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Spatial network analysis as a tool for measuring change in accessibility over time: Limits of transport investment as a driver for UK regional development

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Abstract

This paper develops spatial network metrics that contribute to analysis of regional development. We use the sDNA software to derive longitudinal road network density and efficiency measures based on the network within a 1-hr travel time buffer. We estimate this travel time itself from network shape and show it to be comparable to Google Maps travel time data. Economic analysis of 374 Local Administrative Units in the UK mainland shows cross-sectional association between our network density and efficiency measures and Gross Value Added per capita (GVApc), whether measured in bivariate correlation or in multiple regression controlling for population, education, economic activity rate and rail stations. This is however both mediated and moderated by the proportion of knowledge-based businesses; regions lacking a strong knowledge-based sector show only weak correspondence between GVApc and accessibility. Looking at change over time, increase in network accessibility is linked to growth in the knowledge-based sector, but inversely linked to economic performance during the 8-year period studied, a finding which remains unexplained. Although further substantiation is needed, results suggest that the policy of transport investment as a driver of UK economic growth may be less effective in areas lacking potential to develop a strong knowledge-based sector.

1 | INTRODUCTION

From biological to social systems, numerous phenomena are limited and influenced by the network structure and can thus be analysed from the complex network theory perspective in which the network structure is primary (Barabási & Bonabeau, 2003). In the field of transport, the success of various spatial network analysis approaches has shown this to be a viable prospect (Cooper, 2018; Cooper et al., 2014; Haworth, 2014; Hillier & Iida, 2005; Jayasinghe, 2017; Kang, 2017; Lowry, 2014; Omer et al., 2017; Patterson, 2016; Serra & Hillier, 2017; Turner, 2007). Such empirical fit between the network structure and transport behaviours can be interpreted in multiple ways. In the extreme, we can accept the premise that the network itself is a driving cause, based on an assumption that land use and patterns of transportation will eventually equilibrate so as to make efficient use of the available network (Cooper, 2017). Alternatively, we can reject such strong assumptions but still accept that while networks may not be a primary cause (they are after all, built in response to demand arising from various non-network influences), they are often the slowest element of the built environment to change, owing to the disruption necessary to construct major transport links, so in the short term can be viewed as the most independent variable (Cooper, 2018). Finally, even in cases where this is not an appropriate assumption, it remains the case that network data capture substantial information about the built environment which may not be available from other sources (Chiaradia et al., 2014). The current study takes the latter approach in not relying on any special network assumptions; it seeks neither to endorse nor disprove such assumptions, but instead demonstrates empirically that useful information can be derived from networks either in isolation or in addition to existing data.

Our aim is to extend the spatial network approach into economic analysis. An advantage of emphasis on the importance of network shape is the ability to construct retrospective accessibility analysis based on historic network data. This allows for richer analysis than the limited longitudinal accessibility statistics available from the UK Census. We demonstrate the use of a spatial network approach to the UK economic output at the Local Administrative Unit (roughly corresponding to Local Authority) level. We find that the relationship between accessibility and output is far from straightforward, and likely to be both mediated and moderated by local composition of the industrial sector. This confirms that the existing work suggesting limits to the policy of investing in transport as a driver of UK economic growth, however we urge caution in applying this finding directly to questions of policy for which more sophisticated existing models and meta-analysis should be used. The primary contributions of the current study are to (1) derive longitudinal network shape measures and (2) demonstrate their ability to predict change in economic development.

1.1 | Transport and economic development

In economic geography theories, transport has long been considered influential in determining the cost of production, access to labour and access to markets, starting with the theories of Von Thunen (Alonso, 1967; Kilkenny, 1998). Christaller (1933) claimed that cities will tend to be localized in the most accessible location. In welfare economics, transport is interpreted as the sources of profit making through welfare gains (Mueller, 2003) as industries minimise their generalised cost of transport through a combined operationalisation of cost of travel and time taken for travel (Banister, 2012). In the new economic geography theories, transport infrastructure is considered as a locational phenomenon within the context of imperfect competition (Fujita, 2001; Melo et al., 2013; Proost & Thisse, 2015). Finally, agglomeration effects (Bettencourt, 2013) though typically posited in purely spatial terms are in practice influenced by transport altering accessibility across space, potentially leading to both static and dynamic clustering (Department for Transport, 2014; 2018; Eddington, 2006; Graham et al., 2010).

Today, transport remains one of the crucial driving forces of economic development (Eddington, 2006; Mačiulis et al., 2009) and has been extensively used as a tool for encouraging economic growth (Diaz et al., 2016) by reducing travel time and connecting producers and consumers (Button & Reggiani, 1997), job creation and competitiveness (Clayton et al., 2011; Huggins et al., 2016), and engendering local branding (Heintz et al., 2009). The impact of transport infrastructure improvement differs in terms of spatial scale (Banister & Berechman, 2001; New Zealand Ministry of Transport, 2016), internal characteristics of the region (Eddington, 2006; Holl, 2004; Keeble & Walker, 1994), and significant differences are apparent between developed and developing countries (Bose & Haque, 2005), with economies in the latter showing greater potential to respond to transport investment due to existing undersupply. Transport may increase agglomeration of economies in certain places (De Bok & Van Oort, 2011) and has a significant but variable spill-over effect to neighbouring regions of a targeted region (Persyn et al., 2020). However, provision of transport systems can also affect quality of life negatively through increasing inequalities to access opportunities, increasing competition for jobs and services due to migration and commuting, and by frustration with some forms of travel (Allsop, 1980). There is also evidence of negative effects on small business through increased land and rental value (Castillo-Manzano & López-Valpuesta, 2009).

Numerous econometric studies found a positive link between transport investment and economic growth (Baker et al., 2015; Banister, 2012; Banister & Berechman, 2001; Bose & Haque, 2005; Cidell, 2014; Duran-Fernandez & Santos, 2014; Mejia-Dorantes et al., 2012; Melo et al., 2017) in some cases showing differing results across industrial sectors (Graham et al., 2009). Other approaches have looked at firm births (Holl, 2004, again showing sectoral differences) and the benefits of efficient transport systems on knowledge-based activities or cities (Docherty et al., 2009; Marsden, 2006; Mullen & Marsden, 2015). However, debate is ongoing as to what extent economic growth associated with transport development is additional, versus redistributed from elsewhere (Melia, 2018). Some studies find transport infrastructure alone insufficient to stimulate growth (Yu et al., 2012), which is also dependent on local geography, nature of the built environment, existing labor and property markets, and land use (Mejia-Dorantes & Lucas, 2014). The direction of causality is also not clear cut, i.e., as well as transport investment giving rise to productivity, the reverse is also thought to be true (Graham et al., 2010).

In the case of the UK, there is a strong knowledge-based sector clustered in a subset of regions which is known to affect the transport-productivity relationship (overlapping strongly with the "business services" category in Graham et al., 2009). Also, regional competitiveness is known to affect ability to capture the benefit of transport investment, and proportion of knowledge-based industry within the UK context is a proxy for this (Huggins et al., 2016).

Within this context, this research studies the association between transport accessibility, knowledge-based industry, and economic performance in the UK. Our primary aim however is to test the potential of spatial network analysis as an economic approach. We begin by using network analysis to provide a historic picture of accessibility change. We then compare this to change in both economic outputs measured as Gross Value Added per capita (GVApc) and proportion of knowledge-based industry; our approach follows, e.g., Holl (2004), González-González and Nogués (2019) using multiple longitudinal regression which arguably underpins gap-based approaches also (Manca, 2012). We do not attempt to answer questions of additionality versus redistribution (Melia, 2018).

2 | DATA AND METHODS

2.1 | Socio-economic data

We choose to evaluate accessibility and economic performance at Local Administrative Units Level 1 (LAU1)[1] as this is the finest scale for which economic data are available. The study excludes non-mainland UK to avoid discontinuity in the network dataset. In total, 374 LAU1 units were used. As with any areal analysis, this is susceptible to the Modifiable Areal Unit Problem and Uncertain Geographic Context problem (Kwan, 2012). Although these issues are unavoidable in studies of this sort, the LAU1 unit has contextual relevance due to its correspondence with institutions of local government and economic management (Local/Unitary Authorities in England and Wales, Local Enterprise Companies in Scotland).

