THE PRODUCTIVITY INSTITUTE

Economic and Social Research Council

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

Authors:

Patricia Rice[x]
University of Oxford

Anthony J. Venables[y]
The University of Manchester

Date:

June 2022

The Productivity Institute
Working Paper No. 021

[x] **Department of Economics and St. Anne's College, Oxford**
[y] **The Productivity Institute, Alliance Manchester Business School and Monash University, Melbourne**

Key words
Regional economics, lagging regions, tradability, productivity, disparities

Authors' contacts:
Anthony.venables@manchester.ac.uk

JEL codes
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.

Suggested citation

P. G. Rice, A. J. Venables (2022) *Tradability, Productivity, and Regional Disparities: theory and UK evidence*. Working Paper No. 021, The Productivity Institute.

The Productivity Institute is an organisation that works across academia, business and policy to better understand, measure and enable productivity across the UK. It is funded by the Economic and Social Research Council (grant number ES/V002740/1).

More information can be found on The Productivity Institute's website. Contact us at theproductivityinstitute@manchester.ac.uk

Publisher

The Productivity Institute, headquartered at Alliance Manchester Business School, The University of Manchester, Booth Street West, Manchester, M15 6PB.

Abstract

Variations in productivity across regions and sectors are features of most economies. The impact of such variation depends on the characteristics of these sectors, including the tradability (local, regional, or global) of sectoral output. This paper develops an analytical framework which shows how these sectoral characteristics determine regional outcomes, in real terms and as conventionally measured. We generate predictions about the effects of sectoral structure (in particular tradability), showing the positive effect of an area's bias towards highly tradable activities on its average earnings. Empirical analysis of recent earnings data for the ITL3 areas of GB demonstrates the presence of this relationship. As suggested by the theory, two factors drive this effect. Approximately one-third is a direct result of sectoral composition – on average across GB, tradeable 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, whereas a similar advantage in non-tradables (facing a less elastic demand curve) can lead to lower local prices, cost-of-living, and nominal wages. While our primary analysis is on recent data, we show that our approach also captures the impact of the structural change that occurred in GB during the 1970s and 1980s on regional wage differentials.

1. Introduction

Spatial differences in incomes and productivity are a persistent feature of many economies, including high income countries that have experienced technology and trade shocks over recent decades. These shocks were often highly concentrated in particular regions, removing 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 these places have often failed to find new sources of comparative advantage.

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 skill and other employee attributes. This effect can be quantified by calculating what average earnings would be in a place if all sectors paid their national average wage levels. 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, which vary greatly according to the tradability of the sector's output. If a place has a productivity advantage in a tradable good this leads to higher output, employment, and hence also to higher prices of non-tradable goods and services, and a higher cost-of-living. But non-tradable sectors face a less elastic demand curve and so a productivity advantage here, rather than expanding output and employment, may simply reduce prices, and hence lower the local cost-of-living. High productivity in tradable sectors therefore 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 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.

---

[1] We shall refer to sectors throughout, since the main empirical work is based on fine sectoral data. A final section of the paper uses an occupational rather than sectoral categorization of employment.

[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).

Using the place-sector distribution of employment and UK average earnings by sector, we decompose average earnings in each place into two elements, the sector-differential effect and the area-differential. The sector-differential component contributes relatively little to the variation of average earnings, the larger part coming from the area-differential.

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 '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 accounts for nearly 75% of the spatial variation in average earnings, operating through both the area-differential and sector-differential components . The former as the equilibrium effect of sparsity-bias creates spatial variation in employment and the cost-of-living, causing variation in nominal wages. The latter because sparse sectors tend to be more highly skilled with relatively high earnings, inducing a correlation between the sparsity-bias and the average earnings of each place. The former effect is quantitatively three to four times greater than the latter.

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 any productivity advantage leads to output expansion until the effect is shifted to an increase in the price of local inputs. In contrast, 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 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.

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 regional wage differences by sector and occupation have been undertaken by Rice et al. (2004) and Oguz (2019), these leading to the suggestion that sector-differentials 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. Section five uses data from the period 1971 to 1993 to study the effect of the deindustrialisation and structural change experienced in the UK during that period.[4] Data for this period is less finely spatially disaggregated, but we show that the positive relationship between sparsity-bias and area earnings holds, that structural change reduced sparsity-bias in many places, and that areas' loss of sparsity-bias is significantly associated with a reduction in their average earnings relative to the national average. Section six takes an occupational, rather than a sectoral, cut of the recent data. This is less disaggregate, but nevertheless demonstrates positive correlation between 'occupational-sparsity-bias' and area average earnings. Section seven provides some further checks on our findings and outlines some questions/issues for future research. Section eight concludes, and outlines policy implications of our findings.

[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.

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

2. Theory

A country contains many distinct places, indexed $i = 1 \ldots N$, and many activities or sectors indexed $s = 1 \ldots S$. 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 sector-differential 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, and productivity may be place-sector specific, denoted a_{is}. We assume constant returns to scale and allow productivity levels to exhibit exogenous Ricardian differences, abstracting from other sources of productivity variation such as agglomeration economies. The producer price of a sector s good produced in place i is then

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

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.

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

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

The intra-sector elasticity of substitution is σ, 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. Demand in each place j in the economy is derived

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

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

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

In this expression household income is y_{js} and $e\left(r_j,\ P_{j1} \dots P_{jS}, p_0\right)$ is the unit expenditure function. 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 $x_{ijs} = M_j \beta_s p_{is}^{-\sigma} t_{ijs}^{1-\sigma} / P_{js}^{1-\sigma}$.[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 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 $x_{i0s} = (q p_{is})^{-\sigma} {t_s}^{1-\sigma}$ 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,

$$\beta_0 \sum_i M_i = \sum_s \sum_i (q p_{is} t_s)^{1-\sigma}. \qquad (4)$$

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

$$x_{is} = p_{is}^{-\sigma} \beta_s \sum_j M_j t_{ijs}^{1-\sigma} / P_{js}^{1-\sigma} + (q p_{is})^{-\sigma} {t_s}^{1-\sigma}. \qquad (5)$$

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

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

[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).

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

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

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 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

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

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,

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

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 $e(r_i, P_{i1} \ldots P_{iS}, p_0)$. With the sector and place distribution of workers given by $\pi_{is} L$, full employment is

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

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

[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).

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, t_s. It is convenient to think of a base equilibrium in which there is no exogenous spatial heterogeneity 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. To see this response we start with a simple simulation example, and then use a combination of local comparative static analysis of the model around the base equilibrium and numerical simulation of the full model. This establishes our results about the role of sectoral structure and tradability in creating wage differences, and also introduces and demonstrates the concepts and approach used in the following empirical work.

3.1 A 3-sector example.

Table 1 reports equilibrium outcomes of the model in an example with just three sectors and a large number of places (N = 200). The three sectors have respectively perfect tradability ($t_1 = 1$), intermediate, ($t_2 = 2$) and low ($t_3 = 3$). The places are identical, except that three of the 200 places have a 50% productivity advantage in one of sectors. Place 1 has advantage in the most tradable sector, $a_{11} = 1.5$, place 2 in the intermediate tradability sector, $a_{22} = 1.5$, and place 3 in the least tradable sector, $a_{33} = 1.5$; all other a_{is} = 1. 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.[9] 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.

Productivity levels and equilibrium outcomes in places 1 – 3 are given in columns of the table, all variables expressed relative to their values in the rest of the economy.[10] Place 1 has a productivity advantage in the most tradable sector and sees nominal wages and value added per worker 24% above levels in the rest of the economy, together with higher rents and total employment more than twice the level in most other places. Place 3 has productivity advantage in sector 3, the least tradable, and has a wage lower than elsewhere in the country. With no 'export' response to other places, high productivity in this sector reduces the price of good 3,

[9] See Appendix 2 for discussion of these parameters. Expenditure function parameters are $\alpha = \beta_s = 0.25$. The price elasticity of demand for output of sectors s = 1, 2, 3 can be calculated (equation 11) and takes values E_s ={10, 5.3,1.18} for t_s ={1, 2 ,3}. Perfect labour mobility means that w_{is} takes common value w_i in all sectors in place i.

[10] Since there are 200 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 reducing the cost-of-living and thereby attracting an increase in population, L_3. Place 2 is intermediate, and has an intermediate wage increase. It experiences the highest rents and total employment as expansion of sector 2 is accommodated by contraction of sector 1, readily imported from place 1.

Table 1: Impacts of Ricardian productivity differences:

	Place i = 1;	Place i = 2;	Place i = 3;
Productivity, a_{is}			
$s = 1; \quad t_s = 1.$	$a_{11} = 1.5$	$a_{21} = 1$	$a_{31} = 1$
$s = 2; \quad t_s = 2.$	$a_{12} = 1$	$a_{22} = 1.5$	$a_{32} = 1$
$s = 3; \quad t_s = 3.$	$a_{13} = 1$	$a_{23} = 1$	$a_{33} = 1.5$
Wage, w_i	$w_1 = 1.24$	$w_2 = 1.14$	$w_3 = 0.96$
Rental, r_i	$r_1 = 1.65$	$r_2 = 1.80$	$r_3 = 1.38$
Total employment: $L_i = \sum_s L_{is}$	$L_1 = 2.28$	$L_2 = 2.93$	$L_3 = 1.96$
Sectoral employment $s = 1$	$L_{11} = 4.28$	$L_{21} = 0.28$	$L_{31} = 1.39$
$s = 2$	$L_{12} = 0.58$	$L_{22} = 5.87$	$L_{32} = 1.92$
$s = 3$	$L_{13} = 2.0$	$L_{23} = 2.74$	$L_{33} = 2.58$

All variables relative to their values in the rest of the economy (places i > 3).

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, and is positive if this is in highly tradable sectors, negative if in low-tradability sectors.

