How Do Places' Characteristics Matter? Evidence from AI Location Quotients of LSOAs and TTWAs in Great Britain

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1 Introduction

AI adoption leads to socio-economic inequality issues among cities. On the one hand, complex technologies tend to be spatially concentrated in large cities due to local accumulation of knowledge, human capital, and institutions (Balland et al. 2020). In this way, complex technologies are intertwined with further spatial agglomeration over time, while simple ones are spatially distributed more evenly across space (Balland et al. 2020). Especially, companies and regions with a higher proportion of STEM workers (i.e., Science, Technology, Engineering and Mathematics) are more likely to adopt AI technologies (Draca et al. 2022; Acemoglu et al. 2023). These AI companies generate more benefits and increase efficiency by AI adoption than the others with less human capital (Calvino et al. 2022). On the other hand, AI-exposed enterprises replace non-AI tasks with AI occupations (Acemoglu et al. 2022). For instance, it is more likely for rural areas with higher proportions of low-skill and routine employees to be influenced by AI technologies (Brekelmans and Petropoulos 2020).

Thus, it is important for economic geographers to map the evolution of spatial patterns regarding AI adoption and investigate its driving forces. Limited studies investigate how places' characteristics influence AI spatial concentration within and among cities over time (Bloom et al. 2021). My research focuses on heterogeneous compositional and contextual effects on the AI location quotients at the LSOAs and TTWAs level in the UK between 2016 and 2021. Using a two-level regression model, research finds that at the local level, intensive AI online hiring activities hinge on places' characteristics, for instance, urban infrastructure, intellectual resources, social capital, and productivity. On the scale of regional labor market, more developed regions (i.e., larger travel to work areas) manifest labor demands for AI skills to a relatively greater extent on average across the UK. This research suggests local policy makers to cultivate places' characteristics by facilitating the mode of local-regional industry-university-research-government cooperation and promote up-skilling programs for vulnerable low-skilled workers.

2 Methods

2.1 Construction of variables

Cities with various urban contexts and functions perform differently in terms of AI adoption. Different Lower Layer Super Output Areas (LSOAs) and Travel To Work Areas (TTWAs) in the UK have different socio-economic characteristics such as total gross value added, industrial structure and human capital in LSOAs within London versus Manchester. Thus, there exists heterogeneous compositional and contextual effects on AI employment (Bloom et al. 2020, 2021; McElheran et al. 2023; Muro et al. 2023). The compositional effect indicates how individual attributes or factors at the low geographical level (i.e., LSOAs) influence a dependent variable (i.e., AI location quotients) (Goldfarb et al. 2023). In contrast, the contextual effect refers to broad or group-level effects on a greater scale (Goldfarb et al. 2023).

It is more appropriate to use 'size' variables at the LSOAs level and 'ratio' variables at the TTWAs level; otherwise, regression models may have endogeneity issues caused by geographical typology. For one thing, all LSOAs are defined according to a similar number of local populations (i.e., 1,500 people in average). So, small LSOAs indicating dense urban areas with relatively greater economic levels may tend to have more AI job clustering locally, compared to larger LSOAs (Duranton and Puga 2004; Bloom et al. 2021). These dense areas also tend to have the higher density of public amenities (or productivity), respectively, if this research uses the rate variable, for example, the rate of the number of public facilities (or total GVA) over areas of LSOAs. This inference is because public amenities are normally constructed according to a defined number of populations served. It means that high/low values of the rate variable are determined by the area/shape of LSOAs. In contrast, the size variable does not have this problem since the number of public amenities (or total GVA) is not subject to the area but is influenced partly by local population (1,500 in average for each LSOA). Alternatively, we may use the rate variable such as the number over local population rather than the areas, but this rate variable may have a low variation of values.

For another, all TTWAs are defined according to a similar commuting time range (i.e., Approximately isochronous or Workers' within-one-day commuting zone). In this way, relatively larger TTWAs like London with better transport facilities and economic opportunities may tend to see a higher average level of AI job spatial concentration (Draca et al., 2022). These developed regions also tend to have a higher number of airports, ICT infrastructure, large companies, employment and human capital due to intensive and extensive economic activities. This inference could be explained by existing research demonstrating a positive correlation between regional transport infrastructure and regional economic development. To cope with this endogeneity issue, it would be better to use ‘ratio’ variables at the TTWA level.

