Unpacking the Regional Productivity Paradox of AI Skills: Temporal, Occupational, and Region-sectoral Heterogeneity in Great Britain

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Abstract

The economics literature widely discusses productivity gains of adopting AI technologies, while national productivity growth stays stagnant. Revisiting this productivity paradox, we investigate how regional AI skills associates with regional productivity in Great Britain through a causal pathway of diverse AI applications. Panel IV models find an insignificant effect during 2018-2023. However, this productivity effect shows significant heterogeneity across different occupations, periods, and regional sectors. The productivity effect is significantly positive in 2021-2023 for regions specialised in the professional, scientific, technical activities and financial sectors. Research findings illustrate reinforcing productivity inequalities among regions, contributing to empirical and policy debates.

Keywords: Regional productivity; Skill relatedness density; Skill complementarity; AI skill demand

1 Introduction

Artificial intelligence (AI) has the potential to considerably transform industrial sectors and labour markets and further improve regional productivity (Bonfiglioli et al. 2025; Brynjolfsson et al. 2017, 2021; Johnston and Makridis 2026; Olatunbosun et al. 2025; Stephany and Teutloff 2024). Sharing the productivity gains among industrial sectors and regions is among the development priorities of UK government.[1] This development priority can be achieved by educating and training diverse workers with specialised skills complementary to AI application in various industries, namely AI-complementary skills (Krakauer 2026; Stephany and Teutloff 2024). The nature behind diverse application is that AI as a general purpose technology has key enabling capacities to facilitate pervasive adoption across economic sectors and stimulate complementary downstream innovations (Barzotto and De Propris 2019; Demirev 2026; Goldfarb et al. 2023). AI with considerable predicting capacities comprises a variety of machine intelligence in predictive algorithms, embodied robotics, and pre-trained large language models, for instance, deep learning, forecasting, reasoning, computer vision, language understanding, and content generation based on multimodal, actual data (Chalmers et al. 2026; Goldfarb et al. 2023).

Geographies of AI technologies remain uneven (Zhang et al. 2025a). Existing research uses the demand for AI skills from companies as the proxy of adopting AI technologies (Babina et al. 2024; Wang et al. 2026). AI skills refer to worker capabilities required by companies to accomplish specific tasks by adopting machine learning, robotics, or generative AI tools, according to a task-based definition of skills (Gathmann and Schönberg 2010). These AI skills are more likely to be spatially concentrated in dense regions with related industrial structures such as IT and scientific job clusters (Zhang et al. 2025a). Large companies may tend to employ workers with AI skills intensively in already productive regional labour markets, aiming to

improve the efficiency of production or service activities (Alekseeva et al. 2021; Barzotto and De Propris 2019; McElheran et al. 2024). Thus, it is important to investigate how regional AI skills further influences regional productivity, which can contribute to empirical and policy debates about the economic growth and geographical inequality.

Productivity indicates the economic efficiency of production and service activities among workers at the firm, sector, or country level (Baily et al. 2023). The existing literature demonstrates expectations that different AI technologies can improve company-level productivity and stimulate regional economic growth. For instance, Yang (2022) using AI patents and Czarnitzki et al. (2023) employing survey data find the positive effects of the invention and adoption of AI technologies by companies on the improvement of firm-level productivity. At the regional level, Capello and Lenzi (2024) find significant and positive effects of the adoption of robotics in 4.0 manufacturing industries on regional economic growth, which reveals heterogeneous patterns. Apostol and Hernández-Rodríguez (2025) also demonstrate that European regions with denser digital-related technologies are more likely to specialise in new web technologies. Furthermore, more complex digital technologies regions are specialised in, greater labour productivity the regions potentially reveal (Apostol and Hernández-Rodríguez 2025). Most studies rely on the patent or innovation data about state-of-the-art AI technologies but ignore the adoption and application of such technologies by companies in various industries. Limited research investigates how regional skill structure complementary to AI application across occupations and sectors in regional labour markets influences regional productivity differently.

AI skills such as machine learning, computer vision, robotics, or generative AI can augment and automate various tasks of occupations in different sectors due to their general

purpose technology nature (Goldfarb et al. 2023; Mäkelä and Stephany 2024; Stephany and Teutloff 2024). Occupations with different levels of specialised expertise can heterogeneously benefit from or rely on using AI services (Krakauer 2026). For instance, these AI skills can be utilised differently by professionals, technicians, or general workers in law, customer services, marketing, manufacturing, information technology (IT), or professional and scientific activities sectors based on skill complementarity (Barzotto and De Propris 2019; Olatunbosun et al. 2025). Skill complementarity indicates the potential of any skill like AI to be combined with other proficiencies from different knowledge fields for synergistic effects due to their inherent combinatorial potentials (Stephany and Teutloff 2024). However, some seminal studies mentioned negligible aggregate effects of potential task exposure to AI on the demand for AI skills at the broad industrial and occupational levels in the US during the early stage of AI adoption between 2010-2018 (Acemoglu et al. 2022). In addition, it is found that AI technologies play a limited role in significantly driving macro-economic growth in the early stage (Brynjolfsson et al. 2017, 2021).

Theoretical debates centered around a Solow productivity paradox for decades. The Solow paradox indicates that macro-economic productivity statistics do not reveal significant growth patterns in the early stages, even though it is widely recognised that IT and AI technologies can considerably improve labour productivity at the firm or task level (Acemoglu et al. 2014; Brynjolfsson and Hitt 1996). For instance, Brynjolfsson and Hitt (1996) found significantly positive returns on firm-level investment in IT-related workers and information systems by major Fortune 500 companies with considerable organisational restructuring and adaptation during 1987-1991. Even if the productivity paradox seemed to effectively vanish by the early 1990s, macro-economic and industry-wide aggregate statistics can still fail to observe

and measure productivity gains (Brynjolfsson and Hitt 1996). In contrast, Acemoglu et al. (2014) demonstrated that the early stage of the IT revolution did not support the expectation of a pervasive, IT-generated productivity growth among manufacturing firms during 1980-2009, but considerable job losses. Similarly, Brynjolfsson et al. (2017, 2021) justified a time lag of the productivity growth during the recent advancement and diffusion of AI technologies among global economies. There is a lack of empirical discussion unravelling the productivity paradox of regional AI skills applied in various industries and occupations, beyond tangible capital studied in existing research, based on the detailed evidence in Great Britain.

Filling in these research gaps, this study investigates how the intensity of regional AI skills required by companies can affect regional productivity through diverse AI applications in industries in Great Britain. This study uses online job advertisements (OJA) data as the proxy of labour demand by employers, indicating the usage of AI technologies. OJA data may outperform traditional metrics such as occupations or sectoral employment or the latest data like employee profiles if studies focus on timeliness and detailed skill description. For instance, employment data indicates the supply of labour in each regional sector, which change relatively slow over time. Most workers have to work or switch to another job even if their roles or wages are considerably influenced by new technologies like AI (Brynjolfsson, Li, and Raymond 2025; Johnston and Makridis 2026). In contrast, it is more flexible for OJAs to reveal the emerging patterns of new skill demand for emerging digital technologies, especially AI. Labour demand for new skills can more swiftly capture the gradual evolution of broad economies and labour markets in a short term (Henning et al. 2025).

This study adopts panel IV regression models with an instrumental variable (IV) to investigate how regional AI-complementary skill structure affects regional productivity between

2018-2023 through the pathway of influencing AI skills applied in various industries (2017-2022) in trave-to-work areas (TTWA) in Great Britain. This IV capturing diverse AI applications is relatedness density of regional skill structures to which AI skills are complementary in 2016-2021. Furthermore, this study investigates heterogeneous productivity effects of regional AI skills over time (between 2018-2020 and 2021-2023), across occupations (such as IT, Scientific, Finance, Engineering, and Marketing jobs), and among regional sectors (such as Manufacturing, Energy, Financial, Information and communication technology (ICT), and Professional, scientific, technical activities). In this way, this study examines temporal, occupational, and region-sectoral heterogeneity of the productivity effect. These heterogeneous effects indicate that labour productivity outcome can be influenced by how efficiently AI skills are utilised and managed in each period, occupation, and regional sector.

