Department of Economics
Discussion Paper Series

Tradability, Productivity, and Regional Disparities: theory and UK evidence.

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Number 996
January, 2023

Department of Economics
Manor Road Building, Manor Road
Oxford, OX1 3UQ

ISSN 1471-0498

06/01/23

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Abstract

Spatial variation in the productivity of different sectors is a determinant of sectoral location, with consequences for wages, rents and the cost-of-living in each area. This paper develops an analytical framework which shows how productivity advantage in a highly tradable sector translates into higher nominal wages, rents, and cost of living in an area; in contrast, high physical productivity in non-tradables may result in lower wages, rents and revenue productivity. The theory's prediction that an area's bias towards highly tradable activities is positively correlated with its earnings is confirmed by empirical analysis of earnings data for the ITL3 areas of GB. As suggested by the theory, two factors drive this effect. Approximately one-third is a direct result of sectoral composition – on average across GB, tradable sectors pay higher wages. The remaining two-thirds is an equilibrium effect, arising as a productivity advantage in tradables translates into higher local employment and factor prices. While our primary analysis is on recent data, we show that our approach also captures the impact of the structural change that occurred in Britain during the 1970s and 1980s on regional earnings disparities.

Keywords: Regional economics, lagging regions, tradability, productivity, disparities,
JEL classification: R11, R12, E62, F60

Acknowledgements: Research supported by The Productivity Institute, University of Manchester, under UK-ESRC grant number ES/V002740/1. Thanks to Tor Grondahl for excellent research assistance and participants in seminars at the Productivity Institute (Manchester), Centre for Economic Performance (LSE) and Monash University.

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1. Introduction.

Spatial differences in incomes and productivity are a persistent feature of many economies. In high income countries the emergence of pronounced spatial inequalities is often linked to technology and trade shocks. These shocks were frequently concentrated in particular regions, often eliminating sectors in which these places had traditional comparative advantage. While overall employment levels may have recovered, the shocks led to long-run changes in sectoral structure, and affected places have frequently failed to find new sources of comparative advantage. Commentators attribute the emergence of pronounced regional disparities in the UK to the de-industrialisation of the 1970s and the decline of traditional manufacturing sectors in the North and Midlands.

These issues motivate our central questions. To what extent does the sectoral structure of employment in a place shape its income, productivity, and overall economic performance? Is it the case that the persistent regional disparities in the UK - many of them emerging during periods of structural change - are linked to differences in the ensuing sectoral mix of activities? Our central argument is that the composition of employment – by sector as well as by more fine-grained economic activity – matters greatly for spatial variation in prices and earnings.[1] There are two mechanisms. The first is a direct 'sector-differential effect'. Different sectors pay different average wages, due to variations in skill and other employee attributes. This effect can be quantified by calculating what average earnings in each place would be if all sectors paid their national average wage levels at every location. Such exercises – including one reported in this paper – typically find that only a small part of spatial earnings variation is accounted for by this direct sector-differential component.[2]

The second mechanism through which sectoral composition matters is an equilibrium or indirect effect. Any place-sector productivity differences that shape the sectoral composition of employment in a place have general equilibrium implications for local employment, prices, and wages, and these implications vary greatly according to the tradability of the sector's output. A productivity advantage in a readily tradable good leads to higher output and employment, and hence also to higher prices of non-tradable goods and services, including housing, and a higher local cost-of-living. In contrast, non-tradable sectors face a less elastic demand curve and so a productivity advantage here, rather than expanding output and employment, may simply reduce the price of output and hence lower the local cost-of-living. Thus, high productivity in tradable sectors tends to raise nominal wages in a place – across all sectors as the cost-of-living is raised – while a productivity advantage in non-tradable sectors

[1] We shall refer to sectors throughout, since the main empirical work is based on fine sectoral data. We draw in some occupational data in section 6.2 of the paper.

[2] A number of commentators take the view that industry mix is relatively unimportant, based on decomposition studies of this direct effect, e.g. Zymek and Jones (2020), Oguz (2019), ONS (2018).

may result in lower cost-of-living and nominal wages. We term these equilibrium wage differences, those over and above the direct sector differential effect, the area differential.

We develop this argument theoretically and empirically. The core of the empirical work is based on 163 ITL3 regions of Great Britain and 259 SIC3 sectors for the years 2015 to 2019. Using the place-sector distribution of employment and UK average earnings by sector, we decompose average earnings in each place into the sector differential and the area differential, establishing that the sector differential contributes relatively little to the spatial variation of average earnings.

To make the link with tradability, we proxy the tradability of a sector by the extent to which employment in the sector is spatially dispersed (ubiquitous), or concentrated in a few places, a property that we refer to as sectoral 'sparsity'. A necessary condition for sectoral sparsity is tradability; if, for example, there is spatial variation in a sector's productivity then concentration in highly productive places can only happen if the sector is also relatively highly tradable. A sufficient condition for a sector to be 'ubiquitous' is non-tradability; non-tradables are everywhere, meeting local demand, and taking a similar share of employment in all places. An employment weighted sum of sectoral sparsity provides a measure of the extent to which employment in a place is skewed towards tradable sectors; a measure which we refer to as the 'sparsity bias' of the place.

Our central empirical finding is that sparsity bias can account for nearly 75% of the spatial variation in average earnings, operating through both the sector differential and area differential components. The former because tradable sectors tend to be more highly skilled with relatively high earnings, inducing a correlation between the sparsity bias of a place and local average earnings. The latter through the relationship between sparsity bias and the equilibrium effects of place-sector productivity differences on the cost-of-living and hence nominal wages. The latter effect is estimated to be quantitatively three to four times greater than the former. We also – using less spatially disaggregate data – establish that structural change in the UK between 1971 and 1993 reduced the sparsity bias of many places, and that this loss is significantly associated with a reduction in their local earnings relative to the national average.

The theoretical model we develop establishes that the effects described are a spatial equilibrium, and sets the empirical approach that we follow. It is based on the standard Rosen-Roback model (see e.g. Glaeser and Gottlieb 2009). There are many places and many sectors, and labour is highly mobile between places and sectors. Each place is endowed with a supply curve of an immobile factor – land or housing – such that rents and the cost-of-living increase with the level of economic activity in the place. Sectors vary with respect to their tradability, which we take to be a continuum ranging from purely local, to regional, national or international. Tradability shapes the price elasticity of demand for output, and hence the response to spatial variations in production costs. A perfectly tradable good or service has infinite elasticity of demand, so a productivity advantage expands output until the effect is shifted to an increase in the cost of living and price of local inputs. A productivity advantage in a sector that is only traded locally leads to a lower output price, with quite different implications for equilibrium prices, wages, and observed local economic performance. Sectors may also vary in skill intensity and so pay different average wages; this creating the sector-differential effect described above.

In a base equilibrium of this model, all places are identical – they all have the same sectoral structure, prices, and incomes. Heterogeneity across places is created by introducing Ricardian (place-sector specific) productivity variation, to which output, employment, and prices respond according to the elasticity of demand for output and the elasticity of supply of inputs.[3] This induces a distribution of sectors across places, and an associated distribution of employment, wages, rents, and the cost-of-living. In particular, nominal wages are higher in places with a larger share of the labour force in more highly-tradable sectors, or in more skill intensive sectors. The former is the equilibrium response that creates area-differentials, and the latter is the sector-differential effect. Our empirical work is based closely on these equilibrium relationships generated in the model.

This approach focuses on the production structure and its implications for the effects of productivity differences on local living costs and nominal wages. This is in contrast to work using individual level data to examine the characteristics of workers in the labour force; work which finds that a high proportion of regional variation in earnings can be attributed to these characteristics (Overman and Xu 2022 for the UK and Combes et al. 2008 for France). The two approaches are consistent, and complementary in so far as one looks at the demand side of employment, the other at the supply side of the labour force. The equilibrium lies on both supply and demand curves, and the present paper focuses on features of labour demand. The paper establishes that sectoral composition – in particular the sparsity bias it induces -- is strongly correlated with average earnings, but is agnostic (and lacking data) on the many and complex relationships between sectors and the characteristics of the workers they employ.

The work draws on several existing literatures. The tradable/ non-tradable distinction is central to an old literature on base-multiplier models (Pred 1966) and is developed in Moretti's (2010) paper on local multipliers. The distinction between direct and indirect effects is made in Moretti and Hornbeck's (2021) study of the distributional implications of manufacturing productivity variations across US cities. Place and sector specific productivity shocks are studied in Caliendo et al. (2018) who use US inter-state trade data and input-output data to analyse the transmission of productivity shocks in a calibrated model. From the UK perspective, a complexity framework has been used to explore the relationship between the 'ubiquity' of sectors and regional wages by Coyle and Mealy (2021). Decompositions of

[3] We do not offer a theory of place-sector productivity – there are simply Ricardian productivity differences. Our theoretical contribution is to show how any such differences interact with sector characteristics, in particular tradability/sparsity, to shape the spatial distribution of wages and hence regional disparities. For further discussion see section 3.

regional wage differences by sector and occupation have been undertaken by Rice et al. (2004) and Oguz (2019), these leading to the suggestion that direct sector differential effects are relatively unimportant.

The following two sections of the paper set out and analyse the theory model, and the core empirical work is presented in section four. Using data for 2015 to 2019, we construct measures of sector sparsity and of place sparsity bias, and show that the sparsity bias and the average earnings of a place are highly correlated, an area differential effect over and above the sector differential component. Section five examines data from the period 1971 to 1993 to study the effect of the deindustrialisation and structural change experienced in the UK during that time.[4] Data for this period is less finely spatially disaggregated, but we show that the positive relationship between sparsity bias and the average earnings of a place holds, that structural change reduced the sparsity bias of many places, and that loss of sparsity bias is significantly associated with a reduction in an area's average earnings relative to the national average. Section six provides some further checks on the robustness of our findings and outlines some questions/issues for future research. Section seven concludes, and outlines policy implications of our findings.

2. Theory.

A country contains many distinct places, indexed i = 1….N, and many activities or sectors indexed s = 1….S. Places have identical fundamentals, each being endowed with the same supply function of land which can be used for housing or commercial use, the rental rate of which is denoted r_i. Sectors differ in the tradability of their output and the wage they need to pay to attract workers. The total quantity of labour in the economy is L, and this is endogenously distributed across places and sectors, with place-sector wage w_{is} and employment L_{is}, $\sum_i \sum_s L_{is} = L$. For clarity of exposition we set up the model with a single labour type, adding skill differences later in the paper.

Production and demand: Each sector produces output using labour and land under constant returns to scale. We allow productivity levels to exhibit exogenous Ricardian differences, i.e. to take place-sector specific values denoted a_{is}. We abstract from other sources of productivity variation, such as agglomeration economies, discussing this further in Section 3. The producer price of a sector s good produced in place i is then

$$p_{is} = c_s(w_{is}, r_i)/a_{is} = w_{is}^{\gamma} r_i^{1-\gamma}/a_{is}, \quad i = 1 \dots N, \; s = 1 \dots S, \qquad (1)$$

where $c_s(w_{is}, r_i)/a_{is}$ is the unit cost function and the second equation assumes Cobb-Douglas technology with labour share γ in all sectors.

[4] For analysis of these shocks, and their persistent effects, see Rice and Venables (2021).

Output can be shipped between places, and the iceberg trade cost factor for sector s good shipped from i to j is t_{ijs}, so the consumer prices of a unit of sector s output produced in place i and sold in j is $p_{is}t_{ijs}$. In what follows we assume that there are no trade costs for shipping within a place, so $t_{iis} = 1$ for all sectors, and costs between all pairs of places are the same, $t_{ijs} = t_s \geq 1$ for $i \neq j$, though vary across sectors s. The rest of the world is place 0, and shipping to it incurs the same trade cost as shipping between places within the country.[5]

Households in each place consume goods from each sector, these potentially supplied from all places. There is place specific product differentiation (an Armington approach), so the price index of sector s goods sold in place j is

$$P_{js} = \left[\sum_{i=1}^{N}\left(p_{is}\, t_{ijs}\right)^{1-\sigma}\right]^{1/(1-\sigma)} = \left[\left(p_{js}\right)^{1-\sigma} + \sum_{i\neq j}^{N} \tau_s p_{is}{}^{1-\sigma}\right]^{1/(1-\sigma)}. \qquad (2)$$

Parameter $\sigma > 1$ is the intra-sector elasticity of substitution, assumed the same in all sectors. We think of this as being quite high as it is capturing differentiation within a sector between output produced at different places in the country. In most of what follows trade costs enter in the form ${t_s}^{1-\sigma}$, in which case we use notation $\tau_s \equiv {t_s}^{1-\sigma}$. We refer to τ_s as the tradability of sector s, so perfect tradability is $\tau_s = 1$ and perfect non-tradability $\tau_s = 0, (t_s = \infty)$.

Demand in each place j in the economy is derived from households' indirect utility functions which, for a household in place j employed in sector s, are denoted u_{js} and take the form

$$u_{js} = y_{js}/e\left(r_j,\, P_{j1} \ldots P_{js}, p_0\right) = y_{js}\left[r_j^{\alpha} p_0^{\beta_0} \prod_s P_{js}^{\beta_s}\right]^{-1}. \qquad (3)$$

In this expression household income is y_{js} and $e\left(r_j,\, P_{j1} \ldots P_{js}, p_0\right)$ is the unit expenditure function, capturing the cost of living in each place. This depends on the price of land (or housing), r_j, sectoral price indices, P_{js}, and the price of imports from the rest of the world, p_0. The second equation assumes these upper-level preferences are Cobb-Douglas, with $\alpha + \beta_0 + \sum_s \beta_s = 1$.

Total employment in place j is $L_j = \sum_s L_{js}$, and hence total income and household expenditure in place j is $M_j = \sum_s y_{js}L_{js}$. Demand in place j for sector s output produced in place i is therefore $x_{ijs} = M_j\beta_s p_{is}^{-\sigma}\tau_{ijs}/P_{js}^{1-\sigma}$.[6]

External trade and product market clearing: Imports from the rest of the world are treated as a distinct sector or set of sectors, with fixed and exogenous price p_0 and demand share β_0, as

[5] This is a conservative assumption that slightly weakens the strength of relationships examined in the paper, and that is easily relaxed.

[6] This is the standard Marshallian (uncompensated) demand function from two level preferences (Cobb-Douglas and CES), and can be derived by Roy's identity on the indirect utility function (3).

in equation (3). The price p_0 is the same in all domestic places and will be used as numeraire. There is iso-elastic export demand for the output of all sectors and places, taking the form $x_{i0s} = (qp_{is})^{-\sigma}\tau_s$, where q is the real exchange rate, and σ is the price elasticity of foreign demand set equal to that for domestic demand.

This treatment of the rest of world means that the economy is 'semi-small'; i.e. a price-taker with respect to imports from the rest of the world, while exports face a downwards sloping – although possibly highly elastic – rest of world demand curve. The total value of exports is set by the economy's budget constraint and is therefore equal to the value of imports as determined by domestic demand, $\beta_0 \sum_i M_i$. The real exchange rate, *q*, equates the value of imports with the value of exports,

$$\beta_0 \textstyle\sum_i M_i = \sum_s \sum_i \tau_s (qp_{is})^{1-\sigma}. \qquad (4)$$

Domestic and export demand together give total output of sector *s* in place *i*

$$x_{is} = p_{is}^{-\sigma} \beta_s \textstyle\sum_j M_j \tau_{ijs} / P_{js}^{1-\sigma} + (qp_{is})^{-\sigma}\tau_s. \qquad (5)$$

Given prices, the level of demand, and Cobb-Douglas production with labour share γ, the levels of employment by place and sector are

$$L_{is} = \gamma p_{is} x_{is} / w_{is}, \quad \text{and} \quad L_i = \textstyle\sum_s L_{is}. \qquad (6)$$

Land and urban structure: Each place in the economy has a supply function of land which depends on its price or rental. Denoting the quantity of land occupied in place *i* as K_i and the rental rate r_i, the supply function takes the form $K_i = K(r_i) = {r_i}^{\eta}$, where $\eta \geq 0$ is the supply elasticity. We do not model construction – the transformation of land into structures for housing or commercial use – and refer to K_i simply as 'land'.[7]

The value of demand for land is fraction α of household income plus fraction $(1-\gamma)$ of the value of production, so equality of the value of supply and demand in each place implies $r_i K(r_i) = [\alpha M_i + (1-\gamma) \sum_s p_{is} x_{is}]$. With the iso-elastic land supply function the equilibrium price of land is therefore

$$r_i = [\alpha M_i + (1-\gamma) \textstyle\sum_s p_{is} x_{is}]^{1/(1+\eta)}. \qquad (7)$$

Thus, places that are economically large – with large expenditure and output – will have relatively high land rent and large area, the relationship between the two depending on the elasticity of land supply with respect to rent, η. We assume that the total rent earned in the

[7] This is a simplified version of the 'standard urban model' as in Duranton and Puga (2015).

economy is distributed in an equal lump-sum manner to each household in the economy so the income of each household in place i is

$$y_{is} = w_{is} + \sum_i {r_i}^{1+\eta} /L. \tag{8}$$

Equilibrium: The final element in the model is the distribution of the labour force between places and sectors. This is a utility maximising choice determined by a discrete choice function,

$$\pi_{is} = F(u_{is})/\sum_i \sum_s F(u_{is}), \qquad u_{is} = y_{is}/e(r_i,\ P_{i1} \dots P_{iS}, p_0), \tag{9}$$

where $F(.)$ is an increasing function and π_{is} is the probability that a worker lives and works in place i sector s.[8] The number of workers choosing to live in i and work in sector s is therefore $\pi_{is}L$, and (8) and (9) indicate that this depends on wage offer w_{is} and a place specific cost-of-living element $e(r_i,\ P_{i1} \dots P_{iS}, p_0)$. With the sector and place distribution of workers given by $\pi_{is}L$, full employment is

$$L_{is} = \pi_{is}L, \tag{10}$$

where labour demand, L_{is}, is given by equation (6). This description of the model assumes a single labour type; extension to multiple skill types is straightforward and outlined in section 3.4.

