Isle of Anglesey and Gwynedd; Caithness, Sutherland and Ross and Cromarty, Inverness and Nairn and Moray, Badenoch and Strathspey, Lochaber, Sky, Lochalsh and Argyll and the Islands. The Western Isles, Orkney Islands and Shetland Islands are excluded from the sample.

GVA per (employee) hour worked (g_i).

Estimates of workplace-based gross value added at basic prices from the ONS (2003). Total hours worked by employees computed from data on the numbers of full-time employees and of part-time employees and the average weekly hours worked by each group taken from the Annual Business Inquiry.

Average hourly earnings (e_i).

Average hourly earnings of all full-time employees whose pay was not affected by absence at the NUTS 3 level from the New Earnings Surveys.

Composition index ($c_i = \Sigma_k \overline{w}^k \lambda_i^k$).

Weighted sum of the shares of each occupational major group in employment in area *i*, with weights equal to the GB average earnings of the occupational major group. Data on occupational shares in employment from the Labour Force Survey. Data on the GB average hourly earnings by major occupational group from the New Earnings Survey.

Productivity index ($q_i = \Sigma_k w_i^k \overline{\lambda}^k$)

Weighted sum of the average earnings of each occupational group in area *i*, with weights equal to the share of the occupational group in total GB employment. Data on average hourly earnings of full-time employees at the level of the occupational major group and at the two digit occupational level from the New Earnings Survey. Data on the share of 2-digit occupations in total GB employment from the Labour Force Survey 2001.

Population variables.

Mid-year estimates of the total number of persons of working age (i.e. aged 16 to 65 years) from ONS.

Education variables.

Proportion of economically active population at each of the following qualification levels:

level 4 or higher – first and higher degree; nursing and teaching qualification;

level 3 – A-level; GNVQ Higher level, Advanced Certificate of Vocational Education;

level 2 – GCSE qualifications at grade or higher, GNVQ Intermediate level;

level 1 – GCSE qualifications below grade C, GNVQ Foundation level;

trade apprenticeships; no formal qualifications.

Data from the Labour Force Surveys, averaged for years 1999 to 2001.

Travel times

Driving times between the population centres of NUTS 3 areas, estimated using Microsoft Autoroute 2002.

Appendix 3: Measurement of economic mass.

Points in continuous geographical space are labelled *z*, and are also broken into a finite number of administrative (NUTS3) areas labelled by subscript *i* and containing set of points

Z_i. The 'central point' in area i will be labelled z_i^*. Economic variables are distributed over the space so, for example, $p(z)$ is the value of economic variable p at point z. These values are typically reported at the unit level, so take value $p_i = \int_{z \in Z_i} p(z)dz$.

We are concerned with the distribution of economic activity around the centre of each area. The time (or similar measure of distance) from the centre of i to point z is $t_i(z)$. We generally seek to find a measure of the type

$$A_i = \int_z p(z)a(t_i(z))dz$$

where the function a gives the spatial weights, generally unknown but assumed to be a decreasing function of time. We will refer to A_i as the 'access' of area i to variable p. Given that p is only observed for each administrative area, how should we proceed? One possibility (point mass) is to assume that p is concentrated at the centre of each unit. Thus,

$$A_i = \Sigma_j p_j^* a(t_i(z_j^*))$$

This will be our first measure. To understand the way we use it, consider figure 3. The horizontal plane is time from location i, and the lines are iso-time from its central point, z_i^*. The point mass approach assigns to each time band the total p-values of all areas whose centre is in the band, eg the 60-90 minute band contains $p_j + p_k$.

A second possibility (smoothed mass) is that p-values are spread around the centre points, z_j^*, of each unit. We assume these areas are squares centred on these points, as illustrated in figure 2, and activity p is uniformly distributed in the square. The size of the square is constructed such that it has the same physical area as the actual NUTS3 subregion, and this is converted into the time units of figure 2 at driving speed of 60 kph. The total p-value within a time band from area i is the sum of the areas of these squares within the band. The figure makes it clear why moving from point mass to dispersed mass is potentially important. It smoothes out potential discontinuities that arise as the whole of a point mass is assigned to one time-band or another.

