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To them that hath: economic complexity and local industrial strategy in the UK

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Abstract
Divergent economic performance in many countries has led to renewed interest in place-based policies, such as the UK's local industrial strategies at the level of Combined Authorities or Local Economic Partnerships. However, an analysis of employment data using methods from the economic complexity literature demonstrates great heterogeneity in industrial strengths and future growth opportunities within those jurisdictions, raising challenges in designing common policies suited to all sub-geographies. Moreover, the 'related' industries into which low-complexity, low-wage local authorities could potentially diversify are also low-wage. Incremental policies building on existing local capacities are therefore likely to amplify divergence between prospering and left-behind areas.

Keywords Economic complexity · Relatedness · Regional economic development · Industrial strategy · Place-based policy

JEL O25 · R10 · R58

1 Introduction

Faced with rising spatial inequality and stagnating growth, policymakers in advanced economies are increasingly looking for measures to boost productivity while addressing highly uneven economic development. Political support for place-based policies has grown in a number of countries, despite evidence of their

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mixed success (Barca et al., 2012; Markusen, 1996; Neumark & Simpson, 2015; Overman, 2018). Such government efforts (involving, for example, the funding of infrastructure, support for particular industries, or other local economic development schemes) aim to improve the economic performance of particular areas. The UK Government has introduced local industrial strategies comprising a range of measures to "build on local strengths and deliver on economic opportunities" (HM Government, 2018). Yet the practicalities of rigorously assessing numerous places' key areas of competitiveness and future opportunities for economic development in such strategies can be challenging.

In this paper, we apply methods from the economic complexity literature to analyse industrial strengths and future growth opportunities across UK local authorities. These methods have been shown to provide new insights into development patterns and the growth potential of countries and regions (Hidalgo et al., 2007; Hidalgo & Hausmann, 2009; Neffket et al., 2011; Hausmann et al., 2014; Gao & Zhao, 2018; Cicerone et al., 2019). They have also been used to operationalise applications of smart specialisation strategies (Balland & Rigby, 2017; Chávez et al., 2017) across EU regions. With the exception of Bishop and Mateos-Garcia (2019), however, there has been surprisingly little work applying economic complexity methods to the UK context.

This paper also contributes to a new conceptual understanding of the Economic Complexity Index (ECI) and Product Complexity Index (PCI) in regional settings. In previous studies, the ECI was commonly described as a measure of the diversity and sophistication of a country's (or region's) production, so the analytical framework was frequently used to test or support theories relating to economic variety and diversification. However, more recent analysis has shown that the ECI is mathematically independent (or orthogonal) to diversity (Kemp-Benedict, 2014). Instead, it reflects a ranking of countries (or regions) based on the similarity of their economic activities (Mealy et al., 2019). Here, we describe how these measures should therefore be interpreted and applied in the context of regional data (such as UK employment data) and discuss the key theoretical implications for regional economic development. We also contrast the ECI and PCI to measures like the Krugman Index (Krugman, 1991, 1993), which is commonly used to analyse regional specialisation patterns.

We show that UK local authorities with higher ECI tend to have higher per capita earnings, growth rates and greater ability to develop further industries with greater earnings potential, consistent with previous findings. In contrast to previous studies, however, we stress that this does not imply that these high ECI local authorities necessarily have a greater diversity of industries that few other local authorities are able to develop competencies in. There is, in fact, a negative correlation between diversity and ECI across UK local authorities. Instead, places with higher ECI tend to specialise in particular types of industries that are distinct from industries that low-ECI places tend to specialise in. Drawing on the PCI ranking of industries (which helps identify the types of industries that distinguish local authorities at either end of the ECI spectrum), we show that high-ECI places tend to be specialised in finance, insurance, information and communication, professional, scientific and technical activities, while local authorities with low ECI are more likely to be specialised in industries relating to agriculture, manufacturing and mining activities.

These differences reflect an important challenge for the design of local industrial strategy. In the UK, these strategies are being developed in geographically proximate zones (at the level of Mayoral Combined Authorities or Local Enterprise Partnerships (LEPs)). However, our analysis reveals that extreme heterogeneity across local authorities' industrial profiles can be present even within these small geographical zones. As achieving policy coherence across places with such different industrial contexts is likely to be difficult, local industrial strategies will likely need to consider how to target policies appropriately. Indeed, to best account for 'local' competencies and needs, it may be more appropriate to target policies towards groups of local authorities that share high similarity in their industrial strengths, rather than geographic proximity.

Our findings also highlight important implications for the prospect of rebalancing the UK's economic geography. The extent and persistence of the country's regional inequality have been widely documented (Gardiner et al., 2013; Martin et al., 2015). Although the trend towards polarisation between big cities and other places has been observed in other countries too (for example Autor, 2019), the UK's highly centralised governance arrangements have been identified as one of the contributory factors. This has motivated recent devolution trends, particularly to the new urban Combined Authorities (HM Government, 2011; McCann, 2016). Much of the discourse around local industrial strategy has emphasised the importance of "building on local strengths." However, for many UK local authorities with low ECI, the growth opportunities offered by their existing industrial strengths are extremely limited. Our results illustrate the well-known 'Matthew Effect' of the rich getting richer (Merton, 1968), suggesting incremental policy change is likely to crystallise additional high wage opportunities in high-ECI, high-wage local areas but not in low-ECI, low-wage ones. Unless local industrial strategies can be appropriately designed to address the systemic differences in economic development opportunities across UK local authorities, existing income and productivity differences are likely to remain or even widen.