3. Analysis.

The model contains sectoral heterogeneity arising through different degrees of sector tradability, τ_s. It is convenient to think of a base equilibrium in which there is no exogenous spatial heterogeneity (a_{is} same for all i) and hence all places are identical – they have the same sectoral structures and hence the same average wages. Heterogeneity across places is then created by introducing Ricardian (place-sector specific) productivity variation, a_{is}, to which output, employment, and prices respond. This response depends critically on the fact that the price elasticity of demand is increasing with the tradability of sectoral output. In the next sub-section, we establish this relationship and provide a numerical example to demonstrate how this shapes outcomes. We then use a combination of local comparative static analysis and numerical simulation of the full model to establishes our results about sectoral structure and

[8] The function $F(.)$ can be given micro-foundations by assuming that each household draws an idiosyncratic preference parameter, multiplicative with u_{is}, from some distribution. If this is a Frechet distribution then $F(u_{is}) = u_{is}^{\theta}$, where $\theta > 1$ is the shape parameter of the distribution, measuring heterogeneity in population preferences. We assume that household choice is simultaneous across places and sectors, not separating the choice out into two stages. The Frechet approach draws on Eaton and Kortum (2002), with spatial application developed by Ahlfeldt et al. (2015) and sectoral labour choice developed by Lagakos and Waugh (2013) and Galle et al. (2022).

wage differences, and also to introduce and demonstrate the concepts and approach used in the empirical work.

3.1: Tradability, demand elasticity, and productivity shocks.

The key relationships in the model are the link between the tradability of a product and its price elasticity of demand, and the way that these variables interact with productivity to shape output and employment. With Cobb-Douglas preferences between sectors and CES preferences between sources of supply, the (uncompensated) price elasticity of demand for a product in its home market is $\epsilon_s = \sigma + (1-\sigma)\mu_s$ where μ_s is market share. At the base equilibrium this market share is $\mu_s = 1/\{1+(N-1)\tau_s\}$, since supply from each of the N - 1 other places ('imports') face trade cost factor t_s, and tradability indicator $\tau_s = {t_s}^{1-\sigma}$. The overall elasticity, E_s, is the sales share-weighted average of these, this giving (see Appendix 1)

$$E_s = \sigma + (1-\sigma)\mu_s\{\mu_s + (1-\mu_s)\tau_s\}, \quad (11)$$

with $\mu_s = 1/\{1+(N-1)\tau_s\}$.

These equations give the relationship between a sector's tradability and its price of elasticity of demand, and the limiting cases are:

Zero tradability: $\tau_s = 0$: $\mu_s = E_s = 1$.

Perfect tradability: $\tau_s = 1$: $\mu_s = 1/N$, $E_s = \{\sigma + (1-\sigma)/N\}$.

With zero tradability each place is supplied only with the single locally produced variety, so demand comes from the upper-level Cobb-Douglas preferences giving a price elasticity of unity.[9] With perfect tradability, the demand elasticity tends to σ as N becomes large. Between these extremes the elasticity is monotonically increasing with τ_s (Appendix 1).

The output and employment impacts of sectoral productivity differences depend on the elasticity E_s. For example, if wages, rental rates, and income are held constant and uniform across places, then employment in place i sector s is $L_{is} = (a_{is})^{(E_s-1)}C_s$, (from equations (1) and (6), where C_s is a constant).[10] Thus, if productivity in a particular sector has a distribution across places (e.g. each place draws the sector's a_{is} from the distribution), then the elasticity of demand transforms this into a distribution of employment. With zero tradability ($E_s = 1$) the distribution collapses to a point (the same everywhere), while for $E_s > 1$ both the variance and (right) skewness of the distribution of employment are positive and increasing in E_s. We use these observations in constructing our empirical proxy for tradability in later sections.

These effects are illustrated in Table 1, which reports the equilibrium outcomes of the model in an example with just nine sectors (S = 9) and a large number of places (N = 100). The sectors

[9] More general top-level preferences would allow other values of this elasticity.

[10] Price is the inverse of productivity, the quantity demanded is proportionate to $(a_{is})^{E_s}$, and labour input is quantity divided by productivity.

are ranked by trade costs, from $t_1 = 1$ to $t_9 = 3$. The places are identical, except that each sector has a 50% productivity advantage in just one of the places, and we label these places according to the sector in which they have advantage, so $a_{is} = 1.5,\ i = s = 1 \dots 9$, all other $a_{is} = 1, i \neq s$. Table 1 reports results for just three of the sectors (the most, intermediate, and least tradable) and for the places which have a productivity advantage in these sectors. Elasticities of substitution and land supply are set at $\sigma = 10$ and $\eta = 1$, and there is perfect labour mobility, equalising utility in all places and sectors.[11] There is no external trade, $\beta_0 = 0$, and labour is the only input to production, $\gamma = 1$, so the wage is equal to value added per worker. Price elasticities of demand and home market shares for the sectors come from equations (11).

The table expresses endogenous variables relative to their values in the rest of the economy.[12] Place 1 has a productivity advantage in the most tradable sector and has nominal wages and value added per worker of 17% above levels in the rest of the economy, together with higher rents and larger total employment than any other place. Place 9 has productivity advantage in sector 9, the least tradable, and has a wage lower than elsewhere in the country. With no 'export' response, high productivity in this sector reduces the price of good 9; this reducing the cost-of-living and thereby attracting an increase in population, L_9, despite the lower nominal wage. Place 5 is intermediate, and has an intermediate increase in its wage, rental, and employment.

Table 1: Impacts of Ricardian productivity differences:

	Place *i* = 1	Place *i* = 5	Place *i* = 9
Sector characteristics:			
$s = 1$: $t_s = 1$, $\mu_s = 0.01$, $E_s = 9.9$	$a_{11} = 1.5$	$a_{51} = 1$	$a_{91} = 1$
$s = 5$: $t_s = 2$, $\mu_s = 0.84$, $E_s = 3.7$	$a_{15} = 1$	$a_{55} = 1.5$	$a_{95} = 1$
$s = 9$: $t_s = 3$, $\mu_s = 0.99$, $E_s = 1.1$	$a_{19} = 1$	$a_{59} = 1$	$a_{99} = 1.5$
Place outcomes:			
Wage, w_i	$w_1 = 1.17$	$w_5 = 1.06$	$w_9 = 0.98$
Rental, r_i	$r_1 = 1.40$	$r_5 = 1.27$	$r_9 = 1.12$
Total employment, $L_i = \sum_s L_{is}$	$L_1 = 1.74$	$L_5 = 1.55$	$L_9 = 1.26$
Coefficient of variation of sectoral employment, cv_i	$cv_1 = 0.39$	$cv_5 = 0.26$	$cv_9 = 0.03$

All variables relative to their values in the rest of the economy (places *i* > 9).

[11] See Appendix 2 for discussion of these parameters. Expenditure function parameters are $\alpha = \beta_s = 0.25$. Perfect labour mobility means that w_{is} takes common value w_i in all sectors in place *i*.

[12] Since there are 100 places in total, the rest of the economy is large, implying that values in the rest of the economy are very close to base equilibrium values (i.e. the equilibrium with all a_{is} = 1).

This example illustrates three key points. First, that the response of local nominal wages to a productivity differential depends on the sector in which the productivity advantage occurs. The response is positive if the productivity advantage is in highly tradable sectors, negative if it is in low-tradability sectors.

Second, there is place-sector specific divergence between physical productivity and revenue productivity. With labour the only input to production (in this example), revenue productivity equals the wage rate. Thus, in place 1, physical productivity in all sectors except the first is unity, equal to that in the rest of the economy, but revenue productivity is 17% higher, since each unit of labour employed in these sectors produces output of value w_1 =1.17. This heightened revenue productivity has nothing to do with the performance of these other sectors, but is an equilibrium effect; the performance of sector 1 ($a_{11} = 1.5$) has raised the cost of living in place 1, necessitating that higher nominal wages are paid in all sectors.[13]

Third, the sectoral structure of employment in each place is skewed towards the sector in which the place has a productivity advantage, and this skew is much larger if the productivity advantage is in a highly tradable sector. We summarise this by reporting the coefficient of variation of sectoral employment in each place (Table 1 bottom row); this coefficient is large in place 1, and close to zero in place 9 as the employment effect of advantage in non-tradables is limited by the size of the local market.

3.2: Comparative statics: equilibrium responses and wages.

Analytical results on the effects of Ricardian productivity differences can be found by comparative static techniques, looking at small productivity changes in just one place and letting wages, prices, rents and income in this place change, while holding these variables constant in all other places. We evaluate changes at the base equilibrium in which all places are identical and maintain the assumption of no external trade ($\beta_0 = 0$). We also assume that land is used only for residential purposes ($\gamma = 1$) and rent is spent in the place where it is earned; simplifying assumptions that are removed in the following simulation examples. With changes focused on a single place, (which we take to be place i = 1), we omit place-specific subscripts.

Ricardian productivity differences mean that productivity in place 1 sector s differs by amounts $\hat{a}_s,\ s = 1 \ldots S,$ from the base values that hold elsewhere.[14] The variations $\hat{a}_s$ induce changes in prices and wages in place 1 that satisfy $\hat{p}_s = \hat{w} - \hat{a}_s$ (see equation 1). The change in the

[13] In this example place 1 has average physical productivity 25% higher than the rest of the economy (in equilibrium 50% of its labour force is in sector 1 with $a_{11} = 1.5$, the remainder has $a_{1s} = 1$), and its revenue productivity is 17% higher. It is possible that the revenue productivity differential exceeds the average physical productivity difference, occurring if σ is very large (no terms of trade loss from expanding sector 1) and other sectors are largely non-tradable (do not shrink to accommodate sector 1).

[14] Proportionate deviations from the base equilibrium are denoted ^ .

value of output produced by sector s in place 1 is $\hat{p}_s + \hat{x}_s = (1 - E_s)\hat{p}_s + \mu_s \widehat{M}$, where the terms on the right-hand side are respectively a price and an income effect, the magnitude of the income effect depending on the share of the sector's output sold in the home market, μ_s. Appendix 1 works through the comparative statics, deriving expressions for the change in the cost of living, $\hat{e}$, and in the wage rate, $\widehat{w}$ in place 1. The cost of living change is

$$\hat{e} = \sum_s \beta_s(\widehat{w} - \hat{a}_s)\left[\mu_s + \frac{\alpha}{(1+\eta)}\frac{(1-E_s)}{\sum_s \beta_s(1-\mu_s)}\right]. \tag{12}$$

The first term, $\sum_s \beta_s(\widehat{w} - \hat{a}_s)\mu_s$, is the direct effect of changes in the prices of local output on the cost of living. The remaining term gives the effect through changes in rent. The mechanism is via the effects on output, employment and income, and its magnitude depends on the share of housing in expenditure, α, and the elasticity of land supply, η, the effect going to zero if this elasticity is infinite.

Real wages and worker utility change according to $\hat{u} = \widehat{w} - \hat{e}$, so using (12) the nominal wage change is

$$\widehat{w} = \frac{\hat{u} + \sum_s \beta_s \hat{a}_s \psi_s}{1 + \sum_s \beta_s \psi_s}, \quad with \quad \psi_s \equiv \frac{\alpha}{(1+\eta)}\frac{(E_s - 1)}{\sum_s \beta_s(1-\mu_s)} - \mu_s. \tag{13}$$

With high labour mobility the utility change is common to all places, and is smaller than changes in place 1 by factor $1/N$. For large N this can be taken to be zero, $\hat{u} = 0$. The denominator of (13) is positive.[15]

Equation (13) shows that the response of wages in place 1 to productivity shocks $\hat{a}_s$ depends on the sign of $\sum_s \hat{a}_s \psi_s$. This depends on the correlation between $\hat{a}_s$ and terms in ψ_s, in particular the demand elasticity E_s, with the sign positive if there are relatively large productivity increases in sectors with high elasticity. If the productivity advantage occurs only in a single perfectly non-tradable sector, $\tau_s = 0$ so $E_s = \mu_s = 1$, then $\psi_s = -1$, implying that the affected place has lower wage, as we saw in the example in section 3.1. If it occurs only in a perfectly tradable sector, $\tau_s = 1$, then, with large N, $\psi_s = \alpha(\sigma - 1)/\{(1+\eta)\sum_s \beta_s(1 - \mu_s)\} \geq 0$, so the wage increase is strictly positive as long as the elasticity of land supply is finite.

The economic reasoning is that described earlier. In non-tradable sectors, a productivity advantage translates into a lower price for the good, and hence lower cost-of-living and lower nominal wage. In sufficiently tradable sectors, the demand curve is elastic enough for the price fall to be small and for employment in the place to increase. Rents are bid up, raising the cost-

[15] The denominator $1 + \sum_s \beta_s \psi_s$ is positive if $E_s \geq 1$, since $1 > \sum_s \beta_s \mu_s$.

of-living and hence resulting in a higher nominal wage. The magnitude of this effect is greater, the lower is elasticity of land supply, η, and the greater is the share of land in expenditure, α.

These effects, and the employment implications, are summarised as the following proposition:

Proposition: Suppose that N is large and that there are Ricardian place-sector specific productivity differences. Places that have productivity advantage in highly tradable sectors will have relatively high nominal wages and employment structures skewed towards these highly tradable sectors.

Employment effects are described in Appendix 1, and further illustrated in the numerical simulations of the full model.

3.3 Numerical simulation.

The preceding comparative statics examine the effect of small productivity differentials in a single place around the base equilibrium. How do large productivity differentials occurring throughout the economy show up in the full model? We address this by numerical simulation, and in so doing also introduce and develop concepts and methods that are used in the empirical investigation.

The simulation works with a large number of places (N = 300) and sectors (S = 50). The key elements of sectoral and spatial heterogeneity are as follows. In the central case presented, trade costs vary across sectors from freely tradable, $t_s = 1$, to a maximum value of $t_s = 4$ at which, with our central value of $\sigma = 10$, the proportion of output consumed in the place where it is produced, μ_s, exceeds 99%. Ricardian productivity differences are introduced by assuming that productivity levels a_{is} are equal to unity plus an independently drawn normal variable with mean 0, variance 0.2, and truncated at +/- 0.5. [16] The mobility of labour between sectors is assumed to be high but not perfect (Frechet shape parameter of 50). The rent elasticity of supply of land is set at $\eta = 1$, broadly in line with recent estimates derived by Combes et al. (2019) for Paris. Other parameters are reported and discussed in Appendix 1.

The model generates a spatial distribution of employment in each sector, together with prices, wages, rents and income levels. We first discuss the way in which the spatial distribution of employment varies across sectors, defining and illustrating 'sector sparsity', and then turn to the place characteristics of sparsity bias and its relationship with wages.

Sector location and sector sparsity: Simulation generates a distribution of place-sector employment, L_{is}, which can be expressed in share form $s_{is} \equiv L_{is}/\sum_i L_{is}$, the share of place i in total sector s employment. We compare this with the share of place i in aggregate

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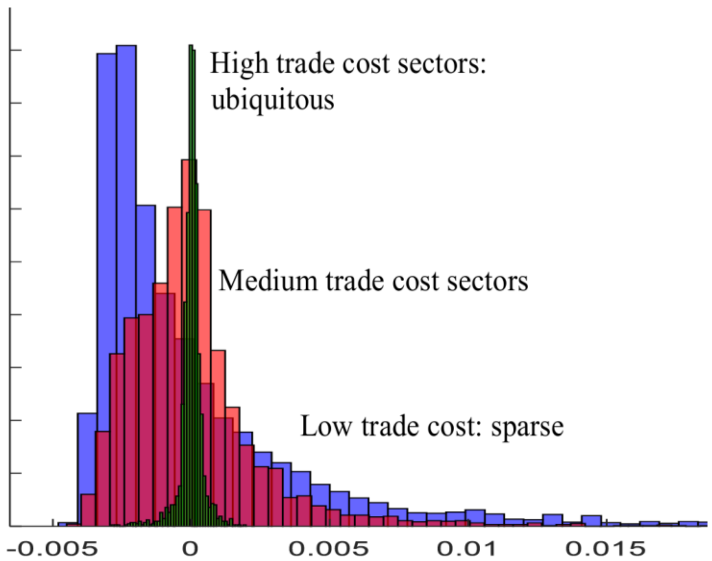
[16] The importance of place-sector specific productivity variation is confirmed by Caliendo et al. (2018) who decompose productivity shocks across US states and 26 sectors and find that 29% of the variation is accounted for by the regional component, 21% sectoral, and 50% (the residual) is region-sector specific.

employment, $x_i \equiv \sum_s L_{is} / \sum_i \sum_s L_{is}$, the comparison taking the form of either the difference, $q_{is} = s_{is} - x_i$, or the ratio $q_{is}{}' \equiv s_{is}/x_i$ (the location quotient). For each sector s, the shape of the distribution of q_{is} (or $q_{is}{}'$) across places captures the 'sparsity' of the sector – the degree to which sectoral employment is concentrated in a relatively small number of locations. If a sector is 'ubiquitous' (located everywhere in proportion to total employment) the distribution of q_{is} is concentrated at zero, and that of $q_{is}{}'$ at unity.