Table A1				
	Ln(GVA per (employee) hour worked, g_i)	Ln(Average hourly earnings, e_i)	Ln(Occupational composition index, c_i)	Ln(Productivity index, q_i)
Population* of working age within travel time of				
Up to 30 mins	0.0059 (0.24)	0.0714 (2.78)	0.0039 (0.47)	0.0506 (2.76)
30-60 mins	0.0198 (1.95)	0.0207 (2.74)	-0.0030 (-1.04)	0.0206 (3.44)
60-90 mins	0.0104 (1.76)	0.0096 (1.95)	0.0032 (1.63)	0.0056 (1.34)
90-120 mins	-0.0005 (-0.11)	0.0040 (1.04)	-0.0000 (-0.00)	0.0039 (1.19)
Ln(% with degree level qualifications	0.1139 (2.29)	0.1857 (5.50)	0.1379 (9.79)	0.0697 (2.74)
Ln(% with no formal educ.qualifications	-0.1378 (-2.10)	-0.1729 (-3.48)	-0.0466 (-2.29)	-0.0995 (-2.81)
Regional dummies	Yes	Yes	Yes	Yes
R-squared	0.5812	0.8599	0.8488	0.7920
Normality	1.8189 (0.40)	1.9418 (0.38)	1.0385 (0.59)	0.9373 (0.63)
LM (spatial error)	3.0053 (0.08)	1.1636 (0.28)	0.7467 (0.39)	1.4544 (0.23)
LM (spatial lag)	3.5739 (0.06)	2.9120 (0.08)	0.0002 (0.99)	3.1984 (0.07)
Population* of working age within travel time of				
Up to 40 mins	0.0044 (0.23)	0.0489 (2.74)	-0.0020 (-0.40)	0.0393 (3.36)
40-60 mins	0.0271 (2.02)	0.0186 (1.80)	-0.0015 (-0.41)	0.0179 (2.35)
60-80 mins	0.0102 (0.79)	0.0111 (1.06)	0.0021 (0.61)	0.0080 (0.91)
80-100 mins	0.0056 (0.43)	0.0061 (0.52)	0.0035 (0.97)	0.0022 (0.22)
100-120 mins	-0.0009 (-0.11)	0.0028 (0.40)	-0.0014 (-0.67)	0.0044 (0.71)
Ln (% with degree level qualifications	0.1149 (2.42)	0.1944 (5.81)	0.1397 (9.16)	0.0746 (2.91)
Ln(%with no formal educ.qualifications	-0.1354 (-1.97)	-0.1728 (-3.36)	-0.0464 (-2.09)	-0.0996 (-2.74)
Regional dummies	Yes	Yes	Yes	Yes
R-squared	0.5837	0.8570	0.8496	0.7904
Normality	1.4478 (0.48)	1.4347 (0.49)	0.5565 (0.76)	0.7408 (0.69)
LM (spatial error)	3.1594 (0.08)	0.9874 (0.32)	1.3188 (0.25)	1.2826 (0.26)
LM (spatial lag)	3.6957 (0.05)	2.9022 (0.09)	0.0001 (0.99)	3.1966 (0.07)

Table A2				
$\ln y_i = \alpha \ln\left[\sum_b p_{bi}\left[\frac{1}{60}\left(30-\theta(t_b-30)+abs(30-\theta(t_b-30))\right)\right]\right]+\sum_j \beta_j x_{ji}+\varepsilon_i$				
	GVA per worker hour, g_i	Average hourly earnings, e_i	Index of occupational composition, c_i	Productivity index, q_i
α	0.0265 (2.77)	0.0415 (5.96)	-0.0020 (-0.67)	0.0359 (6.34)
θ	0.5000 (1.36)	0.5763 (4.93)	0.9998 (0.23)	0.6351 (3.55)
Ln(% of econ active with degree level qualifications)	0.1191 (2.29)	0.2138 (5.65)	0.1399 (10.020)	0.0910 (3.04)
Ln(% of econ active with no formal educ qualification)	-0.1287 (-1.65)	-0.1561 (-2.76)	-0.0517 (-2.50)	-0.0829 (-2.24)
Regional dummies	Yes	Yes	Yes	Yes
R-squared	0.5520	0.8265	0.8449	0.7519