Our research investigates neighborhood effects of places’ characteristics on AI spatial concentration at the level of LSOAs (i.e., $LQ_{lw,t}$). The LSOA is places where Points of Interest (PoIs) cluster spatially to provide basic and commercial services for local people. Important variables at the LSOA level include total amount of local gross value added estimates (i.e., $GVA_{lw,t-1}$) and various PoIs (i.e., $PoI_{lw,t-1}$). Enterprises with more investment in the local market as well as R&D activities and more stock of disposable money tend to demand more AI employees (Alekseeva et al. 2021). Thus, GVA of each LSOA is an alternative and similar variable indicating economic contribution of local industries to gross domestic products. In these prosperous areas, commercial services of ICT, finance as well as insurance are the main suppliers and customers of AI-related products (i.e., $PoI\_ict_{lw,t-1}$ and $PoI\_fin_{lw,t-1}$) (Alekseeva et al. 2021; Gutierrez-Posada et al. 2023). In addition, other PoIs play essential roles in attracting AI companies and workers as well, for instance, the number of universities (i.e., $PoI\_uni_{lw,t-1}$) (Bloom et al. 2021), public transport facilities including bus coach stations, metro and railway stations (i.e., $PoI\_transport_{lw,t-1}$) (Bastiaanssen et al. 2022), central as well as local governments on which social capital is created in each LSOA based (i.e., $PoI\_lg_{lw,t-1}$ and $PoI\_cg_{lw,t-1}$) (Bloom et al. 2021).

The greater level, TTWAs, is an appropriate spatial scale to control labor market effects. Employees interact interpersonally and exchange new ideas in relevant fields by commuting mainly within TTWAs (Atalay et al. 2023; Diodato et al. 2018; Draca et al. 2022). In this way, technology adoption varies among commuting zones, thereby contributing to various labor specialization (Atalay et al. 2023). This variation means that the average of AI location quotients differs from TTWAs to TTWAs, and these average AI quotients exert different average effects on further AI concentration (i.e., random intercepts and effects in multilevel regression models). Proxy of different socio-economic levels of TTWAs include employment rate (i.e., $Emp\_Rate_{w,t-1}$), the proportion of managers, senior officials, professionals, and tech occupations in high-tech industries over total employment (i.e., $Emp\_STEM_{w,t-1}$) (Draca et al. 2022), the rate of all enterprises in TTWAs over economically active population (i.e., $Business_{w,t-1}$) (Bloom et al. 2021), the proportion of large companies with at least 250 employees over all enterprises in TTWAs (i.e., $Large\_Com_{w,t-1}$)

(Acemoglu et al. 2023), areas of TTWAs (i.e., $TTWA\_area_w$) (Bloom et al. 2021), ICT infrastructure such as broadband upload speed (i.e., $ICT\_upload_{w,t-1}$) (Draca et al. 2022), the number of universities (i.e., $University_w$) (Bloom et al. 2021), the geographical distance between TTWAs and London (i.e., $Distance_w$, or $London_w$) (Draca et al. 2022), and airports per economically active populations (i.e., $Airport_{w,t-1}$) (Lloyd and Dicken 1972) (see Table 2 in the Appendix below).

2.2 Regression models

$$LQ_{lw,t} = \beta_{0w} + \beta_{1w} TGVA_{lw,t-1} + \beta_{2w} PoI_{lw,t-1} + \varepsilon_{lw,t} \tag{1}$$

$$\begin{aligned} \beta_{0w} = {} & \gamma_{0w0} + \gamma_{0w1} Emp_{w,t-1} + \gamma_{0w2} Business_{w,t-1} + \gamma_{0w3} Large\_Com_{w,t-1} + \gamma_{0w4} ICT_{w,t-1} + \\ & + \gamma_{0w5} Airport_{w,t-1} + \gamma_{0w6} University_w + \gamma_{0w7} TTWA\_area_w + \gamma_{0w8} Distance_w + \mu_{0w,t} \end{aligned} \tag{2}$$

3 Results

Table 1. Results of Two-level Regression Models

Table 1. Estimated Results of Two-level Regression Models, 2016–2021, LSOAs and TTWAs in the UK