Figure 1 gives the shape of this spatial distribution for three types of sectors for a particular run of the model. The dark-brown histogram is the distribution of values of q_{is} for the 1/3rd least tradable sectors, the blue is the distribution for the 1/3rd most tradable, and the red/orange the middle third. The difference in the shapes of the distributions is apparent, and for empirical work we need a summary measure of their shape. We consider two such measures, the standard deviation, denoted SD_s, and the skewness, SK_s. We refer to these as measures of the 'sector sparsity' of each sector, with low values indicating ubiquity (high trade costs), and high values signifying sparsity (low trade costs). In the empirical section of the paper we do not observe tradability directly, and use these measures as proxies for sectoral tradability. We note that, in this simulation, the cross-sector correlation between trade cost parameter t_s and the standard deviation measure of sector sparsity, SD_s, is -0.958, and that between t_s and the skewness measure, SK_s, is -0.908.

Figure 1: Distribution of sectoral location q_{is} for high (dark brown), intermediate (red/orange) and low (blue) trade cost sectors.



Sparsity bias and wages: We want to measure the extent to which the employment structure of each place is weighted towards sparse sectors. We do so by constructing, for each place, an employment weighted average of sectoral sparsity measures. This is the 'sparsity bias' index of each place,

$$SB_i \equiv \sum_s SK_s(L_{is} / \sum_s L_{is}), \quad or \;\; SB_i \equiv \sum_s SD_s(L_{is} / \sum_s L_{is}). \qquad (14)$$

Values of SB_i, drawn from a single run of the simulation, are on the horizontal axis of each panel of Figure 2, the left panel giving SB_i based on the standard deviation measure of sectoral sparsity, and the right panel based on the skewness measure. Our central hypothesis is that sparsity bias is positively correlated with wages, and simulated equilibrium wages are on the vertical axis of each panel of Figure 2.[17] The positive association between wages and the sparsity bias index generated by the simulation is apparent for both versions.

Figure 2: Area wages and sparsity bias; relative to the base equilibrium value.

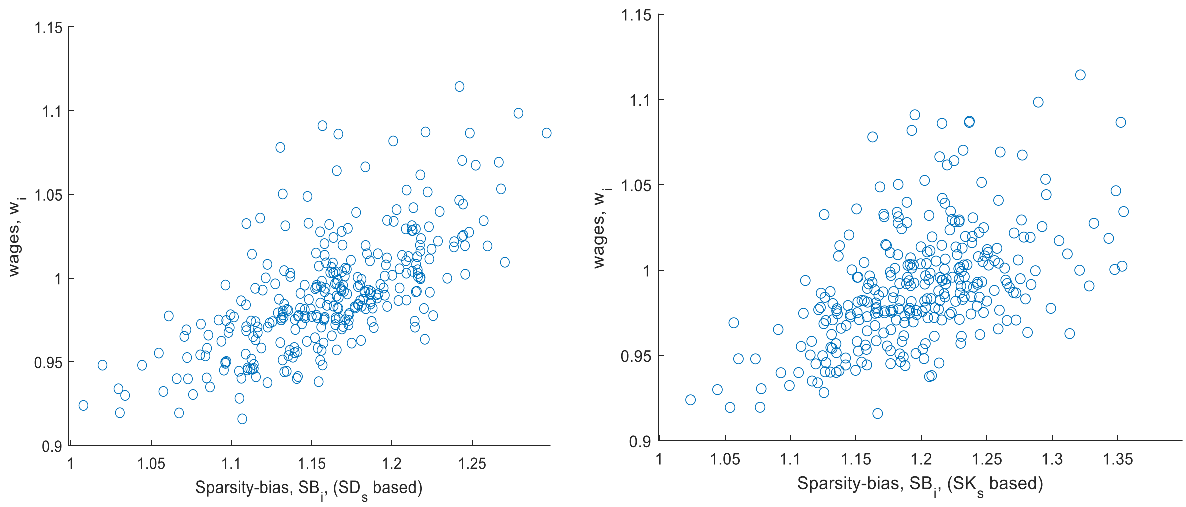


Table 2a gives the regression relationship between these variables, pooling output from 20 simulation runs. Columns 1 and 2 give results for each version of the sparsity bias index and indicates that the relationship between wages and sparsity bias is significant and has adjusted $R^2 = 0.45$ and 0.17 in the two cases.[18] Columns 3 and 4 are based on simulations in which productivity shocks are larger in highly tradable sectors than in less tradable. Specifically, the productivity shock is divided by t_s, so is distributed $N(0,0.2)/t_s$, where, as before, $t_s \in [1,4]$. As indicated in the table, the correlation between wages and sparsity bias becomes considerably stronger in the presence of this correlation. This is as expected, given the relationships established in Section 3. The bottom row of the table gives a further descriptive result from the simulation. The range of values of area wages, w_i, is 21.7 percentage points. This is a direct reflection of the range of productivity shocks fed into the simulation.

Further runs of the model explore the effect of changing other parameters of the model. In brief, a lower value of σ reduces the coefficient on sparsity bias and its t-statistic; this is as

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[17] Employment weighted average wages in place *i* are $w_i = \sum_s w_{is}(L_{is}/\sum_s L_{is})$.

[18] Notice that Figure 2 is for a particular model run, and Table 2a is pooled across 20 such runs.

expected, as wage variation is driven by cross-sector variation in the price elasticity of demand, this increasing with σ. A higher value of η also reduces the coefficient on SB_i and its explanatory power because a higher land supply elasticity reduces spatial variation in rents and hence in the cost of living and nominal wages. Finally, all these results depend on trade costs varying across sectors: reducing the range to one-third of its value ($t_s \in [1,2]$) leaves the coefficient on sparsity bias positive but insignificant, with adjusted $R^2 = 0.014$.[19]

Table 2a. Area Wages and Sparsity Bias: Mean values from 20 simulation results:

	Dependent variable: Average earnings in place i, w_i			
	(1)	(2)	(3) Small $var_i(a_{is})$ in high τ_s sector	(4) Small $var_i(a_{is})$ in high τ_s sector
Sparsity bias SB_i: sector-sparsity measure $SD_s(q_{is})$	0.38 (15.8)		0.34 (39.4)	
Sparsity bias SB_i: sector-sparsity measure $SK_s(q_{is})$		0.16 (7.6)		0.16 (11.45)
Constant	0.39 (13.8)	0.63 (24.7)	0.45 (37.7)	0.68 (32.44)
Adj. R^2	0.45	0.17	0.83	0.29
No. of obs'ns	300	300	300	300
Range of w_i	21.7 ppt	21.7 ppt	22.9 ppt	22.9 ppt

Columns 1, 2: $t_s \in [1,4]$, $\sigma = 10$, $\eta = 1$, $a_{is} \sim 1 + N(1,0.2)$, truncated at 0.5 and 1.5
Columns 3, 4: $t_s \in [1,4]$, $\sigma = 10$, $\eta = 1$, $a_{is} \sim 1 + N(1,0.2)/t_s$, truncated at 0.5 and 1.5

Skill intensity and sector-differentials: To this point we have assumed that labour is homogeneous, but capturing the empirical pattern of earnings disparities requires that skill differentials, and their interaction with sectoral skill-intensity, be added to the model. We do this by assuming two types of labour, skilled and unskilled (types *A*, *B*, respectively). The economy has fixed endowments, L^A and L^B, of each, and wages in each place and sector are now skill specific, w_{is}^A, w_{is}^B. On the household side (labour supply, income, spending and choices of place and sector of work), the model is as in section 2, but with variables super-scripted by skill, *A*, *B*. On the production side, both types of labour are used in all sectors, and have different productivity ($a^A > a^B$). The relative shares of skilled and unskilled labour vary across sectors; v_s capturing the intensity with which sector *s* employs type-*A*, and $1 - v_s$

[19] As the variation in t_s goes to zero, so too does the variation in sparsity bias for large *S*.

capturing the intensity of its use of type-B. Assuming a CES aggregator for the two types of labour, unit cost functions (equation 1) are therefore,

$$p_{is} = c_s\big(f(w_{is}^A, w_{is}^B), r_i\big)/a_{is} = f(w_{is}^A, w_{is}^B)^{\gamma} r_i^{1-\gamma}/a_{is}$$

$$\text{with} \quad f(w_{is}^A, w_{is}^B) = \left\{v_s\big(w_{is}^A/a^A\big)^{1-\rho} + (1-v_s)\big(w_{is}^B/a^B\big)^{1-\rho}\right\}^{1/(1-\rho)}.$$

This generates demand for each type of labour in each place L_i^A, L_i^B (analogous to equation 6), and average wages in each place and each sector, w_i and w_s (see Appendix 1 for expressions). To illustrate results, we run the model for an example with productivity differential between skill types set at $a^A/a^B = 3$, and sectoral skill intensity parameters v_s ranging between 0.25 and 0.75. The elasticity of substitution between labour types is assumed to be small, $\rho = 0.5$.

With skill differentials the model now yields both area differentials (the general equilibrium effects described above) and sector differentials, as sector composition determines skill mix in each place. The interaction between these two forces depends critically on the (exogenous) relationship between tradability and skill-intensity. The first column of Table 2b reports results when it is assumed that the most tradable sector is the most skill intensive and skill intensity declines linearly to the least tradable sector (so the sector with $t_s = 1$ has v_s = 0.75, and that with $t_s = 4$ has v_s = 0.25). The coefficient on sparsity bias is now double that in the case of homogeneous labour (column 1 of Table 2a) and explanatory power somewhat increased. There is a large wage differential between skill types $w^A/w^B = 2.81$ (w^A, w^B being employment weighted averages of wages of each type across all places and sectors). The spatial range of wages, w_i, has increased from around 22 percentage points in Table 2a to 36 percentage points.

The converse case is that in which more tradable sectors are relatively skill un-intensive. Sparsity bias continues to have a large and significant effect on average earnings, but the sector differential effect is now pulling against the area differential effects of scale and cost of living, so overall wage differentials are smaller and the range of spatial variation of average wages is reduced to just 9.5 percentage points. In short, it is the combination of high tradability with high skill intensity that creates the large range of spatial wage variation.

Table 2b. Area Wages and Sparsity Bias: mean values from 20 simulation runs

	Dependent variable: average earnings in place i, w_i	
	(1) More tradable sectors are skill intensive	(2) More tradable sectors are skill un-intensive
Sparsity bias SB_i: based on sector sparsity measure $SD_s(q_{is})$	0.87 (17.9)	0.43 (18.9)
Constant	0.16 (13.8)	0.46 (17.0)
Adj. R^2	0.51	0.54
No. of observations	300	300
w^A/w^B	2.81	1.32
Range of w_i	36.3ppt	9.5ppt

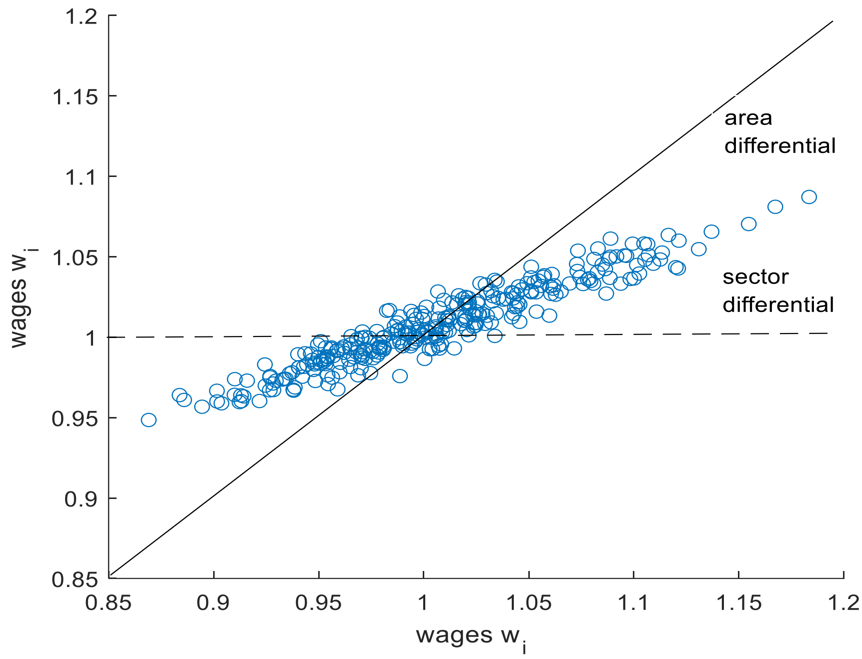
Central case: $t_s \in [1,4]$, $\sigma = 10$, $\eta = 1$, $a_{is} \sim N(1,0.2)$, truncated at 0.5 and 1.5.

The respective contributions of area and sector differentials to average wages can be split out by a simple decomposition, which we will use extensively in the empirical work that follows. The sector differential is defined as what average wages in a place would be if each sector paid workers the national average wage for that sector, expressed relative to the national average wage; it therefore captures a pure compositional effect.[20] The area differential is the difference between this and the actual average wage in the place.

The division of area wages between these two elements is indicated in Figure 3 for the case in which more tradable sectors are relatively skill intensive (column 1 of Table 2b). The axes of this figure are the average wage in each place, and the height of the scatter points (relative to the national average wage of 1) is the sector differential. The difference between the scatter point and the actual average wage in each place (the 45^0 degree line) is the area differential, negative for low wage (and low sparsity bias) places, and increasing with average wages (and sparsity bias). The interaction between tradability and productivity differences drives sectoral composition, this affects wages through both the area differential, and the skill composition and sector differential of each area and, in this example, the two channels pull in the same direction and are of approximately equal magnitude,

[20] A formal definition is given at the beginning of Section 4.1.

Figure 3: Wages, w_i: sector differential and area differential



Tradability, productivity, and prices: The theory and simulations demonstrate the mechanisms at work and the concepts that will be used in the following empirical section. Before moving to this, we summarise our findings and make several further remarks.

First, it is the interplay between the sector characteristic of tradability and place-sector specific variations in productivity that is central to the argument. Tradability matters in so far as it enables output and employment expansion in response to a place specific advantage, such as productivity. Physical productivity is less socially valuable in non-tradable sectors as (other things being equal), these sectors are less able to expand and apply the productivity advantage to a larger set of workers.

Second, differences in physical productivity between places create difference in prices. High physical productivity in highly tradable sectors has little effect on own prices, but output and employment expansion bids up prices of less tradable goods and land and housing, and hence (with high labour mobility) raises nominal wages. High physical productivity in non-tradables reduces the price of these goods, tending to reduce the cost of living and (with high labour mobility) also reducing the nominal wage and revenue productivity in some sectors.

Third, physical productivity may well be endogenous, for example varying with scale because of agglomeration economies. Our analysis abstracts from this, but there is nevertheless a positive relationship between scale and revenue productivity. Tradability and consequent demand and price effects create relationships between revenue productivity and scale even in sectors where technical efficiency is the same everywhere. This points to difficulties posed for empirical work seeking to quantify agglomeration economies. It is important to distinguish between physical and revenue productivity, and to be confident which is being measured. This is particularly so if policy prescriptions are going to be drawn from the analysis.

4. UK evidence.

The model and simulation results suggest that spatial variation in earnings is shaped by sparsity bias, capturing the extent to which places contain employment in sparse sectors, as well as by sector differential effects arising from skill and average wage differences across sectors. Do these relationships hold in the data, and if so what are their magnitudes? In this section we look at data for the UK in the period 2015-2019, and in section 5 we examine the effects of changes in the UK's industrial structure that occurred in the 1970s and 1980s..

Empirical analysis for the period 2015-2019 is based on the 163 ITL3 (formerly NUTS3) areas of Great Britain and 259 SIC2007 3-digit industrial sectors.[21] The annual Business Register and Employment Survey (BRES) provides data on the number of employees for each ITL3 area by SIC3 sector cell (163x259). Values for the years 2015 to 2019 are averaged to reduce year-to-year volatility. Earnings data are provided by the Annual Survey of Hours and Earnings (ASHE, workplace-based analysis) and cover all employees on adult rates whose pay during the April reference period is unaffected by absence. Annual ASHE estimates of mean gross hourly earnings for each of the 163 ITL3 areas and for each of the 259 SIC3 sectors for years 2015 to 2019 are converted to real 2015 values using the GDP deflator and are averaged. Further details of our data are provided in Appendix 2.