Table A3				
$\ln y_i = \beta_0 + \alpha \ln\left[\sum_b p_{bi}\exp(-\theta(t_b-30)/30)\right]+\sum_j \beta_j x_{ji}+\varepsilon_i$				
	GVA per worker hour, g_i	Average hourly earnings, e_i	Index of occupational composition, c_i	Productivity index, q_i
α	0.0251 (1.49)	0.0410 (3.83)	-0.0023 (-0.65)	0.0331 (4.01)
θ	0.9851 (0.85)	1.6369 (2.38)	2.7900 (0.34)	1.8065 (2.46)
Ln(% of econ active with degree level qualifications)	0.1177 (2.23)	0.2130 (5.63)	0.1410 (10.08)	0.0909 (3.04)
Ln(% of econ active with no formal educ qualifications)	-0.1266 (-1.60)	-0.1475 (-2.60)	-0.0491 (-2.35)	-0.0736 (-1.64)
Regional Dummies	Yes	Yes	Yes	Yes
Travel time to central London	-0.0057 (-0.38)	-0.0098 (-0.98)	-0.0013 (-0.40)	-0.0112 (-1.04)
R-squared	0.5502	0.8291	0.8448	0.7564

p_{bi} *: population of working age (ths) within travel time band* (t_b - 10, t_b) *of NUTS3 area i;*
for ($30 \le t_b \le 120$) based on smoothed population estimates

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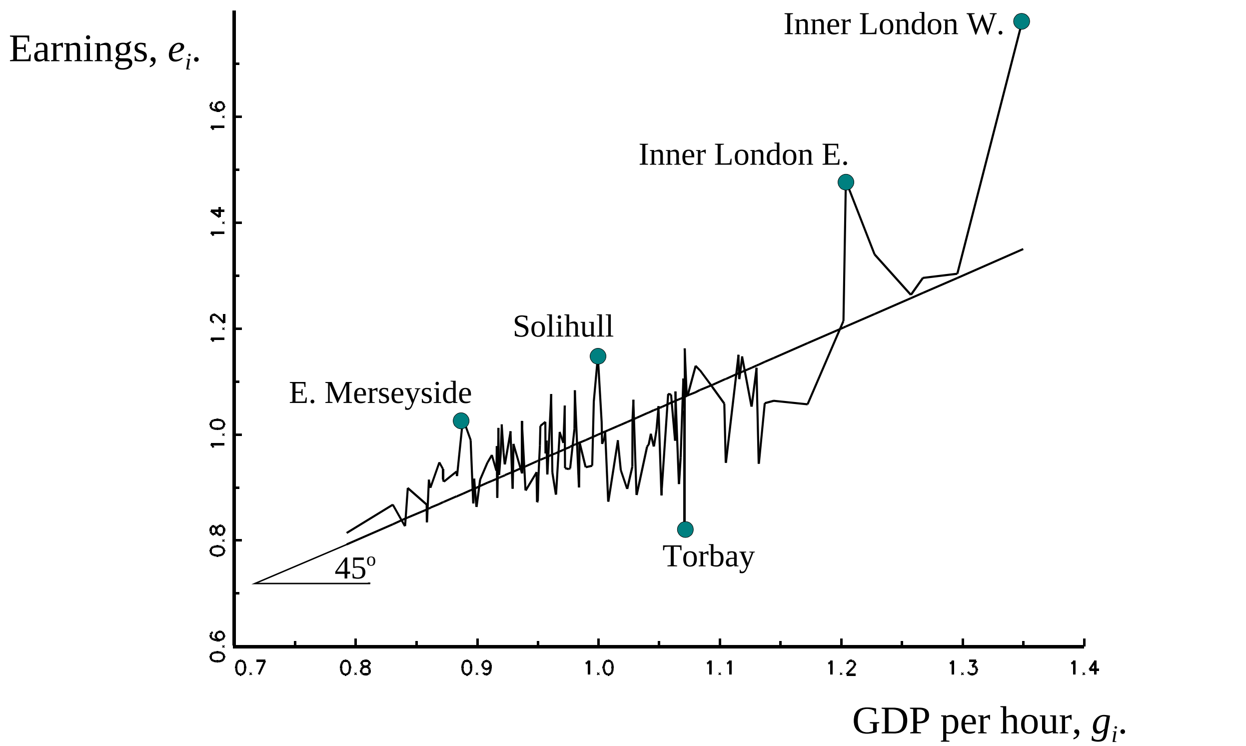

Figure 1a: Earnings and GDP per hour.