2 The ECI and PCI: concepts and methods

The ECI and PCI were originally developed to infer information about the 'complexity' of countries' productive capabilities from export data (Hausmann et al, 2014; Hidalgo & Hausmann, 2009). This was one of a series of efforts to better identify, measure and understand capabilities that are more conducive to economic growth and development. At the country level, the development economics literature has emphasised the importance of technological capabilities for industrial upgrading and boosting countries' growth rates (Bell & Pavitt, 1997; Lall, 1992, 2000; Lall et al 2006; Hausmann et al., 2007; Sutton & Trefler, 2016). At the regional level, scholars have also long stressed the value of developing capabilities for innovation, learning and technological dynamism (Audretsch & Feldman, 1996; Howells, 1999; Lawson & Lorenz, 1999; Tödtling & Trippl, 2005). While significant effort has been devoted to analysing how regions grow by diversifying into new industrial activities that are related to knowledge and capabilities embedded in their existing industrial structures (Frenken, Oort and Verberg, 2007; Frenken & Boschma, 2007; Boschma & Frenken, 2011; Neffke et al, 2011; Boschma et al, 2012), the complexity of a region's knowledge base has also been argued to underpin places' capacities to generate unique competitive advantages and achieve dynamic growth (Balland & Rigby, 2017; Balland et al., 2019; Barzotto et al., 2019).

The novelty in Hausmann and Hidalgo's (H&H) approach was their measurement strategy. Owing to their tacit nature (Polanyi, 1966), 'capabilities' are notoriously difficult to analyse empirically. However, H&H argued that relevant information may nonetheless be indirectly inferred from examining what places were able to produce. Guided by the hypothesis that countries become richer by developing increasingly complex capabilities that allow them to export a greater diversity of products that few other countries are able to export, Hidalgo and Hausmann (2009) introduced a recursive algorithm called the Method of Reflections. This algorithm was said to involve measuring country diversity (the number of products a country can export competitively[1]) and product ubiquity (the number of countries that can competitively export a product) and iteratively weighting a country's diversity by the ubiquity of its products. Although the exact solution to this algorithm was later shown to be found by solving an eigenvalue equation (Caldarelli et al 2012; Cristelli et al 2013; Hausmann et al 2014), the resulting country-based ECI has proven to be notably successful in explaining variation in per capita GDP and growth rates across countries.

The ECI and PCI have also subsequently been applied to analyse productive capabilities in a variety of regional contexts such as the US (Balland & Rigby, 2017; Fritz & Manduca, 2019), Panama (Hausmann et al 2016), Mexico (Chavez et al. 2017), Australia (Reynolds et al 2018) and China (Gao & Zhou, 2018). Consistent with analysis at the country level, a common finding across many of these studies is that regions with higher ECI tend to have higher levels of per capita income. Owing in large part to the intuition that motivated the measures' construction, these findings have often been suggested to underscore the importance of cultivating a diverse set of relatively rare or hard-to-imitate capabilities.

However, more recent work has shown that the ECI and PCI reflect very little information about places' diversity or the ubiquity of products they produce. On the contrary, the ECI has been shown to be mathematically orthogonal to the diversity of exports or industries that places are specialised in (Kemp-Benedict, 2014).[2] Although a positive correlation between diversity and ECI has been observed for countries (Hidalgo & Hausmann, 2009), this empirical relationship is not the result of the construction of the ECI measure. As we show in Fig. 1, when applied to UK employment data, there is actually a negative correlation between the ECI and industrial diversity (see also Mealy et al., 2019).

[1] Where a country is considered to be competitive in a product if its revealed comparative advantage (as measured by the Balassa index (Balassa 1965)) in that product is greater than 1.

[2] The PCI is also mathematically orthogonal to ubiquity.