We start by looking at average earnings across the ITL3 areas, and at the extent to which these are shaped by sector differentials and by area-differentials. We then construct the sparsity bias measure for each area and establish its relationship with earnings.

4.1: Regional variation in earnings: sector differential and area differential.

Mean hourly earnings in each ITL3 area, w_i, are depicted along the horizontal axis of Figure 4, with descriptive statistics for their distribution reported in the first row of Table 3. The spatial distribution has high variance with a strong positive skew; the four values at the extreme right of Figure 4 represent the London areas of Haringey and Islington, Westminster, Camden and the City of London, and Tower Hamlets.

We decompose average earnings in each area, w_i, into three elements, according to

$$w_i = (w_i - \widetilde{w}_i) + (\widetilde{w}_i - \overline{w}) + \overline{w}. \qquad (15)$$

[21] The areas include the 145 ITL3 areas of England and Wales; the ITL2 area Highlands and Island together with the other 17 ITL3 areas of Scotland. The set of SIC3 industrial groups excludes those in; (T) Activities of Households etc and (U) Activities of Extraterritorial Organisations and Bodies

The final term on the RHS of (15) is national average earnings, $\bar{w} \equiv \sum_i \Sigma_s w_{is} L_{is}/L$. The second term is the sector differential effect, where the variable $\tilde{w}_i$ is the level of mean earnings of an area assuming that local wages in each sector equal the sectoral national average, i.e. $\tilde{w}_i = \Sigma_s w_s \lambda_{is}$, where $w_s = \sum_i \theta_{is} w_{is}$ is the sector national average wage, $\theta_{is} \equiv L_{is}/\sum_i L_{is}$ being the employment share of area *i* in sector *s* employment, and $\lambda_{is} \equiv L_{is}/\sum_s L_{is}$ is the employment share of sector *s* in area *i*. The first term on the RHS of (15) is the area differential with $(w_i - \tilde{w}_i) = \Sigma_s (w_{is} - w_s)\lambda_{is}$.[22] Thus, the area-differential of each area is the employment share weighted average of the difference between local earnings in each sector, w_{is}, and the national sector average wage, w_s.[23]

We compute $\tilde{w}_i$ using ASHE data on mean hourly earnings for all UK employees for each of the 259 SIC3 industrial sectors (w_s), together with the BRES data on employment numbers by ITL3 area and SIC3 sector (λ_{is}). The descriptive statistics for w_s are reported in the second row of Table 3. Sectoral variation in average earnings far exceeds that observed across the ITL3 areas, with the maximum value (663: Fund Management Activities) more than four time the minimum value (478: Retail Sale via Stalls and Markets).

Figure 4 is the empirical counterpart of Figure 3, with the vertical height of the scatterplot depicting the decomposition (15) for each of the 163 ITL3 areas. The vertical distance between a scatter point and the national average wage (horizontal line $\bar{w}$) is the sector differential, and the distance between the point and the 45^{o} line is the area differential. For areas in the upper tail of the earnings distribution, typically ITL3 areas of London, the area differential is substantially positive. The third and fourth rows of Table 3 report the descriptive statistics for these variables.

The contribution of the sector differential to the variance of mean hourly earnings across areas is modest at 11 percent (0.58/5.17, Table 3 column 3). By contrast the area differential accounts for 52 percent of this variance, with the covariance between the sector differential and the area differential accounting for the remainder. If London areas are excluded from the sample then the contribution of the sector differential effect increases to 20 percent and the contribution of the area differential is 47 percent. This is with a relatively fine sectoral classification (259 sectors) although a finer classification of sectors, or tasks were it available, would be likely to increase the contribution of the composition effect.[24]

[22] $w_i \equiv \Sigma_s w_{is} \lambda_{is} = \tilde{w}_i + \Sigma_s (w_{is} - w_s)\lambda_{is}$, and see Olley and Pakes (1996).

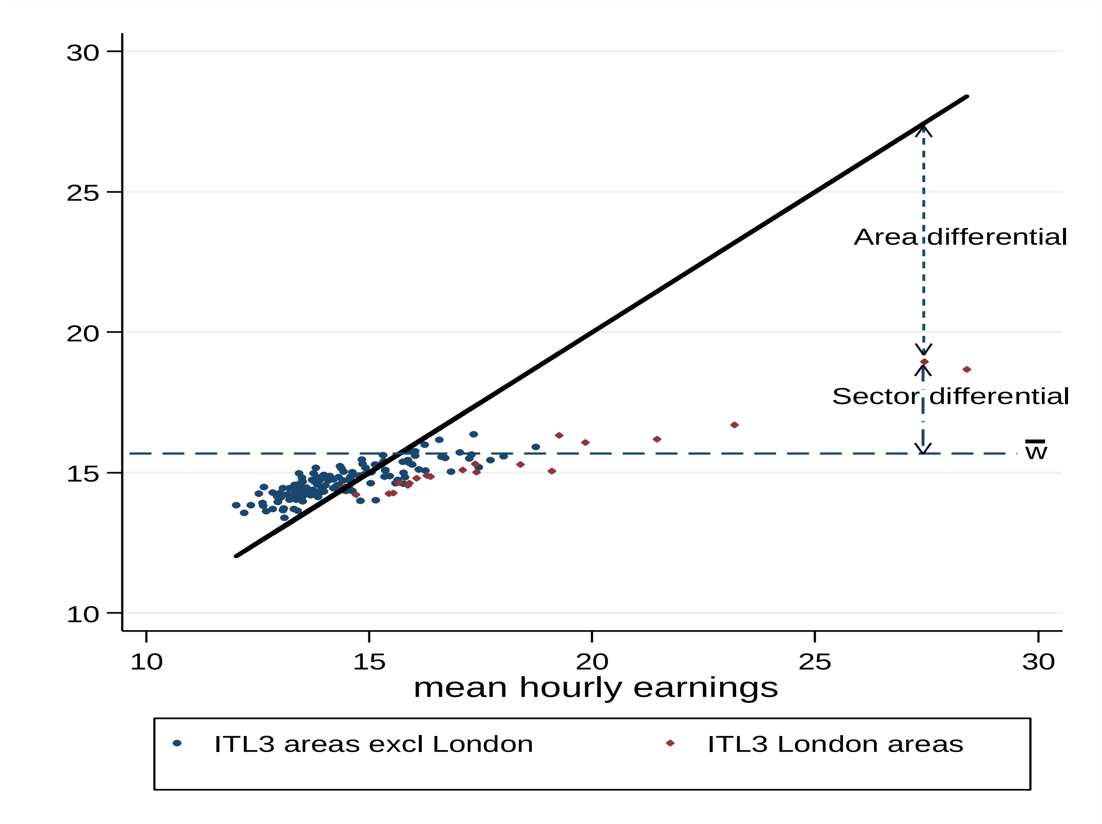
[23] ASHE sample sizes do not allow reliable estimates of local sectoral earnings, w_{is} at this level of disaggregation (163 areas x 259 sectors) but we can compute robust estimates of the area means $w_i$and the sectoral means w_s.t

[24] Following our focus on labour demand, this decomposition is with respect to an employer characteristic (i.e. it is the sector differential), rather than employee characteristics as in Overman and Xu (2022).

Table 3: Hourly earnings; descriptive statistics by area and by sector. £ per hour.

	Mean	Median	Variance	Min	Max
ITL3 area mean hourly earnings (all sectors): w_i	14.87	14.31	5.174	12.01	28.41
SIC3 sector mean hourly earnings (all UK): w_s	15.65	14.96	17.61	8.10	34.49
ITL3 sector differential: $(\tilde{w}_i - \overline{w})$	-0.9474	-1.0493	0.576	-2.32	3.23
ITL3 area differential: $(w_i - \tilde{w}_i)$	0.1019	-0.3214	2.711	-1.83	9.83

Figure 4: Area Earnings (£ per hour): sector differential and area differential



4.2: Sectoral sparsity indices

Our central hypothesis concerns the role of the tradability of output in shaping labour demand and wages. We do not observe tradability directly, but we do observe employment by sector and area, and hence can calculate a sectoral sparsity index, based on the spatial distribution of relative employment shares for each sector as discussed in Section 3.3. The share of sector s employment that occurs in area i, $s_{is} \equiv L_{is}/\sum_i L_{is}$, is compared to the share of area i in total

GB employment, x_i, with the relativity expressed in terms of either the ratio s_{is}/x_i, (the location quotient) or the difference, $s_{is} - x_i$. We focus here on results for the difference measure with comparable results for quotient-based measures reported in Appendix 3.[25] As discussed in Section 3.3, salient features of the shape of the distribution are captured by the second and the third moments of the distribution. We discuss the results obtained using skewness, SK_s; results for the alternative of standard deviation are presented in Appendix 3.

Sparsity varies widely, and intuitively, across sectors. Figure 5 illustrates the distribution of SK_s across sectors. Sectors with high sparsity measures include a number of specialised manufacturing industries – manufacture of precious metals (244); manufacture of articles of fur (142); manufacture of porcelain and ceramic products (234), manufacture of coke ovens (191). Outside manufacturing, the sparse sectors are extraction of crude petroleum (061) and support activities for petroleum (091); radio broadcasting (601); wireless communications (612); re-insurance (652), and activities auxiliary to insurance (662). At the other extreme, the ubiquitous sectors, those with negative or very small values for the sparsity index, include primary and secondary education (852, 853); medical and dental practises (862); residential care for elderly (873); sale of and maintenance and repair of motor vehicles (451, 452); retail sales (471, 475); electrical, plumbing and other construction installation activities (432); building completion and finishing (433). More generally as the box-plot in Figure 6 shows 'sparse' sectors tend to be within financial, insurance and real estate activities, transportation and storage, information and communication, and mining and quarrying. As expected, industries in wholesale and retail trades, construction, public administration and education, and health and social work tend to be more evenly distributed across ITL3 areas and have low sparsity indices.[26]

We note one further point about sectoral sparsity indices, and this is that they are positively correlated with sectoral average earnings, with correlation coefficient 0.46. This correlation simply reflects the fact that technologies of production and tradability happen to be such that highly tradable products tend to be relatively high skill intensive, and is not an equilibrium relationship generated by economic behaviour in the model.

[25] An argument for focusing on the difference measure in preference to the quotient measure is that it is less sensitive to variation in the size of ITL3 areas.

[26] Boundaries of the box are LQ and UQ , the median is given by the vertical line. Whiskers extend between LQ-1.5(UQ-LQ) and UQ+1.5(UQ-LQ) and dots are any data points outside this range.

Figure 5: Distribution of sector sparsity-indices, SK_s

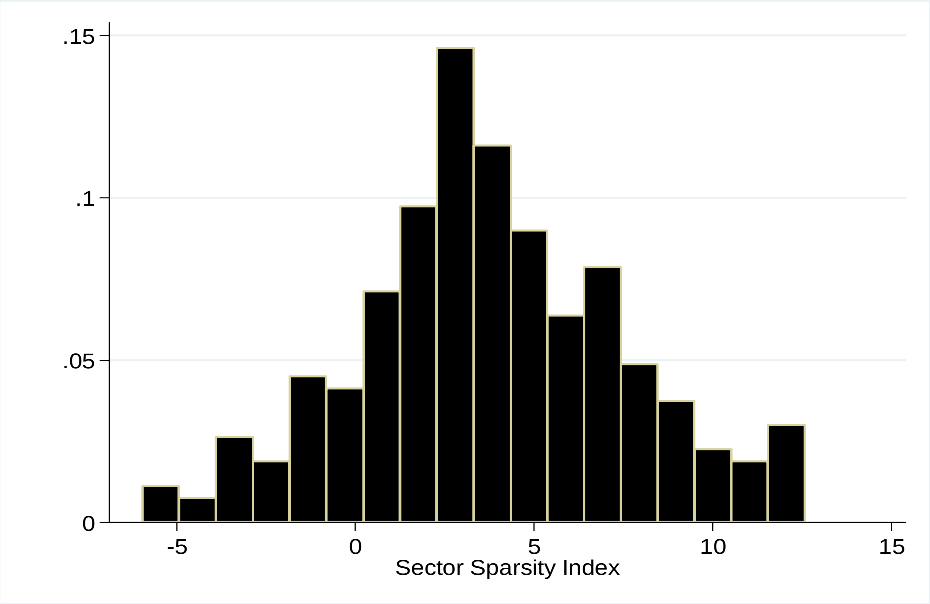
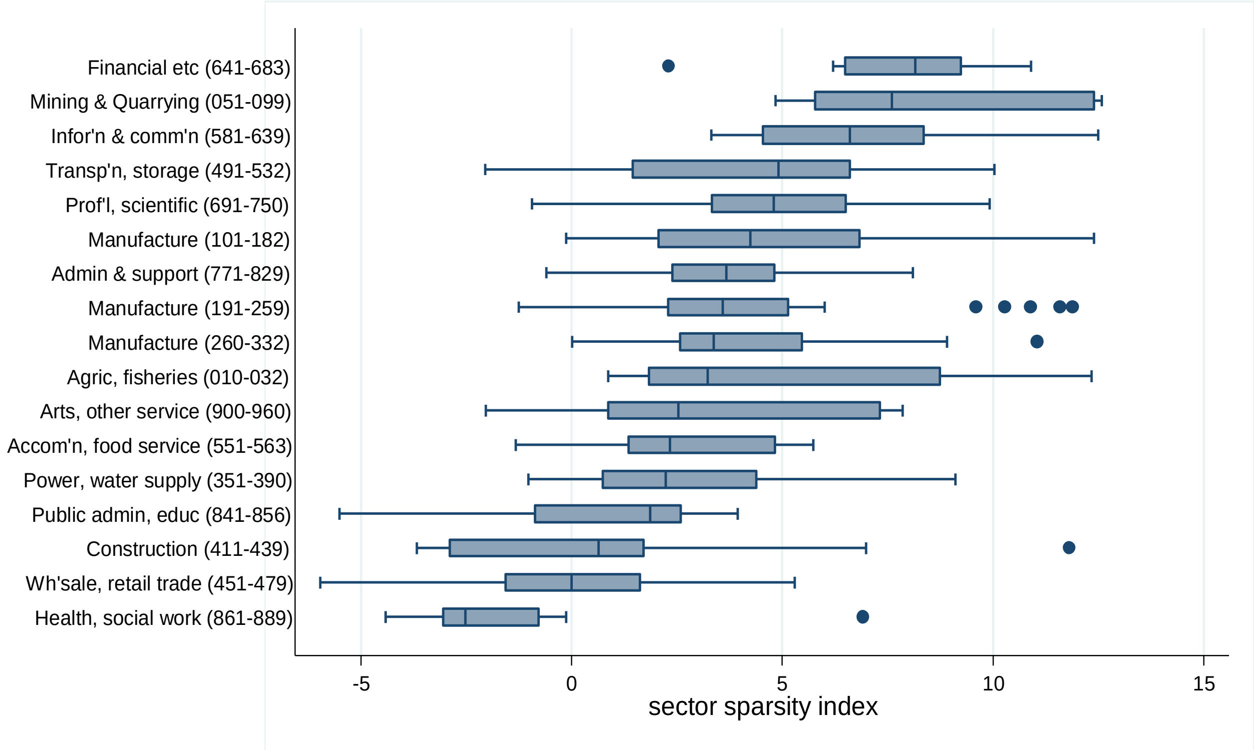


Figure 6: Sparsity-indices by Broad Industrial Divisions



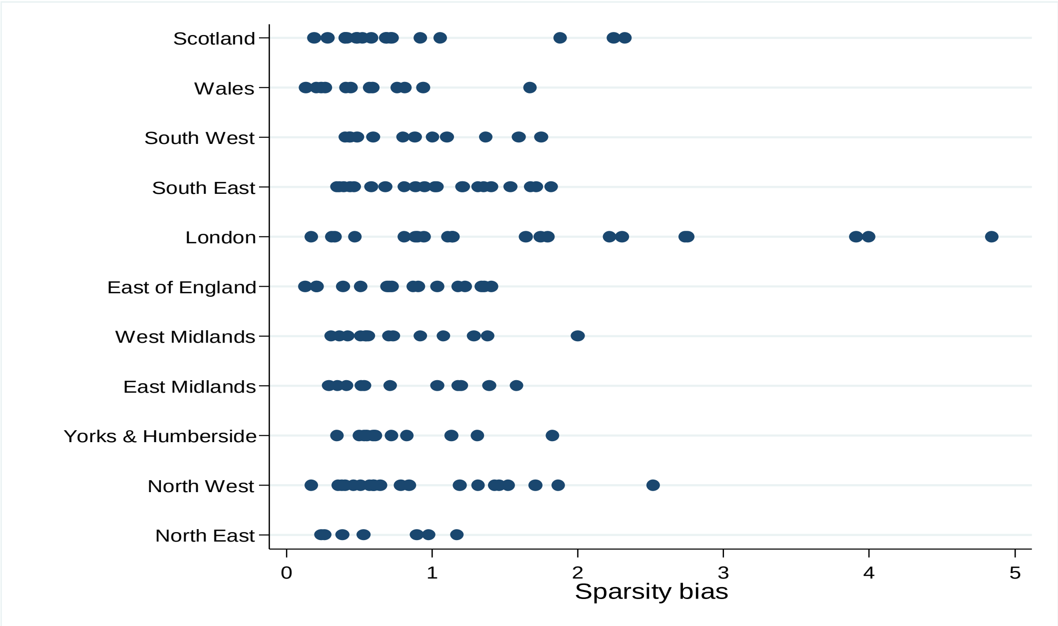
4.3: Sparsity bias and earnings.