Panel IV models find insignificant effects of broad AI skill demand on regional productivity between 2018-2023. However, these models find temporal, occupational, and region-sectoral heterogeneity of the productivity effect, statistically justifying a potential productivity paradox and reinforcing regional inequalities. More particularly, regional AI skill demand only from the scientific jobs shows a significant and positive effect on regional productivity between 2018-2023 for the regions at the Top 25th percentile with the greatest share of AI OJAs. The labour markets with the highest AI skill demand can more efficiently utilise AI skills required by companies for scientific and quality assurance tasks to improve labour productivity in general. During 2021-2023, the productivity effect of all AI skill demand is significant and positive, especially for the regions specialised in the professional, scientific, technical activities sector or the financial sector. The labour markets with such sectoral specialisation can coordinate broad AI skills among local companies more efficiently to improve

productivity in recent years. These heterogeneous effects may further reinforce existing regional economic inequalities.

This study contributes to empirical debates in the field of economic geography of AI by unravelling how regional AI skills required by local companies can potentially increase economic inequalities among regions. AI skills play a role of intangible capital investment by companies in influencing labour productivity. These AI skills may reinforce unequal redistribution of productivity gains among regions over time, especially through the professional, scientific, technical activities and financial sectors. This unequal pattern can be attributed to pre-existing geographies of spatial divisions of labour and digital transformation, such as digital infrastructure, data quality, digital skills, industrial digitalisation, and other complementary assets (Babina et al. 2024; Brynjolfsson et al. 2021; Olatunbosun et al. 2025; Tranos et al. 2021, 2026; Zhang et al. 2025a). Based on these discussions, regional policies should promote reskilling programs improving the digital literacy of local workers in lagging regions and cultivating AI-complementary skills among occupations in sectors. In this way, workers and companies can diffuse AI application and share productivity gains more evenly among regional labour markets across sectors.

The structure of this paper is as follows. The next section reviews the literature of empirical research on how the adoption of AI technologies influences productivity both at the firm and regional levels. Two hypotheses are proposed based on the literature. The third section introduces research data, regression model specifications, the instrumental variable, and heterogeneity analyses to test the hypotheses. Next, the fourth section presents and discusses regression results and robustness tests. The final section concludes the paper.

2 Literature review

This literature in both regional studies and empirical economics investigates roles of emerging digital technologies either in regional productivity or total factor productivity (TFP) at different scales. Regional productivity reflects the labour efficiency of regional economies, measured as economic outputs per unit of labour in regional labour markets (Barzotto and De Propris 2019). This metric reveals economic competitiveness of each region. In comparison, TFP indicates the production efficiency with which inputs such as technology, capital, and labour are utilised to generate outputs in all economic activities (Gao and Feng 2023). In our study, we focus on regional productivity since employer demand for AI skills, which is different from technological innovation or capital investment in AI, influences the economic outputs of production or services and employment in labour markets more directly than TFP. The demand for AI skills acts as the proxy of the AI usage by companies in this study.

AI skill demand improves labour productivity through two primary mechanisms (Baily et al. 2023). The first mechanism is that companies requiring workers to adopt AI methods can directly increase the total output or its quality in production with higher value added, which decreases costs per unit of outputs (Baily et al. 2023). More particularly, AI automate (un)routine administrative and cognitive tasks and augment non-routine analytical and interactive skills of workers (Acemoglu et al. 2025; Demirev 2026; Mäkelä and Stephany 2024). In this way, AI skills facilitate redistribution of labour efforts and inputs to more complex tasks with higher value added for better efficiency and accelerated decision making (Olatunbosun et al. 2025). This type of creative destruction of AI in production or services can improve productivity gains by potentially turning old skills obsolete, utilising and creating skills complementary to AI, and improving the quality of diverse products and services (Aghion and Howitt 1992; Goldfarb et al.

2023). The second mechanism refers to the evolutionary accumulation of practical and management experience in a longer period, which can facilitate product innovation or process re-organisation (Brynjolfsson et al. 2017, 2021; Gao and Feng 2023). It should take longer time to restructure production organisation and redesign management by companies, and re-build AI-complementary capabilities by regional institutions to promote productivity growth in general (Olatunbosun et al. 2025). For instance, the sustainable management of AI depends on newly bespoke production processes, generating and accumulating practical experience for new AI applications over time (Gao and Feng 2023).

Existing empirical research finds significant effects of diverse AI applications on the productivity growth at the company and occupational levels. For instance, Taiwanese electronics firms with more AI patents promote efficiency gains by utilising AI technologies to introduce highly customized new products and intermediate components (Yang 2022). Similarly, German companies adopting AI methods in business processes and generating the demand for AI skills achieve 3.4% greater total factor productivity than their counterparts without such AI adoption (Czarnitzki et al. 2023). Rather than achieving immediate productivity gains and cost reduction, U.S. companies intensively employing AI-skilled labour significantly grow in corporate size, sales, and market valuation in a longer term by product innovation (Babina et al. 2024).

More recently, generative AI tools such as ChatGPT also improve workers' productivity by decreasing working time and improving output quality of writing tasks (Noy and Zhang 2023). As for customer services, randomised experiments find that using a generative AI tool enables each customer service worker in U.S. companies to improve a 15% of labour productivity by decreasing the time input per case and per unit of labour and gradually learning from AI solutions (Brynjolfsson et al. 2025). Generative AI or, in general, AI skills, can potentially

substitute basic data or administration tasks and this be reflected in the demand for new skills such as analytical thinking, prompt engineering, human-machine interaction, or AI-enhanced creativity (Mäkelä and Stephany 2024; Wang et al. 2026). In this way, AI is complementary to and can be combined with specialised expertise to perform new tasks across occupations at the same time replacing inefficient, old skills (Johnston and Makridis 2026).

At the regional level in Europe, the regional share of workers with the skill mix between machine learning and production expertise has a significant and positive effect on labour productivity (Barzotto and De Propris 2019). Except for machine learning, embodied AI technologies such as robotics in 4.0 manufacturing industries also show a significant and positive effect on real GDP growth in these regions (Capello and Lenzi 2024). Limited studies investigate the regional productivity effect of AI skills in various industries. Regions can generate greater productivity gains in the future if they have specialised skill structures to which AI skills are complementary in various AI application domains. Based on these literatures, we propose the first hypothesis:

H1: Regions with denser labour demand for AI skills experience an increase in regional productivity through diverse AI applications.

Nonetheless, the productivity paradox of IT and AI disrupts the prevailing narrative that emerging digital technologies tend to promote the productivity growth and economic development. During the early stage of IT revolution, manufacturing industries in the U.S. did not experience a significant productivity growth between 1980-2009 in general (Acemoglu et al. 2014). Labour productivity increased only in the computer manufacturing industry, such as semiconductors and electronic equipment (Acemoglu et al. 2014). Four potential explanations of the productivity paradox are raised based on another similar case: AI, including overly optimistic

expectations, unmeasurable latent gains in macro-economic productivity metrics, redistribution of productivity gains, and time lags of materialization (Brynjolfsson et al. 2017, 2021). The time lag is one of the most promising reasons, which demonstrates that productivity would grow faster in a longer term when the pervasive diffusion of AI skills can fully materialise productivity gains based on steady accumulation of complementary resources (Aghion and Howitt 1992; Brynjolfsson et al. 2017, 2021). So, there should be temporal heterogeneity of the regional productivity effect of AI skills between periods.