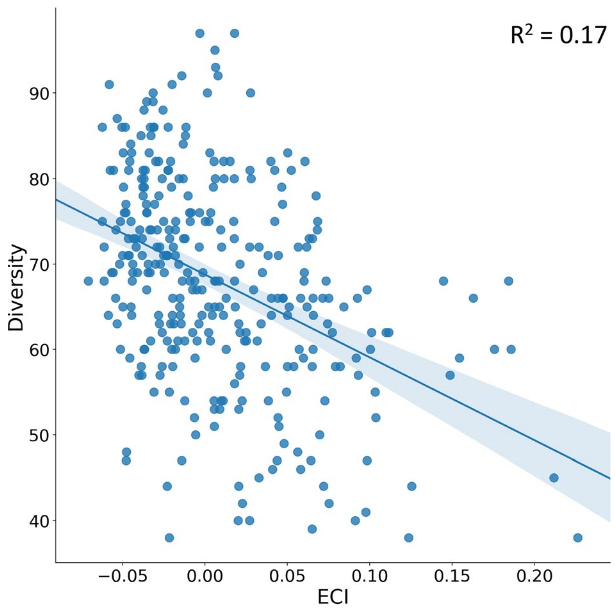

Fig. 1 Relationship between ECI and diversity for UK local authorities

A more accurate way to think about the ECI and PCI is as a type of dimensionality reduction tool (Mealy et al., 2019). Dimensionality reduction algorithms aim to reduce high dimensional data (data with a large number of random variables) to a space of much fewer dimensions. One analogy to the ECI and PCI is the Dewey Decimal System for classifying books (Mealy, 2018). Housing all sorts of books on various topics, libraries try to solve the problem of how best to place books on shelves such that they can roughly minimise the time people spend searching for any particular title. The Dewey Decimal System aims to place books about similar topics close together on the library shelf, so people who are interested in a given topic know where to look.

The ECI and PCI are similar in spirit. When applied to country-export data (e.g. Hausmann et al., 2014; Hidalgo & Hausmann, 2009), the measures essentially collapse the high dimensional space of countries' export portfolios onto a single dimension (like an ordering by topic along a library shelf) which aims to find an optimal arrangement that positions local authorities with similar industrial strengths as closely together as possible, and local authorities with dissimilar industrial strengths far apart. The PCI provides a similar one-dimensional arrangement for exports and gives a useful indication of the type of products that particular countries tend to have in common (Mealy et al., 2019).

Other measures, such as the Krugman Index, have also been used in the economic geography literature to analyse patterns of similarity in industrial structure across regions (Krugman, 1991, 1993). Commonly referred to as an index of specialisation or dissimilarity, the Krugman Index is often used to quantify the difference in industrial structure between two regions A and B by summing up the differences in their employment shares across industries. That is:

$$\mathrm{KI}_{\mathrm{AB}} = \sum_{i} \left| \frac{E_{i\mathrm{A}}}{\sum_i E_{i\mathrm{A}}} - \frac{E_{i\mathrm{B}}}{\sum_i E_{i\mathrm{B}}} \right|,$$

where $\frac{E_{i\mathrm{A}}}{\sum_i E_{i\mathrm{A}}}$ and $\frac{E_{i\mathrm{B}}}{\sum_i E_{i\mathrm{B}}}$ represent the employment share in industry i for region A and B, respectively. Here, a value of 0 indicates that the two employment distributions are exactly the same, and a value of 2 indicates that the distributions share nothing in common.[3]

While the Krugman Index provides a useful indication of which places have similar industrial structures, and whether places are becoming more or less specialised over time, the measure provides no insights into how regions differ. Returning to our library analogy, the Krugman Index could help us compare how similar two books' word frequencies are. However, unlike the ECI and PCI measures, the Krugman Index could not tell us anything about where in the library those two books are likely to be found, or what topics we might expect to find in them. The ECI and PCI measures thus represent an important addition to the set of analytical techniques available for analysing regional specialisation patterns.

3 Applying the ECI and PCI to UK local authorities

In this paper, we draw on data from the Business Register and Employment Survey (BRES). This data set provides employment data at the three-digit Standard Industry Classification (SIC) level of granularity for 380 of the GB local authorities (Northern Ireland is not included).

We calculate the ECI for local authorities by first constructing a binary M matrix based on local authorities' location quotients in different industries. An industry j's location quotient in a given area i is calculated as the ratio of the industry's share of employment in that location to its share of employment nationally. Defining E_{ij} as the number of people in local authority i employed in industry j, the location quotient for industry j in area i (denoted LQ_{ij}) is given by.

$$\mathrm{LQ}_{ij} = \frac{E_{ij} / \sum_j E_{ij}}{\sum_i E_{ij} / \sum_i \sum_j E_{ij}}.$$

We assume that a location quotient greater than 1 (which indicates that the local authority's employment share in that industry is greater than the national average)

[3] In order to avoid having N×N pairwise comparisons for N different regions, the Krugman Index is often used to compare each region's employment distribution to that of the nation, which yields N comparisons. Average or weighted averages of the pairwise comparisons are also commonly used to summarise regional specialisation patterns into a single number, which can then be compared over time.

conveys that the local authority has some degree of competitive strength in that industry.

Summing across the rows of M gives a local authority's diversity (the number of industries it is competitive in), while summing across the columns of M gives an industry's ubiquity (the number of local authorities that it is concentrated within).

To capture how similar one local authority's industrial strengths are to another, we calculate a new matrix $\tilde{M}$, which is given by.

$$\tilde{M} = D^{-1}MU^{-1}M'.$$

Here, D is the diagonal matrix formed from the vector of local authority diversity values and U is the diagonal matrix formed from the vector of industry ubiquity values. One way to conceptualise this matrix is as.

$$\tilde{M} = D^{-1}S,$$

where $S = MU^{-1}M'$ is a symmetric matrix in which each element S_{ij} represents the competitive industries that local authority i has in common with local authority j, weighted by the inverse of each industry's ubiquity. That is, S_{ij} will be higher if two local authorities have more industrial strengths in common with each other, and if those industries are less likely to be present in other local authorities. Then, $\tilde{M}$ just divides the S matrix through by local authority i's diversity. This also means that the $\tilde{M}$ matrix is row-stochastic (i.e. all the rows sum to one).