GVA per head of resident population for 2015 was used as the main indicator of economic performance. Data on knowledge-based businesses were collected from UK Competitiveness Index reports (Centre for International Competitiveness, 2017). The definition of knowledge-based business (Department for Business Innovation & Skills, 2012) includes, in decreasing order of sector size, financial, computing, legal, accounting, telecom, engineering, advertising, scientific, and creative industries (Office for National Statistics, 2016). Figure 1 shows the maps log of GVA per capita (henceforth abbreviated as GVApc) and proportion of knowledge-based business (KB).

Following González-González and Nogués (2019), we include three socio-economic variables: education, economic activity rate, and population. All these measure human capital, while the first two also quantify local market potential. All are measured at the LAU1 level. In our case, we include population as a density rather than absolute count. This is because our target of analysis is GVA per capita, hence, the effect of raw population count has already been factored out; we are interested in population

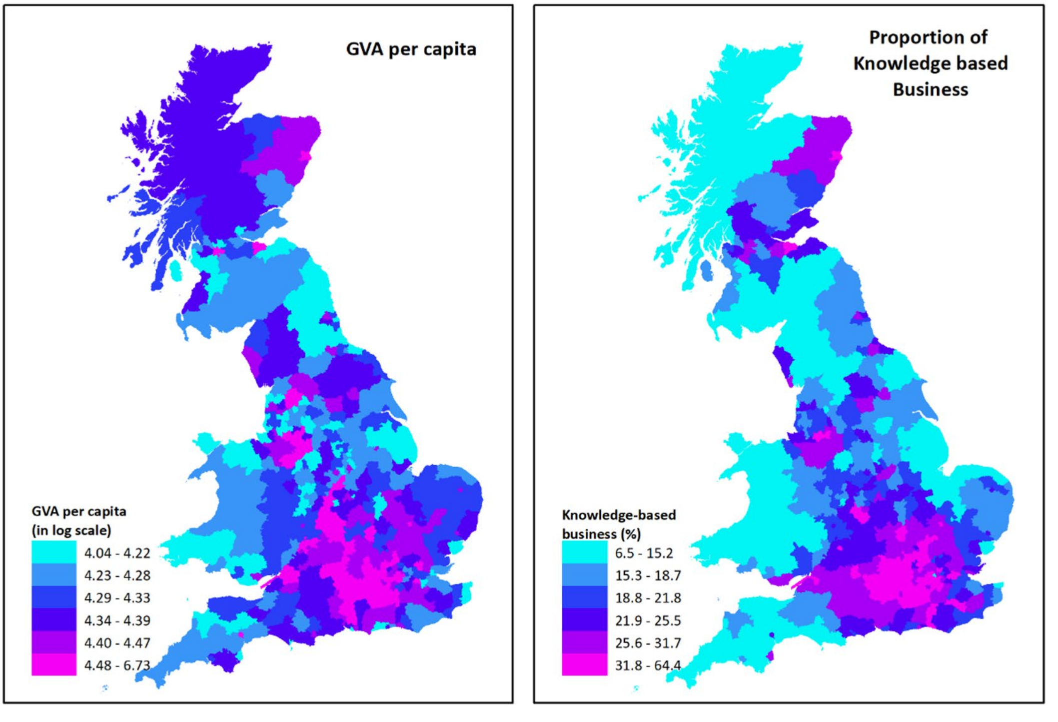


FIGURE 1 GVA per capita and proportion of knowledge-based business in the UK by LAU1 in 2015

primarily as an indicator of agglomeration. It is also important to check whether network density measures add information not already present in population density (with which they will correlate). Table 1 shows a summary of variables used with descriptive statistics. Following Huggins et al. (2019), we expect all variables shown in Table 1 to have a positive association with GVApc and growth of the same.

2.2 | Network data

We use the Integrated Transport Network (Ordnance Survey, 2017) data, a complete road network for the United Kingdom. Before processing, we used the sDNA software (Cooper & Chiaradia, 2020) to straighten traffic island links (which introduce spurious angular change to the network) and removed alleyways and private roads. Initially, we attempted removal of local streets to simplify computation; however, this introduced errors due to the frequency of minor roads being misclassified as local streets in the data; therefore, we chose to include local streets in the final analyses. The processed network contains approximately 3 million links.

2.3 | Proxying travel time

The aim of the travel time model is to capture the accessibility impact of major changes to the road network, based on a historic road network map. To this end, it makes use only of network shape data, which

TABLE 1 Descriptive statistics of the variables

Variables	Variable description	Minimum	Maximum	Mean	Std. dev
GVApc	Log of Gross Value Added per capita	4.04	6.73	4.35	0.18
KB	Proportion of businesses that are knowledge-based	6.50	64.42	23.10	8.44
Links	Network links within 1 hr travel time	2.93E+03	4.66E+05	2.37E+05	1.22E+05
Length	Network length within 1 hr travel time	7.72E+05	4.71E+07	2.66E+07	1.17E+07
HullA	Convex hull area of 1 hr travel time buffer	2.68E+09	1.69E+10	1.11E+10	2.99E+09
HullR	Maximum radius of 1-hr convex hull	5.06E+04	9.16E+04	7.80E+04	6.38E+03
PopDen	Population density per square kilometre	8.84	15,322.58	1,473.03	2,281.83
Edu	Proportion of working age population educated to NVQ level 4 or above	10.20	69.70	35.18	10.14
EAR	Economic activity rate; population of working age population in employment or seeking employment	49.70	89.10	78.41	4.53
Rail. St	Number of rail stations	0.00	61.00	7.02	6.92
ΔGVApc	Log difference in GVApc 2015–2007	1.46	6.01	3.37	0.39
ΔKB	KB2015-KB2007	−6.32	14.58	3.68	3.29
ΔHullA	HullA2017-HullA2007	−1.29E+08	7.98E+08	1.67E+08	1.34E+08
ΔLnk	Links2017-Links2007	173.00	27,414.60	10,007.67	4,859.43
ΔPopDen	Popden2017-Popden2007	−417.00	3,245.00	120.44	323.84
ΔEdu	Edu2014-Edu2007	−14.00	27.00	6.94	5.60
ΔEAR	EAR2014-EAR2007	−44.00	12.00	−1.66	4.59

for the historical networks we found to be recorded with greater accuracy than other data such as road classification or speed limits. Our model thus takes as its basis an average speed to travel through the network, adjusted with (1) a time penalty for change of direction whether at a junction or turn in the road and (2) a time penalty for all junctions even if there is no change of direction, as traffic is typically slowed by vehicles joining or leaving a carriageway. Cumulative change of direction is known to correlate with lower vehicle speeds on routes (Ciscal-Terry et al., 2016; Jayasinghe, 2017; Papinski & Scott, 2011). Therefore (1) above can reasonably be incorporated as a time penalty to proxy speed information as, for example, expressways are generally straighter than minor roads (and also have fewer junctions, which we capture in (2)). These factors allow sensitivity to major changes in the network, e.g., construction of bypasses and straighter roads with fewer junctions, but not changed junction designs, traffic light timings, allocation of space within the carriageway, e.g., bus lanes, or overall levels of congestion.

The travel time model is calibrated against an estimated travel time matrix for 50 randomly chosen origins and destinations throughout the UK mainland, with inter-peak travel time estimates derived from Google Maps in 2017. Google travel time estimates are derived from ongoing GPS tracking of smartphones and therefore account for traffic congestion; they are thus assumed to be significantly more accurate than our own model and assumed to be correct for the purpose of verification. The model is fitted through iterative application of network modelling software sDNA (Cooper & Chiaradia, 2020) to compute shortest time routes as predicted by the model, followed by OLS regression attempting to predict the Google time estimate from the characteristics (length, cumulative directional change, junctions) of the routes computed by sDNA. For each iteration, sDNA computes shortest routes based on OLS coefficients estimated in the previous iteration, and for the first iteration we begin with shortest-distance routes.