	Dependent variable:												
	scale(log(LQ + 0.001))												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
scale(log(GVA + 0.001))	0.138***	0.110***	0.104***	0.095***	0.094***	0.094***	0.094***	0.094***	0.094***	0.094***	0.094***	0.094***	0.094***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
scale(log(Pol_fin + 0.001))		0.035***	0.033***	0.036***	0.037***	0.037***	0.037***	0.037***	0.037***	0.037***	0.037***	0.037***	0.037***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
scale(log(Pol_ict + 0.001))		0.023***	0.021***	0.024***	0.024***	0.024***	0.024***	0.024***	0.024***	0.024***	0.024***	0.024***	0.024***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
scale(log(Pol_uni + 0.001))		0.022***	0.021***	0.020***	0.020***	0.020***	0.020***	0.020***	0.020***	0.020***	0.020***	0.020***	0.020***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
scale(log(Pol_cg + 0.001))		0.018***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
scale(log(Pol_lg + 0.001))		0.034***	0.032***	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
scale(log(Pol_coach + 0.001))			0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***
			(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
scale(log(Pol_railway + 0.001))			0.033***	0.033***	0.033***	0.033***	0.033***	0.033***	0.033***	0.033***	0.033***	0.033***	0.033***
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
scale(log(Pol_Metro + 0.001))			0.020***	0.019***	0.020***	0.020***	0.020***	0.019***	0.019***	0.019***	0.020***	0.020***	0.020***
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
factor(Y_Year)2017				0.041***	0.041***	0.042***	0.042***	0.042***	0.044***	0.044***	0.043***	0.044***	0.043***
				(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
factor(Y_Year)2018				0.062***	0.062***	0.065***	0.065***	0.065***	0.070***	0.070***	0.070***	0.070***	0.070***
				(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
factor(Y_Year)2019				0.086***	0.086***	0.089***	0.089***	0.090***	0.098***	0.098***	0.098***	0.099***	0.098***
				(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
factor(Y_Year)2020				0.107***	0.107***	0.112***	0.112***	0.112***	0.123***	0.123***	0.123***	0.123***	0.122***
				(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
factor(Y_Year)2021				0.201***	0.201***	0.206***	0.206***	0.207***	0.219***	0.219***	0.217***	0.218***	0.216***
				(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
scale(log(TTWA_area + 0.001))					0.030***	0.032***	0.033***	0.031***	0.031***	0.032***	0.030***	0.030***	0.031***
					(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
scale(Emp_STEM)						−0.004	−0.004	−0.005	−0.005	−0.004	−0.003	−0.003	−0.002
						(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
scale(Emp_Rate)						−0.006	−0.006	−0.005	−0.005	−0.005	−0.005	−0.005	−0.005
						(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
scale(Business)							−0.001	0.004	0.004	0.004	0.002	0.001	0.003
							(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
scale(Large_Com)								0.010	0.011	0.011	0.012	0.012	0.012
								(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
scale(log(ICT_upload + 0.001))									−0.005	−0.005	−0.005	−0.005	−0.005
									(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
scale(University)										−0.003	−0.003	−0.003	−0.003
										(0.006)	(0.006)	(0.006)	(0.006)
scale(Pol_Airport)											0.008	0.008	0.008
											(0.005)	(0.005)	(0.005)
scale(log(Distance + 0.001))												−0.013	
												(0.025)	
factor(London)1													−0.073
													(0.079)
Constant	0.007	0.007	0.008	−0.076***	−0.067***	−0.070***	−0.070***	−0.068***	−0.075***	−0.075***	−0.077***	−0.073***	−0.075***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.013)	(0.013)	(0.013)	(0.015)	(0.013)
Observations	216,192	216,192	216,192	216,192	216,192	216,192	216,192	216,192	216,192	216,192	216,192	216,192	216,192
Log Likelihood	−268,752.100	−268,548.600	−268,495.400	−267,894.600	−267,890.400	−267,897.500	−267,901.800	−267,904.600	−267,908.400	−267,912.500	−267,915.400	−267,918.000	−267,916.600
Akaike Inf. Crit.	537,516.100	537,119.200	537,018.800	535,827.100	535,820.800	535,839.100	535,849.500	535,857.200	535,866.800	535,877.000	535,884.800	535,892.100	535,889.100
Bayesian Inf. Crit.	537,577.800	537,232.300	537,162.800	536,022.500	536,026.500	536,065.300	536,086.100	536,104.000	536,123.900	536,144.400	536,162.400	536,180.000	536,177.100