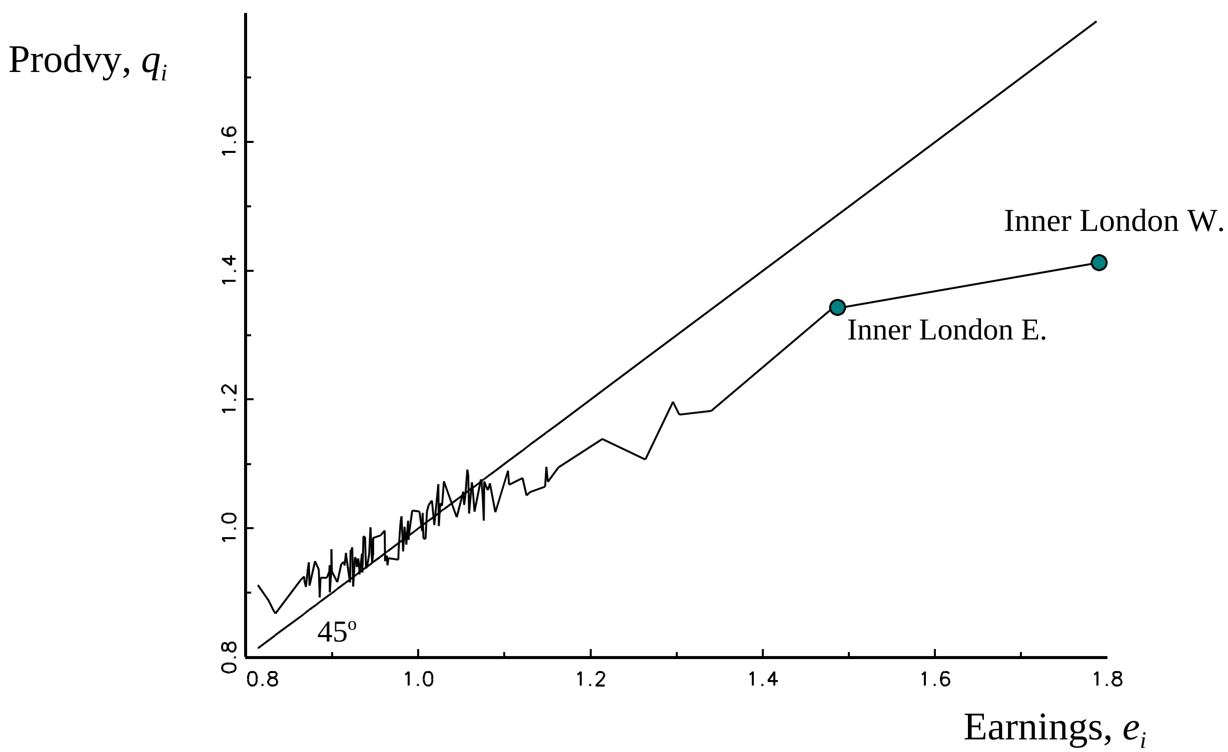

Figure 1b: Productivity and earnings.

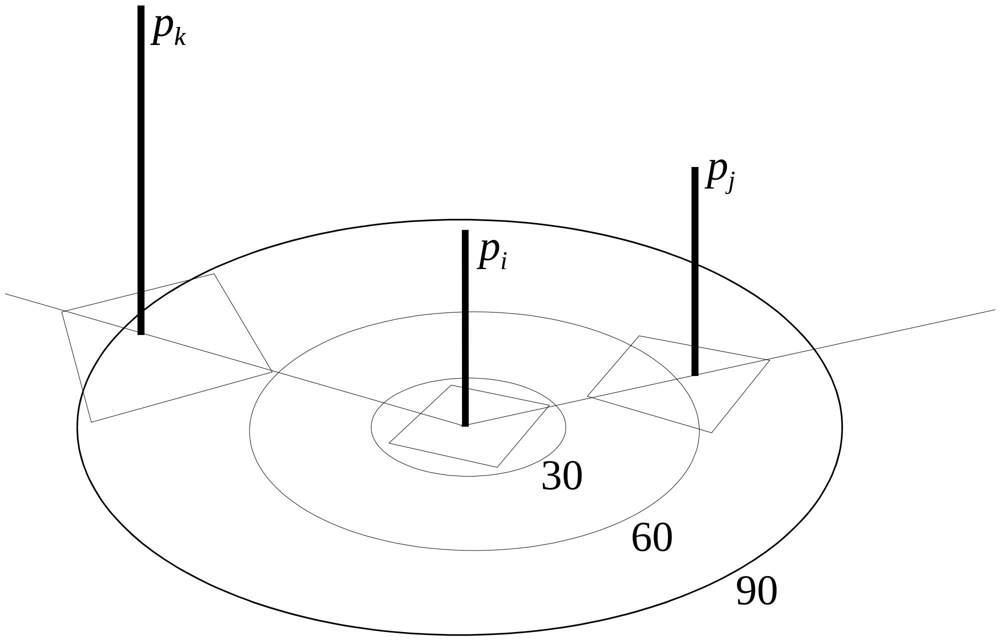

Figure 2: Time bands around area i.