Second, there is place-sector specific divergence between physical productivity and revenue productivity. For example, physical productivity in sectors 2 and 3 in place 1 is the same as it in the rest of the economy, ($a_{12} = a_{13} = 1$), but revenue productivity is 24% higher, since each unit of labour employed in these sectors produces output of value $w_1 = 1.24$. This heightened revenue productivity has nothing to do with the performance of sectors 2 and 3, 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.[11]

Third, the sectoral structure of employment in each place is skewed towards the sector in which the place has productivity advantage. This is as expected, and is illustrated by the sectoral employment structure – measured as levels relative to those in the rest of the economy -- given in the bottom part of Table 1.

Going beyond Table 1, if the productivity advantages are taken separately (rather than all three

[11] The extent to which variation in local wages can be passed on depends on the tradability of output. Thus, physical productivity in sectors 1 and 2 in place 3 is the same as it in the rest of the economy ($a_{31} = a_{32} = 1$), but revenue productivity is different, at just $w_3 = 0.96$ of that elsewhere. This divergence is relatively small as sectors 1 and 2 are highly tradable.

together, as in the table), then the social gain (increase in utility, equal to all workers in the economy), is largest for a productivity advantage a_{11}. The fact that this sector is highly tradable means its output increase is large, and the productivity gain spread over more workers than would be the case with equivalent size productivity differential in other sectors.

3.2 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 $\epsilon_s = \mu_s + (1-\mu_s)\sigma$ where μ_s is market share. At the base equilibrium this market share is $\mu_s = 1/\{1+(N-1)t_s^{1-\sigma}\}$, since supply from each of the N - 1 other places ('imports') face trade cost factor t_s. Similarly, supply to other places has lower market share by factor $t_s^{1-\sigma}$, so the elasticity of demand in 'export' markets is $\epsilon_s^* = \mu_s t_s^{1-\sigma} + (1-\mu_s t_s^{1-\sigma})\sigma$. The overall elasticity is the sales share weighted average of these, i.e. $E_s = \mu_s\epsilon_s + (1-\mu_s)\epsilon_s^*$, where since all markets are the same size in the base equilibrium, μ_s is also the share of place 1's sales that goes to the home market.[12] It follows that

$$E_s = \mu_s\{\mu_s + (1-\mu_s)\sigma\} + (1-\mu_s)\{\mu_s t_s^{1-\sigma} + (1-\mu_s t_s^{1-\sigma})\sigma\}$$

$$= \sigma + (1-\sigma)\mu_s\{\mu_s + (1-\mu_s)t_s^{1-\sigma}\} \qquad (11)$$

with $\mu_s = 1/\{1+(N-1)t_s^{1-\sigma}\}$.

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

Zero tradability: $t_s^{1-\sigma} = 0$: $\mu_s = E_s = 1$.

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

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.[13] With perfect tradability the demand elasticity tends to σ as N becomes large. Between these extremes the elasticity is monotonically decreasing with t_s.

To see the impact on employment, suppose that wages, rental rates, and income are held constant and are the same across places. Employment in place i sector s is $L_{is} = (a_{is})^{(E_s-1)}C$,

[12] If total expenditure on good s in each market is Z, then total sales of a place's output are $Z\{\mu_s + (N-1)\mu_s t_s^{1-\sigma}\}$, with home market sales $Z\mu_s$ and total 'exports' $Z(N-1)\mu_s t_s^{1-\sigma}$. The share of a place's output sold in the home market is $Z\mu_s/Z\{\mu_s + (N-1)\mu_s t_s^{1-\sigma}\} = 1/\{1+(N-1)t_s^{1-\sigma}\}$.

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

(from equations (1) and (6), where C is a constant).[14] Thus, if productivity in a particular sector has a distribution across places (e.g. each place draws the sector's a_{is} from some distribution), then the elasticity of demand transforms this into a distribution of employment impacts. With zero tradability and $E_s = 1$, the distribution of employment impact collapses to a point (i.e. is the same everywhere,), while for $E_s > 1$ both the variance and (right) skewness of the distribution of employment impacts are increasing in E_s. We use these observations in constructing our empirical proxy for tradability in later sections.

3.3 Comparative statics: equilibrium responses and wages

The equilibrium effects of Ricardian productivity differences can be found by comparative static techniques, looking at small productivity changes in just one place, (which we take to be place i = 1), 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, we omit place-specific subscripts.

Ricardian productivity differences mean that productivity in place 1 takes values which differ by amount $\hat{a}_s$ from the base values that hold elsewhere. The variation in $\hat{a}_s$ induces changes in prices and wages in place 1 according to $\hat{p}_s = \hat{w} - \hat{a}_s,\ s = 1 \ldots S$ (equation 1). The change in the 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.

The change in income is the share weighted sum of output change and rent, $\widehat{M} = \sum_s \beta_s(\hat{p}_s + \hat{x}_s) + \alpha\hat{R}$ where, in the base equilibrium, output shares are equal to consumption shares. Furthermore, since the share of income going on rent is constant, $\hat{R} = \widehat{M}$. The change in the cost-of-living is driven by changes in price indices (hence prices) and rent, so $\hat{e} = \sum_s \beta_s \hat{P}_s + \alpha\hat{r} = \sum_s \beta_s \mu_s \hat{p}_s + \alpha\hat{R}/(1+\eta)$. And finally, utility changes according to $\hat{u} = \hat{w} - \hat{e}$. Appendix 1 spells this out in greater detail and derives the following expression for the change in wages,

$$\hat{w} = \frac{\hat{u} + \sum_s \beta_s \hat{a}_s[(E_s - 1)\alpha/(1+\eta) - \mu_s B]}{B + \sum_s \beta_s[(E_s - 1)\alpha/(1+\eta) - \mu_s B]}, \quad B \equiv \sum_s \beta_s(1 - \mu_s) \in (0,1). \qquad (12)$$

The variable B gives the share of expenditure in the place that goes on imports from other places. With high labour mobility the utility change is common to all places, and is smaller

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

than changes in place 1 by factor $1/N$. For large N this can be taken to be zero. The denominator of (12) is positive.[15]

Equation (12) shows that the response of wages in place 1 to small productivity shocks $\hat{a}_s$ depends on the sign of $\sum_s \hat{a}_s[(E_s - 1)/(1+\eta) - \mu_s B] > 0$. This depends on the correlation between $\hat{a}_s$ and variables in the square brackets, in particular the demand elasticity E_s, with the sign positive if there are large productivity increases in sectors with high elasticity.

If the productivity advantage occurs only in a single perfectly non-tradable sector in which $t_s^{1-\sigma} = 0$, and $E_s = \mu_s = 1$, then $[(E_s - 1)/(1+\eta) - \mu_s B] = -B < 0$, 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, $t_s^{1-\sigma} = 1$, then, with large N, the expression becomes $(\sigma - 1)/(1+\eta) \geq 0$, 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-of-living and hence being associated with 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, (larger α, smaller $\sum_s \beta_s$).

These effects can be summarised as the following proposition:

Proposition: Suppose that N is large and that a single place has productivity advantage in some sectors*:*

i) The wage rate: The nominal wage will be higher than that elsewhere if productivity advantage is sufficiently concentrated in highly tradable (low t_s) sectors. The nominal wage will be lower if productivity advantage is sufficiently concentrated in low tradable (high t_s) sectors.

ii) Employment will be higher than elsewhere in sectors in which $\hat{a}_s(E_s - 1) + \mu_s \widehat{M} > \widehat{w}$, and conversely (Appendix 1).

iii) The overall change in place 1 employment depends on the extent to which productivity advantage is biased towards highly tradable sectors.

3.4 Numerical simulation

The preceding comparative statics look at the effect of small productivity differentials in a single place around the base equilibrium. How do large productivity differentials show up in

[15] The denominator is positive if $E_s \geq 1$, since $B(1 - \sum_s \beta_s \mu_s) > 0$

the full model? We address this by numerical simulation, and in so doing also introduce and demonstrate concepts and methods that we apply in the following empirical sections.

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 our central case, 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 $\sigma = 10$, more than 99% of output is consumed in the place where it is produced. 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] Other parameters are reported and discussed in Appendix 1, and here we simply note that we set $\sigma = 10$ and $\eta = 1$, the latter broadly in line with recent estimates derived by Combes et al. (2019) for Paris. We report results for both a particular run of the model and as averages for 20 runs.

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.

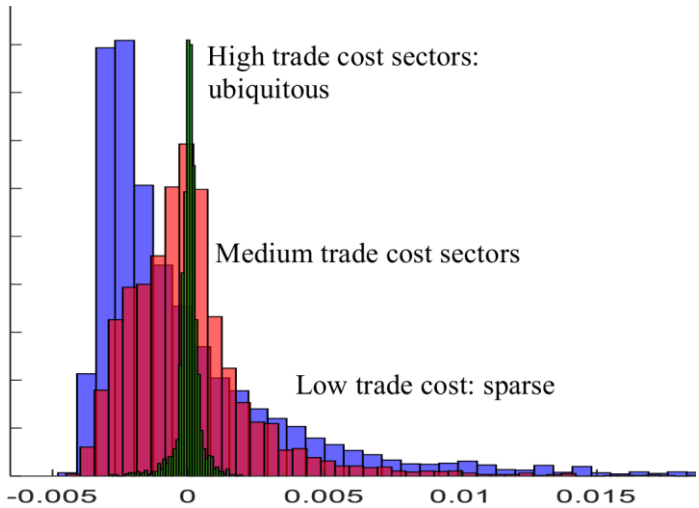
Sector location and sector-sparsity: Simulation generates a distribution of place-sector employment, L_{is}, which can be expressed in share form, $s_{is} \equiv L_{is}/\sum_i L_{is}$, the share of place i in total sector s employment. We compare this with the share of place i in aggregate employment, $x_i \equiv \sum_s L_{is}/\sum_i \sum_s L_{is}$, 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, so 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 industries. The dark-brown histogram is the distribution of values of q_{is} for the 1/3rd of sectors with highest trade costs, the blue is the distribution for the 1/3rd lowest trade cost sectors, 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, both of which capture aspects of the differences apparent in Figure 1. One is the standard deviation, denoted SD_s, and the other skewness, SK_s. We refer to these as measures of the 'sector-sparsity' of each sector. A low value indicates ubiquity (high trade costs), and a high value sparsity (low trade costs). In the empirical section of the paper we do not observe tradability directly, and will use these measures as proxies for tradability. We note that, in this simulation,

[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.

the correlation between the trade cost parameter t_s and the standard deviation sector-sparsity, SD_s, is -0.958, and that between t_s and skewness sector-sparsity, 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 places is biased towards sectors which are sparse. This bias can be captured in a natural way by an employment weighted index of the sparsity-index of each sector. This is the 'sparsity-bias' of each place,

$$SB_i \equiv \sum_s SK_s (L_{is} / \sum_s L_{is}), \quad or \;\; SB_i \equiv \sum_s SD_s (L_{is} / \sum_s L_{is}) \,. \tag{13}$$

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 both measures sparsity-bias generated by the simulation is apparent.