Heterogeneity of the productivity effect also exists across occupations. Professionals or technicians in companies and regions can facilitate the adoption and diffusion of AI skills and greater gains of AI application, which further improves labour productivity (Bonfiglioli et al. 2025; Demirev 2026; Gao and Feng 2023). More specifically, AI skills can be intensely adopted by professionals or technicians who have complementary skills in production processes to produce products or services more efficiently, for example, IT-skilled jobs (Calvino et al. 2026), managers in business services (Alekseeva et al. 2021), engineering in semiconductor manufacturing (Yang 2022), or professionals in bioscience (Zhang et al. 2025b). The main explanation may be that AI technologies can redistribute productivity gains and labour from occupations with routine-cognitive tasks to other occupations with complex and capital-intensive tasks (Acemoglu et al. 2025; Babina et al. 2024; Olatunbosun et al. 2025). This heterogeneity may lead to the between-occupation inequality (Acemoglu and Restrepo 2026; Lynch, 2025).

Heterogeneity exists across regional sectors as well. The efficient adoption of AI skills depends on organisational, industrial, and institutional foundations. More specifically, regions with greater ICT infrastructure, technological sectors, reskilling schemes, and stable data regulation policies can attract and guide AI-complementary investment by companies, which

reduces uncertainties and steep costs (Olatunbosun et al., 2025). These dominant regions can utilise their existing informational advantages of proprietary data and AI-complementary capacities in technological industries to outperform other regions in terms of productivity gains (Babina et al. 2024; Olatunbosun et al., 2025). In contrast, companies or industries in lagging regions are the laggards of adopting AI and scaling the demand for AI skills due to adoption barriers such as limited digital skills and infrastructure, stagnant management, and low capacities to learn AI application (Apostol and Hernández-Rodríguez, 2025; Babina et al., 2024; Calvino et al., 2026). Empirically, firms adopting AI technologies in manufacturing application produce greater productivity gains in regions with concentrated, technology-intensive industries than labour-intensive industries in China (Gao and Feng, 2023). Similarly, European regions intensively utilising industrial robots promote greater regional economic growth of GDP per capita if they are specialised in 4.0 manufacturing industries (Capello and Lenzi, 2024). It is the composition of industrial demand and local capacities that may influence the divergence of AI-driven productivity gains among regions. Based on these discussions, we propose the second hypothesis:

H2: The effect of the demand for AI skills on regional productivity is heterogeneous across different periods, occupations, and regional sectors.

In sum, this section reviews and discusses how the demand for AI skills influences labour productivity at the company, occupational, and regional scales through an application pathway. Based on these literatures, we have proposed two hypotheses. To test them, the following section introduces the data and the methods we use.

3 Methodology

3.1 Data

This study investigates how the intensity of regional demand for AI skills is associated with regional productivity. Following Apostol and Hernández-Rodríguez (2025), Barzotto and De Propris (2019), and Tranos et al. (2021), the paper computes regional productivity as gross value added (GVA) per unit of total employment in each travel-to-work-area (TTWA) in Great Britain. TTWA represent labour markets within which workers tend to commute daily, and economic activities interact intensively. This productivity measure depends on the estimated volume of goods and services produced in all industries within a TTWA, standardised by regional employment (Office for National Statistics, 2025). Further, this measurement indicates labour productivity broadly among employed workers under service contracts, self-employed, and unpaid family workers (Office for National Statistics, 2025). The data for constructing this labour productivity metric is directly retrieved and downloaded from ONS, the Office for National Statistics (2025).

Figure 1 illustrates a trend of increasing regional productivity in Great Britain over time with fluctuation in 2020. Figure 2 indicates that in England, many productive regions are spatially concentrated in the south, especially along the corridor between London and Swindon. In contrast, Scotland shows dispersed geographies where Edinburg leads the economic development with other distant regions following close, such as Elgin, Arbroath and Montrose.

Our research employs online job advertisements (OJA) data from Adzuna (2025) to measure labour demand for AI skills by employers in regional labour markets. Adzuna, a powerful online job search platform, collects and manages hundreds of millions of OJAs from company websites and online job boards. Each OJA includes a timestamp of each job vacancy

posted online, job category, skill keywords, job description, job location longitude and latitude, and others. Skill keywords of an OJA indicate the employer demand for specific skills. Commonly demanded skills include soft skills such as resilience or team communication and hard skills referring to more tangible capabilities, for instance, python, time-series forecasting, cloud computing, or cheesemaking. Job description in an OJA usually mentions role responsibilities, tasks, a company profile, and so on.

To identify AI jobs, this study harnesses a dictionary of AI skill keywords from a Stanford AI 2025 report[2] and then, adds additional AI skills from Lightcast Open Skill Taxonomy[3] (see the Appendix A). We define an OJA as an AI OJA if it includes at least one general AI keyword and another specific AI skill keyword in either its skill requirement or job description (Goldfarb et al., 2023; Zhang et al 2025). As shown in the Appendix A, a general AI keyword is the broad AI group such as artificial intelligence, machine learning, natural language processing, robotics, or generative AI. A specific AI skill keyword is the specific technique within any AI group, for instance, stable diffusion, gradient boosting, text-to-speech, long short-term memory, ChatGPT, or generative AI agents. Then, we compute the share of AI OJAs in each TTWA in each year because the share indicates the intensity of AI skill demand in regional labour markets. In this way, we mainly capture AI OJAs using any AI method, technique, or tool in the broad AI context, avoiding AI-washing jobs.

As illustrated in Figure 3, the regional share of AI OJAs gradually increased between 2017 and 2022 for TTWAs in its upper 25th quartile, median, and lower 25th quartile among TTWAs. Furthermore, TTWAs from the higher quartile group reveal a greater increasing pattern of the AI OJA share over time, which matches with the increasing pattern of regional productivity in Figure 1. Regions obtaining the greatest AI share include Cambridge, Oxford,

Stevenage and Welwyn Garden City, London, Edinburgh, Bristol, and Huntingdon (see Figure 4). Connecting regional productivity with the regional AI share, Figure 5 plots a significant and positive correlation between (logged) regional productivity in each year and the regional share of AI OJAs in the last year across TTWAs in Great Britain.