We do not assume the coefficients derived remain constant over time; their correct interpretation is as approximate relative time costs sensitive to change in the fundamental building blocks of any spatial network, namely, nodes and shaped links.

2.4 | Network modelling and measurement of accessibility

In contrast to existing models which rely, e.g., on gravity measures or employment accessibility, our aim in the current study is to derive predictions from the spatial structure of the network itself. We classify all the network measures used as accessibility measures, subdividing these into two types: density and efficiency. Each are computed for a given *radius* around each measured point on the network, in this case, within 1 hr estimated travel time of that point. We use 1 hr travel time as this is the maximum considered relevant by the UK Department for Transport in analysis of access to services/employment centres (Department for Transport, 2019). Network density, whether measured as built length or number of links, is indicative of built environment density; a count of links is more biased towards measuring intensification of land use at urban centres where link lengths are shorter (Chiaradia et al., 2012). These measures can also proxy population density however in the current study we include population density explicitly to see whether network density is capturing variance in GVApc above and beyond what population density tells us. We define network efficiency as either the maximum distance achievable as the crow flies (convex hull radius) or the area we can access (convex hull area) within the 1-hr travel time radius. Convex hull area is thus an omnidirectional measure while convex hull radius considers only the single most efficient route from the point of measurement. These can be related to the traditional measure of accessibility—usually defined as circuity, a ratio of length of direct paths to network paths (Barthélemy, 2011)—by realising that in the case of convex hull radius we restrict consideration to the maximum length of direct path achievable for a fixed time spent in travelling the network, i.e., the minimum circuity achievable for a fixed travel time. Convex hull area is this seen as a generalization of this concept to consider the average of all directions. The accessibility indicators are summarized in Table 2.

Network modelling was conducted with the sDNA+software using a hybrid network radius (Cooper & Chiaradia, 2020) to implement the estimated travel time model based on length, junctions and angular change. Due to the length of some long motorway segments, we required a sub-link level of accuracy. sDNA usually supports this via continuous space analysis (Cooper & Chiaradia, 2020) however this is not compatible with hybrid radii, so we took the alternative approach of splitting links into segments no longer than 500 metres. As we only required estimates for each LAU, it would be inefficient to calculate accessibility for every link in the network. Therefore, five population-weighted Middle Layer Super Output Area (MSOA) centroids were selected at random within each LAU1. For each centroid, the nearest link was identified that was present in the network for both analysis years. Accessibility was then computed for these links and an average taken for the LAU1. Figure 2 shows street level maps of the accessibility measures for Birmingham and surroundings, in order to illustrate typical variance of the measures at sub-LAU1 level. As some LAU1 units exhibit greater internal variance in accessibility than others, regression results are checked for heteroscedasticity.

After comparing the multiple years of road network data, accessibility change outliers were inspected manually by first exporting convex hull, then geodesic geometries to manually identify the network changes responsible for extreme accessibility changes. This inspection process revealed the errors discussed above (long links and road misclassification). Once these were corrected, the greatest increases in accessibility were attributable to construction of bypasses and new motorway junctions, while the greatest decreases were attributable to changes in urban layouts and new developments.

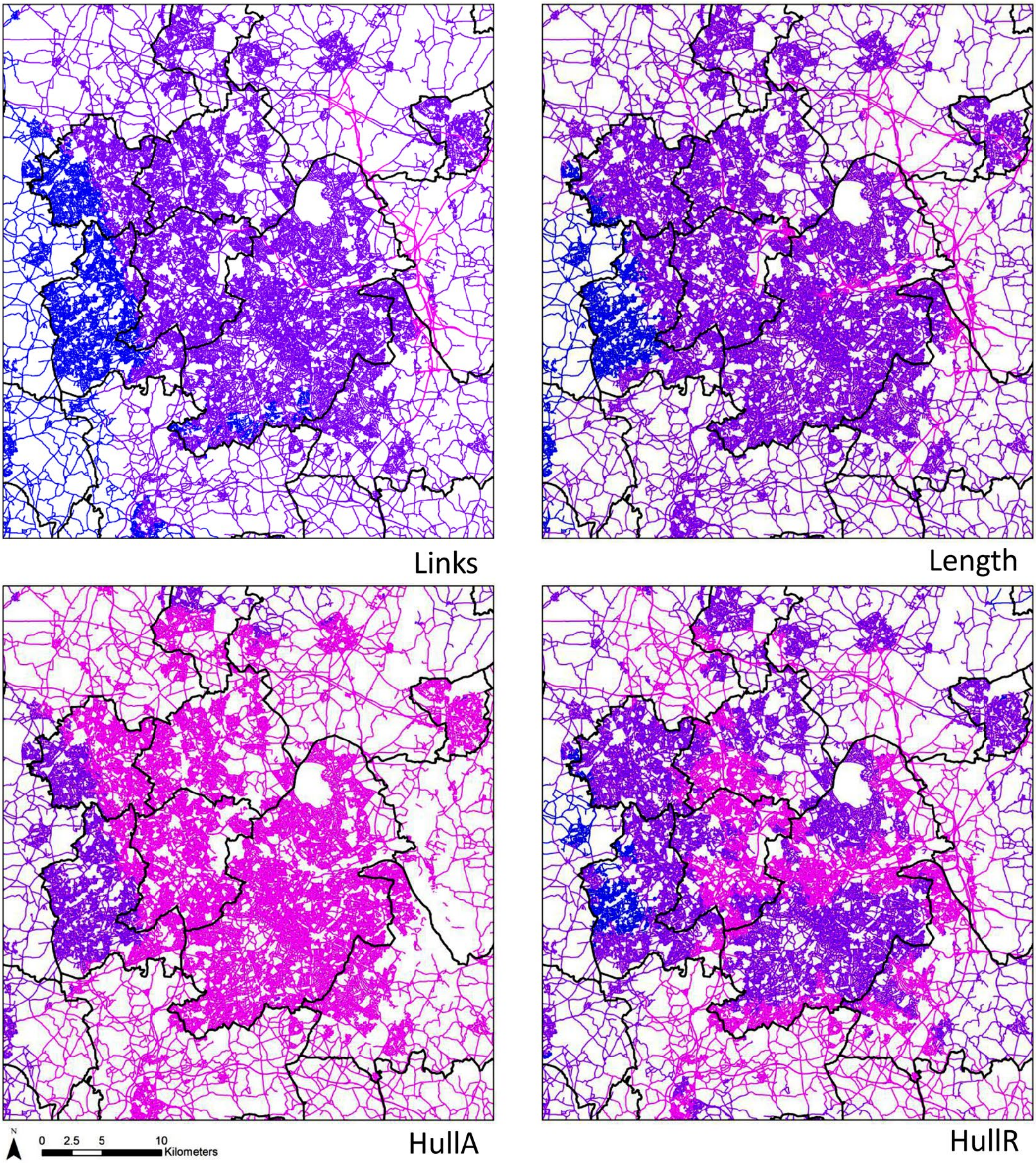
3 | RESULTS AND DISCUSSIONS

3.1 | Travel time model

The final regression R^2 for the travel time model compared to Google's congestion free estimate is 0.997 ($n = 2,500$). Although this represents a very high level of fit, it masks a standard error which is independent

TABLE 2 Accessibility indicators (always for network within 1 hr of travel time)

Accessibility indicator	Explanation
Network links (Links) Network length (Length)	Both measures of network density. Length is a direct measure of built length; a count of links is more biased towards measuring intensification of land use at urban centers where link lengths are shorter (Chiaradia et al., 2012)
Maximum radius of convex hull (HullR)	Measures network efficiency in a single direction; the furthest distance from the origin (as the crow flies) that can be achieved within the allotted time. Differs slightly from traditional definitions of efficiency (Barthélemy, 2011) by focus on maximum for a given radius, but principle of comparing crow-flight-Euclidean to network paths remains. Known to influence pedestrian and vehicle flows (Cooper et al., 2014; Kang, 2017)
Area of convex hull (HullA)	Measures network coverage in all directions; the total area reachable within an allotted time. This can also be as a measure of efficiency by generalizing HullR above to consider all directions.