Finally, to collapse this $\tilde{M}$ matrix onto a single dimension that places local authorities with similar industrial strengths close together, we find the eigenvector associated with the second largest right eigenvalue of the $\tilde{M}$ matrix.[4] This eigenvector is the ECI.

When applied to our UK employment data, the PCI provides a useful indication of the type of industries that UK local authorities at either end of the ECI spectrum have in common. The PCI is calculated by simply transposing the M matrix and finding the eigenvector associated with the second largest right eigenvalue of an $\hat{M}$ matrix, given by.

$$\hat{M} = U^{-1}M'D^{-1}M.$$

In Table 1, we show the top and bottom ranked local authorities in terms of their ECI in 2015. High ranked local authorities like the City of London, Tower Hamlets and Islington have similar industrial strengths to each other and 'maximally different' industrial strengths from bottom ranked local authorities, such as East Staffordshire, Sedgemoor and Falkirk.

Table 2 shows the top and bottom ranked industries in terms of their PCI for the year 2015.

Here, the top 10 industries relate to skilled professional, financial or information-related sectors, which characterise key industrial strengths shared by high ECI

[4] Since $\tilde{M}$ is row-stochastic, its leading eigenvector is constant and consequently uninformative (its leading eigenvalue is 1).

Table 1 Top and bottom ranked Local Authorities by ECI

ECI Rank	Local authority	Rank	Local authority
1	City of London	371	Neath Port Talbot
2	Tower Hamlets	372	Pendle
3	Islington	373	Telford and Wrekin
4	Westminster	374	Rotherham
5	Southwark	375	South Derbyshire
6	Camden	376	Dudley
7	Hammersmith and Fulham	377	North Lincolnshire
8	Kensington and Chelsea	378	East Staffordshire
9	Hackney	379	Sedgemoor
10	Lambeth	380	Falkirk

places (shown in Table 1). The bottom 10 industries ranked by their PCI largely relate to manufacturing activities, which are common to low-ranking ECI places.

Figure 2 illustrates how the PCI helps distinguish the types of industries in which UK local authorities (ordered in accordance with the ECI) are specialised. Here, we show a box and whisker plot, based on the distribution of PCI values for industries falling within broader (2-digit) SIC categories. In this plot, the middle band of each box represents the median PCI value for industries falling within a given broad category, the box shows the quartiles of the distribution, and the whiskers extend to highlight the rest of the distribution (points outside the whiskers are outliers). We have ordered the broad SIC categories in order of the median PCI value of their three-digit industries.

As mentioned in Sect. 2, one can think of this ordering as loosely analogous to a Dewey Decimal Classification system helping to identify the types of industries along the ECI spectrum that local authorities are more likely to be specialised in. Local authorities with high ECI are more likely to be specialised in industries shown on the left hand side (finance, insurance, information and communication, professional, scientific and technical activities), while local authorities with lower ECI are more likely to be specialised in industries shown on the right hand side (agriculture, manufacturing and mining activities).

In Fig. 3, we show the relationship between local authorities' ECI and their per capita earnings. Consistent with previous applications of the ECI to country-export data (Hausmann et al., 2014) and regional data (Chávez et al., 2017; Gao & Zhou, 2018; Hausmann et al., 2016), we find a strong positive relationship ($R^2 = 0.58$).

As the ECI reflects the type of industries concentrated in places, this remarkably robust relationship is suggestive of the economic importance of what places specialise in (Kemeny & Storper, 2015; Martin et al., 2018). UK local authorities that tend to specialise in highly skilled professional, financial or information-related activities (as shown by the ECI and PCI metrics) are more likely to have higher per capita earnings than UK local authorities that specialise in mining, manufacturing and agricultural activities. Moreover, as we show in Table 3, local authorities that have higher ECI (and are thus more specialised in knowledge-based industries) are

Table 2 Top and bottom ranked industries by PCI

PCI rank	SIC (three-digit) industry	Rank	Local authority
1	Reinsurance	249	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semitrailers
2	Fund management activities	250	Manufacture of products of wood, cork, straw and plaiting materials
3	Television programming and broadcasting activities	251	Manufacture of basic chemicals, fertilisers and nitrogen compounds, plastics and synthetic rubber in primary forms
4	Trusts, funds and similar financial entities	252	Processing and preserving of meat and production of meat products
5	Motion picture, video and television programme activities	253	Manufacture of articles of concrete, cement and plaster
6	Advertising	254	Preparation and spinning of textile fibres
7	Market research and public opinion polling	255	Manufacture of cement, lime and plaster
8	Other information service activities	256	Manufacture of basic iron and steel and of ferro-alloys
9	Management consultancy activities	257	Mining of hard coal
10	Computer programming, consultancy and related activities	258	Manufacture of coke oven products