Table 2a, first two columns, gives the regression relationship between these variables, pooling output from 20 simulation runs. The central case is given for both versions 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] The bottom two rows of the table give further descriptive results from the simulations. The range of values of sectoral-wages, w_s, is small (8.5 percentage points around a mean of 100), and so too is the range of area-wages, w_i, at 21.7

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

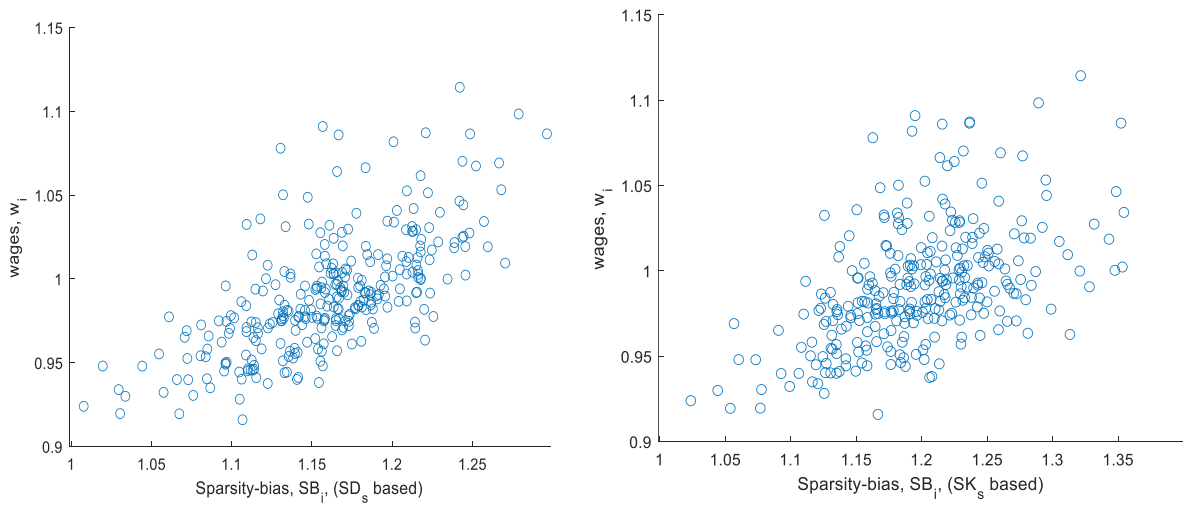
[18] Notice that Figure 2 is for a particular model run, and Table 2a is pooled across 20 such runs.

percentage points. This is a direct reflection of the range of productivity shocks fed into the simulation.

The last two columns of Table 2a explore the effect of allowing correlation between the distributions of trade costs and productivity. In these columns the size of the productivity shock is set to be, on average, of smaller absolute value in less tradable sectors than in more 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, although the range of wages across places and sectors remains similar.

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 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 rent (and hence nominal wage) variation, while increasing the variation (and the influence of SB_i on) total employment in each area. 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]

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



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

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

	Dependent variable: Average earnings in place i, w_i			
	Central case:	Central case:	Small $var_i(a_{is})$ in high t_s sector	Small $var_i(a_{is})$ in high t_s sector
Sparsity-bias SB_i: based on sector-sparsity measure $SD_s(q_{is})$	0.38 (15.8)		0.34 (39.4)	
Sparsity-bias SB_i: based on 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
Range of w_s	8.5 ppt	8.5 ppt	9.3 ppt	9.3 ppt

Cols 1, 2: Central case: $t_s \in [1,4]$, $\sigma = 10$, $\eta = 1$, $a_{is} \sim 1 + N(1,0.2)$, truncated at 0.5 and 1.5
Cols 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: To this point we have assumed that labour is homogeneous, but capturing the empirical pattern of earnings disparities requires that skill differentials be added to the model. We do this by assuming just two types of labour, skilled and unskilled (types *A*, *B*, respectively). The economy has a fixed endowment of each type, L^A and L^B, and households now have skill specific wages, w_{is}^A *and* w_{is}^B. On the household side, (labour supply, income, spending and choices of place and sector of work), the model is 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 shares of the two factors vary across sectors, v_s capturing the intensity with which sector s employs type-*A*, and $1 - v_s$ 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 (analogous to equation 6), and average wages in each place and each sector, w_i and w_s, taking the form,

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

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

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

Table 2b reports results of model simulations for this case, with productivity differential between skill types $a^A/a^B = 3$, and factor intensity parameters v_s lying between 0.25 and 0.75 (see appendix 1 for full description). The elasticity of substitution between labour types is assumed to be small, $\rho = 0.5$. The first column of Table 2b reports results when the most tradable sector is the most skill intensive (sector with $t_s = 1$ has v_s = 0.75), and skill intensity declines linearly to the least tradable sector ($t_s = 4$ with v_s = 0.25). The second column looks at the converse case, where the highly tradable sector is relatively skill unintensive (Appendix 1).

Comparing these columns (together with column 1 of Table 2a) three results stand out. First, the relationship between sparsity-bias and wages is strong, particularly when highly tradable sectors are also skill-intensive. Second, there is a large wage differential between skill types, but this is much larger in the case where highly tradable sectors are also skill-intensive. In this the average wage differential is $w^A/w^B = 2.81$, in the converse case $w^A/w^B = 1.32$.[20]

Third, spatial disparities – as indicated by the range of average wages across places, w_i -- are considerably larger in the case where highly tradable sectors are also skill intensive (a range of 36 percentage points between the most and the least sparsity-biased places, compared to 9.5 percentage points in the converse case). This is because wage differences are now driven both by the area-differential effect and by the sector-differential effect, pulling in the same direction if highly tradable sectors are also skill intensive. The division between these two elements is indicated for this case in Figure 3. The horizontal axis is the average wage in each place, and the height of the scatter points is the sector-differential effect, i.e. the average wage formed by sectoral average wages, w_s, weighted by the place specific employment shares. The difference between this 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). We return to this decomposition in greater detail in the empirical analysis of Section 4. The important theoretical point is that – in this model -- the interaction between tradability and productivity differentials (assumed exogenous) drives sectoral composition and hence both the area-differential and the skill composition and sector-differential of each area.

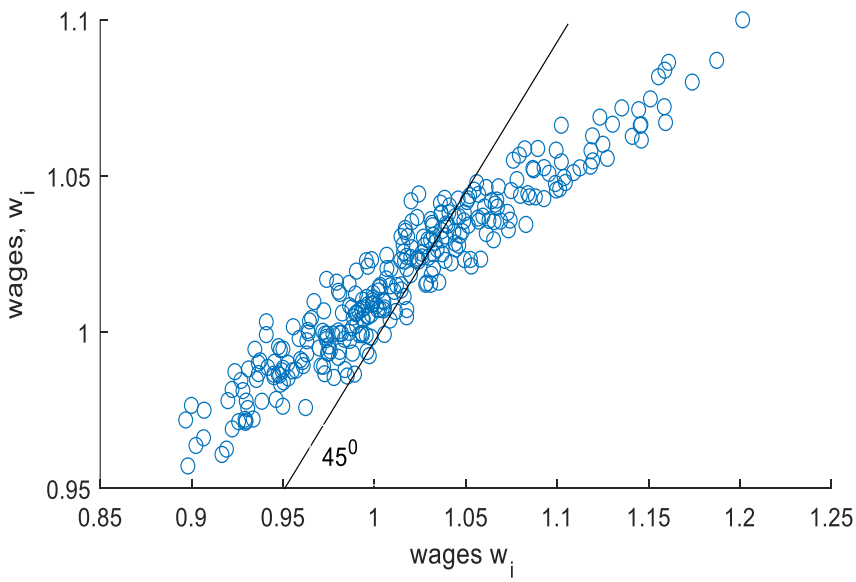
[20] Wage rates without subscripts or superscripts are employment weighted averages.

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

	Dependent variable: average earnings in place i, w_i	
	low t_s sector is skill intensive	low t_s sector is 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 obs'ns	300	300
w^A/w^B	2.81	1.32
Range of w_i	36.3ppt	9.5ppt
Range of w_s	73.5ppt	31.8ppt

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.

Figure 3: Wages, w_i: sector-differential effect 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 findings and make several further remarks.

First, it is the interplay between the sector characteristic of tradability and place-sector specific variations in productivity (or some other source of advantage) that is central to the argument.

Tradability matters in so far as it enables a place to expand 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, more so for less tradable goods and particularly for land and housing, goods which we take to be immobile and in less than perfectly elastic supply. In goods with a limited degree of tradability, these price effects can be large enough that physical productivity and revenue productivity move in opposite directions. These price differences create differences in the cost-of-living and hence nominal wages, and therefore also differences in revenue productivity, even in sectors where there are no spatial variation in physical productivity.