Links	Length	HullA	HullR	Legend
0	0	0	41	
97	10	3.6	52	
193	21	7.2	63	
290	31	11	75	
386	42	14	86	
483	52	18	97	
x 1000	x 1000 km	x 1000 km^2	km	

FIGURE 2 Street level maps of the accessibility variables for Birmingham, illustrating variation through dense urban areas. Thick black lines show local authority boundaries. Legend class boundaries are equal interval based on minimum/maximum of national scale

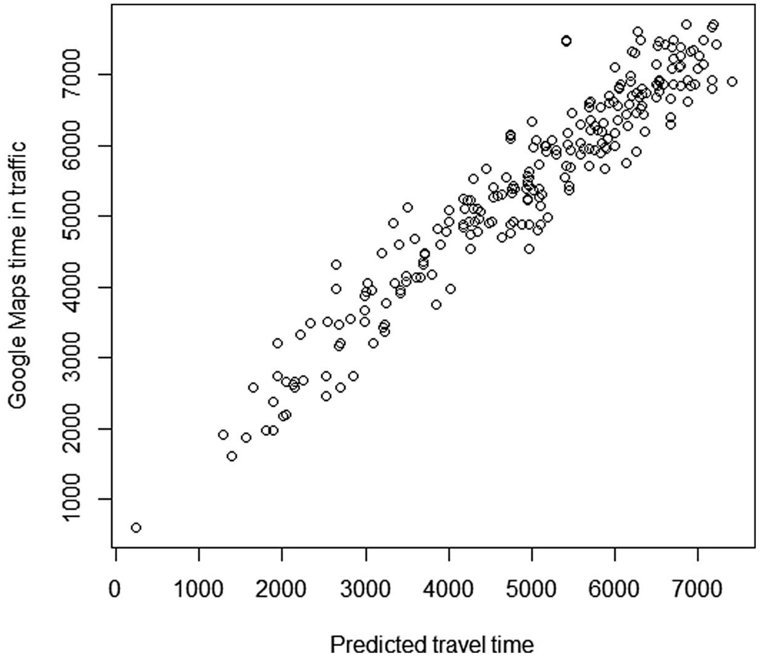


FIGURE 3 Scatterplot of predicted travel times from the network shape model versus in-traffic estimates from Google (trips commencing weekdays 10 a.m., showing trips under 2 hr only)

of scale: mean standard error (*MSE*) is ±361 s for each journey; errors are homoscedastic, so the fixed standard error will have a greater influence on shorter journey estimates. Restricting the test to shorter journeys only (defined as those for which Google estimates travel time under two hours in the absence of congestion) we find $R^2 = 0.968$ and $MSE \pm 265$ s ($n = 244$). If we include congestion according to Google's estimates, we obtain $R^2 = 0.993$, $MSE \pm 367$ s; or for short journeys alone, $R^2 = 0.919$, $MSE \pm$ 425 s. Figure 3 shows a scatter plot of this latter test and coefficient estimates are shown in Table 3.

3.2 | Bivariate correlations

Figure 4 shows the maps of network statistics at LAU1 level. As can be seen in Figure 4, network links and length are highly correlated. Convex hull area (HullA) exhibits an edge effect as coastal locations are lacking in potential land area which might be covered by a network. Using Hull Radius (HullR) to examine network efficiency in a single direction only, removes this effect. Comparing all network to economic statistics with bivariate correlation (Table 4) shows significant association between all network measures and GVApc. The correlation is stronger for density measures (Links and Length) than it is for efficiency (HullA and HullR). Presence of high numbers of links and network length are mostly urban phenomena, implying as we would expect, that cities and their neighboring areas enjoy better economic performance. Considering the efficiency measures, HullA exhibits stronger correlation with GVApc in spite of the edge effect noted above, implying that the edge effect is relevant to economic performance of peripheral areas.

A significant association is also found between the accessibility measures and concentration of knowledge-based business; this is likewise stronger for density than efficiency measures (Table 4).

TABLE 3 Calibrated estimates of contribution of different network features to travel time

Feature	Estimated time (seconds)
1 km network distance	32.0 (=69.9 mph)
90° cumulative change of direction	7.61
Junction	3.75

This result indicates that the concentration of knowledge-based business is higher in urban areas and areas with better accessibility. The proportion of knowledge-based business is also strongly correlated with GVApc, indicating that economic performance is better in those areas where there is a higher concentration of knowledge-based business. Moreover, both population density and education have significance association with the network accessibility and economic development, while economic activity rate has no significant association with network and other socio-economic variables.

The relationship between network accessibility and economic performance is explored in further detail by splitting LAU1 districts into two categories, those with concentration of knowledge-based business above the median (high-KB) and below the median (low-KB). Table 5 shows moderate and significant association between all four accessibility measures and GVApc for the high-KB group. For the low-KB group, however, network density measures do not show significant association to GVApc, and network efficiency measures show reduced correlation with only HullA retaining significance. Additionally, the association between concentration of knowledge-based business and GVApc is found to be strong in high-KB areas and insignificant otherwise. It can be argued from the above findings that the association between transport accessibility and economic performance depends on the internal characteristics of the economy. Areas without a strong knowledge-based sector exhibit weaker association between GVApc and accessibility, and where a correlation is measurable, it relates to efficiency of the network at traversing long distances rather than its density.

3.3 | Multiple regression models

Table 6 shows overall R^2 for a variety of GVA per capita models. Scatter plots of residuals were inspected and show no obvious evidence of heteroscedasticity or nonlinearity. Due to strong correlations and resulting overfit we cannot usefully include all network measures together in an ordinary least squares regression (VIF for Links, Length and HullA is 56, 75 and 6 respectively). We therefore select one density measure—Links—and one efficiency measure—HullA—for further individual exploration, as the overall model fit with each of these outperformed Length and HullR respectively. Likewise, we do not combine KB with Links because Links adds nothing to the performance of a model already including KB (Table 6 Model 6 & 7); HullA and KB can be included together but only adding marginal information (Table 6 Model 6 & 8). On the other hand, with or without KB, rail stations (RailSt) add very insignificant information. Overall, proportion of knowledge-based business outperforms network accessibility as a predictor of GVApc, but two questions remain open: (1) how does network accessibility influence the proportion of knowledge-based business and (2) how does the proportion of knowledge-based business affects the accessibility-GVApc relationship? In statistical terms, to what extent is KB a mediating variable and to what extent is it a moderating variable?

With KB excluded, Table 6 shows HullA to be more effective than Links as a predictor of GVApc. Therefore, we focus on HullA while splitting the dataset on KB. Table 7 shows this analysis, in which we can see that network efficiency as measured by HullA has far more influence on GVApc for