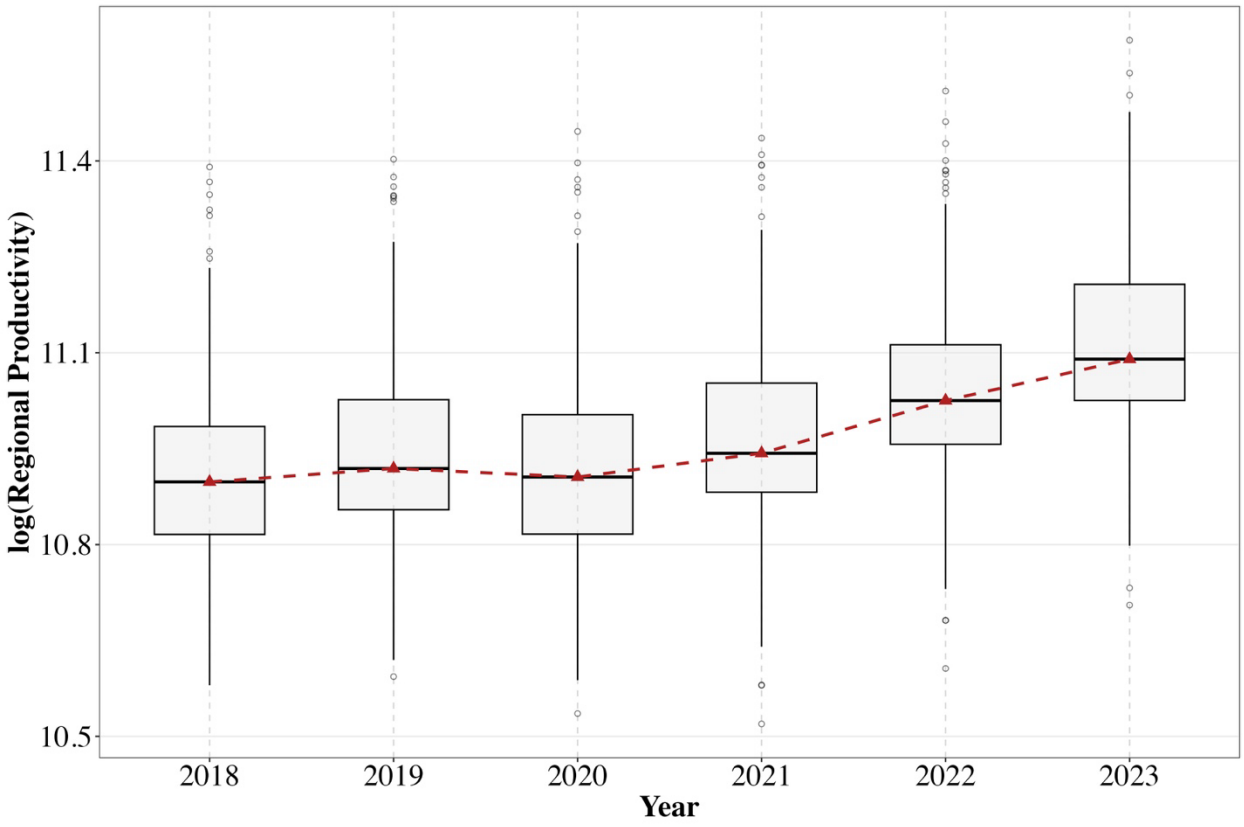


Figure 1. Regional productivity ((logged) GVA per employee) in each TTWA in each year between 2018 and 2023, Great Britain

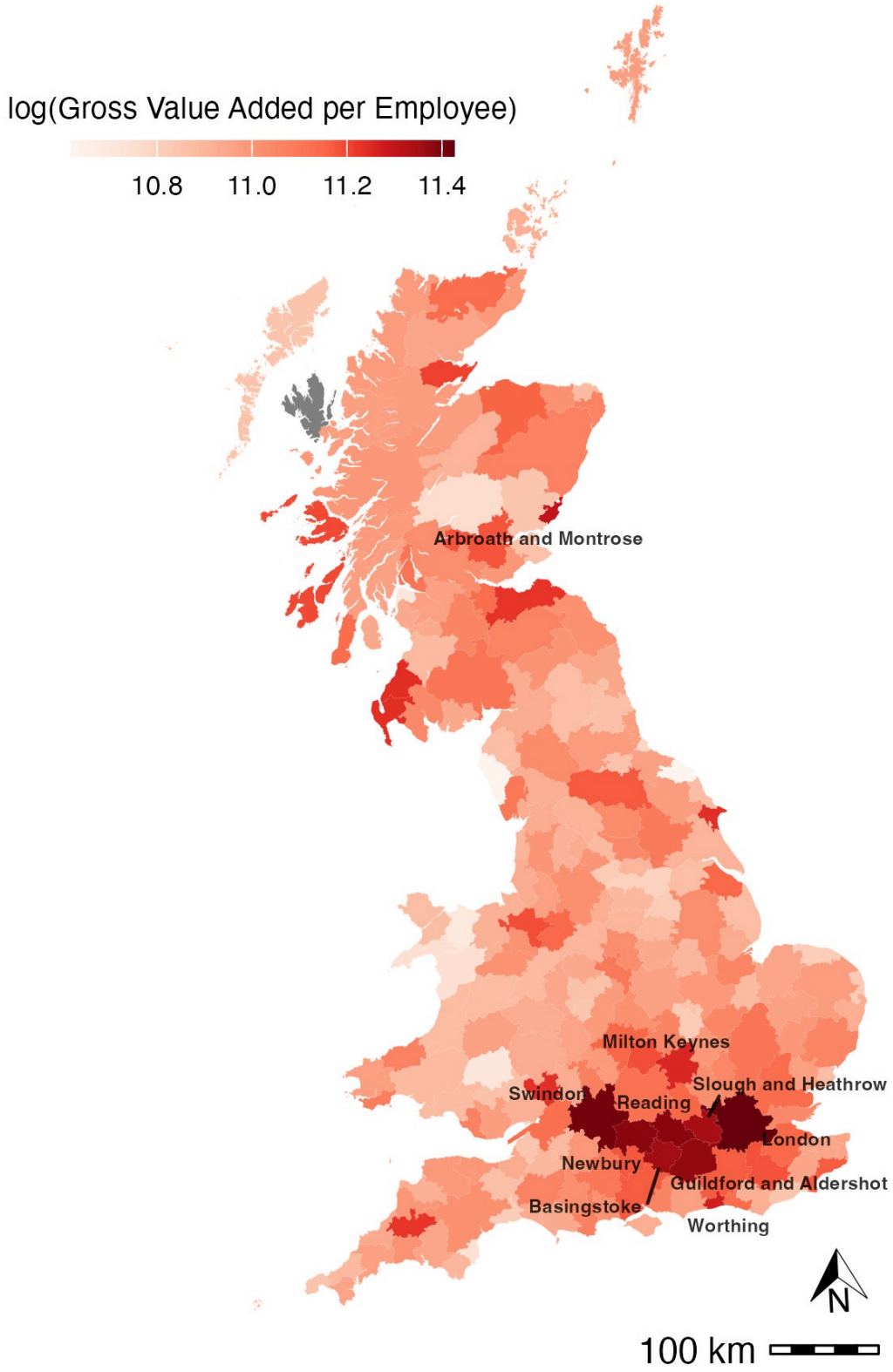


Figure 2. (logged) Average productivity (GVA per employee) in TTWAs during 2018 and 2023.