Third, physical productivity may well be endogenous, for example varying with scale because of agglomeration economies. We abstract from this, but nevertheless see a positive relationship between scale and revenue productivity. As we have shown, tradability and consequent demand effects create relationships between revenue productivity and scale which may show up in sectors where technical efficiency is the same everywhere, and that have nothing to do with agglomeration. 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 wages in each place are 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? The empirical analysis 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 from 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.

[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

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

4.1 Regional variation in earnings; sector-differential effects and area-differentials

Mean hourly earnings in each ITL3 area, w_i, are depicted on the horizontal axis of Figure 3, 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 3 being those for 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

$$w_i = (w_i - \widetilde{w}_i) + (\widetilde{w}_i - \overline{w}) + \overline{w}. \qquad (14)$$

The final term is population average earnings, $\overline{w} \equiv \sum_i \Sigma_s w_{is} L_{is}/L$. The second term is the sector-differential effect, where the variable $\widetilde{w}_i$ is defined as what average earnings for an area would be if local wages in each sector equalled the sectoral national average, i.e. $\widetilde{w}_i = \Sigma_s w_s \lambda_{is}$, where $w_s = \sum_i \theta_{is} w_{is}$ is the sector national average, $\lambda_{is} \equiv L_{is}/\sum_s L_{is}$ 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. The first term in (14) is the area-differential. It can be shown that the difference between mean hourly earnings w_i and $\widetilde{w}_i$ is $w_i - \widetilde{w}_i = \Sigma_s (w_{is} - w_s)\lambda_{is}$. Thus, the area-differential of each place 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. [22, 23]

We compute $\widetilde{w}_i$ using ASHE data on mean hourly earnings for all UK employees for each of the 259 SIC3 industrial sectors, together with the BRES data on employment numbers by ITL3 area and SIC3 sector. The second row of Table 3 reports the descriptive statistics for w_s. Sectoral variation 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).

In Figure 3, the vertical height of the scatterplot depicts this decomposition for each of the 163 ITL3 areas. The vertical distance between these points and the population mean (horizontal line $\overline{w}$) is the sector-differential effect, and the distance between these points and the 45° line is the area-differential. For areas in the upper tail of the earnings distribution, typically ITL3

[22] $w_i \equiv \Sigma_s w_{is} \lambda_{is} = \widetilde{w}_i + \Sigma_s (w_{is} - w_s)\lambda_{is}$, 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.

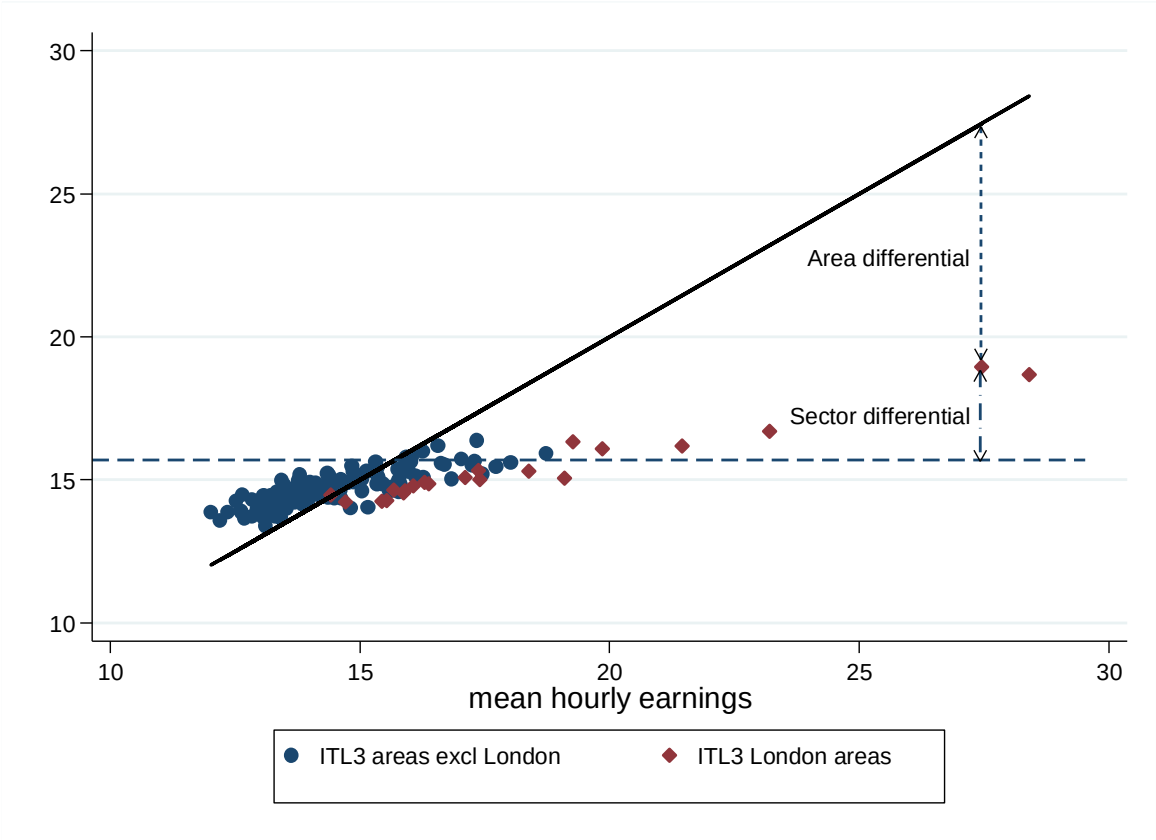
areas of London, the area-differential is substantially positive. The third and fourth rows of Table 3 give descriptive statistics for these variables.

The contribution of the sector-differential effect 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 effect and the area-differential accounting for the remainder. This is with a relatively fine sectoral classification – 259 sectors – although a finer classification of sectors, tasks and activities, were it available, would be likely to increase the contribution of the composition effect.

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 effect: $(\widetilde{w}_i - \overline{w})$	-0.9474	-1.0493	0.576	-2.32	3.23
ITL3 area-differential: $w_i - \widetilde{w}_i$	0.1019	-0.3214	2.711	-1.83	9.83

Figure 3: Area Earnings (£ per hour): sector-differential effect and area-differential



4.2 Sectoral sparsity-indices

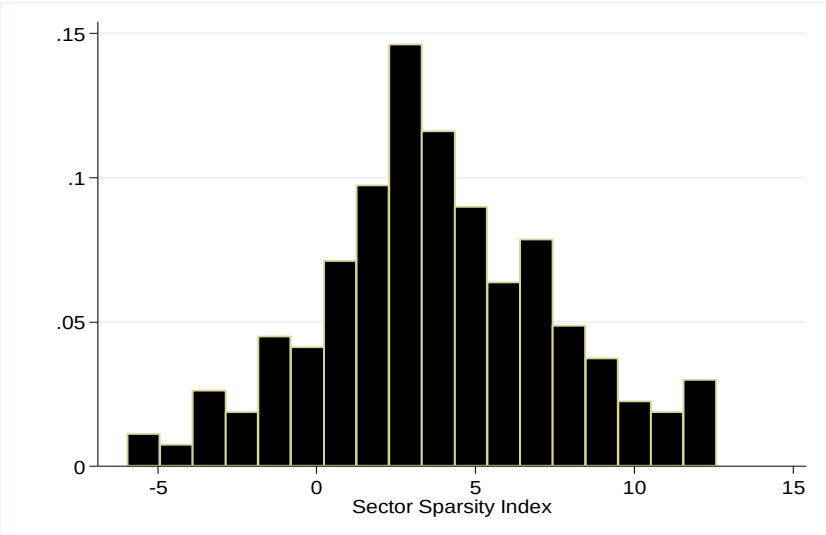
Our central hypothesis concerns the role of the tradability of output in shaping labour demand and wages. We do not observe tradability directly, but we do observe employment by sector and place, and hence can calculate a sparsity-index, based on the spatial distribution of relative employment shares for each sector. The distribution is that of the share of total sector s employment that occurs in place i, s_{is}, relative to the share of place i in total GB employment, x_i. The relativity can be expressed either on the ratio s_{is}/x_i, (the location quotient) or the difference, $s_{is} - x_i$. We focus on results for the difference measure in preference to the location quotient because it appears to be less sensitive to variations in the size of the ITL3 areas. Comparable results for quotient based measures are reported in Appendix 3. As discussed in the theory section, the second and third moments of the distribution of this variable are both ways of summarising salient aspects of the shape of the distribution. We use skewness, SK_s, once again presenting results for the alternative of standard deviation in Appendix 3.

Sparsity varies widely, and intuitively, across sectors. Figure 4a illustrates the distribution of SK_s across sectors. Sectors with high sparsity measures include a number of specialised manufacturing industries – manufacture of articles of fur (142); manufacture of precious metals (244); 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 4b 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.[24]

We note one further point about sectoral sparsity indices, and this is that they are positively correlated with sectoral average earnings, as illustrated on Figure 5 (correlation coefficient 0.46). This correlation is simply reflecting the fact that technologies of production and tradability happen to be such that highly tradable products tend to also be relatively high skill intensive, and is not an equilibrium relationship generated by economic behaviour in the model.