We use the sectoral sparsity indices to calculate the sparsity bias of each area, i.e. the extent to which the employment structure of the area is biased towards more or less sparse sectors. As in section 3.3 (equation 14) this is the average of the sectoral sparsity measures weighted by the sector's share of area employment i.e. $SB_i \equiv \sum_s SK_s L_{is} / \sum_s L_{is}$. The distribution of sparsity bias within each of the ITL1 regions of Great Britain is shown in Figure 7, with summary statistics reported below the figure.

The ITL3 areas with the smallest values for sparsity bias are Thurrock; the Central Valleys (Wales); Barking and Dagenham and Havering; the Wirral; East Ayrshire and North Ayrshire mainland. Those with the highest values are the London areas of Camden and City of London; Tower Hamlets; Westminster; Haringey and Islington; Hounslow and Richmond upon Thames. The next highest values are those for Manchester in the North-West and Aberdeen City and Aberdeenshire in Scotland.

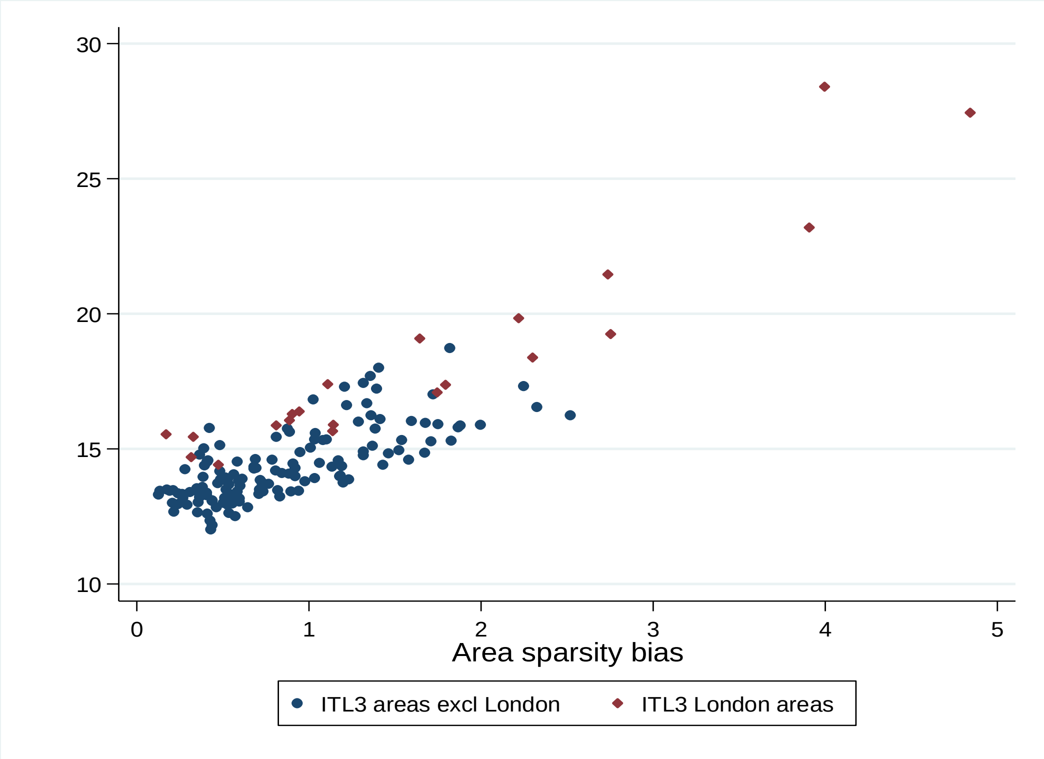
A clear prediction of the theory is a positive relationship between the sparsity bias of an area and its average earnings. Figure 8 plots this relationship, and the raw correlation coefficient between the variables is 0.86. If the London ITL3 areas (marked as red diamonds in Figure 8) are excluded then the correlation coefficient drops to 0.74.

Figure 7: Sparsity Bias by ITL areas.



	Mean	Median	Standard deviation	Min	Max
Sparsity bias	0.961	0.765	0.721	0.127	4.845

Figure 8: Mean hourly earnings and the sparsity bias of an area



The results for the bivariate regression of mean hourly earnings on sparsity bias are reported in the first column of Table 4. The estimated coefficient for the sparsity bias measure is very well determined with a t-value in excess of 10.[27] The point estimate implies that a one standard deviation increase in the sparsity bias measure (equivalent to 0.72 units in the full sample) is associated with an 13.2% percent increase in hourly earnings at the sample mean (approx. 0.9 standard deviations), and in the range 12% to 14.5% based on the 95% confidence interval. The results in the lower section of column 1 confirm that these findings are not being entirely driven by London areas. With all London areas excluded from the sample, the relationship between the sparsity bias measure and earnings remains strongly positive and well-determined. In this case, a one standard deviation increase in the sparsity bias results in an estimated increase in hourly earnings at the sample mean of 9.6%, and with range of 8% to 11%.

We have emphasised throughout that sectoral composition influences earnings through two mechanisms, the sector differential effect and the equilibrium or area differential effect; the two components of earnings that are illustrated in Figure 4. Sparsity bias is correlated with both of these, and the remaining columns of Table 4 show these relationships. We expect the sector differential to be positively correlated with sparsity bias because, as noted above,

[27] Throughout, t-values and confidence intervals are computed using the maximum of the conventional OLS variance estimator and the robust HC_3 variance estimator as suggested by Angrist and Pischke (2009), pp 302-308.

sectoral wages are positively correlated with sectoral sparsity indices. This is what we see in the second column of the table.

Over and above the sector differential effect, the area differential is also positively correlated with sparsity bias, in line with the central economic mechanism developed in our model. The final column of Table 4 shows a strong positive relationship between sparsity bias and this element of earnings. The estimated coefficients suggest that nearly two-thirds of the increase in mean hourly earnings associated with a higher value of sparsity bias is driven by the area differential, while just over one-third (35 percent) comes about through sector differential. The central result continues to hold with all London areas excluded from the sample, although here the split between sector differential and area differential effects is close to 50 percent.

Table 4: Earnings and Sparsity Bias

	Mean Hourly Earnings	Sector-differential effect, $(\widetilde{w}_i - \overline{w})$	Area-differential $(w_i - \widetilde{w}_i)$
Sparsity bias index SB_i	2.7180 (10.06)	0.9552 (14.42)	1.7628 (7.69)
95% CI for SB_i coeff.	2.18, 3.25	0.82, 1.09	1.31, 2.22
Constant	12.256 (53.50)	-1.8654 (-30.63)	-1.592 (-8.24)
Adj. R-squared	0.7413	0.8177	0.5939
No. of obs'ns	163	163	163
Excluding London regions			
Sparsity bias index SB_i	1.9144 (11.82)	0.9742 (17.54)	0.9402 (6.94)
95% CI for SB_i coeff.	1.59, 2.23	0.86, 1.08	0.67, 1.21
Constant	12.729 (86.69)	-1.8741 (-34.00)	-1.12 (-8.83)
Adj. R-squared	0.5387	0.7144	0.2752
No. of obs'ns	142	142	142

t-values reported in parentheses.

Comparable results using sparsity bias measures based on the location quotient (s_{is}/x_i) reported in Table A2 of Appendix 3. While less well-determined, the estimated relationships are very similar to those reported in Table 4. The point estimates imply that a one standard deviation increase in the sparsity bias measure based on the location quotient is associated with an 10% percent increase in hourly earnings at the sample mean. Moreover, the estimated coefficients indicate that approximately one-third of the increase in mean earnings comes through sector differential effects and two-thirds through area differential effects as in Table 4.

4.3: Alternative decomposition of sector and area effects:

A drawback of the conventional decomposition of earnings used above is that it does not provide a clean partition of sector effects and area effects. Area effects enter w_s, the UK average sectoral wage, in so far as variation in the location of sectors means that w_s picks up some of the area differential. In this section we consider an alternative approach to the decomposition of area average earnings that avoids this weakness.

Suppose that area-sector wages, w_{is}, deviate from the national average according to a function of an area component of the wage, d_i and a sector component d_s, so $w_{is} = \bar{w}f(d_i, d_s)$. It follows that area average earnings and sector average earnings are

$$w_i = \sum_s \lambda_{is} w_{is} = \sum_s \lambda_{is} \bar{w} f(d_i, d_s), \quad w_s = \sum_i \theta_{is} w_{is} = \sum_i \theta_{is} \bar{w} f(d_i, d_s), \qquad (16)$$

where $\lambda_{is} \equiv L_{is}/\sum_s L_{is}$ is the employment share of sector *s* in area *i* and $\theta_{is} \equiv L_{is}/\sum_i L_{is}$ is the employment share of area *i* in sector *s* employment. We do not observe w_{is} (see footnote 23), but equations (16) are N + S equations which, assuming a functional form for $f(d_i, d_s)$, can be solved numerically for the N + S unknowns, d_i and d_s, using the available data for area average and sector average earnings, w_i, w_s and employment shares, $\lambda_{is}, \theta_{is}$. Adopting a linear functional form $f(d_i, d_s) = d_i + d_s$, the sector differential is $\tilde{w}_i = \Sigma_s \bar{w}(0 + d_s)\lambda_{is}$, and the area differential is $(w_i - \tilde{w}_i)$.

Proceeding as before, but with sector differentials and area differentials calculated in this way, gives results reported in Table 5. They confirm the findings in Table 4 with both the sector differential and the area differential increasing with sparsity bias. In comparison with Table 4, the relationship between area differential and sparsity bias is somewhat better determined, with smaller standard errors and improved fit. Moreover with the revised measure only approximately one-quarter of the relationship between mean hourly earnings and sparsity bias comes about through the sector differential and three-quarters through the area differential. This is as might be expected, since by construction, this alternative measure of sector differentials has been stripped of local area influences. If instead of an additive form of $f(d_i, d_s)$ a multiplicative form is used, results are similar. [28]

In summary, these results indicate that sparsity bias is able to account for 75% of the variation in average earnings across the 163 ITL3 areas. Of this, between 25% and 33% comes through the sector differential (given disaggregation to our level of 259 sectors) and the remainder through the area differential, arising from the equilibrium effect of sparsity bias.

[28] The multiplicative forms is $f(d_i, d_s) = d_i d_s$, and sector differential $\tilde{w}_i = \Sigma_s \bar{w}(1 d_s)\lambda_{is}$.

Table 5: Earnings, sectoral composition and sparsity bias: Alternative decomposition

	Mean Hourly Earnings	Sector differential effect, $(\widetilde{w}_i - \overline{w})$	Area differential $(w_i - \widetilde{w}_i)$
Sparsity bias index SB_i	2.718 (10.06)	0.7164 (11.37)	2.0016 (8.40)
95% CI for SB_i coeff.	2.18, 3.25	0.59, 0.84	1.53, 2.47
Constant	12.2558 (53.50)	-0.9159 (-15.94)	-2.5416 (-12.64)
Adj. R-squared	0.7413	0.7305	0.6325
No. of obs'ns	163	163	163
Excluding London regions			
Sparsity bias index SB_i	1.9144 (11.82)	0.7747 (14.83)	1.1397 (8.07)
95% CI for SB_i coeff.	1.59, 2.23	0.67, 0.88	0.86, 1.42
Constant	12.7292 (86.69)	-0.9405 (-17.87)	-2.0435 (-15.77)
Adj. R-squared	0.5387	0.6434	0.3454
No. of obs'ns	142	142	142

t-values reported in parentheses.

5. Sparsity and historical change

In the introduction to this paper we refer to the loss of tradable sectors that occurred in many parts of the UK during the 1970s and 1980s. Manufacturing employment in the UK fell from over 7.9 million in 1971 to 6 million in 1981, declining further to 4.6 million by 1991. Some sectors were particularly badly affected losing nearly half of their total employment; in metal manufacturing employment fell by 238K (43 percent), in Iron and Steel by 135K (50 percent), in Textiles by 259K (45 percent). Employment declines of similar magnitude were recorded in the Mechanical Engineering sector (225K) and Vehicles (201K).

These sectors, and these declines, were not evenly distributed across areas, but concentrated in a number of the larger metropolitan counties. In earlier work, we document how the shocks experienced by the UK economy at this time shaped current UK regional disparities (Rice and Venables, 2021). These shocks were largely due to international competition – a loss of UK competitiveness with effects similar to a loss of productivity in our model. We now consider whether the experience of the shocks experienced during this period is consistent with, and captured by, the analysis of this paper.

We address this question in three stages, first calculating sectoral sparsity indices and area sparsity bias for this earlier period and looking at the relationship between earnings and sparsity bias. We then check the extent to which known declines in manufacturing in the worst affected areas are reflected in changes in our sparsity bias measures. Finally, we look at the relationship between changes in regional earnings and changes in regional sparsity bias between the mid-1970s and mid-1990s.

Regional data for the 1970s and 1980s is only available at a much higher level of spatial aggregation than for the recent period. We use data from the annual Census of Employment for 1971, 1981 and 1991 on employment by sector for the 64 metropolitan and non-metropolitan counties of England and Wales and regions of Scotland that pre-dated the 1995 local government reorganisation. An added complication is that the standard industrial classification changes between the 1971 census and the 1991 census, although the employment data for 1981 is available for both classifications, facilitating linking over time. Average earnings data for the 64 metropolitan and non-metropolitan counties identified in the Census of Employment are available from the New Earnings Survey from 1974 onwards, but for some of the areas the sample sizes are small, and the figures are subject to wide margins of sampling error. To mitigate this, we consider two-year average values and some of the least populated counties are dropped from the sample for analysis.

5.1: Sectoral sparsity indices, sparsity bias and earnings: historical cross-sections

Our earlier findings identify a strong robust relationship between the sparsity bias of an area and its average earnings in recent data. Is there evidence of similar relationship in this earlier period?

Given data on employment by sector and area, we compute a sparsity index for each sector based on the skewness of the distribution of relative employment shares, as in section 4.2. Overall, sectoral sparsity declined between 1971 and 1981 with a decrease in the mean and the median value of the sectoral sparsity indices of approximately 12 percent. The correlation between the indices for 1971 and 1981 is high - a correlation coefficient of 0.9 and Spearman rank correlation of 0.9 - but we observe significant relative movements in some sectors. Iron and steel production, parts of the mechanical engineering and vehicle sectors (sectors that experienced substantial falls in employment over the decade) saw large increases in their sparsity index relative to the average. Declines in sectoral sparsity were greatest among the distributive trades, transport and communications and miscellaneous services. Some of these trends continue through the early 1990s with the mean and the median value of sectoral sparsity indices declining further, while the sparsity index for iron and steel production, and parts of the mechanical engineering and vehicles sectors continue to increase in relative terms.

Using sectoral sparsity indices, we calculate sparsity bias for the 64 areas at each date. To match with the employment data for 1971, 1981 and 1991, we consider area average real hourly earnings for males aged 21 years or more in full-time employment whose pay was not affected by absence in the survey week for April 1974 and 1975; April 1982 and 1983, and April 1992 and 1993 respectively. The results of the bivariate regression of the area average earnings on sparsity bias are reported in Table 6. While the results are not as strong as those reported in section 4, particularly for the 1970s, the estimated coefficient for sparsity bias is statistically significant at the 0.01 level in all cases. The estimated semi-elasticity at the sample mean is 0.08 for 1974/75, 0.11 for 1982/83 and 0.17 for 1992/93. The corresponding figure using the 2015-2019 data is 0.18; although direct comparisons between the two sets of results are problematic given the very different geographies used in each case.

Table 6: Earnings and sparsity bias: cross-sections

	Mean Hourly Earnings (full-time males aged 21 years or more) £ per hour		
	1974/75	1982/83	1992/93
Sparsity bias index SB_i (1971, 1981, 1991)	0.0783 (3.96)	0.12 (4.73)	0.2271 (7.91)
95% CI for SB_i coeff.	0.039, 0.118	0.224, 0.552	0.17, 0.28
Constant	1.035 (159.9)	1.1171 (143.24)	1.3568 (112.16)
Adj. R-squared	0.4071	0.4724	0.6380
No. of obs'ns	58	60	61
Excluding London Region			
Sparsity bias index SB_i (1971, 1981, 1991)	0.0634 (4.34)	0.10 (4.81)	0.2088 (6.50)
95% CI for SB_i coeff.	0.034, 0.093	0.058, 0.142	0.144, 0.273
Constant	1.0335 (165.2)	1.1152 (143.36)	1.3544 (106.58)
Adj. R-squared	0.2876	0.3318	0.5242
No. of obs'ns	57	59	60

t-values reported in parentheses.