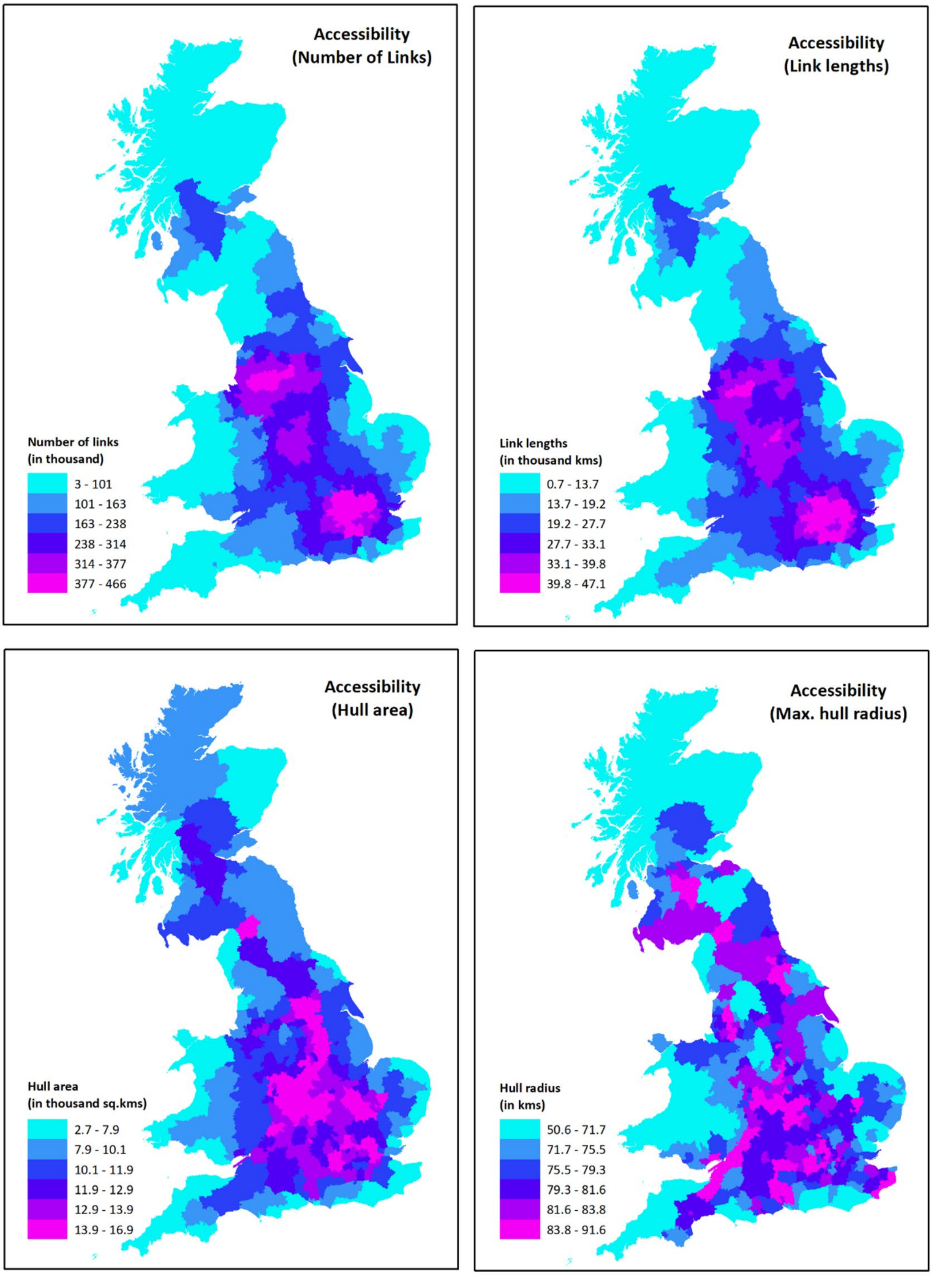


FIGURE 4 Accessibility measures within one-hour travel time by LAU1 in 2017

high-KB regions. Meanwhile in low-KB regions, the effect of network efficiency is reduced and not significant. Notably, population density and economic activity rate have significant influences in low-KB regions while in high-KB regions population density is not significant and level of education

TABLE 4 Correlations between indicators

Variables		GVApc	KB	Links	Length	HullA	HullR	PopDen	Edu	EAR
GVApc	r	1	0.632**	0.320**	0.349**	0.298**	0.254**	0.287**	0.461**	−0.096
	Sig.		*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.065*
KB	r	0.632**	1	0.531**	0.548**	0.382**	0.368**	0.371**	0.684**	0.100
	Sig.	*0.000*		*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.054*
Links	r	0.320**	0.531**	1	0.984**	0.723**	0.525**	0.439**	0.261**	−0.083
	Sig.	*0.000*	*0.000*		*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.108*
Length	r	0.349**	0.548**	0.984**	1	0.798**	0.570**	0.438**	0.291**	−0.023
	Sig.	*0.000*	*0.000*	*0.000*		*0.000*	*0.000*	*0.000*	*0.000*	*0.662*
HullA	r	0.298**	0.382**	0.723**	0.798**	1	0.694**	0.209**	0.242**	0.118*
	Sig.	*0.000*	*0.000*	*0.000*	*0.000*		*0.000*	*0.000*	*0.000*	*0.023*
HullR	r	0.254**	0.368**	0.525**	0.570**	0.694**	1	0.217**	0.202**	0.015
	Sig.	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*		*0.000*	*0.000*	*0.777*
PopDen	r	0.287**	0.371**	0.439**	0.438**	0.209**	0.217**	1	0.326**	−0.194**
	Sig.	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*		*0.000*	*0.000*
Edu	r	0.461**	0.684**	0.261**	0.291**	0.242**	0.202**	0.326**	1	0.249**
	Sig.	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*		*0.000*
EAR	r	−0.096	0.100	−0.083	−0.023	0.118*	0.015	−0.194**	0.249**	1
	Sig.	*0.065*	*0.054*	*0.108*	*0.662*	*0.023*	*0.777*	*0.000*	*0.000*	
Rail. St	r	0.037	0.061	0.017	−0.022	−0.113*	−0.072	0.115*	0.158**	−0.168**
	Sig.	*0.475*	*0.240*	*0.744*	*0.667*	*0.029*	*0.163*	*0.026*	*0.002*	*0.001*

**Correlation is significant at the 0.01 level (2-tailed).; *Correlation is significant at the 0.05 level (2-tailed).

TABLE 5 Correlations between Log of GVA per capita and accessibility indicators by knowledge based LAU1 categories

Variables		GVApc High KB	GVApc Low KB	GVApc All
KB	r	0.644**	0.038	0.632**
	Sig.	*0.000*	*0.604*	*0.000*
Links	r	0.284**	0.029	0.320**
	Sig.	*0.000*	*0.696*	*0.000*
Length	r	0.303**	0.063	0.349**
	Sig.	*0.000*	*0.388*	*0.000*
HullA	r	0.236**	0.156*	0.298**
	Sig.	*0.001*	*0.033*	*0.000*
HullR	r	0.182*	0.111	0.254**
	Sig.	*0.013*	*0.131*	*0.000*

**Correlation is significant at the 0.01 level (2-tailed).; *Correlation is significant at the 0.05 level (2-tailed).

TABLE 6 Multiple regression models of GVA per capita (in log scale)

Variables	Without KB					With KB				
Model no.	M-1	M-2	M-3	M-4	M-5	M-6	M-7	M-8	M-9	M-10
Adj. R^2	**0.260**	**0.283**	**0.297**	**0.286**	**0.298**	**0.426**	**0.426**	**0.430**	**0.426**	**0.430**
PopDen	√	√	√	√	√	√	√	√	√	√
Edu	√	√	√	√	√	√	√	√	√	√
EAR	√	√	√	√	√	√	√	√	√	√
KB						√	√	√	√	√
Links		√		√			√		√	
HullA			√		√			√		√
Rait. St				√	√				√	√

Bold was used to emphasize R^2 row.

TABLE 7 Multiple regression models of GVA per capita (in log scale) for low-KB and high-KB subgroups

	All		Low-KB		High-KB		All (KB as dummy)	
Variables	St. B	Sig.	St. B	Sig.	St. B	Sig.	St. B	Sig.
PopDen	0.058	0.237	0.381	0.000	−0.106	0.130	0.030	0.530
Edu	0.462	0.000	0.141	0.053	0.435	0.000	0.366	0.000
EAR	−0.232	0.000	0.159	0.033	−0.451	0.000	−0.247	0.000
KB							0.152	0.001
HullA	0.194	0.000	0.097	0.171	0.170	0.008	0.228	0.000
Rail. St	−0.060	0.190	0.037	0.599	−0.131	0.046	−0.065	0.147
Adj. R^2	**0.298**		**0.150**		**0.305**		**0.331**	

Bold was used to emphasize R^2 row.

is. This result suggests that the accessibility-GVApc relationship is moderated by KB (which we test below) and that if KB is low then accessibility does not help GVApc so much; indeed, the factors affecting GVApc in these cases are population density and economic activity rate. Returning to the question of what influences KB, Table 8 shows that both network density and efficiency are effective predictors of knowledge-based industry, displacing some of the variance otherwise explained by population density and education. It is likely that network density is proxying population density albeit on a scale better suited to economic outcomes than the LAU1 level, while the effect of network efficiency is independent of this. We also tested whether there is any effect of rail stations, however, found that number of rail stations do not add any further information and insignificant in regression models. Thus, for any further analysis, we dropped number of rail stations as a predictor.