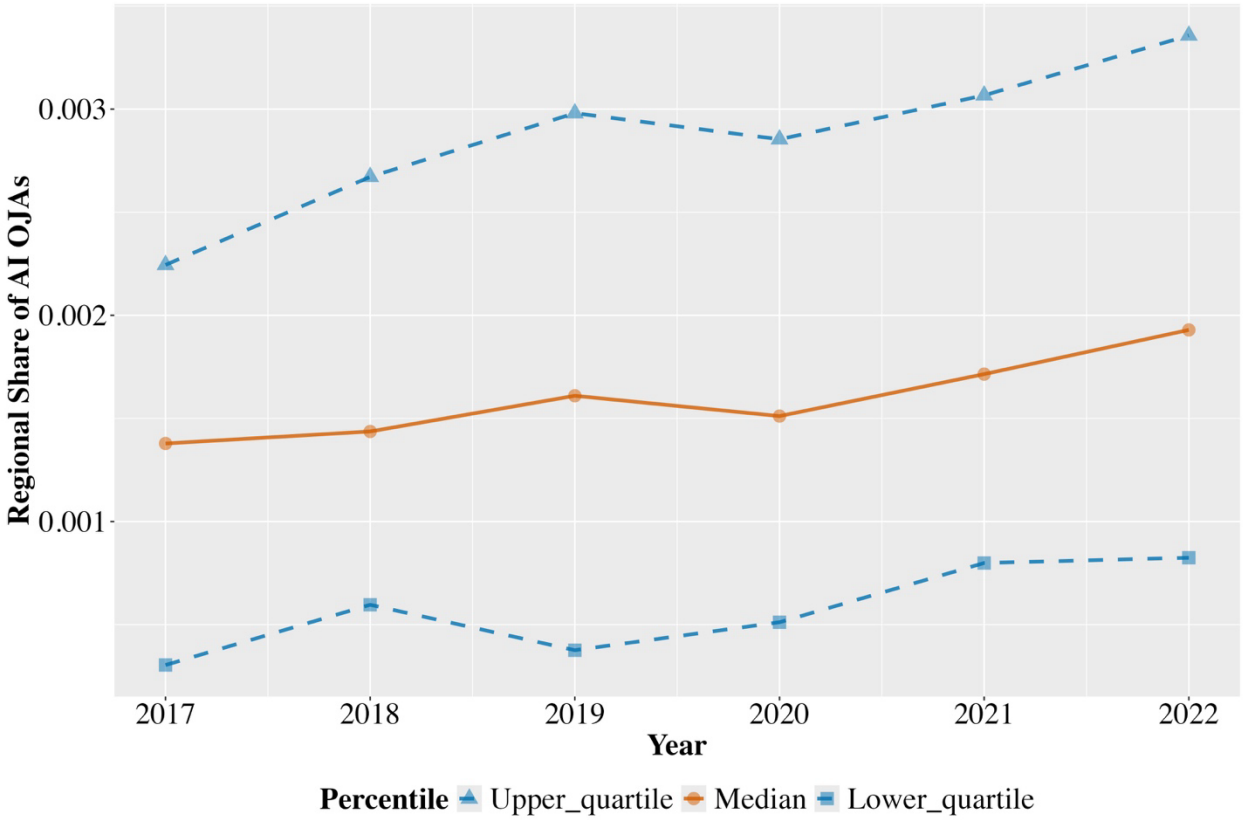


Figure 3. Regional share of AI OJAs in each TTWA for the Upper Quartile, Median, and Lower Quartile groups in each year between 2017 and 2022, Great Britain

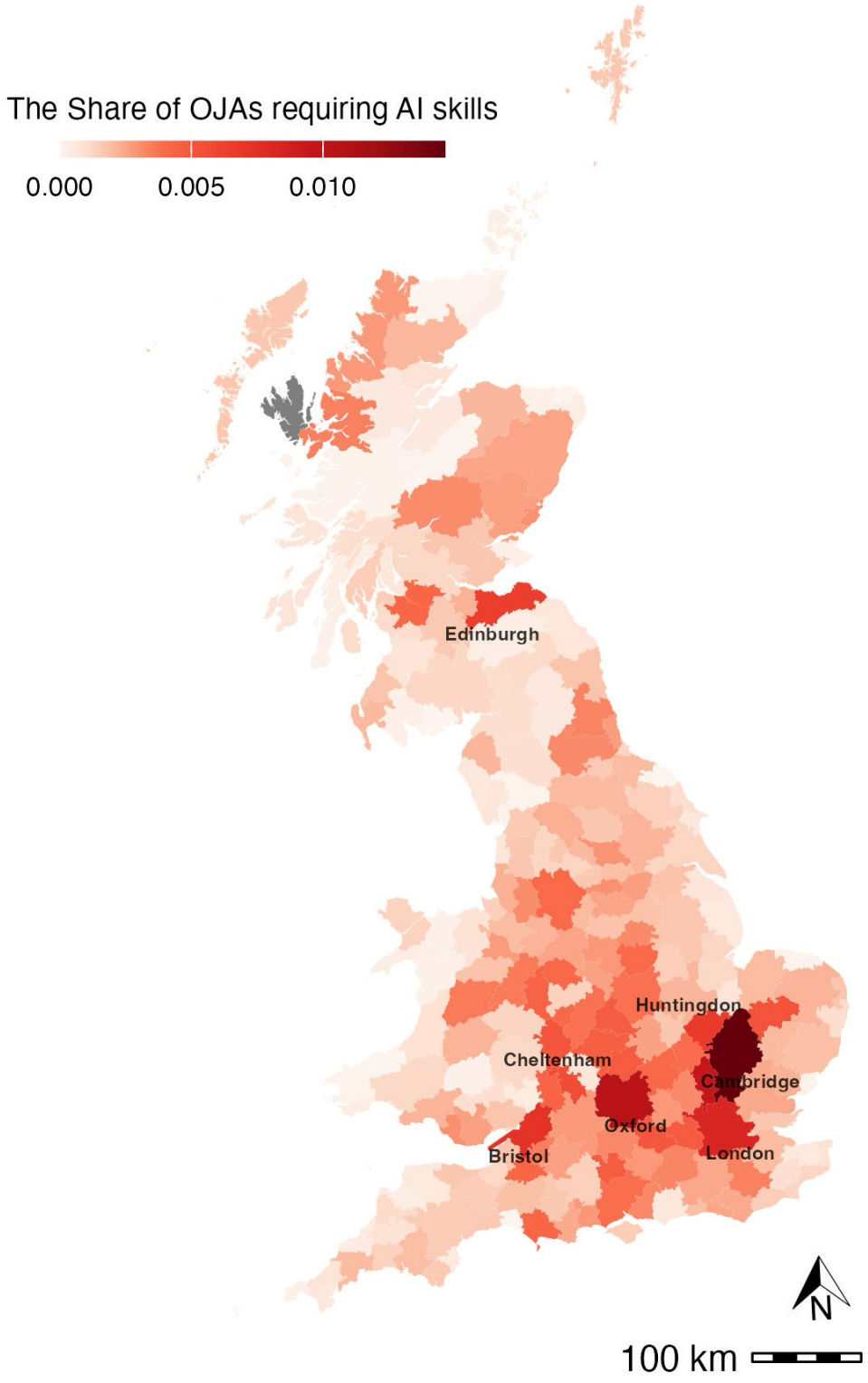


Figure 4. The average share of AI online job adverts posted between 2017 and 2022 in TTWAs in Great Britain

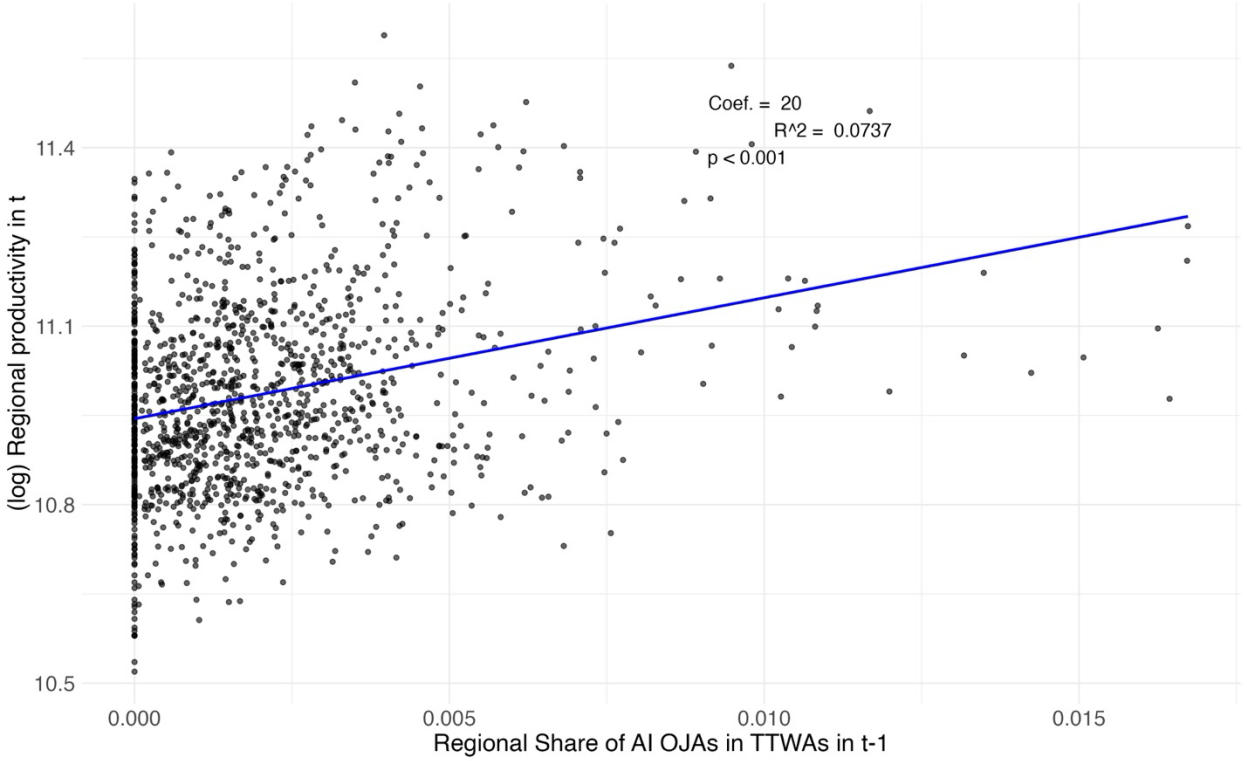


Figure 5. Correlation between (logged) regional productivity in each year between 2018-2023 and the regional share of AI OJAs in the last year between 2017-2022, Great Britain