5.2: The decline of manufacturing: area impacts

Major changes in manufacturing employment in UK areas are shown in Table 7 which lists the areas in the lowest quartile for changes in the share of manufacturing in total employment; all experienced declines greater than 9.6 percent (compared to median value for the 64 areas of -6 percent). The West Midlands, Cleveland, Greater Manchester, West Glamorgan, and Strathclyde experienced the largest declines, losing more than 14 percent of their total employment. While Greater London experienced the largest absolute decline with the loss of 36 percent of its manufacturing employment, this accounted for just 9.6 percent of its total employment.

What effect did these marked changes in their employment composition have on their sparsity bias? Sparsity bias declined between 1971 and 1981 in all the areas listed in Table 7 with the exception of Tyne and Wear and, in most cases, this was associated with a fall in their ranking relative to other areas of Great Britain. The vast majority of areas listed saw a further decline in their sparsity bias between 1981 and 1991, and with it their GB ranking. These findings support that view that for many areas, the sharp decline in manufacturing employment of the 1970s led to a persistent shift in the composition of local employment away from tradeable sectors.

Table 7: Area sparsity bias, 1971, 1981, 1991.

Area	Change in manufacturing employment 1971 - 1981			Sparsity bias: (GB rank in parentheses)		
	'000s	As % 1971 manuf empl't	As % 1971 total empl't	1971	1981	1991
West Midlands	-260	-34.2	-18.6	1.49 (2)	0.98 (2)	0.62 (8)
Cleveland	-39	-34.7	-16.7	0.09 (31)	0.003 (32)	-0.39 (48)
Greater Manchester	-172	-33.4	-14.9	0.82 (4)	0.38 (9)	0.33 (17)
West Glamorgan	-23	-36.8	-14.9	0.27 (16)	0.03 (30)	0.04 (31)
Strathclyde region	-146	-37.5	-14.5	0.39 (12)	0.25 (15)	0.24 (21)
West Yorkshire	-117	-30.3	-13.6	0.93 (3)	0.49 (5)	0.37 (12)
Merseyside	-89.5	-36.8	-13.3	0.8 (5)	0.57 (3)	0.29 (18)
Bedfordshire	-23.5	-25.3	-12.7	0.6 (7)	0.22 (20)	0.35 (14)
Gwent	-20	-27.8	-12.3	-0.1 (38)	-0.02 (33)	-0.19 (40)
South Yorkshire	-65.5	-29.2	-12.2	0.16 (24)	0.09 (28)	0.08 (29)
Tyne and Wear	-60	-31.7	-11.8	0.16 (23)	0.20 (22)	0.23 (20)
Clwyd	-12.5	-28.1	-11.2	-0.53 (55)	-0.51 (58)	-0.66 (58)
Tayside region	-16.5	-31.4	-10.5	0.37 (13)	0.08 (29)	-0.23 (42)
Staffordshire	-36.5	-21	-10.1	0.63 (6)	0.27 (12)	-0.00 (34)
Greater London	-379	-36.1	-9.6	1.77 (1)	1.73 (1)	2.22 (1)

5.3: Earnings and sparsity bias: historical changes.

Spatial disparities in average area earnings increased markedly during this time; the coefficient of variation almost doubled from 0.061 in 1973/74 to 0.114 in 1992/93 with an increase in positive skew from 0.71 to 1.55. To what extent can changes in area sparsity bias account for these changes in regional earnings? Figure 8 gives the scatter plot relationship between the change in sparsity bias 1971 to 1991 and the change in average earnings 1974/75 to 1992/93;

both series are shown relative to the mean for Great Britain as a whole. Green triangles indicate the regions with the largest declines in manufacturing employment (Table 7), and of these 15 regions, 11 experienced a decline in both sparsity bias and relative earnings. For the full period, the simple correlation coefficient is 0.56. Breaking this into two sub-periods the correlation coefficient for changes in the first sub-period is 0.53, and for changes in the second, 0.56.

Table 8 shows the results of the bivariate regression of changes in earnings on changes in sparsity bias. While as to be expected the goodness of fit is not high, the estimated coefficient is positive and statistically significant at the 0.01 level for the whole period and each of the sub-periods. These findings offer further support for the argument that changes in the sectoral composition of employment leading to a reduction in the sparsity bias of an area are associated with a decline in local average earnings.

Figure 9: Wages and sparsity bias: changes from the 1970s to 1990s

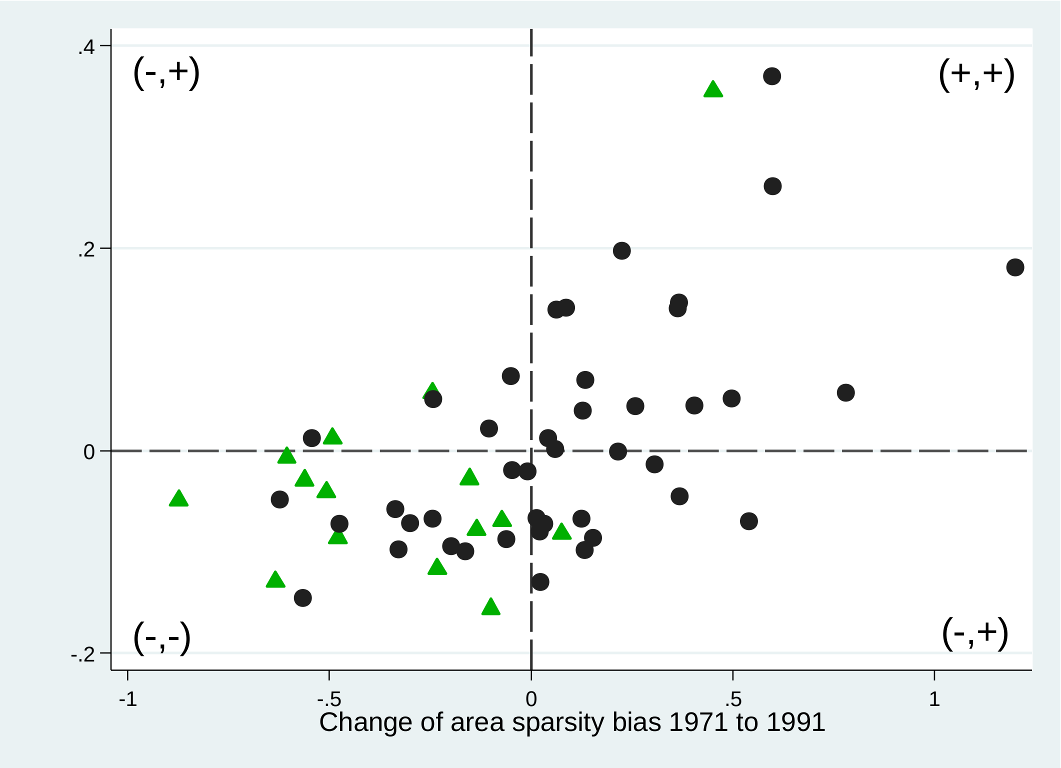


Table 8: Wages and sparsity bias: changes from the 1970s to 1990s

	Change in mean real hourly earnings		
	1974/75 to 1982/83	1982/83 to 1992/93	1974/75 to 1992/93
Change in sparsity bias index SB_i	0.0927 (2.78)	0.1531 (3.93)	0.1609 (4.46)
95% CI for SB_i coeff.	0.026, 0.158	0.075, 0.231	0.089, 0.233
Constant	0.0727 (12.59)	0.3166 (13.12)	0.3864 (17.04)
Adj. R-squared	0.2861	0.2648	0.3009
No. of obs'ns	58	60	58

6. Further predictions and robustness checks:

Our analytical framework has implications for other economic variables and in this section we examine whether the data on these variables is consistent with the framework and also undertake a number of robustness checks on our findings. Further details are provided in Appendix A3.

6.1: Sparsity bias and the cost-of-living.

Central to the model is that the equilibrium response to a productivity advantage may change the cost-of-living in an area, and this raises nominal wages, including those in non-tradeable sectors where higher costs can be passed on to local consumers. A large component of any such change is in the price of housing and land. Absent consumer price data that would allow full cost-of-living comparisons across ITL3 areas, we investigate the relationships between housing costs (as measured by the median monthly rental for 2-bedroom accommodation), sparsity bias, and earnings.

As expected, there is a strong positive correlation between house rents and both sparsity bias and earnings. The estimated elasticity of area rents with respect to earnings is 2.27 (see third column of Table A5). If, for example, housing expenditure were the only element of the cost-of-living that varied across space and amounted for 25% of income then real wage equalisation would be supported by an elasticity of 4.[29] However, if other less than perfectly tradable goods also vary in price (relatively cheap in low wage areas), or housing expenditure takes more than 25% of income then 4 is an upper bound, and the estimate of 2.27 is broadly consistent with the predictions of the model.

[29] I.e. a 10% increase in rents is fully offset by a 2.5% increase in earnings.

6.3: Sparsity bias and earnings by occupation

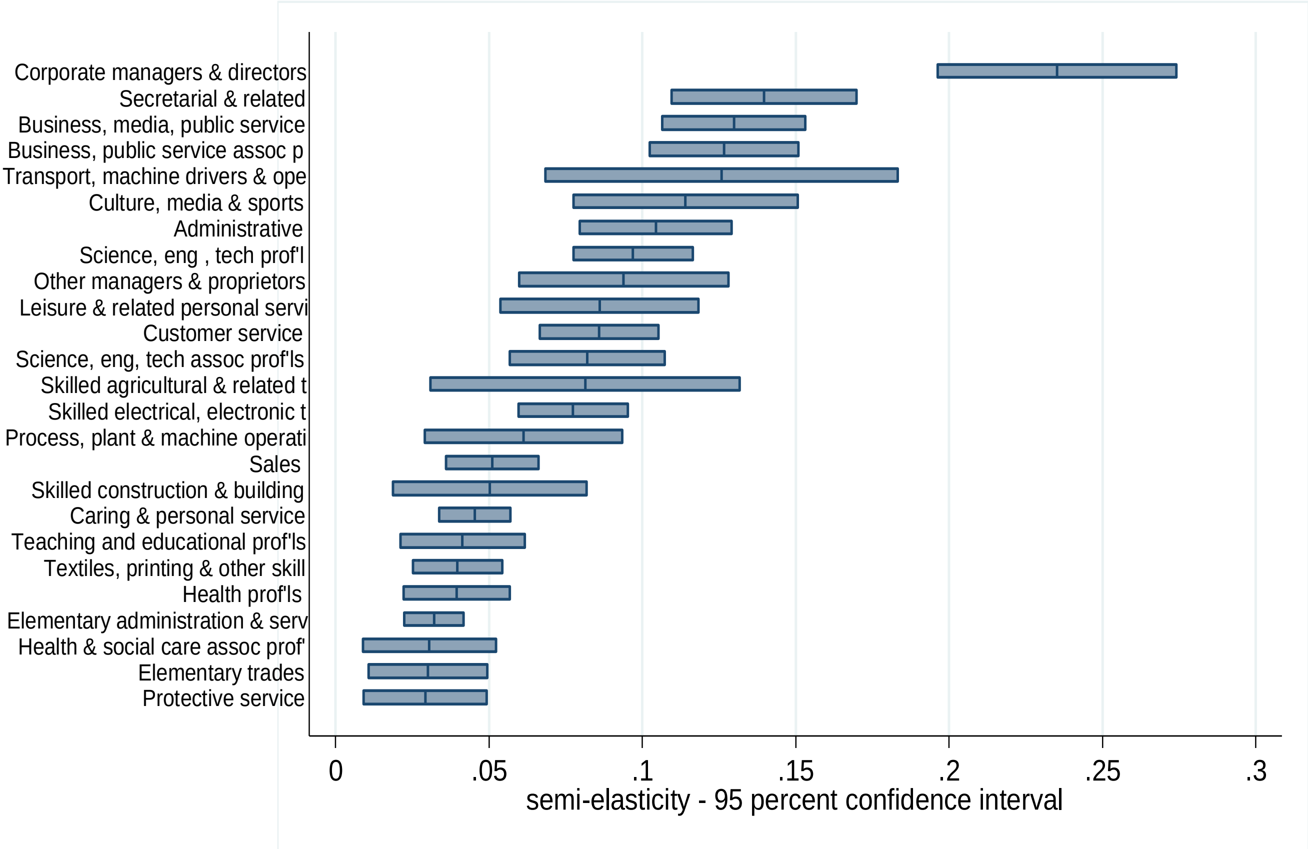
There are a number of reasons for expecting the elasticity of earnings with respect to sparsity bias to vary across occupation groups. For many in the workforce, particularly among those employed in the public sector, national pay scales reduce the responsiveness of earnings to local labour market conditions; while for the lowest paid workers, the UK national minimum wage sets a wage floor. Outside of these groups, differences in the elasticity of labour supply play a role. We investigate these differences using ASHE data on mean hourly earnings by ITL3 area for each of the 25 SOC2010 sub-major occupational groups.

The bivariate regressions of average earnings on sparsity bias (sector-based, i.e. as constructed in section 4) for each of 25 occupational groups are reported in full in Table A4 of Appendix 3, and Figure 10 shows the central estimate of the semi-elasticity along with the 95 percent confidence interval in each case.[30] The estimated coefficient on the sparsity bias measure is statistically significantly different from zero for all occupations; values of the t-statistic range from 2.78 (Health and Social Care Professionals) to 11.9 (Corporate Managers and Directors). The explanatory power of the simple regression varies substantially across the occupational groups, with adjusted R-squared values of less than 0.1 for Protective Services, Health and Social Care Associate Professionals, Elementary Trades and Skilled Building and Construction Trades, to in excess of 0.5 for Business and Public Service Associate Professionals, Administrative occupations, Secretarial occupations and Corporate Managers and Directors.

The estimated semi-elasticity varies as expected, being relatively low in occupations dominated by the public sector – teaching professionals, health and social care professionals and associate professionals, and protective service occupations (police, fire and prison service) – where national pay scales prevail, and also for elementary trades and services where spatial variation in earnings may be expected to be constrained by the national minimum wage. Among the remaining occupational groups, the estimated semi-elasticities lie in the interval 0.05 to 0.15, with the notable exception of Corporate Managers where the estimated value is significantly larger at 0.23. We conjecture that this is linked to tradability as exporting firms are larger than average and managerial compensation increases with firm size.

[30] The semi-elasticity is the proportionate change in earnings per unit change in sparsity bias. We use this since the absolute level of earnings varies widely across occupations. The corresponding semi-elasticity for the full labour force (from Table 4) is 0.18.

Figure 10: Semi-elasticity of occupational earnings with respect to sparsity bias



6.3: Sparsity bias v specialisation*:*

An alternative explanation for our findings is that areas benefit from employment specialisation, but the nature of that specialisation – whether it is in tradable sectors or otherwise – is not a key driver for earnings. To assess this argument, we examine the relationship between area earnings and the value of the area's Krugman Specialisation Index (Table A6 , Appendix 3). The Krugman Specialisation Index, while statistically significant, has limited explanatory power for either mean hourly earnings or area differentials. Including the Krugman specialisation index together with the sparsity bias measure adds little additional explanatory power and the coefficient on the sparsity bias index is only marginally reduced in magnitude and remains well determined. The same is true when the Krugman specialisation index is included in our results on historical change (Tables A7, A8, Appendix 3).

6.4: Alternative geographies: Travel-to-Work areas.

The ITL3 geography of Great Britain is based on the local administrative units – counties, unitary authorities, local authority districts in England and Wales; council areas in Scotland – and as such the boundaries are determined by administrative, rather than economic, considerations. Travel-to-work areas (TTWA) provide an alternative spatial classification intended to approximate labour market areas – self-contained areas in which most people both live and work. The criteria for the TTWA (2011) are that at least 75% of the area's resident population work in the area and at least 75% of the people who work in the area also live in the area; subject to the area having an economically active population of at least 3500. The resulting 218 TTWA areas of Great Britain vary greatly in size, with employment numbers varying from approximately 3,000 to nearly 5 million, compared with a range of 20,000 to 845,000 for ITL3 areas.

To test the robustness of our key findings, we undertake a parallel analysis using the TTWA geography. The spatial distribution of mean hourly earnings across TTWAs is markedly less dispersed than for ITL3 areas. The smaller dispersion is apparent for both the sector differential and the area differential components, but particularly the latter (see Table A11). The bivariate regression results are reported in full in Table A12. Estimated coefficients are very well-determined as before. The coefficients are of smaller absolute magnitude than those reported in Table 4 but are significant at the 0.01 level. The estimates imply that an increase in sparsity bias of one standard deviation is associated with a 9.1 percent increase in area mean hourly earnings at the sample mean. Just over 40 percent of this increase in area mean earnings is driven by the sector-differential effect and nearly 60 percent through the area differential, numbers extremely close to those found using the ITL3 geography.