Figure 4a: Distribution of sector sparsity-indices, SK_s



[24] Boundaries of the box are LQ and UQ , and 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 4b: Sparsity-indices by Broad Industrial Divisions

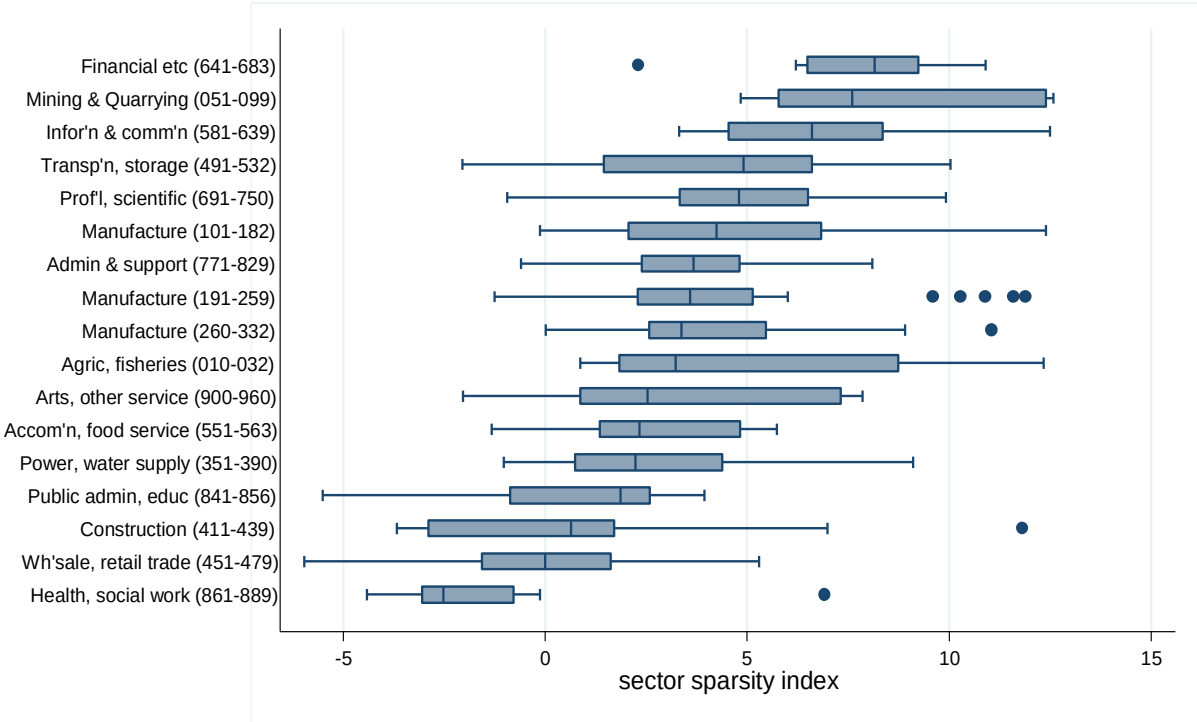
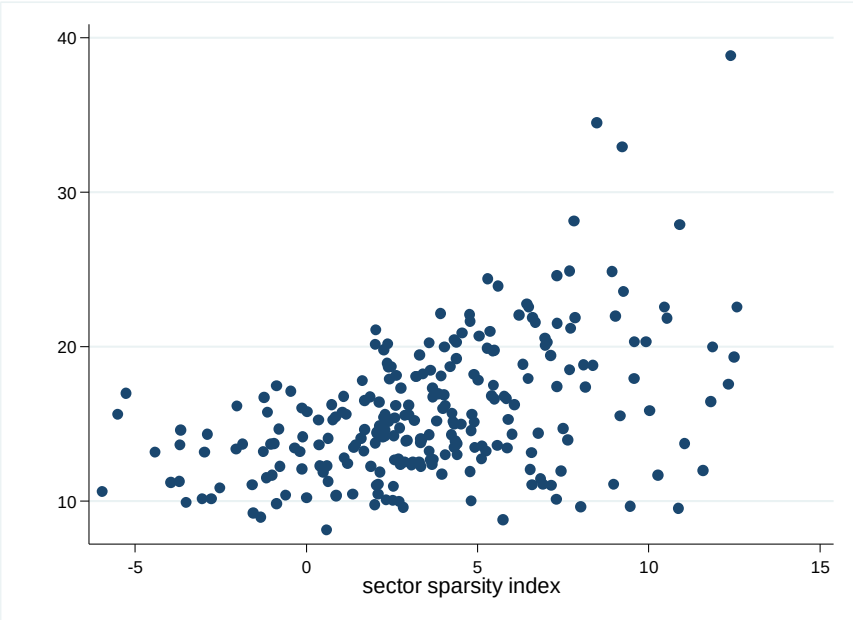


Figure 5: Sectoral sparsity-indices and sectoral average earnings, w_s.



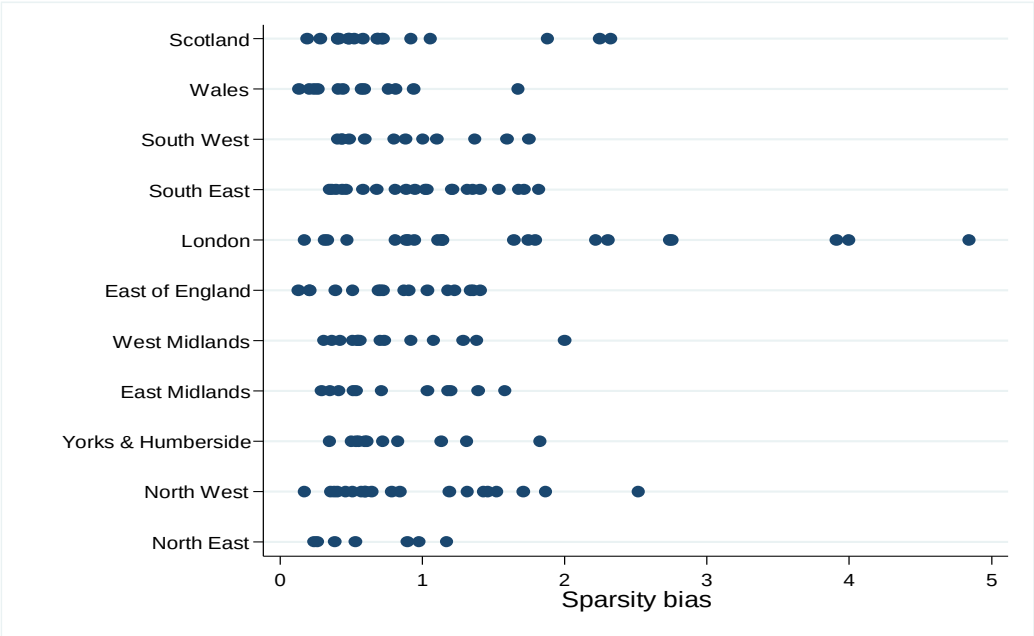
4.3 Sparsity-bias and earnings.

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 place is biased towards more or less sparse sectors. As in section 3.4 (equation 13) 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 6, and summary statistics are given 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

Figure 6: Sparsity-Bias by ITL Areas



Mean, median	0.9610, 0.7647
Standard deviation	0.7213
Minimum, maximum	0.1274, 4.8448

A clear prediction of the theory is a positive relationship between the sparsity-bias of an area and its average earnings. Figure 7 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 7) are excluded then the correlation coefficient drops to 0.74.

Bivariate regression of mean hourly earnings on sparsity-bias is 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.[25] 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 matters for 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 3. Sparsity-bias is correlated with both of these, and the remaining columns of Table 3 show these relationships. We expect the sector-differential effect to be positively correlated with sparsity-bias because, as illustrated in Figure 5, sectoral wages are positively correlated with sectoral sparsity-indices. This is what we see in the second column of Table 4.

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 impact of sparsity-bias on 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 effects. 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.

Comparable results using sparsity bias measures based on the location quotient (s_{is}/x_i) and on $\log((s_{is}/x_i) + 1)$ are reported in Tables A2 and A3 of Appendix 2. While less well-determined, the estimated relationships are qualitatively 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; for the sparsity bias measure based on the log of the location quotient, the Figure is 12%. Moreover, the estimated coefficients indicate that approximately one-third of the increase in mean earnings comes through sector-differential effects and two-thirds through the area-differential as in Table 4.

[25] 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

Figure 7: Mean hourly earnings and the sparsity-bias of an area

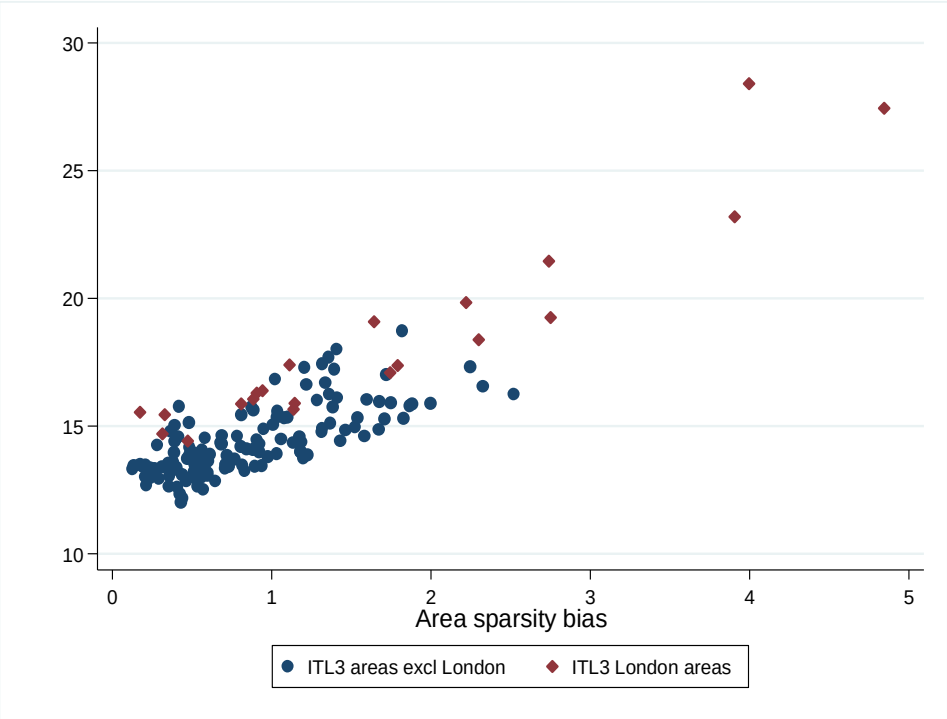


Table 4: Earnings and Sparsity Bias

	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.

4.3: Alternative measure of sector-differential 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 area average earnings decomposition that avoids this weakness.