3.2 Baseline panel model

The baseline model in Equation (1) is a two-way fixed effect panel model which tests the average yearly effect of AI skill demand on regional productivity during 2018-2023.

$$\text{Log}(productivity)_{it} = \beta_0 + \beta_1 Share_AI_{it-1} + \beta_2 \sum_{j=2}^{9} \beta_j X_{it-1} + \gamma_i + \delta_t + \varepsilon_{it} \quad (1)$$

where $productivity_{it}$ is defined as $\frac{GVA}{E}_{it}$, computed by dividing gross value added (GVA) by total employment (E) in each TTWA (i) in each year (t) between 2018 and 2023. $Share_AI_{it-1}$ is the regional share of AI OJAs in $t-1$ between 2017 and 2022. γ_i and δ_t are TTWA and year fixed effects, respectively. ε_{it} refers to an error term in the panel model specification.

Following the tradition of a growth theory, the baseline model further includes control variables (X_{it-1}) demonstrating the roles of technology, labour, and capital inputs in regional productivity (Acemoglu et al., 2014; Aghion and Howitt, 1992; Baily et al., 2023). The first group of controls consists of regional employment specialisations (measured as location quotient) in the ICT (Emp_ICT_{it-1}), Professional, scientific, technical activities (Emp_Pro_{it-1}), Financial and insurance activities ($Emp_Finance_{it-1}$), Manufacturing ($Emp_Manufacturing_{it-1}$), and Electricity, gas, steam and air conditioning supply (Emp_Energy_{it-1}) sectors. Such place-based industrial specialisations can directly influence regional productivity and its growth (Gao and Feng, 2023; Tranos et al., 2021). In addition, the model also includes sectoral employment diversity ($Emp_Diversity_{it-1}$), which indicates Jacobian externalities influencing labour productivity (Barzotto and De Propris, 2019).

The second group of control variables includes median internet upload speed ($Broadband_{it-1}$) and the regional share of large companies with at least 250 employees ($Large_Com_{it-1}$). Existing firm-level studies consider the roles of broadband quality and large company (as tangible capital investment) in labour productivity. In a multi-level research by Tranos et al., (2026), company experienced internet upload speed shows a significantly positive effect on labour productivity which is firm-level revenue per worker in the UK. Another recent OECD study employing micro-survey data finds that the firm adoption of AI has an insignificant effect on labour productivity (i.e., firm turnover per employee) in Great Britain between 2021-2024 (Calvino et al., 2026). In contrast, digital technology intensity within these firms shows a significant and positive productivity effect, while other controls are insignificant, for instance, broadband quality and ICT specialists (Calvino et al., 2026). Furthermore, Babina et al. (2024) find that large companies investing in AI-skilled labour can drive greater corporate expansion

regarding overall sales, workforce size, and market valuation by greater product innovation based on informational advantages.

Models with two-way fixed effects and serial correlation of TTWAs. In this way, models control time-invariant and -variant unobservable (Barzotto and De Propris, 2019). Construction of all variables and data sources are introduced in Table B.1 in Appendix B.

3.3 Identification

This study adopts a dual strategy to cope with potential endogeneity issues, especially reverse causality. First, the model takes one year lag for all explanatory variables, for instance, $Share_AI_{it-1}$. There is a time lag between posting a job advert and filling in this vacancy, and between finding the competent employee and producing any productivity effect. Second, this study adopts the method of two-stage least squares (2SLS) with an instrumental variable (IV) to exogenise the potential endogenous effect of regional AI skill demand. As for this reverse causality issue, a productive region could attract more human capital with digital skills such as data science and coding and engage in professional or technical occupations for advanced production services using AI to improve productivity.

The primary causal pathway through which demand for AI skills can affect regional productivity is through diverse AI applications (Goldfarb et al., 2023; Stephany and Teutloff, 2024). In other words, the increased demand for the skills to which AI is complementary can improve regional productivity because of applying AI tools or technologies in various industries. Thus, we use relatedness density of regional skill structures to which AI skills are complementary in each TTWA in each year between 2016-2021 as an IV (see Equation (2)). These skill structures in each region exclude Information Technology (IT) and Mathematical Modelling (Math) skills to mainly focus on the potentiality of combining AI skills with other

non-AI, -IT or -math (complementary) skills in various application domains in regional labour markets. According to our AI OJA data, machine learning is often combined with complementary skills that are specific to particular industries. For example, in the legal sector, machine learning is paired with skills such as drafting clear legal contracts, attention to contract detail, and commercial awareness to support the development and application of computable legal smart contracts. Similarly, advanced robotics skills are sought in the grocery retail sector, where they are used to support retail operations and deliver physical infrastructure solutions for clients. More recently, knowledge of ChatGPT has emerged as a complementary skill in customer advocacy and marketing roles, where it is used to identify trends and insights and optimise the content of product marketing in social media. These examples illustrate how AI-complementary skills are combined with sector-specific competencies to enable diverse AI applications across industries.

$$IV_AIRD_Complementary_{\mathrm{it}-2} = \left(\frac{\sum_{s\in r, s\neq a}^{r} S_{\mathrm{is}} * \phi_{sa}}{\sum_{s\in r, s\neq a}^{r} \phi_{sa}}\right)_{t-2} \quad (2)$$

Where S_{is} is 1 if the TTWA (i) has a regional specialisation in the skill (s); otherwise, S_{is} is 0. ϕ_{sa} is the relatedness index of each skill (s) related to AI skills (a), which indicates the probability of its co-occurrence with the AI skills in every OJA in Great Britain in each year in 2016-2021 (Apostol and Hernández-Rodríguez, 2025; Balland et al., 2019). This skill relatedness index captures the likelihood of any complementary skill demanded in the combination with AI skills generally among OJAs. The skill range (r)[4] excludes IT and Math skills as classified and grouped by Lightcast (2025). We compute each factor including the skill relatedness index of AI (ϕ_{sa}), regional specialisation in each skill (S_{is}), and this relatedness density variable

($IV_AIRD_Complementary_{\mathrm{it}-2}$) in R (Version 2024.04.1+748) by using an 'EconGeo' package developed by Balland (2017).

Figure 6 illustrates core-periphery structure of $IV_AIRD_Complementary_{\mathrm{it}-2}$ with two areas with high intensity: the London-Cambridge-Oxford triangle and the Edinburgh-Glasgow corridor. This geographical pattern highly matches with Figure 4 of regional AI skill demand (corr.=0.686) but differs from geographies of regional productivity in Figure 2 with a clear corridor along London-Swindon in England and spatial dispersion in Scotland (corr.=0.258).

$IV_AIRD_Complementary_{\mathrm{it}-2}$ is constructed to satisfy the three IV conditions of relevance, exclusion, and independence. As for the relevance condition, relatedness density of these regionally specialised, AI-complementary skills measures the general opportunity space within which AI skills can be combined with other non-AI, -IT and -math skills for various applications. Greater skill relatedness density relative to AI implies the potential diffusion of AI skills increasingly into new AI application jobs utilising existing regionally specialised skills. Some of these AI-complementary skills are hard skills central to any specific sector (e.g. cheesemaking in manufacturing, risk assessment in insurance, or forecasting in finance), while others are soft skills facilitating the usage of AI application methods, techniques, or tools (e.g. scientific curiosity, problem solving, and analytical thinking).