7. Concluding comments

This paper shows the importance of the sectoral employment composition of areas in determining their levels of earnings, thereby shaping regional disparities within a country. In the theoretical section we show how the tradability of a sector determines the equilibrium response to productivity differentials (assumed to be exogenous), with a productivity advantage in highly tradable sectors tending to increase employment and wages, while a similar advantage in a non-tradable sector can reduce nominal wages. In the empirical section we show how the bias of an area's employment towards sectors that are 'sparse' (our empirical proxy for tradability) is strongly positively correlated with average earnings in the area. The effect is greater than the simple composition effect (arising from sectoral wage differences), and reflects the equilibrium response of employment, prices, and wages in an area to productivity variation, as suggested by the theory.

The study draws out a number of points that need to inform the design of policy. The first is simply the recognition that different areas have significantly different economic structures. This matters for many aspects of policy. Currency depreciation or fiscal expansions will have quite different effects on areas whose employment is skewed towards internationally tradable sectors, compared to those that are producing principally for the domestic or local market.

The second is the importance of diagnosing the causes of apparent productivity differences. We have shown how spatial variations in revenue productivity can be very different from variations in physical productivity. It is possible that, while the physical productivity of a sector in an area is relatively high, local prices and hence revenue productivity are low. The policy prescription is then not to seek higher efficiency in the sector, but to look to the overall economic structure of the area. What the area does may matter more than how well it performs in particular activities.

The third is the danger of being stuck with sectors that are non-tradable and probably also relatively unskilled labour intensive. It is understandable that regional policies have focussed on short-run job creation, but this has often led to an emphasis on attracting non-tradable sectors in which there is an assured local and national demand. This can accelerate the process of lock-in to low-value jobs, reinforcing the long-run problems we observe.

Fourth, the fundamental market failure that creates regional inequalities is the locational 'stickiness' of many highly tradable sectors. Where areas have lost sectors in which they had a traditional comparative advantage, they have typically not replaced these sectors with others that are highly tradable. The representation of shocks of this type in the present paper is simply as Ricardian productivity differences, differences that do not get ironed out by technology transfer. A richer story would be based on agglomeration economies, so that productivity differentials become endogenous to the scale of activity in an area-sector. Then stickiness arises from coordination failure and the first-mover problem, making it hard for a newly established activity that has not reached the scale to achieve agglomeration economies to compete against established centres.

Does it follow from this that all areas should strive to have 'sparse' sectors? Since locational stickiness is largely due to agglomeration economies, scale, and the benefits derived from clustering related activities together, it is inefficient (and likely impossible) to spread sparse sectors over many relatively small locations. Some areas will benefit from hosting sparse sectors, and others need to be well-enough connected to them to be profitable for sectors that are sufficiently tradable to benefit from interaction with these areas.

Finally, agglomeration economies and stickiness mean that the proportion of the labour force of the country as a whole that is employed in tradable sectors is not uniquely determined by the fundamentals of technology, endowments and preferences. It is possible that an economy has 'too few' such industries, this reducing real income for the economy as a whole (Venables 2018, 2020). This is the counterpart of poor performance of particular regions, impacting the country as a whole through the equilibrium location of sectors of activity.

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Appendix 1: Section 3

Price elasticities of demand: From equation (5) with foreign trade set to zero and income the same in all places (*M*) total sector *s* sales of place 1 are

$$x_{1s} = p_{1s}^{-\sigma}\beta_s \sum_j M_j \tau_{ijs} P_{js}^{\sigma-1} = p_{1s}^{-\sigma}\left[P_{1s}^{\sigma-1} + \sum_{j\neq 1}^{N} \tau_s P_{js}^{\sigma-1}\right]\beta_s M \qquad \text{(A1)}$$

Equation (2) gives the price indices as:

$$P_{1s}^{1-\sigma} = (p_{1s})^{1-\sigma} + \sum_{j\neq 1}^{N} \tau_s p_{js}^{1-\sigma}, \qquad \text{(A2)}$$

$$P_{js}^{1-\sigma} = \left(p_{js}\right)^{1-\sigma} + \tau_s p_{1s}^{1-\sigma} + \sum_{i\neq 1,j}^{N} \tau_s p_{is}^{1-\sigma} \; for \;\; j \neq 1. \qquad \text{(A3)}$$

Differentiating A2, A3 with respect to p_{1s} around the symmetric equilibrium gives $\hat{P}_{1s} = \hat{p}_{1s}\mu_s$, and for $j \neq 1$, $\hat{P}_{js} = \hat{p}_{1s}\mu_s\tau_s$. In these expressions μ_s is the share of the local sector *s* market which is supplied by local firms and $\mu_s\tau_s$ the share supplied by 'imports' from one other region. In the symmetric base equilibrium $\mu_s$is also the share of local sector s output which is sold in the local market and $\mu_s\tau_s$ the share that is 'exported' to each other place. It follows that,

$$\mu_s + (N-1)\mu_s\tau_s = 1, \;\text{so}\; (N-1)\tau_s = (1-\mu_s)/\mu_s. \qquad \text{(A4)}$$

Differentiating (A1) with respect to p_{1s} ,

$$\hat{x}_{1s} = -\sigma\hat{p}_{1s} + (\sigma-1)\hat{p}_{1s}\left[\frac{\hat{P}_{1s}P_{1s}^{\sigma-1} + \hat{P}_{js}(N-1)\tau_s P_{js}^{\sigma-1}}{P_{1s}^{\sigma-1} + (N-1)\tau_s P_{js}^{\sigma-1}}\right],$$

$$\hat{x}_{1s} = -\sigma\hat{p}_{1s} + (\sigma-1)\hat{p}_{1s}\left[\frac{\mu_s + (N-1)\mu_s{\tau_s}^2}{1+(N-1)\tau_s}\right],$$

Hence, with (A4),

$$E_s \equiv -\hat{x}_{1s}/\hat{p}_{1s} = \sigma - (\sigma-1)\mu_s[\mu_s + (1-\mu_s)\tau_s]. \qquad \text{(A5)}$$

Notice that μ_s is decreasing in τ_s (greater tradability reduces home market dominance) and that E_s is increasing in τ_s (by differentiation of A5 using A4).

Comparative Statics: Income is $M = \sum_s p_s x_s + R$, where R is total rent generated in the region, $R = rK = \alpha M$ (equation 7 with $\gamma = 1$). In the base equilibrium sectoral shares of income equal sectoral shares of consumption so deviations of income from base equilibrium values satisfy $\widehat{M} = \sum_s \beta_s(\hat{p}_s + \hat{x}_s) + \alpha\hat{R}$, with $\sum_s \beta_s = 1 - \alpha$. The comparative static experiment is to change variables in one small region with national aggregates constant. We assume that rental income generated in a region is spent in that region, according to the same preferences as wage income. Since rent is a fixed share of income changes satisfy $\hat{R} = \widehat{M}$ and hence

$$\widehat{M} = \sum_s \beta_s(\hat{p}_s + \hat{x}_s)\,/(1-\alpha)\,. \tag{A6}$$

The value of demand and hence output in each sector depends on price and income, according to $\hat{p}_s + \hat{x}_s = (1 - E_s)\hat{p}_s + \mu_s\widehat{M}$, where the last term is the income effect, i.e. the growth in place 1 income times the share of the sector's sales that are made in the place 1 market. This is unity for perfectly non-tradable goods, and $1/N$ for perfectly tradable, since $\mu_s = 1/\{1 + (N-1)\tau_s\}$ (section 3.1). As in section 3.1, at the base equilibrium, μ_s is, for each sector, both the place's market share in its home market, and the share of its output that goes to its home market. Prices change according to $\hat{p}_s = \widehat{w} - \hat{a}_s$, so

$$\hat{p}_s + \hat{x}_s = (1 - E_s)(\widehat{w} - \hat{a}_s) + \mu_s\widehat{M}. \tag{A7}$$

Using this in (A6) gives, $\widehat{M} = \sum_s \beta_s\{(1 - E_s)(\widehat{w} - \hat{a}_s) + \mu_s\widehat{M}\}/(1-\alpha)$, so rearranging and using $1 - \alpha = \sum_s \beta_s$ gives

$$\widehat{M} = \sum_s \beta_s(1 - E_s)(\widehat{w} - \hat{a}_s)\,/\sum_s \beta_s(1 - \mu_s). \tag{A8}$$

The expression $\sum_s \beta_s(1 - \mu_s)$ is the share of expenditure spent on 'imports' (across all sectors).

Since prices in all places except place 1 are constant, changes in sectoral price indices in place 1 are $\hat{P}_s = \mu_s\hat{p}_s = \mu_s(\widehat{w} - \hat{a}_s)$. The change in the cost-of-living is $\hat{e} = \sum_s \beta_s\hat{P}_s + \alpha\hat{r}$, and the rental rate is $\hat{r} = \widehat{M}/(1+\eta)$, so

$$\hat{e} = \sum_s \beta_s\hat{P}_s + \alpha\hat{r} = \sum_s \beta_s\mu_s(\widehat{w} - \hat{a}_s) + \alpha\widehat{M}/(1+\eta). \tag{A9}$$

Using (A8) in (A9),

$$\hat{e} = \sum_s \beta_s(\widehat{w} - \hat{a}_s)\left[\mu_s + \frac{\alpha}{(1+\eta)}\frac{(1 - E_s)}{\sum_s \beta_s(1 - \mu_s)}\right] \tag{A10}$$

The first term, $\sum_s \beta_s(\widehat{w} - \hat{a}_s)\mu_s$, gives the direct effect of changes in the prices of goods and services on the cost of living. The remainder gives an equilibrium effect through changes in rent. The mechanism is via the effect of price changes on demand and hence output and income (A8), times the share of housing in expenditure and divided by one plus the elasticity of land supply, the effect going to zero if this elasticity is infinite.[31]

[31] In a closed region $\mu_s = 1$ for all s. As $\sum_s \beta_s(1 - \mu_s) \to 0$ so $E_s \to 1$, see (A5), and $\hat{e} = \sum_s \beta_s(\widehat{w} - \hat{a}_s)\,[1 + \alpha/(1+\eta)]$.

Worker utility changes according to $\hat{u} = \hat{w} - \hat{e}$, so the wage change is

$$\hat{w} = \frac{\hat{u} + \sum_s \beta_s \hat{a}_s \psi_s}{1 + \sum_s \beta_s \psi_s}, \quad with \quad \psi_s \equiv \frac{\alpha}{(1+\eta)} \frac{(E_s - 1)}{\sum_s \beta_s (1 - \mu_s)} - \mu_s. \qquad \text{(A11)}$$

Productivity change occurs only in place 1 so if N is large $\hat{u} \cong 0$ implying $\hat{w} = \hat{e}$. The denominator, $1 + \sum_s \beta_s \psi_s$, is positive if $E_s \geq 1$, since it is increasing in E_s and at $E_s = 1$, it becomes $1 - \sum_s \beta_s \mu_s > 0$. Hence $\hat{w} > 0$ if there is a positive correlation between $\hat{a}_s$ and ψ_s.

If $\hat{w} > 0$ and all $\hat{a}_s > 0$ then, for some sector s, $\hat{a}_s > \hat{w}$, since $1 = \sum_s \beta_s \psi_s (\hat{a}_s - \hat{w})/\hat{w}$

Using (6) and (A7) the sectoral employment change is $\hat{L}_s = \hat{p}_s + \hat{x}_s - \hat{w} = (E_s - 1)(\hat{a}_s - \hat{w}) + \mu_s \widehat{M} - \hat{w}$. The change in total employment in place 1 is $\hat{L} = \widehat{M} - \hat{w}$, so the change in the share of sector s in place 1 employment is $\hat{L}_s - \hat{L} = (E_s - 1)(\hat{a}_s - \hat{w}) - (1 - \mu_s)\widehat{M}$. The first term $(E_s - 1)(\hat{a}_s - \hat{w})$ amplifies variance in these employment shares, creating high employment shares of sectors for which each of the terms $(E_s - 1)$, $(\hat{a}_s - \hat{w})$ are positive.

Parameters in simulation: section 3.3. The price elasticity of supply of land, $\eta = 1$: Combes et al. (2019) use data on Paris to derive estimates for the elasticity of house prices with respect to city population, and land prices with respect to population. Their preferred estimates are respectively 0.21 and 0.60. From equation (7) holding income per household constant, the elasticity of rent with respect to population is $1/(1+\eta)$. Setting $\eta = 1$ places this in the centre of the range found by Combes et al. The elasticity of substitution in consumption between two products in the same sector produced in different places we assume to be high, $\sigma = 10$. A recent survey of literature on the use of these elasticities in trade modelling places them in the range 2.5 – 5.1 (Bajzik et al. 2020). The product differentiation literature often uses much higher values, in the range 5 – 15 (Broda and Weinstein 2006).

Consumption shares:
Housing: $\alpha = 0.25$.
Imports: $\beta_0 = 0.25(1 - \alpha) = 0.1875$
Sector shares: $\beta_s = (1 - \alpha - \beta_0)/m = 0.011$, (number of sectors m = 50)
Factor shares
Share of labour in production: $\gamma = 0.9$
Skill productivity and shares: $a^A = 3$, $a^B = 1$, $\rho = 0.5$, $v_s \in [0.25, 075]$.
Skill endowments: type A 30%, type B 70%.

Factor demand, average wages with two skill levels:

$$L_{is}^A = \frac{\gamma p_{is} x_{is}}{f(w_{is}^A, w_{is}^B)} \frac{v_s}{a^A} \left(\frac{w_{is}^A}{a^A} \right)^{-\rho}, \quad L_{is}^B = \frac{\gamma p_{is} x_{is}}{f(w_{is}^A, w_{is}^B)} \frac{(1 - v_s)}{a^B} \left(\frac{w_{is}^B}{a^B} \right)^{-\rho}.$$

$$For\ H = A, B:\ L_i^A = \sum_s L_{is}^A,\quad w_i^A = \sum_s w_{is}^A L_{is}^A / L_i^A,\quad w_i = \sum_{H=A,B} w_i^H L_i^H \,/\, \sum_{H=A,B} L_i^H.$$

$$For\ H = A, B:\ L_s^H = \sum_i L_{is}^H,\quad w_s^H = \sum_i w_{is}^H L_{is}^H / L_s^H,\quad w_s = \sum_{H=A,B} w_s^H L_s^H \,/\, \sum_H L_s^H$$

Appendix 2: Data Sources

Employment

(i) Number of employees by ITL3 area of Great Britain and SIC 2007 3-digit industry group (163x259) , 2015 to 2019.
Annual Business Register and Employment Survey 2015-2019. Data downloaded from National Online Manpower Information System (NOMIS)

(ii) Number of employees by ITL3 area of Great Britain and SOC 2010 sub-major occupational group (163x25), 2015 to 2019
Annual Population Survey (workplace-based), 2015-2019. ONS user requested data

(iii) Number of employees by pre-96 county/Scottish region and SIC-1968 industry minimum list heading (64x181), 1971 and 1981.
Census of Employment 1971 and 1981. Data downloaded from NOMIS

(iv) Number of employees by pre-96 county/Scottish region and SIC-1980 3-digit industry group (64x220), 1981 and 1991
Census of Employment 1981 and 1991. Data downloaded from NOMIS

Earnings

(i) Mean gross hourly earnings (all employees on adult rates) by ITL3 area (workplace-based)(163x1), 2015 to 2019.
Annual Survey of Hours and Earnings, Table 22.5a
https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/adhocs/12453earningsandhoursworkedworkandhomenuts2014revisedto2020provisional

(i) Mean gross hourly earnings (all UK employees on adult rates) by SIC2007 3-digit industry group (259x1), 2015 to 2019
Annual Survey of Hours and Earnings, Table 16.5a
https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/datasets/industry4digitsic2007ashetable16

(ii) Mean gross hourly earnings (all UK employees on adult rates) by SOC2010 sub-major occupational group (25x1), 2015 to 2019
Annual Survey of Hours and Earnings, Table 3.5a
https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/datasets/regionbyoccupation2digitsocashetable3

(iii) Mean gross hourly earnings (full-time male employees aged 21 and over) by pre-96 county/Scottish region (64x1), 1974 to 1993
New Earnings Survey: Analysis by Region, Table 110
https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/adhocs/005464newearningssurveynesgrossmeanweeklyearningsbyregionfortheyears1970to1996

Other data series

(i) Housing costs: median monthly rental (private sector) for two-bedroom accommodation by ITL3 (163x1), 2019.