Suppose that area-sector wages, w_{is} are a function of some area component of the wage, d_i and a sector-specific component d_s, so $w_{is} = f(d_i, d_s)$. It follows that area average earnings and sector average earnings are

$$w_i = \sum_s \lambda_{is} w_{is} = \sum_s \lambda_{is} f(d_i, d_s), \quad w_s = \sum_i \theta_{is} w_{is} = \sum_i \theta_{is} f(d_i, d_s), \qquad (15)$$

where λ_{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 (15) are N + M equations in the N + M unknowns, d_i and d_s which, assuming a functional form for $f(d_i, d_s)$, can be solved numerically using the available data for area average and sector average earnings, w_i, w_s and employment shares, $\lambda_{is}, \theta_{is}$. Adopting a functional form for which $f(1,1)$ equals national average earnings $\sum_i L_i w_i / L$, the sector-differential is $\widetilde{w}_i = \Sigma_s f(1, d_s)\lambda_{is}$, and the area-differential is $w_i - \widetilde{w}_i$, as before.[26]

Proceeding as before, but with sector-differential and area-differentials calculated in this way, gives results reported in Table 5. They confirm the findings in Table 4 with both sector-differential effects and area-differentials 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 effect 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.

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

[26] The additive and multiplicative functional forms are $f(d_i, d_s) = (d_i + d_s)W$, $f(d_i, d_s) = d_i d_s W$, where *W* is economy wide average earnings, $W = \sum_i L_i w_i / L = \sum_s L_s w_s / L$.

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 alluded to the loss of tradable sectors that occurred in many parts of the UK during the 1970s and 1980s. The decade of the 1970s saw manufacturing employment fall from over 7.9mn in 1971 to 6mn in 1981, falling further to 4.6mn in 1991, this decline unevenly spread across sectors and regions. 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). In what follows, we consider whether the experience of this period is consistent with and captured by the measures of sectoral sparsity developed in this paper.

We address this question in three stages, first calculating sectoral sparsity indices and area sparsity-bias for these earlier dates 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 regions 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.

However, 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 chain-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 it is necessary to drop some of the least populated counties from the sample for analysis.

5.1: Sectoral sparsity indices, sparsity-bias and earnings: 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 place, we compute sparsity measures 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 measures of approximately 12 percent. The correlation between the measures 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 – experienced large increases in their sparsity measures 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 measures declining further while sparsity measures for iron and steel production, and parts of the mechanical engineering and vehicles sectors continue to increase in relative terms.

Using sectoral sparsity measures for each of these dates we calculate sparsity bias for the 64 areas at each date. To match with the employment data for 1971, 1981 and 1991, we consider 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.

The results of the bivariate regression of the level of hourly earnings on the level of 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 Regions			
Sparsity-bias index SB_i	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: Structural change and the decline of manufacturing.

The fall in manufacturing employment during the 1970s hit some sectors particularly hard. Across the metal manufacturing sector, employment fell by 238K (43 percent), with Iron and Steel employment decreasing by 135K (50%). Textiles were hit with employment falling by 259K (45 percent), and 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 of 1971 Great Britain, but rather concentrated in a number of the larger metropolitan counties. The following areas experienced falls in manufacturing employment over the decade of between 30 and 40 percent: Greater London – 379K; West Midlands – 260K; Greater Manchester – 172K; Strathclyde – 146K; West Yorkshire -117K; Merseyside – 90K; South Yorkshire – 66K; Cleveland – 60K; Tyne and Wear – 60K; West Glamorgan – 23K; Tayside – 17K

What effect did these marked changes in their employment composition have on their sparsity-bias? Table 7 reports those areas that were most affected by the decline in manufacturing in terms of the impact on their total employment. The areas identified are in the lower quartile of the distribution of changes in manufacturing employment with falls of 10 percent or more as a percentage of total employment (median value for the 64 areas of 6 percent).

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

Area	Change in manufacturing employment 1971 - 1981			Sparsity-Bias			Sparsity-Bias (1971 sectoral sparsity)		
	'000s	As % 1971 manuf emplt	As % 1971 total emplt	1971	1981	1991	1971	1981	1991
West Midlands	-260	-34.2	-18.6	1.49 (2)	0.98 (2)	0.62 (8)	1.49 (2)	1.06 (2)	0.72 (5)
Cleveland	-39	-34.7	-16.7	0.09 (31)	0.003 (32)	-0.39 (48)	0.09 (31)	-0.04 (33)	-0.43 (52)
Greater Manchester	-172	-33.4	-14.9	0.82 (4)	0.38 (9)	0.33 (17)	0.82 (4)	0.48 (7)	0.28 (23)
West Glamorgan	-23	-36.8	-14.9	0.27 (16)	0.03 (30)	0.04 (31)	0.27 (16)	-0.05 (34)	-0.31 (44)
Strathclyde region	-146	-37.5	-14.5	0.39 (12)	0.25 (15)	0.24 (21)	0.39 (12)	0.18 (24)	0.14 (27)
West Yorkshire	-117	-30.3	-13.6	0.93 (3)	0.49 (5)	0.37 (12)	0.93 (3)	0.53 (6)	0.48 (15)
Merseyside	-89.5	-36.8	-13.3	0.8 (5)	0.57 (3)	0.29 (18)	0.8 (5)	0.64 (3)	0.37 (19)
Bedfordshire	-23.5	-25.3	-12.7	0.6 (7)	0.22 (20)	0.35 (14)	0.6 (7)	0.3 (18)	0.4 (18)
Gwent	-20	-27.8	-12.3	-0.1 (38)	-0.02 (33)	-0.19 (40)	-0.1 (38)	-0.2 (42)	-0.08 (35)
South Yorkshire	-65.5	-29.2	-12.2	0.16 (24)	0.09 (28)	0.08 (29)	0.16 (24)	0.02 (30)	-0.12 (39)
Tyne and Wear	-60	-31.7	-11.8	0.16 (23)	0.20 (22)	0.23 (20)	0.16 (23)	0.26 (21)	0.31 (20)
Clwyd	-12.5	-28.1	-11.2	-0.53 (55)	-0.51 (58)	-0.66 (58)	-0.53 (55)	-0.64 (61)	-0.83 (57)
Tayside region	-16.5	-31.4	-10.5	0.37 (13)	0.08 (29)	-0.23 (42)	0.37 (13)	-0.01 (32)	-0.5 (53)
Staffordshire	-36.5	-21	-10.1	0.63 (6)	0.27 (12)	-0.00 (34)	0.63 (6)	0.35 (11)	0.10 (28)
Greater London	-379	-36.1	-9.6	1.77 (1)	1.73 (1)	2.22 (1)	1.77 (1)	1.69 (1)	1.80 (1)

GB ranking of area with respect to sparsity-bias reported in parentheses.

Areas are ranked according to the change in manufacturing employment as a share of total employment. By this measure the West Midlands, Cleveland, Greater Manchester, West Glamorgan, and Strathclyde experienced the largest declines (losing more than 14 percent of total employment). While Greater London experience the largest absolute decline, 36 percent of its manufacturing employment, this was just 9.6 percent of its total employment. Area

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 places listed saw their sparsity bias index decline further 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.

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? 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 GB 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 on changes. 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 earnings.

Figure 8: Wages and sparsity-bias: changes.

Table 8: Wages and sparsity-bias: 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	0.0927 (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. Sparsity-Bias and Occupations

Thus far our analysis has focused on the sectoral composition of employment and its relationship to regional disparities in average earnings. In this section, we turn to consideration of the role of occupations and address two questions. First, does the relationship between sparsity-bias and earnings vary across occupational categories? And second, do we obtain results consistent with those derived for sectors, if we switch to categorizing economic activity by occupation, i.e. calculating sparsity indices and sparsity-bias on occupational rather than sectoral employment? The analytical model should still apply to the extent that some occupations (or the functions provided by these occupations) are tradable (e.g. IT enabled), while others have to be performed at point of consumption.

Regional data on employment by occupation are not routinely available at such a fine level of disaggregation as the 259 SIC3 sectors, so this analysis is based on employees in each ITL3 area for 25 SOC2010 sub-major occupational groups, available from the Annual Population Survey. As before, the values for years 2015 to 2019 are averaged.