As for the exclusion condition, our IV excludes advanced digital skills (AI, IT, and Mathematical modelling) and consists of various complementary skills relative to AI. Theoretically speaking, a skill can generate greater added values if it is more widely demanded and combined with as many skills as possible in a skill co-occurrence network (Stephany and Teutloff, 2024). Advanced digital skills, such as AI, IT, and Math, being the foundation of key enabling technologies (including AI) are more likely to be demanded and combined with more

diverse skills than the complementary skills in this digital and AI era (Acemoglu et al. 2022; Goldfarb et al., 2023; Hunt et al. 2024; Li et al., 2024). They drive superior value creation by reducing costs, leveraging network effects, realising scope economies, and catalyzing innovation (Babina et al., 2024; Li et al., 2024). Compared with these advanced digital skills, the complementary (non-AI, -IT, and -math) skills reveal significant divergence of economic values, for instance, corporate law or financial projection with greater economic values than manufacture of papers or cheese (Stephany and Teutloff, 2024). As illustrated in Figure 6, a region like Reading specialised in IT and professional industries has a similar AI relatedness density of the complementary skills as another region like Huntingdon specialised in manufacturing and transport logistics, but their levels of labour productivity are vastly different.

Furthermore, it is technological complexity rather than skill relatedness that directly drives regional productivity (Balland et al., 2020). Indeed, the relatedness between skills influences how efficiently any task is conducted by the related skills but not determine the added values per unit of labour input (Apostol and Hernández-Rodríguez et al., 2025; Henning et al., 2025). For instance, lagging regions may tend to specialise in simple related industries and technologies with low productivity, while large regions can diversify into new specialisations in complex, productive economic activities (Balland et al. 2019). These complex skills and technologies, such as computer and mathematics, communications, and software are spatially concentrated in large regions and can drive productivity and economic development, for example, in the U.S. (Balland et al., 2020). In Europe, the complexity of digital technologies also has a significant and positive association with regional productivity (Apostol and Hernández-Rodríguez et al., 2025). So, the IV excluding these advanced digital skills is not directly correlated with regional productivity.

The IV capturing potentials of AI application theoretically and empirically does not determine and is not determined by regional productivity. It measures the potential of regions with high specialisations in the complementary skills to employ new AI skills in various application domains, excluding those complex digital skills. These application potentials of combining AI skills with the complementary skills are theoretically determined by the general purpose technology nature of AI rather than productivity (Goldfarb et al., 2023; Mäkelä and Stephany, 2024). These application potentials are empirically computed based on a co-occurrence (skill relatedness) index between each complementary skill and the AI skills among up to 15 million OJAs in the entire Great Britain in each year. Covering the full dataset, this measurement is not biased to single productive or lagging regions.

As for the third condition of independence, the panel IV models control variables with potential correlations with both the dependent variable and IV, for instance, employment specialisations, sectoral diversity, digital infrastructure, and large companies. In this way, this IV does not influence regional productivity through other pathways like Jacobian externalities, tangible capital investment, or regional concentration of specialised labour. In addition, the models include regional and year fixed effects to control other unobservable factors. In sum, $IV_AIRD_Complementary_{\mathrm{it}-2}$ can facilitate regions to employ more new AI skills that are closer to its existing skill structure for diverse AI applications, thereby potentially promoting more productivity gains. As a robustness test, a different IV is constructed and showed in Appendix C, and robustness tests are shown in Table C.1 and C.2.

3.4 Heterogeneity

To test the second hypothesis, the study further investigates the regional productivity effect of AI skill demand in separate periods, different job categories and occupations, and regional sectors.

For instance, we run the panel model separately for two periods before and after the Covid-19 crisis (2018-2020 and 2021-2023). During the Covid-19 period, companies switch working patterns from office to work from home and increase investment in ICT resources, training, and management (Boeri et al., 2025). Even though work from home during the pandemic in 2020 negatively influences firm productivity, firms with more employees, complementary ICT resources, and skilled workers can generate productivity benefits, for instance, in the case of Italy (Boeri et al., 2025).

As for AI discussed in the literature review, it may take a longer term for intangible capital such as AI skills to create aggregate added values which can be measured by national statistics. In the early stage of AI application, some companies investing in digitalisation, AI skills, and complementary resources do not immediately produce measurable products or services, for instance, re-design of production processes, re-organization of business management, retraining skilled labour, and creation of new market supply and demand (Brynjolfsson et al., 2021). Thus, before and after the Covid-19 shock, regional productivity gains from the adoption of AI skills by local companies should be different.

In addition, the study replaces the independent variable ($Share_AI_{it-1}$) with $Share_AI_IT_{it-1}$, $Share_AI_Science_{it-1}$, $Share_AI_Finance_{it-1}$, $Share_AI_Engineering_{it-1}$, or $Share_AI_Marketing_{it-1}$. These new variables indicate the share of AI skill demand only from IT jobs, Scientific jobs, Accounting, finance, and consultancy jobs, Engineering jobs, and

Marketing, sales, and customer services jobs. These categories are jobs that require digital skills intensively should be more likely to adopt AI skills in tasks and generate greater productivity gains (Zhang et al., 2025a). In addition, occupational heterogeneity is tested among UK's Standard Occupational Classification 2020 (SOC 2020) broad major groups in Table C.3 and C.4 in the Appendix C.

Considering regional heterogeneity, this study also investigates the productivity effect in different groups of regions, especially those at the Top 25th percentile with the highest share of AI OJAs (see Figure 3 and 4). These regions with denser population, more complementary industrial structure, and human capital can have a greater share of AI OJAs and should gain first-mover advantages (Zhang et al., 2025a). Additionally, the study further examines how regional employment specialisation in each sector moderates the productivity effect in each period. All continuous variables are logarithmically transformed, excluding the shares (such as all $Share_AI_{it-1}$, $IV_AIRD_Complementary_{\mathrm{it}-2}$, $Emp_Diversity_{it-1}$, and $Large_Com_{it-1}$). Table 1 shows descriptive statistics of each variable.