3.4 | Mediation and moderation

Following our suspicion earlier that there may be moderation or mediation effects of KB in the accessibility-GVApc relationship, we performed both mediation and moderation analyses. The mediation analysis was conducted by estimating proportion of knowledge-based business (KB) from transport accessibility (HullA) as well as per capita GVA (GVApc, in log scale) from both transport accessibility (HullA) and proportion of knowledge-based business (KB). The analysis results (Table 9) show that HullA was positively related to KB (standardized $a = 0.3819$, $p < .001$) and KB positively predicted GVApc while controlling for HullA (standardized $b = 0.6072$, $p < .001$). A bias-corrected bootstrap confidence interval for the indirect effect (completely standardized) of HullA ($ab = 0.2319$) based on 5,000 bootstrap samples was entirely above zero (0.1686 to 0.3003), meaning the indirect effect is significant. There was no evidence that HullA influenced GVApc independent of its effect on KB ($c' = 0.0660$, $p = .1292$).

The moderation analysis shows that the interaction effects between HullA and KB is statistically significant (<0.001), meaning there is a moderating effect of KB while predicting GVApc from HullA (Table 10). A bias-corrected bootstrap confidence interval for the interaction based on 5,000 bootstrap samples was entirely above zero (0.0001 to 0.0002), meaning the existence of moderating effect of KB. Effects of HullA at different levels of KB shown in Figure 5. The figure indicates that there is no (or negative or insignificant) moderation effect where the KB is lower (about less than 20%). However, with the increase of the KB, the moderation effect increases.

The moderation and mediation analyses confirm that accessibility has a higher effect on economic performance in those regions who have better knowledge-based economic base.

3.5 | Changes over time

Figure 6 shows changes in GVA per capita and KB; Figure 7 shows changes in network statistics. In analysis of change over time, we do not include both network efficiency and density together due to high correlation ($R = 0.48$) between changes in Links and HullA.

The multiple regression picture of change in GVA per capita is complex (Table 11). Model 1 shows that changes in all socio-economic variables including changes in KB have very low influence ($R^2 = 0.030$) on GVApc change. Adding changes in accessibility variables (HullA or Links) cannot add much information (values are respectively 0.048 and 0.033 in Model 2 and Model 3 respectively). However, adding benchmark conditions of the variables with changes in condition can explain GVApc change much better (R^2 is 0.290 for Model 4). Adding network accessibility variables (either HullA

TABLE 8 Multiple regression model of KB

Variables	No network				Including links				Including HullA			
	No station		With station		No station		With station		No station		With station	
	St. B	Sig.	St. B	Sig.	St. B	Sig.	St. B	Sig.	St. B	Sig.	St. B	Sig.
PopDen	0.156	0.000	0.156	0.000	0.014	0.713	0.016	0.686	0.117	0.004	0.118	0.003
Edu	0.641	0.000	0.655	0.000	0.586	0.000	0.596	0.000	0.607	0.000	0.616	0.000
EAR	−0.029	0.462	−0.045	0.276	−0.013	0.725	−0.023	0.534	−0.054	0.161	−0.062	0.118
Rail. St			−0.068	0.076			−0.045	0.186			−0.037	0.327
Links					0.370	0.000	0.367	0.000				
HullA									0.217	0.000	0.211	0.000
Adj. R^2	**0.489**		**0.492**		**0.597**		**0.598**		**0.531**		**0.531**	

Bold was used to emphasize R^2 row.

TABLE 9 Coefficients for the mediation analysis (using HullA)

	Consequent			
	M (KB)		*Y* (log of GVApc)	
Antecedent	***Std. Coeff.***	***p***	***Std. Coeff.***	***p***
X (HullA)	$a = 0.3819$	$p < .001$	$c' = 0.0660$	$p = .1292$
M (KB)	–		$b = 0.6072$	$p < .001$
R^2	0.1459		0.4036	
N	374		374	
F	63.5332		125.5356	
p	$p < .001$		$p < .001$	

Note: X, accessibility variable; M, mediator; Y, output variable.

TABLE 10 Coefficients for the moderation analysis

Antecedent	Coeff.	*t*	*p*	LLCI	ULCI
HullA	−0.0024	−3.2721	<.001	−0.0038	−0.0010
KB	−0.0029	−0.7151	.4750	−0.0108	−0.0050
Interaction	0.0001	4.1008	<.001	0.0001	0.0002
R^2	0.4295				
N	374				
F	92.8636				
p	<0.001				

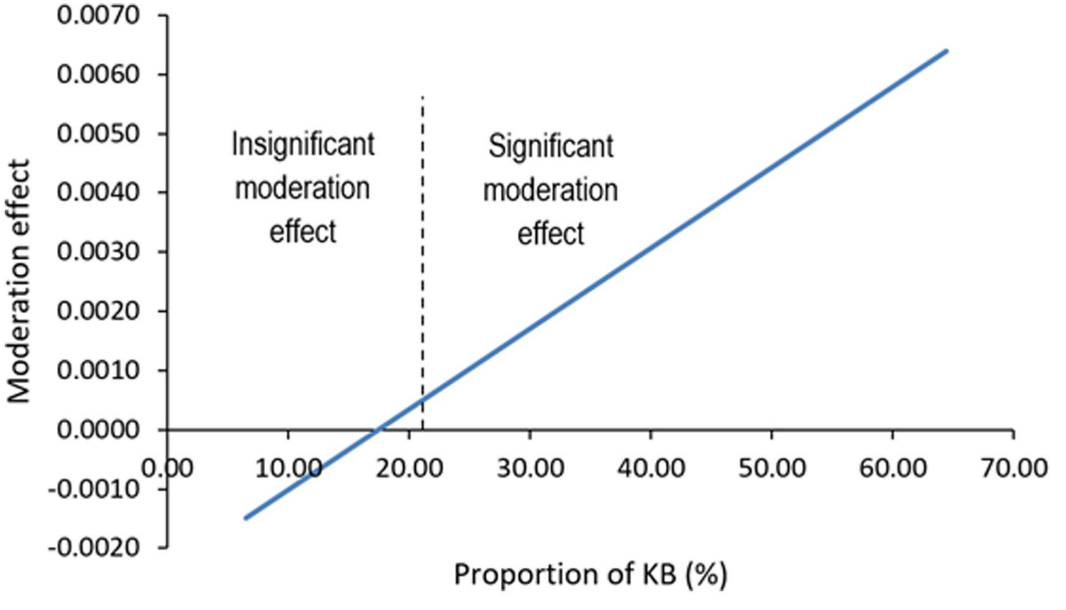


FIGURE 5 Effect of predictor (HullA) at different values of the moderator (KB)