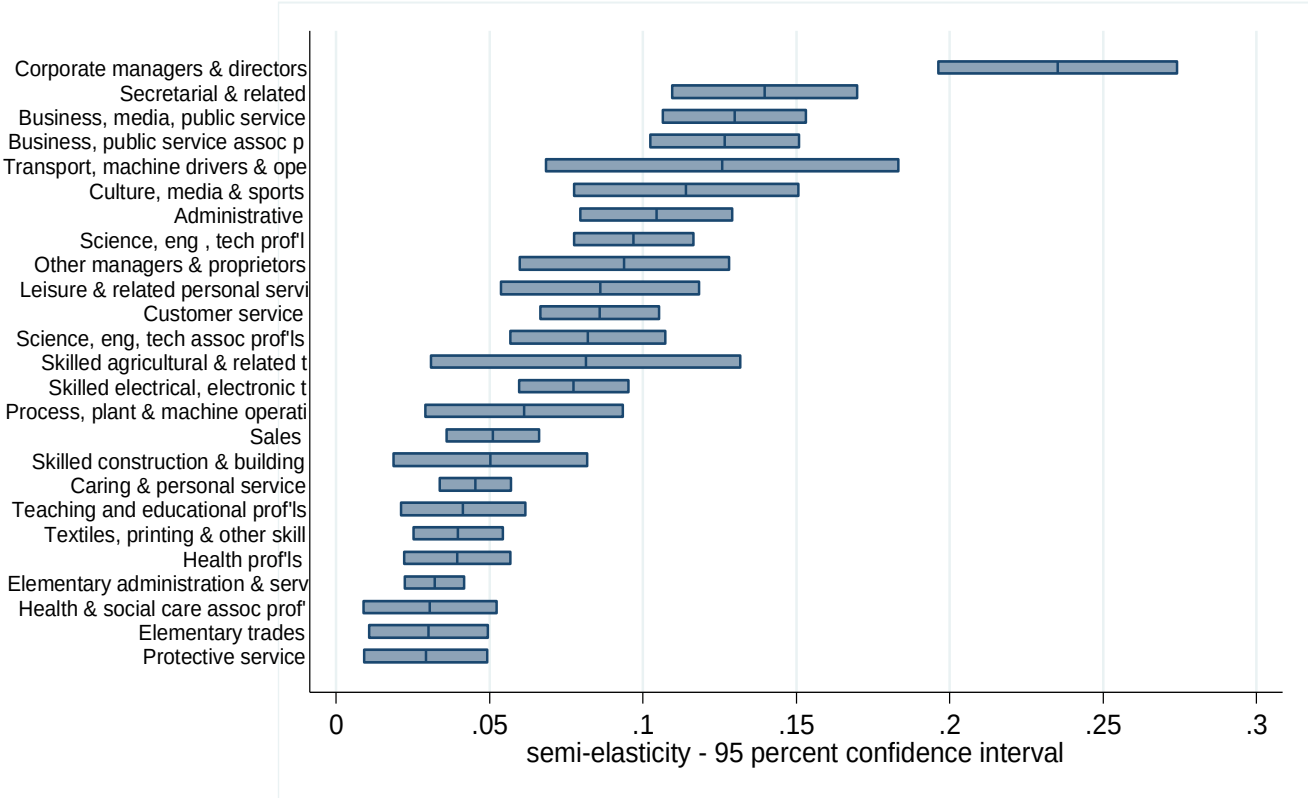
6.1: Occupational earnings and sector-based sparsity-bias

There are a number of reasons for expecting the elasticity of earning 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 national minimum wage sets a wage floor. Outside of these groups, differences in the elasticity of labour supply plays a role.

The regressions of earnings in each of the 25 occupational groups on sparsity-bias (sector-based, i.e. as constructed in section 4) are reported in full in Table A4 of the Appendix, and Figure 9 shows the central estimate of the semi-elasticity along with the 95 percent confidence

interval in each case.[27] The estimated coefficient on the sparsity-bias measure is statistically significantly different from zero for all occupations, with values of the t-statistic ranging 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 25 occupational groups identified, 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.

Figure 9: Semi-elasticity of occupational earnings with respect to sparsity-bias



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 variations in earnings may be expected to be restricted 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

[27] 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

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.

6.2: Occupational sparsity-indices and occupational sparsity-bias

Our core analysis is based on a sectoral rather than an occupational categorisation of employment, mainly because of the much finer degree of disaggregation of the former. But as a check, we replicate this analysis using occupational data. How much of the variation in average earnings across areas is attributable to occupational composition, and what is the relationship between a measure of occupational-sparsity bias and the average earnings of an area?

The decomposition now asks what average earnings for an area would be if wages in each occupation equalled the occupational national average. The occupation-differential, is $(\breve{w}_i - \overline{w})$ with $\breve{w}_i = \Sigma_o w_o \lambda_{io}$, where $\lambda_{io} \equiv L_{io}/\sum_o L_{io}$ is the employment share of occupation o in area i and $\overline{w}$ is population average earnings as before. The new measure of the area-differential is, $w_i - \breve{w}_i$, and we find that the contribution of the occupation-differential effect to the variance of mean hourly earnings across areas is modest; just over 10%. By contrast the area-differential accounts for more than half of this variance, with the covariance between the occupation-differential effect and the area-differential accounting for the remainder, similar to that found in Table 3.

We calculate the occupational-sparsity-index for each of these occupational categories in the equivalent way to sectors in section 4.2 and then, using occupational employment shares in each area, λ_{io}, construct the occupational-sparsity-bias measure of each area, OSB_i. The relationship between this and earnings in each area is given in the first column of Table 9.

The point estimate implies that a one standard deviation increase in the occupational sparsity-bias measure (equivalent to 0.85 units in the full sample) is associated with an 13.3% percent increase in hourly earnings at the sample mean (approx. 0.9 standard deviations). 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 10%. In this case nearly 40% (38.7) of the increase in mean earnings comes through occupation-differential effects, with the remaining 60% through area differential effects. Comparison of Tables 4 and 9 indicates the similarity of results between the two approaches.

Table 9: Earnings, Occupational Composition and Occupational-Sparsity-Bias

	Mean Hourly Earnings	Occupation-differential effect, $(\breve{w}_i - \bar{w})$	Area-differential $(w_i - \breve{w}_i)$,
Sparsity-bias index (occupational) SB_i	2.3133 (9.78)	0.8942 (26.29)	1.4191 (5.88)
95% CI for SB_i coeff.	1.85, 2.78	0.83, 0.96	0.94,1.90
Constant	16.0806 (85.95)	-0.5904 (-19.95)	0.9577 (5.09)
Adj. R-squared	0.7497	0.8899	0.5508
No. of obs'ns	163	163	163
Excluding London regions			
Sparsity-bias index SB_i	1.6716 (14.39)	0.9571 (30.32)	0.7146 (6.40)
95% CI for SB_i coeff.	1.44, 1.90	0.89, 1.02	0.49, 0.93
Constant	15.44 (136.85)	-0.5806 (-21.86)	0.3119 (2.95)
Adj. R-squared	0.6219	0.8860	0.2434
No. of obs'ns	142	142	142

t-values reported in parentheses..

7: Further predictions and correlates:

Our framework has implications for other economic variables and measures, and in this section we report on a series of checks that data on these variables is consistent with the framework. Further details are provided in Appendix A3.

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 different areas, and this raises nominal wages, including those in non-tradadable 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 check 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 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 accounted for 25% of total spending then real wage equalisation would be supported by an elasticity of 4. However, if other less than perfectly tradable goods also vary in price, being relatively cheap in low wage areas, then 4 is an upper bound, and the estimate of 2.27 is broadly consistent with the predictions of the model.

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 sparse 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).

8. Concluding comments

This paper has shown the importance of the sectoral (and occupational) employment composition of places in determining their levels of earnings, thereby shaping regional disparities within a country. In the theoretical section we showed how the tradability of a sector determined the equilibrium response to productivity differentials (assumed 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 have the opposite effect. In the empirical section we showed how the bias of a place's employment towards sectors that are 'sparse' (our empirical proxy for tradability) is strongly positively correlated with average earnings in the place. 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 response to productivity variation, as suggested by the theory.

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

Second, is the importance of diagnosing the causes of apparent productivity differences. We have shown how spatial variations in revenue productivity are not necessarily related to variations in physical productivity. It is quite possible that physical productivity of a sector in a place is relatively high, but value productivity is low. The policy prescription is then not to seek higher efficiency in the sector, but to look to the overall economic structure of the place. What the place does matters more than how well it performs in particular activities.

Third, is the danger of being stuck with sectors that are non-tradable and probably also relatively unskilled labour intensive. Securing physical productivity improvements in such a place yields benefits in terms of lower prices and, as equilibrium processes work through, lower

nominal wages, and land and housing prices. It is understandable that regional policies have focused on short-run job creation, often in non-tradable sectors in which there is an assured local and national demand. However, 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 places have lost sectors in which they had a traditional comparative advantage they have typically not replaced these sectors with others that are highly tradable. Doing so would require that they become competitive with established centres in which firms are likely to be benefiting from agglomeration economies. The first-mover problem and coordination failure means that it is hard to establish these sectors in new places, creating this locational stickiness.

Does it follow from this that all places 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 possibly impossible) to seek to spread sparse sectors over many relatively small locations. Some places will benefit from hosting sparse sectors, and others need to be sufficiently connected to them to be profitable locations for sectors that are sufficiently tradable to benefit from interaction with these places.

Finally, agglomeration economies and stickiness mean that the proportion of employment in tradable sectors with these properties 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 simply the counterpart of poor performance of particular regions, impacting the country as a whole through the equilibrium location of sectors of activity.

References:

Ahlfeldt, G.M., S. J. Redding, D M. Sturm, and N. Wolf (2015), 'The economics of density: Evidence from the Berlin Wall', *Econometric*a, 83(6), 2127-2189

Bajzik, J., T. Havranek, Z. Irsova, & J. Schwarz (2020): "Estimating the Armington Elasticity: The Importance of Study Design and Publication Bias", *Journal of International Economics* 127, 103383.

Beaudry, Paul, David Green, and Ben Sand. 2012. "Does Industrial Composition Matter for Wages? A Test of Search and Bargaining Theory." *Econometrica*, 40(1): 7–72.

Broda, C. and D. Weinstein, (2006). Globalization and the gains from variety, *Quarterly Journal of Economics*, 541-585.

Caliendo, L., F. Parro, E. Rossi-Hansberg, and P-D. Sarte. (2018). "The Impact of Regional and Sectoral Productivity Changes on the U.S. Economy." *Review of Economic Studies*, 85(4): 2042–2096.

Combes, P-P., G. Duranton and L. Gobillon (2019) The costs of agglomeration; house and land prices in French cities', *Review of Economic Studies*, 86, 1556-89.

Combes, P-P. and L. Gobillon (2015). The Empirics of Agglomeration Economies. In G. Duranton, J.V. Henderson, and W. Strange (eds.) *Handbook of Regional and Urban Economics, volume 5A*, 247–348. Elsevier, Amsterdam.

Coyle, D. and P. Mealy (2021) 'To them that hath; economic complexity and local industrial strategy in the UK', *International Tax and Public Finance*, April.

Diamond R. and E. Moretti, (2022) "Where is Standard of Living the Highest? Local Prices and the Geography of Consumption"

Duranton, G. and D. Puga, (2004). 'Micro-foundations of urban agglomeration economies', in: J. V. Henderson and J. F. Thisse (eds.) *Handbook of Regional and Urban Economics, volume 4*, 2063-2117. Elsevier, Amsterdam.