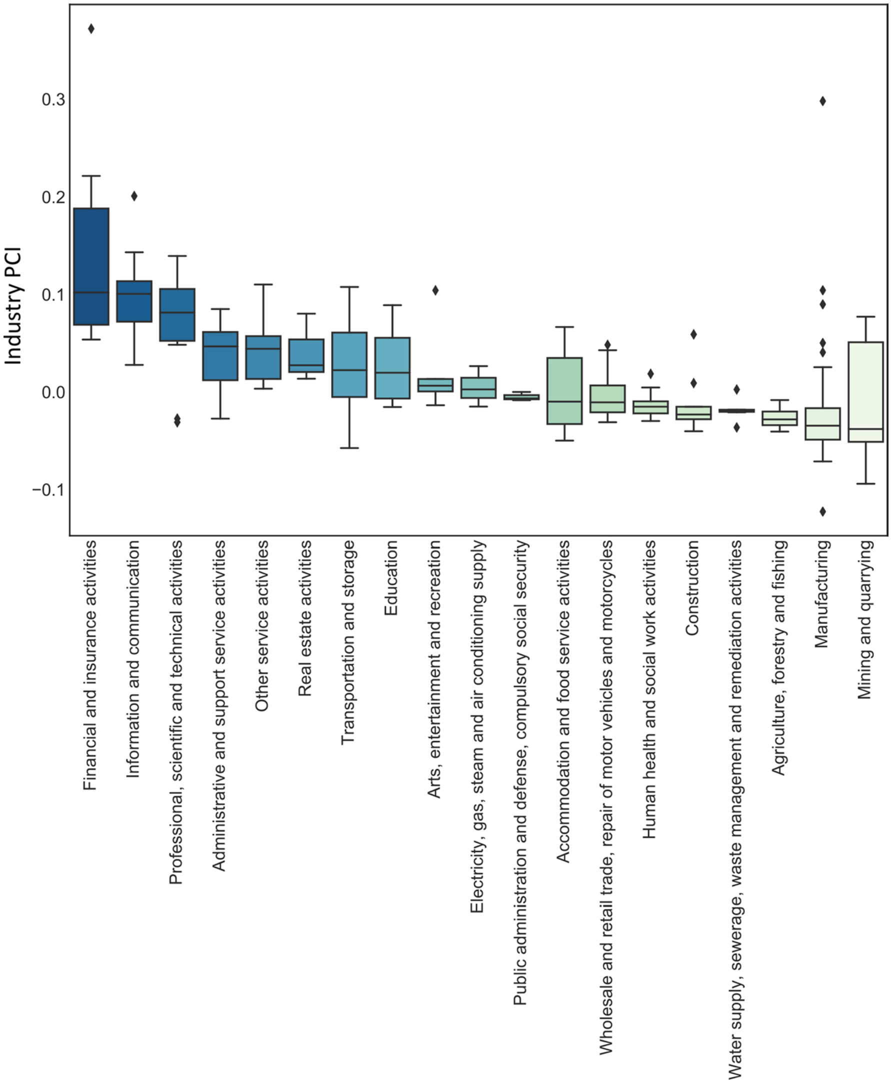

Fig. 2 Boxplot showing distribution of PCI values within broad SIC industry categories

significantly more likely to experience higher future earnings growth (see model 1). We show that this finding is robust to the inclusion of a number of controls, such as local authorities' diversity (model 2), urban–rural fixed effects (model 3) and region fixed effects (model 4).

In many respects, it is hardly surprising to find that urban UK local authorities specialised in knowledge-based industries have higher earnings and growth rates than rural areas specialised in agriculture or industrial activities. However, it is important to highlight that the algorithm for calculating the ECI and PCI is blind to the type of industries places are specialised in or the earnings associated with each

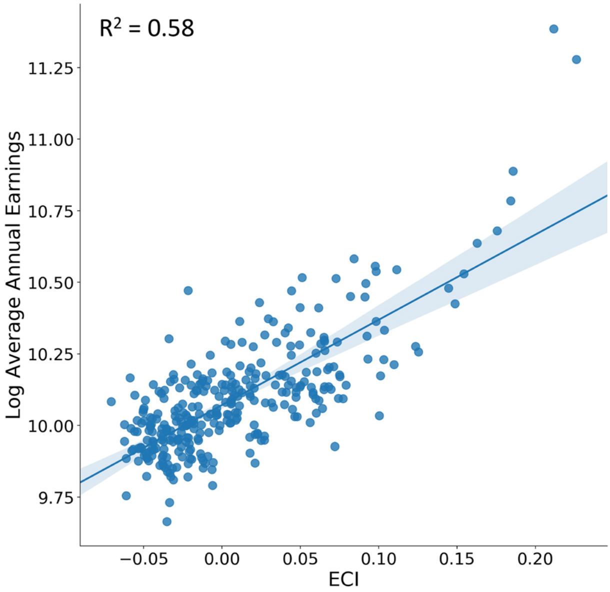

Fig. 3 Relationship between UK Local Authorities' ECI and average annual earnings in 2011

industry. It generates the ECI and PCI rankings purely by considering the pattern of similarities in places' industrial strengths captured by the $\tilde{M}$ matrix. The fact that the ECI ranking has been found to correlate with per capita income and growth rates so consistently across an increasing range of contexts suggests the existence of an important empirical regularity that, to the best of our knowledge, does not yet have an accompanying explanatory theory.