Note: *p<0.05; **p<0.01; ***p<0.001

4 Discussions

Geographical vicinity to local environments such as urban infrastructure, intellectual resources, and productive economic actors plays essential roles in extensive AI hiring activities. AI online vacancies tend to be more spatially concentrated in LSOAs with more various transport facilities and departments of central and local governments, namely the sharing mechanism of urban agglomeration (Crevoisier & Jeannerat 2009; Duranton & Puga 2004). For one thing, these local areas with better locations facilitate companies and employees to travel within and between cities or even internationally for personal interactions (Atalay et al. 2023). For another, central and local governments create urban milieus based on local contexts by facilitating interpersonal interactions (Gertler 2003). Aligning with findings of Bloom et al. (2021), the positive effect of university faculties is attributed to the nature of AI technologies, which is skill-biased technological development. This skill-biased technology (i.e., AI) requires a local knowledge milieu to a greater extent than other technologies to obtain a higher proportion of employees with greater capabilities and academic performance (Bloom et al. 2021).

Prosperous areas manifest great local labor demands for AI skills. One the one hand, LSOAs with more gross value added as well as finance and ICT services tend to have greater capacities to adopt emerging technologies. In this way, these local areas attract more AI workers over time (Alekseeva et al., 2021; Acemoglu et al. 2023). They are consumers and suppliers of AI-related services cultivated by local milieus (Geenhuizen 2008; Gertler 2003). At a greater level, AI online job vacancies tend to be more spatially concentrated in larger TTWAs, normally commuting zones with more sophisticated levels of urban transport and economy. This virtuous circle is called indirect benefits gained from co-location in industrial and regional high-tech clusters (Dahlke et al. 2024). On the other hand, AI divide is becoming a concerning issue in the last decade (McElheran et al. 2023).

However, our regression models still have limitations such as heteroskedasticity, non-normality and autocorrelation of residuals. Firstly, the estimated fixed effects do not indicate heterogeneous effects in each LSOA or TTWA but assume spatial homogeneity, which is not the case according to the argument in Section 2 above. In addition, we do not control time lag effects of the dependent variable.

Appendix

Table 2. Description of variables

Type	Symbol	Meaning
Dependent variable (LSOAs level)	$LQ_{lw,t}$	Location quotients of online AI job advertisements requiring both general and specific AI skills.
	$GVA_{lw,t-1}$	Total amount of local gross value added (GVA) estimates indicates the level of economic contribution of local industries to gross domestic products. (see: Website)
		$PoI\_transport_{lw,t-1}$: The number of each transport facility such as coach, metro and railway stations, which decrease transport costs of companies/employees travelling between local areas. (see: Website)

Control variables (LSOAs level)	$PoI_{lw,t-1}$	$PoI\_ict_{lw,t-1}$: The number of commercial services of information technology in each LSOA, including 'Computer Security', 'Computer Systems Services', 'Database Services', and so on(see: Website)
		$PoI\_fin_{lw,t-1}$: The number of commercial services of finance as well as insurance in each LSOA, including 'Credit Reference Agencies', 'Financial Advice Services' and so on. (see: Website)
		$PoI\_uni_{lw,t-1}$: The number of higher education establishments in each LSOA. (see: Website)
		$PoI\_lg_{lw,t-1}$ and $PoI\_cg_{lw,t-1}$: The number of central or local governments on which social capital is created based in each LSOA. (see: Website)
	$London_{lw}$	A dummy variable indicates whether each LSOA is located within the London TTWA.
Control variables (TTWAs level)	$Emp_{w,t-1}$	$Emp\_Rate_{w,t-1}$: The employment rate (see: Website)
		$Emp\_STEM_{w,t-1}$: The proportion of managers, senior officials, professionals, and tech occupations in high-tech industries over total employment. These high-tech industries are defined according to SIC 2007, including (B,D,E) Energy & water, (K-N) Banking finance & insurance, etc. (see: Website)
	$Business_{w,t-1}$	The proportion of all enterprises in TTWAs over economically active population. (see: Website)
	$Large\_Com_{w,t-1}$	The proportion of large companies with more than 250 employees over the total number of companies in each TTWA. (see: Website)
	$ICT_{w,t-1}$	$ICT\_upload_{w,t-1}$: Users' experiences of broadband upload speeds.
	$Airport_{w,t-1}$	The rate of airports over economically active population in each TTWA. (see: Website)
	$University_w$	The proportion of universities over human capital in each TTWA. (see: Website)
	$TTWA\_area_w$	The area of each TTWA as a proxy of socio-economic levels and urban transport infrastructure in general.
	$Distance_w$	Spatial distance between each TTWA and London.