Duranton, G. and D. Puga, (2015). 'Urban Land Use', in: G. Duranton, J. V. Henderson and W. Strange (eds.), *Handbook of Regional and Urban Economics*, volume 5, chapter 8, pages 467-560, Elsevier, Amsterdam

Eaton, Jonathan and Samuel Kortum, (2002), "Technology, Geography, and Trade," *Econometrica*, 70 (5), 1741–1779.

Fajgelbaum P, and S.J. Redding (2022) 'Trade, Structural Transformation and development; evidence from Argentina; 1869-1914', *Journal of Political Economy*, 130, 1249-1318.

Galle, S., A. Rodriguez-Clare and M. Yi, (2022), 'Slicing the Pie: Quantifying the Aggregate and Distributional Effects of Trade', forthcoming, *Review of Economic Studies.*

Glaeser, E., and J. Gottlieb (2009): "The Wealth of Cities: Agglomeration Economies and Spatial Equilibrium in the United States," *Journal of Economic Literature*, 47 (4), [10641

Haldane, A. (2019) 'Is all economics local?' Bank of England, London,

Hornbeck, R. and E. Moretti (2022) "Estimating Who Benefits from Productivity Growth: Local and Distant Effects of City Productivity Growth on Wages, Rents, and Inequality" *Review of Economics and Statistics*, forthcoming

Lagakos, David and Michael E. Waugh, (2013), "Selection, Agriculture, and Cross-Country Productivity Differences," *American Economic Review*, 103 (2), 948–980

Moretti, E. (2010) "Local Multipliers." *American Economic Review*, 100(2): 373–77

Moretti, E. (2013) *The New Geography of Jobs*, Mariner Books, New York.

Olley G. S.and A. Pakes (1996). "The Dynamics of Productivity in the Telecommunications Equipment Industry". *Econometrica*, Vol. 64, 6, 1263-1297.

ONS (2018), *Regional Firm-Level Productivity Analysis for the Non-Financial Business Economy, Great Britain*, April. Retrieved from: https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/compendium/economicreview/april2018/regionalfirmlevelproductivityanalysisforthenonfinancialbusinesseconomygreatbritainapril2018

Oguz, S. (2019), *"Understanding spatial labour productivity in the UK"*. ONS, London, Retrieved from: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/labourproductivity/articles/understandingspatiallabourproductivityintheuk/2019-05-03

Pred, A. (1966) 'The Spatial Dynamics of U.S. Urban-Industrial Growth'. Cambridge, MIT press.

Rice, P.G., A.J. Venables, E. Patacchini (2004). Spatial determinants of productivity: Analysis for the regions of Great Britain , *Regional Science and Urban Economics 36(6), 727-752*

Rice, P.G. and A.J. Venables (2021) 'The persistent consequences of adverse shocks: how the 1970s shaped UK regional inequality, *Oxford Review of Economic Policy* 37 (1), 132-151

Rosenthal S. & W. Strange. (2004). 'Evidence on the nature and sources of agglomeration economies', in V. Henderson & J-F. Thisse (eds) *Handbook of Regional and Urban Economics*,vol 4, pp 2119-2171. Elsevier, Amsterdam.

Storper, M. (2018) 'Separate Worlds? Explaining the current wave of regional economic polarization', *Journal of Economic Geography*, 18, 247-270

Venables, A. J. (2018) 'Globalisation and Urban Polarisation', *Review of International Economics*, 26, 981-996.

Venables, A. J. (2020) 'Why some places are left behind: urban adjustment to trade and policy shocks', *Oxford Review of Economic Policy*, 36.3, , 604-620.

Zymek, R. and B. Jones (2020) *UK Regional Productivity Differences: An Evidence Review Industrial Strategy Council Research paper*. Retrieved from https://industrialstrategycouncil.org/sites/default/files/attachments/UK%20Regional%20Productivity%20Differences%20-%20An%20Evidence%20Review_0.pdf

Appendix 1:

Comparative Statics: Income is $M = \sum_s p_s x_s + R$, and in the base equilibrium sectoral shares of income generation equal sectoral shares of consumption so deviations of income from base equilibrium values satisfy $\widehat{M} = \sum_s \beta_s(\hat{p}_s + \hat{x}_s) + \alpha\hat{R}$. Rental income is $R = \alpha M$, so

$$\widehat{M} = \hat{R} = \sum_s \beta_s(\hat{p}_s + \hat{x}_s)\,/(1-\alpha)\,. \tag{A1}$$

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

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 place 1 sales in the place 1 market. This is unity for perfectly non-tradable goods, and 1/*N* for perfectly tradable, since $\mu_s = 1/\{1+(N-1)t_s^{1-\sigma}\}$ (section 3.2). As in section 3.2, 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

$$\hat{p}_s + \hat{x}_s = (1-E_s)(\widehat{w} - \hat{a}_s) + \mu_s\widehat{M}. \tag{A2}$$

Using this in (A1) gives, $\widehat{M} = \sum_s \beta_s\big((1-E_s)(\widehat{w} - \hat{a}_s) + \mu_s\widehat{M}\big)/(1-\alpha)$, so rearranging and using the fact that $1-\alpha = \sum_s \beta_s$, gives

$$\widehat{M} = \hat{R} = \sum_s \beta_s(1-E_s)(\widehat{w} - \hat{a}_s)\,/\sum_s \beta_s(1-\mu_s). \tag{A3}$$

Changes in the expenditure function are

$$\hat{e} = \sum_s \beta_s\hat{P}_s + \alpha\hat{r} = \sum_s \beta_s\mu_s(\widehat{w} - \hat{a}_s) + \alpha\hat{R}/(1+\eta), \tag{A4}$$

so using (A3) in (A4),

$$\hat{e} = \sum_s \beta_s(\hat{a}_s - \widehat{w})\left[\frac{\alpha(E_s-1)}{(1+\eta)\sum_s \beta_s(1-\mu_s)} - \mu_s\right] \tag{A5}$$

Utility changes according to $\hat{u} = \widehat{w} - \hat{e}$, so this and (A5) give the following expression:

$$\widehat{w} = \frac{\hat{u} + \sum_s \beta_s\hat{a}_s[(E_s-1)\alpha/(1+\eta) - \mu_s B]}{B + \sum_s \beta_s[(E_s-1)\alpha/(1+\eta) - \mu_s B]}, \qquad B = \sum_s \beta_s(1-\mu_s) \in (0,1). \tag{A5}$$

Productivity change occurs only in place 1 so if *N* is large $\hat{u} \cong 0$ and $\widehat{w} = \hat{e}$. *B* is the share of imports in overall spending. The denominator is positive if $E_s \geq 1$, since $B(1-\sum_s \beta_s\mu_s) > 0$.

Using (6) and (A2) the change in sectoral employment is

$$\hat{L}_s = \hat{p}_s + \hat{x}_s - \widehat{w} = (E_s - 1)(\hat{a}_s - \widehat{w}) + \mu_s \widehat{M} - \widehat{w}. \quad \text{(A6)}$$

Parameters in simulation: 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: $\beta_0 = 0.25(1-\alpha) = 0.1875$
Sectoral 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 (section 3.4)
$a^A = 3$, $a^B = 1$, $\rho = 0.5$, $v_s \in [0.25, 075]$.

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

(ii) 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

(iii) 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

(iv) 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:

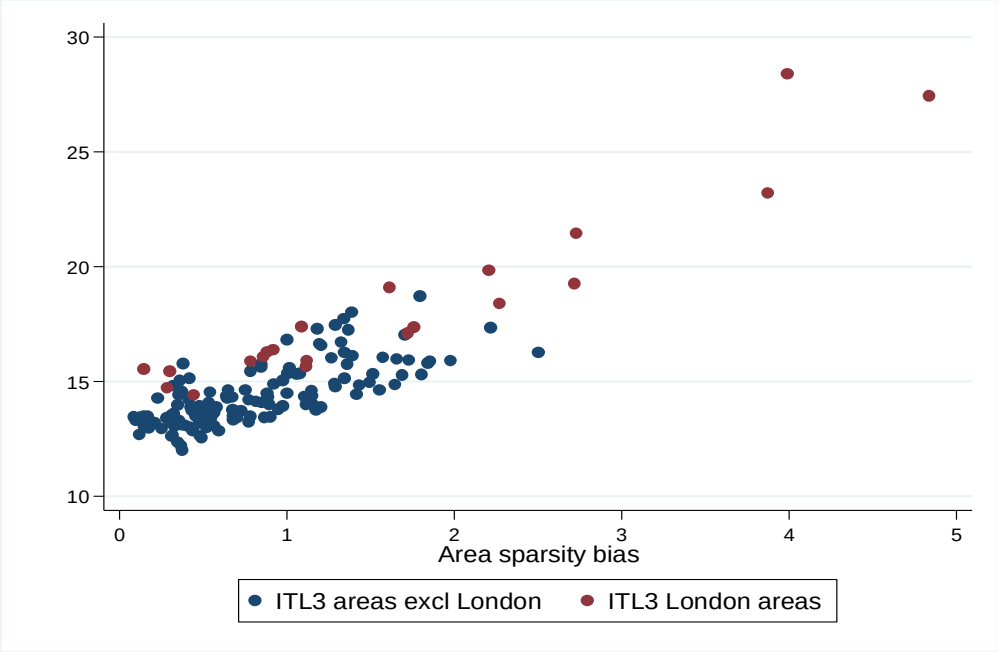


Table A1: Earnings, Sectoral Composition and Sparsity Bias:

	Mean Hourly Earnings	Sector-differential effect, $(\widetilde{w}_i - \overline{w})$	Area-differential $(w_i - \widetilde{w}_i)$
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. Table 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, $(\widetilde{w}_i - \overline{w})$	Area-differential $(w_i - \widetilde{w}_i)$
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) Table A5: Occupational Earnings and Sparsity Bias

	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

t-values reported in parentheses.

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