4 Implications for the UK's local industrial strategies

From the perspective of place-based policies and locally focused industrial strategies, gaining a better understanding of the geographical distribution of industrial capabilities is key. In the UK, Local Industrial Strategies are being developed at the level of Mayoral Combined Authorities or Local Enterprise Partnerships (LEPs). These strategies are intended to build on places' unique industrial strengths and set priorities for place-based development at the local level (HM Government, 2018).

While it is well known that the UK has stark spatial disparities in economic performance, these differences are often measured in terms of productivity (Zymek & Jones, 2020), population growth (Overman, 2017) or wages (Gibbons et al., 2014). Such measures do not provide a clear sense of how places' underpinning industrial structures differ. Figure 4, which shows how UK local authorities' ECI values are distributed geographically is particularly useful in this regard. Darker colours on the map denote higher ECI values, while lighter colours denote lower ECI values. It is not surprising to see most high ECI places specialised in finance

Table 3 Regression analysis of the relationship between growth in local authorities' annual earnings and economic complexity

Variables	Dependent variable: Annualised growth rate in average annual earnings (2011–2016)			
	(1)	(2)	(3)	(4)
Economic Complexity	0.091***	0.091***	0.090***	0.098***
	(0.027)	(0.029)	(0.029)	(0.029)
Log average annual earnings	−0.053***	−0.053***	−0.053***	−0.050***
	(0.007)	(0.007)	(0.007)	(0.007)
Diversity		0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
Intercept	0.545***	0.545***	0.543***	0.519***
	(0.074)	(0.073)	(0.073)	(0.074)
Urban–rural fixed effects	No	No	Yes	Yes
Region fixed effects	No	No	No	Yes
Observations	317	317	317	317
Adjusted R-squared	0.232	0.230	0.227	0.239

Robust standard errors in parenthesis

Workplace earnings data are sourced from the ONS Annual Survey of Hours and Earnings. Not all workplace earnings data were available for all 380 local authorities. Urban & rural classifications adopted from 2011 UK Urban Rural Classification https://www.gov.uk/government/statistics/2011-rural-urban-classification-of-local-authority-and-other-higher-level-geographies-for-statistical-purposes

*p value < 0.1

**p value < 0.05

***p value < 0.01

and knowledge-based industries concentrated in London and the South East. However, as we show in the inset of Fig. 4, which highlights the ten local authorities that comprise the Greater Manchester Combined Authority, quite striking differences in industrial strengths can be present within geographically proximate jurisdictions. Central Manchester stands out as having a very high ECI (indicating it is specialised in finance, information and professional activities), while Wigan—which is geographically close—has an industrial profile at the other end of the ECI spectrum indicating it has completely different industrial strengths.

While differences between cities and their surrounding hinterlands are frequently acknowledged (Etherington & Jones, 2009; Keuschnigg et al., 2019), such extreme industrial heterogeneity within relatively small geographical radii suggests that there could be some difficulty setting policies at the Combined Authority level. In particular, given the tendency for regions to diversify into new industries that are related to industries they are already competitive in (Boschma et al., 2013; Hidalgo et al., 2007, 2018; Neffke et al., 2011), the diversification opportunities and corresponding policy priorities for Wigan could look particularly different to Manchester.

To explore this in more concrete terms, we draw on measures of relatedness proposed by Hidalgo et al. (2007) to make comparisons between Manchester and

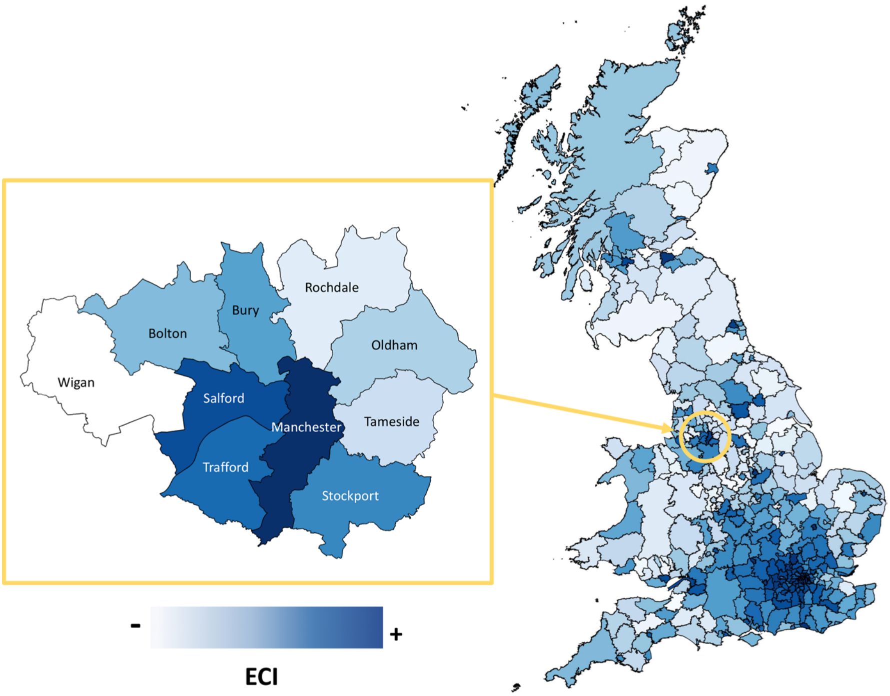

Fig. 4 Geographical distribution of UK Local Authority ECI. Inset shows the Local Authorities encompassing the Greater Manchester Combined Authority. Source: Mealy & Coyle, 2019