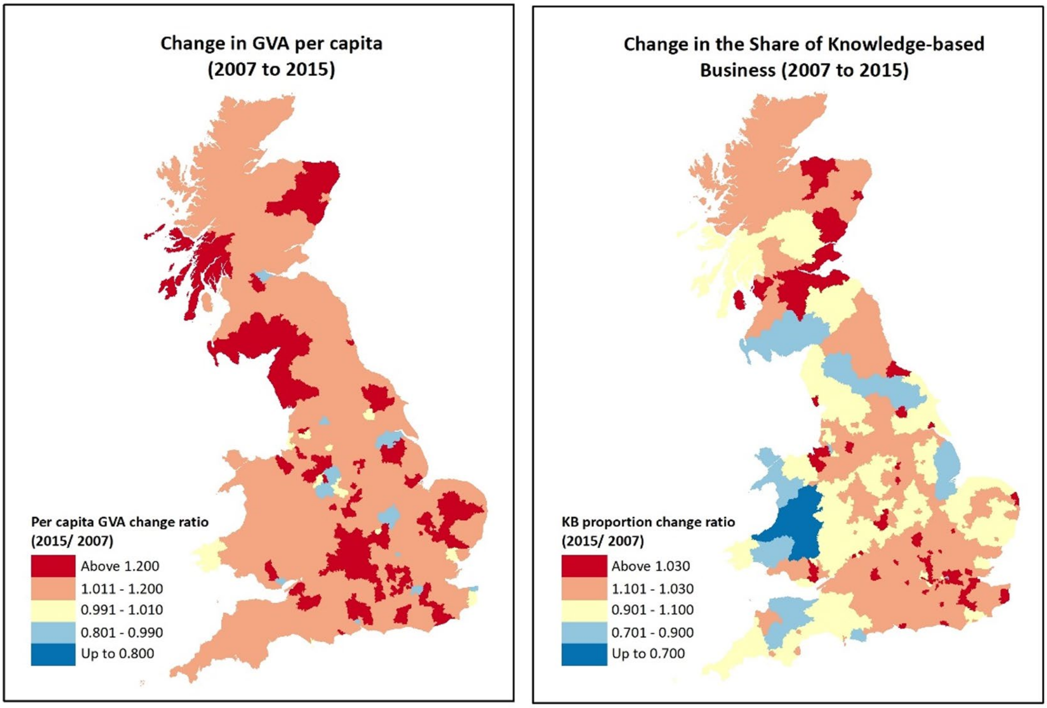


FIGURE 6 Change in GVA per capita and proportion of knowledge-based business in the UK by LAU1 2007–2015

or Links—Models 5 & 6) adds very little information and these variables do not appear significant. Table 11 also shows that GVA per capita growth is associated with a higher proportion of knowledge-based industry, but negatively associated with growth of the same. This result is robust to removal of insignificant variables from the analysis along with candidates for collinearity issues (GVApc2007 and KB2007). This is contrary to expectation and we discuss it further in conclusions below.

On the other hand, study of change in knowledge-based industry growth (Table 12) reveals increase in network density and efficiency to be significant positive predictors, increasing the performance of models based on socio-economic change variables alone (Models 1–3). When we include socio-economic benchmarks the improvement in performance is still present but marginal (Models 4–6) and while change in density retains significance (p = .015), change in network efficiency narrowly misses the usual cutoff (p = .056), likely due to its correlation with, and hence replacement by, KB2007 (R = 0.224).

4 | CONCLUSIONS

4.1 | Methodological conclusions

This study fulfils its primary aim of showing that information can successfully be extracted from spatial networks to inform economic analysis; all included measures of network density and efficiency were shown to be at least indirectly relevant in prediction of both GVA per capita and industrial mix; the former relationship also being mediated and moderated by the latter. The use of either links or

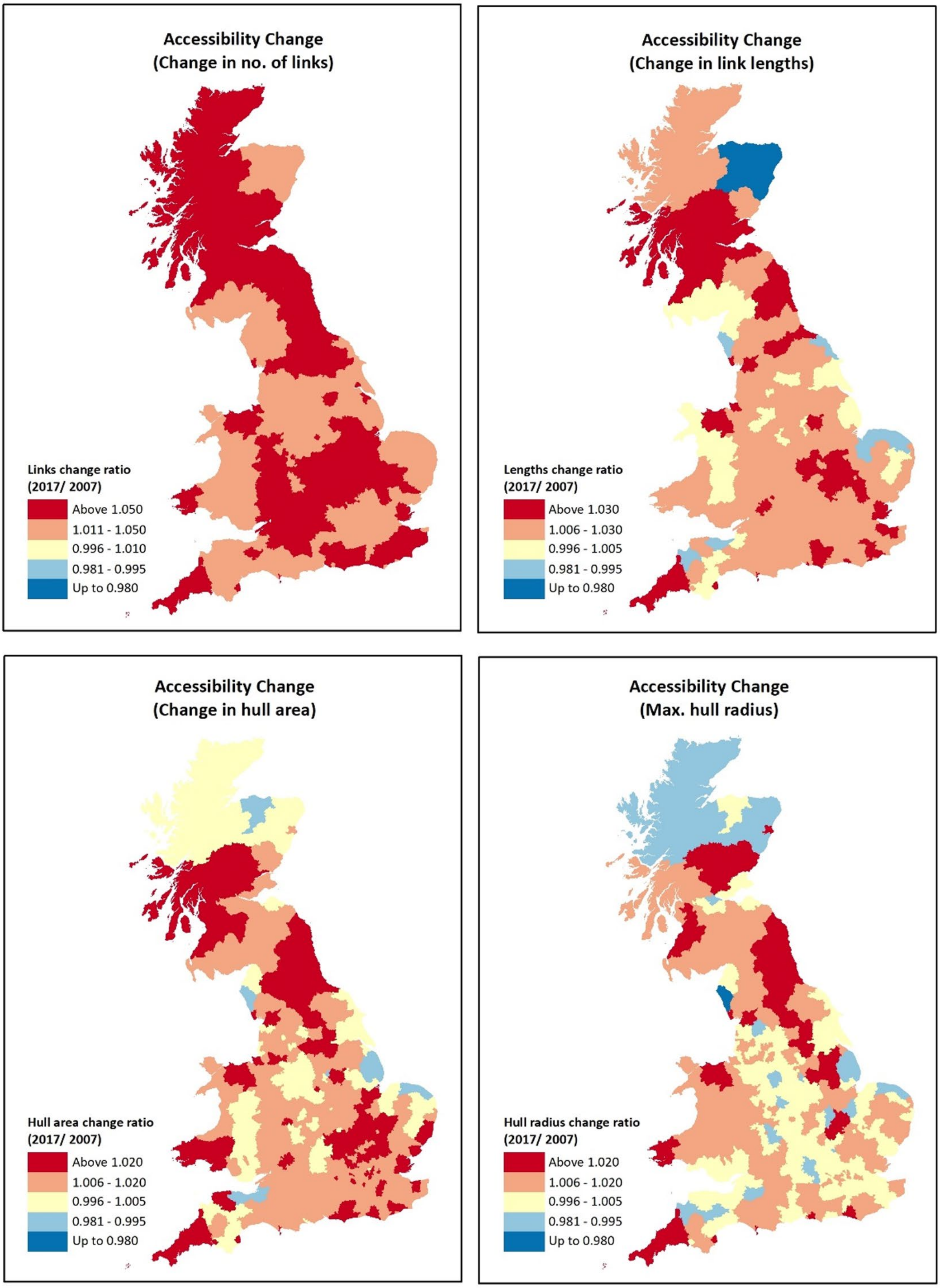


FIGURE 7 Change in accessibility measures within one-hour travel time by LAU1 2007–2017

length as a proxy for urban density adds information to the analysis, which is not present in population density alone, while convex hull area captures major changes in network efficiency. Hull area outperforms hull radius as a predictor of GVA per capita and industrial mix; perhaps because the edge

TABLE 11 Model of change in GVA per capita (in log scale)