ONS, Private Rental Market Statistics,
Table 2.4: Summary of 'Two Bedrooms' monthly rents recorded between 1 October 2018 to 30 September 2019 by administrative area for England
https://www.ons.gov.uk/peoplepopulationandcommunity/housing/datasets/privaterentalmarketsummarystatisticsinengland

Statistics for Wales, Private Sector Rents for Wales, SFR 48/2020, 21 May 2020
Table 2 - Median monthly rents recorded by property type and local authority area, January to December 2019
https://gov.wales/sites/default/files/statistics-and-research/2020-05/private-sector-rents-2019-047.pdf

Scottish Government, Private Sector Rent Statistics Scotland 2010 to 2019.
https://www.gov.scot/publications/private-sector-rent-statistics-2010-2019/

Administrative areas mapped into ITL3 areas using

ONS Local Authority District (December 2018) to NUTS3 to NUTS2 to NUTS1 (January 2018) Lookup in United Kingdom.

https://data.gov.uk/dataset/86beb640-9fa4-4131-b330-fc26d74c074f/local-authority-district-december-2018-to-nuts3-to-nuts2-to-nuts1-january-2018-lookup-in-united-kingdom

Appendix 3: Additional results on the relationship between sparsity bias and earnings

(i) Excluding the Agriculture, Forestry and Fishing and the Mining and Quarrying sectors .

Given the importance of physical geography in determining the location of sectors in Agriculture, Forestry and Fishing and the Mining and Quarrying., it may be argued that these parts of the economy should be excluded for the analysis. To check the robustness of our findings, we repeat the analysis of section 4 here excluding these sectors from our measures.

Figure A1: Mean hourly earnings and the sparsity bias of an area:

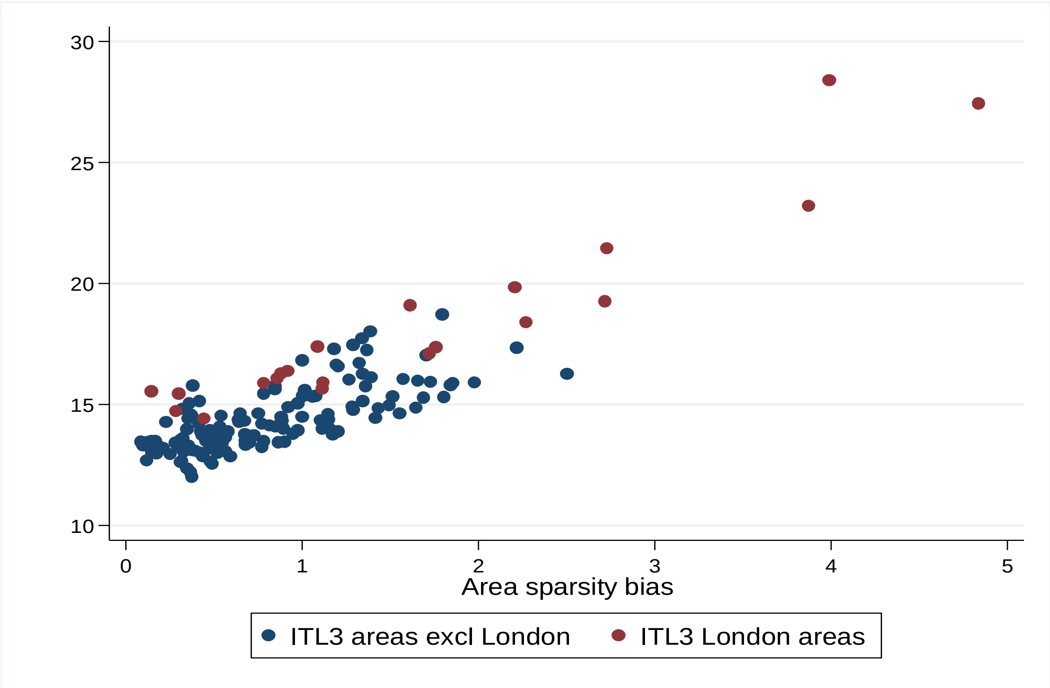

Table A1: Earnings, Sectoral Composition and Sparsity Bias:

	Mean Hourly Earnings	Sector-differential effect, $(\tilde{w}_i - \bar{w})$	Area-differential $(w_i - \tilde{w}_i)$
Sparsity bias index SB_i	2.7206 (10.31)	0.9193 (13.45)	1.8014 (8.24)
95% CI for SB_i coeff.	2.2, 3.24	0.78, 1.05	1.37, 2.23
Constant	12.3738 (58.05)	-1.766 (-30.33)	-1.5734 (-8.89)
Adj. R-squared	0.7477	0.8233	0.6104
No. of obs'ns	163	163	163
	Excluding London regions		
Sparsity bias index SB_i	1.9262 (11.45)	0.9203 (16.88)	1.0059 (7.12)
95% CI for SB_i coeff.	1.59, 2.26	0.81, 1.03	0.73, 1.28
Constant	12.8102 (90.64)	-1.7565 (-35.22)	-1.1464 (-9.37)
Adj. R-squared	0.5392	0.7166	0.2964
No. of obs'ns	142	142	142

(ii) Alternative measures of sparsity bias

The sparsity bias of each area is computed as the average of the sectoral sparsity measures weighted by the share of area employment in each sector. The results presented in the main text use as a measure of sectoral sparsity, the skewness of the spatial distribution of the location difference ($s_{is} - x_i$) where s_{is} is the share of total sector s employment that occurs in place i, and x_i.is the share of place i in total GB employment, x_i. Tables A2 and A3 report comparable results using measures based on the skewness of the spatial distribution location quotient s_{is}/x_i and log((s_{is}/x_i)+1). Table A4 shows the results using the standard deviation, rather than the skewness of the distribution of the location difference ($s_{is} - x_i$)

Table A2: Earnings and Sparsity Bias: sparsity bias measure based on skewness of distribution of the location quotient, s_{is}/x_i

	Mean Hourly Earnings	Sector-differential effect, ($\widetilde{w}_i - \overline{w}$)	Area-differential ($w_i - \widetilde{w}_i$)
Sparsity bias index SB_i	4.9614 (3.53)	1.8451 (4.38)	3.1163 (3.06)
95% CI for SB_i coeff.	2.18, 7.74	1.01, 2.68	1.11, 5.13
Constant	5.6819 (2.26)	-4.3635 (-5.78)	-5.6678 (-3.11)
Adj. R-squared	0.3589	0.4444	0.2872
No. of obs'ns	163	163	163
	Excluding London regions		
Sparsity bias index SB_i	2.5424 (4.53)	1.2507 (3.27)	1.2917 (4.07)
95% CI for SB_i coeff.	1.43, 3.65	0.49, 2.01	0.66, 1.92
Constant	9.6855 (9.57)	-3.3438 (-4.86)	-2.6839 (-4.57)
Adj. R-squared	0.1855	0.2309	0.1059
No. of obs'ns	142	142	142

t value in parentheses

Table A3: Earnings and Sparsity Bias: sparsity bias measure based on the skewness of the distribution of $\log((s_{is}/x_i)+1)$

	Mean Hourly Earnings	Sector-differential effect, $(\widetilde{w}_i - \overline{w})$	Area-differential $(w_i - \widetilde{w}_i)$
Sparsity bias index SB_i	10.867 (4.67)	3.9414 (6.88)	6.926 (3.86)
95% CI for SB_i coeff.	6.27, 15.46	2.81, 5.07	3.39,10.47
Constant	8.1648 (6.00)	-3.3784 (-10.04)	-4.17 (-3.98)
Adj. R-squared	0.5333	0.6270	0.4156
No. of obs'ns	163	163	163
	Excluding London regions		
Sparsity bias index SB_i	6.3271 (4.22)	3.2053 (5.30)	3.1217 (3.20)
95% CI for SB_i coeff.	3.36, 9.29	2.01, 4.00	1.19, 5.05
Constant	10.55 (12.08)	-2.9734 (-8.45)	-2.19 (-3.85)
Adj. R-squared	0.3193	0.4206	0.1633
No. of obs'ns	142	142	142

t-values reported in parentheses.

Table A4: Earnings and Sparsity Bias: sparsity bias measure based on the standard deviation of the distribution of $(s_{is} - x_i)$)

	Mean Hourly Earnings	Sector-differential effect, $(\tilde{w}_i - \bar{w})$	Area-differential $(w_i - \tilde{w}_i)$
Sparsity bias index SB_i	1282.61 (2.35)	520.89 (3.10)	761.72 (1.97)
95% CI for SB_i coeff.	918.5, 1646.7	188.7, 853.0	1.41, 1524.9
Constant	7.9506 (2.79)	-3.7566 (-4.28)	-4.0061 (-1.99)
Adj. R-squared	0.2264	0.3361	0.1556
No. of obs'ns	163	163	163
	Excluding London regions		
Sparsity bias index SB_i	658.56 (2.94)	344.95 (3.03)	313.61 (2.19)
95% CI for SB_i coeff.	215.7, 1101.4	199.9, 569.9	30.58, 596.64
Constant	10.82 (9.15)	-2.9008 (-4.85)	-2.00 (-2.63)
Adj. R-squared	0.1326	0.1885	0.0675
No. of obs'ns	142	142	142

t-values reported in parentheses.

(iii) Occupational Earnings and Sparsity Bias

Table A5: Wages and sparsity bias by occupation

	Mean gross hourly earnings 2015-19 (sample mean)	Estimated coefficient for sparsity bias	t -value	Semi-elasticity (at sample mean)	Adjusted R-sqd
Corporate managers and directors	21.59	5.0799	11.9	0.2353	0.6562
Secretarial and related	9.91	1.3837	9.14	0.1397	0.5949
Business, media and public service professionals	18.76	2.4351	11.01	0.1298	0.4742
Transport and mobile machine drivers and operatives	16.23	2.056	10.33	0.1267	0.5223
Business and public service associate professionals	10.87	1.3676	4.33	0.1258	0.3662
Culture, media and sports	12.55	1.4312	6.16	0.1141	0.2502
Administrative occupations	11.30	1.1787	8.32	0.1043	0.5416
Science, research, engineering and technology professionals	19.56	1.8969	9.82	0.0970	0.3707
Other managers and proprietors	14.73	1.3828	5.44	0.0939	0.1559
Leisure, travel and related personal service	9.18	0.79	5.27	0.0860	0.2421
Customer service	10.22	0.8776	8.8	0.0859	0.33
Science, engineering, technology associate professionals	13.92	1.142	6.41	0.0821	0.1986
Skilled agricultural and related trades	9.48	0.7713	3.2	0.0814	0.1502
Skilled metal, electrical and electronic trades	13.64	1.0563	8.57	0.0774	0.3092
Process, plant and machine operatives	10.71	0.6567	3.77	0.0613	0.0954
Sales occupations	8.39	0.429	6.71	0.0511	0.4544
Skilled construction and building trades	12.35	0.6211	3.15	0.0503	0.0744
Caring personal service	9.15	0.4155	7.74	0.0454	0.2757
Teaching and educational professionals	21.63	0.8939	4.02	0.0413	0.1198
Textiles, printing and other skilled trades	9.11	0.3623	5.37	0.0398	0.1475
Health professionals	19.08	0.7512	4.49	0.0394	0.1058
Elementary administration and service occupations	8.39	0.269	6.51	0.0320	0.271
Health and social care associate professionals	12.80	0.3913	2.78	0.0306	0.04
Elementary trades and related occupations	9.05	0.272	3.06	0.0301	0.0721
Protective service occupations	16.38	0.4788	2.88	0.0292	0.044

(iv) The relationship between housing costs, sparsity bias and earnings

Table A5 reports evidence of a strong positive relationship between area housing costs, sparsity bias and mean earnings. The direct relationship between housing costs and area sparsity bias is shown in column 1. Columns 2 and 3 reports the estimates of the regression of housing costs on mean hourly earnings, and on sector-differentials and area-differentials. These results show that the relationship between rents and area average earnings is driven by the area-differentials, with the estimated coefficient on sector-differentials insignificantly different from zero.

Table A6: House rents, sparsity bias, and earnings.

	House rent	House rent	House rent	House rent (log)
Sparsity bias index SB_i	335.1 (7.07)			
Hourly earnings (log)				2.27 (10.33)
Hourly earnings		129.4 (6.49)		
Sector differential			-40.474 (-1.00)	
Area differential			216.26 (6.57)	
Constant	445.1 (10.85)	-1156 (-4.05)	730.11 (20.28)	0.45 (0.77)
Adj. R-squared	0.409	0.609	0.663	0.592
No. of obs'ns	163	163	163	163

House rental: median monthly rental (private sector) for 2 bedroom accommodation, 2019

(v) Sparsity bias vs. specialisation

Table A7: Relationship between Earnings, sparsity bias and specialisation, 2015-2019

	Mean Hourly Earnings (av. 2015-19)		
Sparsity bias index SB_i	2.7180 (10.06)		2.6042 (11.84)
95% CI for SB_i coeff.	2.18, 3.25		2.17, 3.04
Krugman Specialisation Index		8.8484 (2.11)	2.4313 (2.04)
Constant	12.256 (53.5)	10.63 (5.59)	11.201 (17.23)
Adj. R-squared	0.7413	0.1443	0.7498
No. of observations	163	163	163

	Area-Differential		
Sparsity bias index SB_i	1.7628 (7.69)		1.6106 (9.22)
95% CI for SB_i coeff.	1.31, 2.22		1.27, 1.96
Krugman Specialisation Index		7.2216 (2.64)	3.253 (3.39)
Constant	-1.5921 (-8.24)	-3.3565 (-2.70)	-3.0037 (-5.91)
Adj. R-squared	0.5939	0.1851	0.6305
No. of observations	163	163	163

(vi) Sparsity bias and wages: historical relationships and changes

Table A8: Relationship between Earnings, sparsity bias and specialisation: historical levels

	Mean Hourly Earnings (full-time males aged 21 years or more) £ per hour		
	1974/75	1982/83	1992/93
Sparsity bias index SB_i (1971, 1981, 1991)	0.0783 (3.79)	0.1154 (4.22)	0.2431 (7.37)
95% CI for SB_i coeff.	0.037, 0.119	0.061, 0.170	0.177, 0.309
Krugman Specialisation Index	0.0011 (0.01)	-0.0565 (-0.072)	0.188 (1.27)
Constant	0.9767 (19.65)	1.0467 (20.21)	1.1812 (16.39)
Adj. R-squared	0.3964	0.4678	0.6411
No. of obs'ns	58	60	61

Table A9: Relationship between Earnings, sparsity bias and specialisation, historical changes

	Change in mean real hourly earnings		
	1974/75 to 1982/83	1982/83 to 1992/93	1974/75 to 1992/93
Change in Sparsity bias index SB_i	0.0887 (2.23)	0.1392 (3.34)	0.1482 (4.81)
95% CI for SB_i coeff.	0.009, 0.168	0.056, 0.223	0.086, 0.21
Change in Krugman Specialisation Index	0.0406 (0.28)	0.2070 (0.062)	0.2948 (1.09)
Constant	0.0755 (6.05)	0.2619 (7.59)	0.426 (8.35)
Adj. R-squared	0.2749	0.2605	0.3174
No. of obs'ns	58	60	58

Appendix 4: Earnings and Sparsity Bias: Alternative UK Geographies

Table A10 reports the summary statistics for the distribution of employment numbers (2015-2019 average) for the 163 ITLs areas and the 2018 TTWA areas for comparison.

Table A10: Distribution of total employment by area (average for 2015 to 2019)

	ITL3 2015	**TTWA 2011**
Mean	180,681	134,317
Median	140,568	60,039
Standard deviation	120,849.6	360,742.6
Minimum	20,334	2,752
Maximum	844,628	4,929,610
Number	163	218

Table A11: Hourly earnings; descriptive statistics by "travel to work area" and by sector. £ per hour.

	Mean	Median	Variance	Min	Max
TTWA area mean hourly earnings (all sectors): w_i	13.60	13.48	2.8332	10.47	20.65
SIC3 sector mean hourly earnings (all UK): w_s	15.65	14.96	17.61	8.10	34.49
TTWA sector-differential effect: $(\tilde{w}_i - \overline{w})$	-1.2487	-1.2647	0.503	-2.65	1.007
TTWA area-differential: $w_i - \tilde{w}_i$	-0.771	-0.9345	1.2431	-2.92	3.242

Table A12 Earnings and Sparsity Bias: travel to work areas

	Mean Hourly Earnings	Sector-differential effect, $(\tilde{w}_i - \bar{w})$	Area-differential $(w_i - \tilde{w}_i)$
TTWA Sparsity bias index SB_i	0.9431 (13.11)	0.3980 (15.37)	0.5509 (8.74)
95% CI for SB_i coeff.	0.80, 1.09	0.34, 0.44	0.43, 0.68
Constant	15.3 (93.74)	-0.5399 (-9.30)	0.2249 (1.61)
Adj. R-squared	0.5341	0.5201	0.4143
No. of obs'ns	218	218	218
Excluding London travel to work area			
Sparsity bias index SB_i	0.9126 (12.64)	0.3980 (15.14)	0.5146 (8.95)
95% CI for SB_i coeff.	0.77, 1.05	0.35, 0.45	0.40, 0.63
Constant	15.2353 (92.40)	-0.5276 (-8.66)	0.1479 (1.14)
Adj. R-squared	0.4997	0.5068	0.3697
No. of obs'ns	217	217	217

t-values reported in parentheses.