Wigan's most related diversification opportunities. We first calculate the proximity ϕ_{jk} between two industries j and k on the basis of their pairwise conditional probability of co-locating in a local authority. This is given by:

$$\phi_{jk} = \min\left(\frac{\sum_i M_{ij}M_{ik}}{\sum_i M_{ij}}, \frac{\sum_i M_{ij}M_{ik}}{\sum_i M_{ik}}\right).$$

Following Hidalgo et al. (2007), we take the minimum of these terms to ensure $\phi_{jk} = \phi_{kj}$. We then analyse how related a new industry is to a local authority's current set of industries by calculating proximity density. This measure (denoted ω_{ik}) calculates the average proximity of a new industry k to all the other industries in which local authority i is currently concentrated and is given by:

$$\omega_{ik} = \frac{\sum_j M_{ij}\phi_{jk}}{\sum_j \phi_{jk}}.$$

Figure 5 combines the PCI and resulting proximity density measure to identify industrial diversification opportunities for a selection of UK local authorities. While similar approaches have been applied to identify new export diversification opportunities across countries (Hausmann et al., 2014), and new areas of

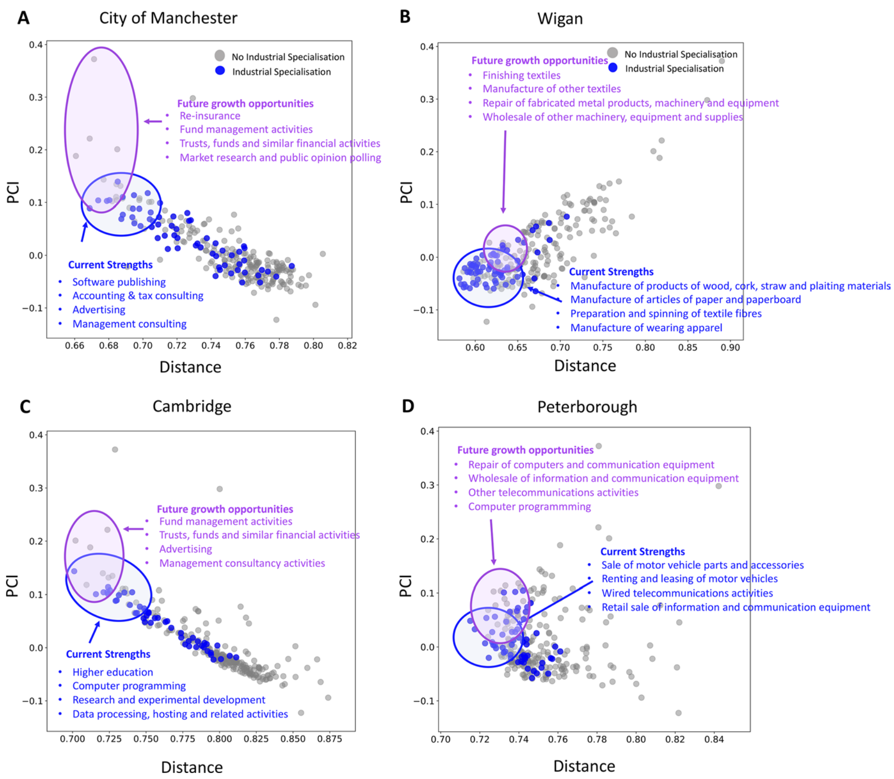

Fig. 5 Identifying industrial growth opportunities using PCI and Proximity Density measures for selected UK Local Authorities

technological competency across EU regions (Balland et al., 2019), we are not aware of any studies using this method to identify industrial opportunities for UK regions.

In Fig. 5, dark dots represent industries in which a local authority is currently competitive, while grey dots are industries a local authority is not competitive in. The y-axis plots each industry's PCI and the x-axis plots each industry's 'distance' from the local authority's existing industrial strengths, which is defined as $1 - \omega_{ik}$. For each local authority, we label a selection of their current areas of industrial competitiveness in dark blue. Industries shaded in purple represent new industrial possibilities that are well aligned with the place's current industrial strengths (in terms of having a small 'distance') and have higher PCI, which could be advantageous in terms of earnings and growth outcomes.

Panel A shows the current strengths and new industrial opportunities identified for City of Manchester. Given its existing competitiveness in industries such as accounting, tax and management consulting, the distance metric suggests that Manchester is well positioned to develop new businesses in the management of trusts, funds and re-insurance. Market research activities could also be advantageous given Manchester's existing industrial competitiveness in advertising. However, Panel B, which performs the same analysis for Wigan, underscores the challenges of developing such policy measures at the Greater Manchester Combined Authority level. Wigan's current industrial base and most closely related diversification opportunities are strongly focused on manufacturing activities. Thus, although the City of Manchester and Wigan fall under the same Combined Authority, policies targeted towards unlocking Wigan's future potential opportunities in textiles and machinery will be very different from policies relevant to the City of Manchester's skilled, knowledge-driven industrial base.