Variables	Model-1	Model-2	Model-3	Model-4	Model-5	Model-6
Adjusted R^2	**0.030**	**0.048**	**0.033**	**0.290**	**0.293**	**0.287**
ΔPopDen	0.072 *(0.208)*	0.063 *(0.260)*	0.075 *(0.188)*	−0.050 *(0.499)*	−0.055 *(0.461)*	−0.048 *(0.519)*
ΔEdu	0.061 *(0.284)*	0.061 *(0.279)*	0.063 *(0.273)*	0.071 *(0.173)*	0.071 *(0.174)*	0.069 *(0.185)*
ΔEAR	**−0.198** *(0.000)*	**−0.197** *(0.000)*	**−0.190** *(0.001)*	−0.025 *(0.673)*	−0.031 *(0.610)*	−0.025 *(0.673)*
ΔKB	0.055 *(0.338)*	0.026 *(0.695)*	0.031 *(0.601)*	**−0.184** *(0.002)*	**−0.197** *(0.001)*	**−0.183** *(0.002)*
PopDen_2007				−0.005 *(0.954)*	−0.007 *(0.936)*	0.010 *(0.904)*
Edu_07				0.105 *(0.111)*	0.113 *(0.088)*	0.096 *(0.157)*
EAR_07				−0.051 *(0.422)*	−0.054 *(0.393)*	−0.052 *(0.410)*
KB_2007				**0.244** *(0.006)*	**0.225** *(0.012)*	**0.264** *(0.006)*
GVApc_2007_log				**0.340** *(0.000)*	**0.330** *(0.000)*	**0.337** *(0.000)*
HullA_2007					0.037 *(0.463)*	
ΔHullA		**0.147** *(0.006)*			0.069 *(0.145)*	
Links_2007						−0.048 *(0.507)*
ΔLnk			0.075 *(0.170)*			0.023 *(0.697)*

Bold was used for R^2. Italic was used for all p values. Bold was also used to emphasize coefficients with $p < .05$.

TABLE 12 Longitudinal models of change in KB

Variables	Model-1	Model-2	Model-3	Model-4	Model-5	Model-6
Adjusted R^2	**0.163**	**0.192**	**0.230**	**0.404**	**0.410**	**0.416**
ΔPopDen	**0.282** *(0.000)*	**0.263** *(0.000)*	**0.270** *(0.000)*	0.012 *(0.857)*	0.006 *(0.930)*	0.014 *(0.834)*
ΔEdu	**0.200** *(0.000)*	**0.193** *(0.000)*	**0.189** *(0.000)*	**0.114** *(0.013)*	**0.112** *(0.014)*	**0.120** *(0.008)*
ΔEAR	0.076 *(0.130)*	0.073 *(0.139)*	**0.095** *(0.048)*	0.017 *(0.742)*	0.009 *(0.863)*	0.028 *(0.590)*
PopDen_2007				**0.283** *(0.000)*	**0.276** *(0.000)*	**0.276** *(0.000)*
Edu_07				0.015 *(0.793)*	0.026 *(0.658)*	0.046 *(0.447)*
EAR_07				**−0.117** *(0.036)*	**−0.122** *(0.029)*	**−0.108** *(0.049)*
KB_2007				**0.561** *(0.000)*	**0.526** *(0.000)*	**0.486** *(0.000)*
GVApc_2007_log				**−0.212** *(0.001)*	**−0.220** *(0.000)*	**−0.197** *(0.002)*
HullA_2007					0.052 *(0.246)*	
ΔHullA		**0.177** *(0.000)*			0.080 *(0.056)*	
Links_2007						0.007 *(0.913)*
ΔLnk			**0.263** *(0.000)*			**0.128** *(0.015)*

Bold was used for R^2. Italic was used for all *p* values. Bold was also used to emphasize coefficients with $p < .05$.

effect noted in hull area represents a feature of real life, namely, lost opportunities for agglomeration in coastal areas due to the reduced area of land accessible when compared to inland locations.

Further work is needed to examine the impact of accessibility changes over time: having established that historical network analysis generates valuable new information, follow-on studies could improve on this using time series techniques such as vector auto regression over a longer period. That said, more nuanced methods may not yield new results as the existing literature is conflicted on the accessibility—economic output relationship. In particular, in developed countries already possessing good transport infrastructure, the effect may be weak, so further examination of the international context is recommended.

GVA was measured per capita of resident population, but as workers commute, the analysis could likely be improved by measuring GVA per job as (at least prior to the COVID19 pandemic) this is more localised to the location of economic production.

4.2 | Economic conclusions

We begin this section with the caveat that the primary aim of this study is to explore new methods and any policy application should be based on more sophisticated models and meta-analysis. In particular we have not accounted for spatial lag or endogeneity; results are not compared with prevailing gravity models (Hansen, 1959) and the analysis omits capital input as would be normal in a Cobb-Douglas framework (Douglas, 1976). As with any areal analysis, our results are potentially susceptible to the Modifiable Areal Unit Problem and Uncertain Geographic Context problem (Kwan, 2012); linking results to individual spatial trajectories derived, e.g., from mobile cell data may provide an approach to mitigating the latter.

The conventional narrative is that investment in transport infrastructure will, barring cases where the infrastructure is already good enough, generate economic growth as well as development. However this is an ongoing topic of research and despite a literature rich in empirical study, conclusive evidence is still lacking (Melia, 2018) particularly on the question of whether such growth is additional or merely redistributed, which is not possible to answer with correlation/regression based techniques alone. On the question of whether any growth occurs even locally, however, this study adds to those which show an inconclusive result in the long term but adds the footnote that *if* transport infrastructure can stimulate growth in developed nations, this dynamic is likely to be moderated by the composition of existing industry—in other words, better transport benefits some industries more than others. Graham et al., (2009) suggests the same thing, namely that knowledge-based industry might moderate the accessibility-GVA per capita relationship.

Our explicit study of the proportion of knowledge-based industry as an independent variable has suggested an additional causal pathway of mediation: accessibility seems to benefit knowledge-based business in particular which in turn contributes to GVApc. This finding fits the mechanisms outlined in the existing literature, most notably industry-specific agglomeration effects, although to some extent it could also reflect other locational preferences (Graham et al., 2009). Note that the applicability of this model may be confined to countries which, like the UK currently, have a strong knowledge-based sector concentrated in a subset of regions. Also, the analysis of change over time appears to contradict the mediation and moderation results, with growth of knowledge-based business being inversely associated with growth in GVA per capita. Two explanations for this are plausible: (i) that the relationship acts on different timescale than that studied i.e., areas with a growing knowledge-based sector may not yet be reaping the rewards in terms of GVA per capita, or conversely, areas with an already established knowledge-based sector may be showing less growth of the same, but still showing increase in GVA per capita; (ii) that both of these hypotheses may be wrong, and further research is needed to investigate the likely causal pathway.

If explanation (i) holds, then it would imply that in contexts comparable to the UK, transport will only significantly stimulate growth in regions which at least have the potential to support a strong knowledge-based sector. Where this is not thought to be the case, other forms of investment might be more effective or more desirable. The overarching question of how such regions can catch up economically remains unsolved, as the association of socio-economic and accessibility with growth which applies in knowledge-based regions is not replicated outside of them.

Further disaggregation of results by industry within the knowledge-based category might help to shed more light on mechanisms. In any case, disaggregation of these results by industry is also of strategic importance, as the "knowledge based" category covers a wide variety of activity (Department for Business Innovation & Skills, 2012). In fact, the long-term implications of developing different types of knowledge-based business will certainly differ substantially from one another. For example, although scientific and engineering innovation can potentially help address a global sustainability crisis, ongoing research questions whether further expansion of the already large financial, legal and advertising sectors would result in any net public good (Ashraf & Bandiera, 2017; Dur & van Lent, 2018; Lockwood et al., 2017). Lang (2016) argues that a focus on the foundational economy—food, shelter, education and healthcare—might be more appropriate than transport investment for lagging regions. All these factors should likely be considered in modelling the future of these regions, for which—unless a clear path to prosperity can be found—we are left only with the normative question of to what extent it is desirable to redistribute income from wealthier places.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available from the Centre for International Competitiveness, http://cforic.org.

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ENDNOTE

[1] LAU 1 units are defined by Eurostat's Nomenclature of Territorial Units for Statistics; they indicate local authority districts/unitary authorities in England, combination of council areas, Local Enterprise Companies and part of thereof in Scotland, Unitary authorities in Wales. (Details can be found at: https://data.gov.uk/dataset/8742f03b-bcce-4d78-8c22-331e8f03bda8/local-administrative-units-lau-level-1).

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