Panel C and D show Cambridge and Peterborough as comparator local authorities in a different Combined Authority. Similar to Manchester and Wigan, Cambridge and Peterborough are very geographically proximate but also have fairly different industrial strengths and related diversification opportunities. Interestingly, many of the future growth opportunities identified for Cambridge are similar to the City of Manchester. While this is not surprising given that both Manchester and Cambridge have higher ECI values (and are therefore specialised in more similar industries), it does suggest that the lessons learned from industrial policy experimentation in the City of Manchester are likely to be much more applicable to Cambridge (and vice versa) than to Wigan. As such, rather than designing local industrial strategy only from the perspective of geographical proximity, it could be particularly useful to consider local authorities' industrial similarities (and differences) as well.

One further important feature that stands out when comparing Panel A to Panel B is the difference in the slopes of the two plots. In Panel A, all of Manchester's closest development opportunities are associated with higher PCI values, which are more likely to be associated with higher average earnings and growth performance. However, Wigan has the opposite situation. Wigan's nearby industrial development opportunities are associated with lower PCI values. It is important to stress that the tendency for high (low) ECI places to have downward (upward) slopes is to be expected, given the way the distance metric and ECI/PCI measures are constructed. However, since the ECI ordering is so strongly associated with earnings and growth outcomes, the slope differential translates into important economic consequences for places with high and low ECI. Underscoring what is ultimately a rich-get-richer effect, these results indicate that it is much easier for places with high ECI (which already have higher per capita earnings) to develop new industries with higher earnings and growth potential than it is for places with low ECI (which currently have lower per capita earnings). Indeed, their future opportunities are for the most part likely to also be low-earning ones.

This has a key policy implication, namely that a strategy building on existing strengths only will be insufficient to start to narrow the geographic inequalities driving the current policy interest in local place-based policies. The smart specialisation literature emphasises institutional weaknesses, along with weaker infrastructure and social capital, as the drivers of different regional trajectories (Gianelle et al., 2019), but our results suggest a more profound challenge, namely the inherent difficulty for low-ECI places of closing the 'distance' between low and high ECI industries.

5 Concluding comments

In this paper, we have extended economic complexity approaches to analyse data on UK local authorities and highlighted the unique ability of the ECI and PCI measures to provide novel insights into regional specialisation patterns. In contrast to previous work, which cast the ECI and PCI measures in terms of capturing the diversity and sophistication of production, here, we demonstrate that the measures instead provide a useful approach for reducing the dimensionality of the data and show how they usefully add to the tool-kit for analysing place-based industrial specialisation.

Our results have key implications for the design of place-based policy and local industrial strategy. They reveal considerable heterogeneity in industrial strengths and growth opportunities in geographically proximate locations. These differences in industrial profiles pose significant issues for designing coherent industrial strategies at the level of LEPs or Combined Authorities. However, this variation does suggest that industrial policies could be usefully targeted towards groups of places that are more similar in their industrial strengths—rather than just considering geographical groupings.

Such a proposal is closely aligned with recent calls for 'place-sensitive distributed development', which has sought to address regional inequality across European regions (Iammarino et al., 2019). While the place-sensitive distributed development approach segments regions into groups (or 'economic clubs') having similar income levels and targeting development policy to each group, it might be particularly advantageous to stratify regions into groups that are specialised in similar industries. Policy experimentation and learning are likely to be more effective within groups of local authorities having more comparable industrial profiles. And indeed, designing local industrial strategies that account for both geographical and industrial proximity could be particularly important in helping address place-based productivity differences.

Our findings are also relevant to existing work on smart specialisation strategies (S3). While previous work has applied economic complexity approaches patent data across EU regions to inform S3 frameworks (Balland et al., 2019; Rigby et al., 2019), we show how such methods can also be fruitfully applied to employment data within a given country. In providing further clarity on the interpretation and intuition underpinning the ECI and PCI—which are frequently used in existing work to calculate measures of 'knowledge complexity'—our paper also opens up new avenues of inquiry: why are more prosperous places likely to have more similar industrial specialisations? And why do we observe a similar pattern in regional-patent data (Balland & Rigby, 2017; Balland et al., 2019) and country-export data (Hausmann et al., 2014)?

Finally, the 'rich-get-richer' dynamic underlined by our analysis is closely connected to the growing literature on regional divergence and polarisation (Martin et al., 2016; Storper, 2018; Collier, 2018; Venables, 2020) and suggests that policy interventions aimed at 'building on local strengths' may well exacerbate geographic inequalities in productivity and income. The economic and political challenge of place-based inequality needs to face the reality that many places do not have significant local strengths to start with (Barzotto et al., 2019; Fothergill et al., 2019). Successfully addressing the reinforcing dynamics driving the widening geographic inequalities observed in many OECD countries will require new, non-incremental policy approaches. Exactly what major, non-marginal policy interventions might take such places onto a different trajectory and more promising set of opportunities is a question for future analysis.

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Code availability Code will be provided on reasonable request.

Declarations

Conflict of interest We have no conflicts or competing interests to declare.

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