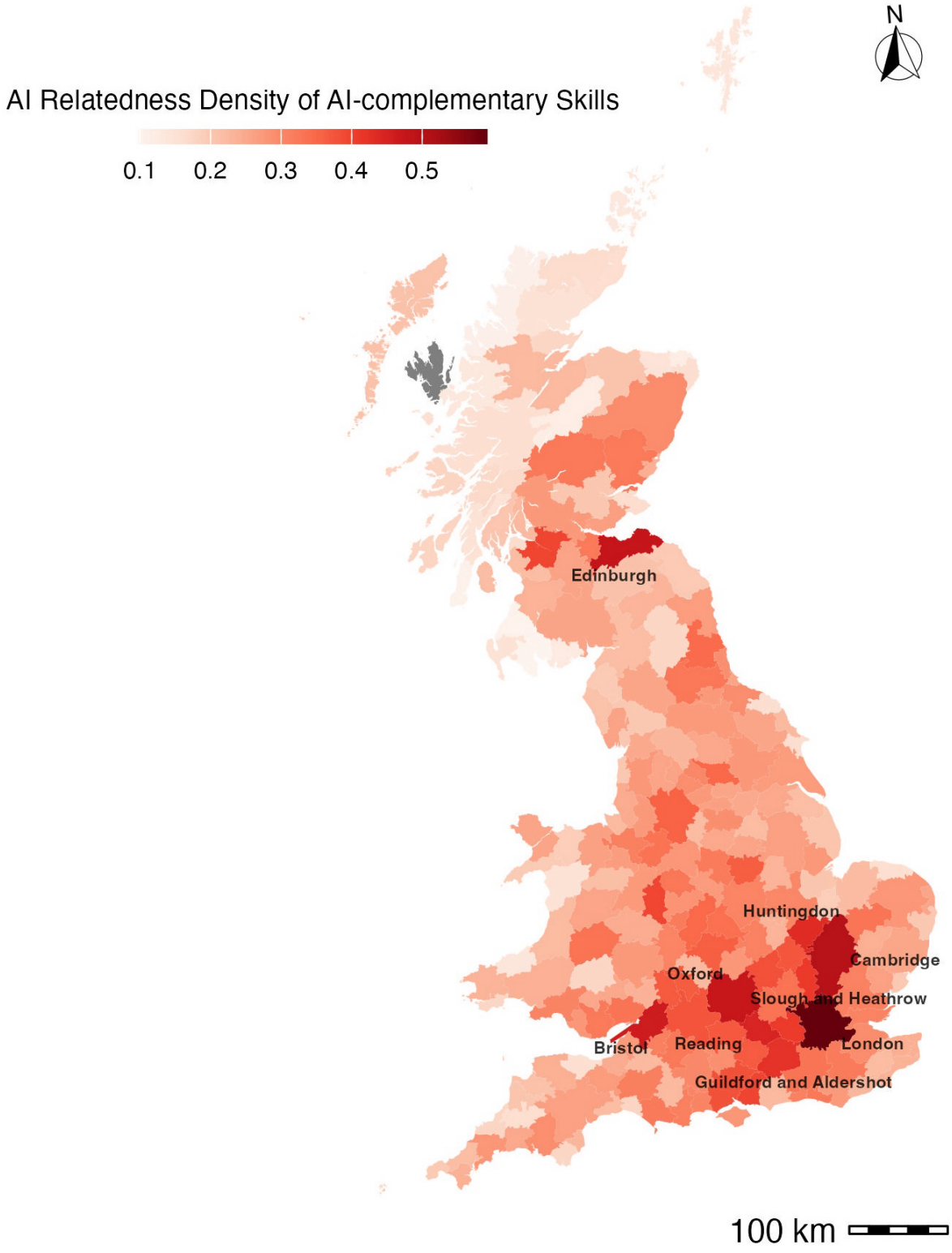


Figure 6. Average AI relatedness density of the AI-complementary skills (exc. IT and Math) in travel to work areas in Great Britain between 2016-2021.

Table 1. Descriptive statistics of each variable

Statistic	N	Mean	St. Dev.	Min	Max
Productivity (log)	1,302	10.99	0.1645	10.52	11.59
Share_AI	1,302	0.0021	0.0022	0.0000	0.0167
Share_AI_IT	1,302	0.0008	0.0013	0.0000	0.0106
Share_AI_Science	1,302	0.00007	0.0002	0.0000	0.0034
Share_AI_Finance	1,302	0.00005	0.0001	0.0000	0.0020
Share_AI_Engineering	1,302	0.0008	0.0010	0.0000	0.0110
Share_AI_Marketing	1,302	0.00009	0.0002	0.0000	0.0021
Emp_ICT (log)	1,302	-0.7964	0.6983	-3.4813	1.3120
Emp_Pro (log)	1,302	-0.4294	0.4003	-1.9394	0.6385
Emp_Finance (log)	1,302	-0.7253	0.6374	-2.3026	1.1185
Emp_Manufacturing (log)	1,302	0.1230	0.5163	-1.3700	1.5121
Emp_Energy (log)	1,302	-0.0465	0.6218	-2.3992	2.9846
Emp_Diversity	1,302	9.588	1.1727	5.595	12.242
Broadband (log)	1,302	8.851	0.5612	6.877	10.582
Large_Com	1,302	0.0028	0.0017	0.0000	0.0074
IV_AIRD_Complementary	1,302	0.2604	0.0844	0.0576	0.6517

Note: (log) indicates that the natural logarithm of that variable is used.

4 Results

4.1 Productivity paradox

The baseline, two-way fixed effect panel regression model investigates the effect of regional AI skill demand in all jobs on regional productivity between 2018-2023 (see Table 2). Control variables are incrementally included from Model (1) to (4). All models account for serial autocorrelation of regional errors. Estimates of the Model (4) with fixed effects and all variables can approximately explain a 92.45 percent of the variation of the outcome variable. The following discussion mainly focuses on Model (4) estimates.

All models in Table 2 consistently indicate that the intensity of regional AI skill demand does not significantly influence regional productivity in our dataset. This finding is in line with the delayed productivity effects of previous rounds of technological revolution and related discussions about AI (Acemoglu et al. 2014; Brynjolfsson et al. 2021). Simply put, in order for such productivity effects to be materialised, companies need to reorganise their structures and adjust to the new production processes shaped by AI technologies.

Reverse causality may generate biased estimates, so we introduce 2SLS/IV to estimate the causal effect of AI skill demand on regional productivity through the pathway of diverse AI applications. This causal pathway is operationalised by using $IV_AIRD_Complementary_{\mathrm{it}-1}$, which is the relatedness density of regionally specialised skill structures to which AI skills are complementary, as discussed in the previous section.

In Table 3, Panel A and B show the first and second stage regressions. Both Model (1) and (2) in Table 3 have a significant Wald F-statistic higher than the rule of thumb criterion of 13, which means that the IV is not a weak instrument. However, the Wu-Hausman statistic of Model (1) and Model (2) is insignificant, indicating that the productivity effect of the fitted AI share in

each panel IV model is significantly undistinguishable from that in its OLS model in Table 2. This result can be supported by Zhang et al. (2025a) finding insignificant effects of labour productivity on the number and share of AI OJAs at the local authority level in Great Britain between 2016-2022. The productivity effects of broad AI skill demand are all insignificant across models in Table 2 and Table 3 between 2018-2023. In robustness tests, these results remain robust (insignificant) in models using two distinct IVs to distinguish the causal pathways of diverse AI applications and the adoption of AI academic knowledge in Table C.2 in the Appendix C. Therefore, results do not support the first theoretical hypotheses.

Table 2. Baseline models of two-way fixed effect panel regressions between 2018 and 2023.

	Dependent variable: Productivity			
	GVA per employee			
	(1)	(2)	(3)	(4)
Share_AI	-1.5358	-1.5302	-1.4652	-1.4137
	(1.5231)	(1.5082)	(1.4495)	(1.4628)
Broadband		-0.0084	-0.0077	-0.0079
		(0.0078)	(0.0078)	(0.0078)
Emp_ICT			0.0018	0.0020
			(0.0121)	(0.0122)
Emp_Pro			0.0192	0.0192
			(0.0190)	(0.0190)
Emp_Finance			0.0087	0.0091
			(0.0132)	(0.0133)
Emp_Manufacturing			0.0083	0.0078
			(0.0284)	(0.0284)
Emp_Energy			-0.0054	-0.0054
			(0.0073)	(0.0073)
Emp_Diversity			0.0066	0.0067
			(0.0060)	(0.0060)
Large_Com				-2.5844
				(4.8953)

Constant	10.7296***	10.7985***	10.7392***	10.7503***
	(0.0057)	(0.0652)	(0.0906)	(0.0954)
Year fixed effects	YES	YES	YES	YES
TTWA fixed effects	YES	YES	YES	YES
Model Summary				
Observations	1302	1302	1302	1302
P-value	0.0000	0.0000	0.0000	0.0000
R-squared	0.9371	0.9373	0.9378	0.9378
Adjusted R-squared	0.9242	0.9243	0.9245	0.9245
Akaike Inf. Cri.	-4161.294	-4162.373	-4160.533	-4159.355
Bayesian Inf. Crit.	-3002.843	-2998.75	-2965.88	-2959.53

Notes: Standard errors are included in parenthesis. All models account for serial correlation (temporal autocorrelation of errors) by including clustered standard errors of 'TTWA' based on the 'HC1' function of the 'Arellano' method from the 'vcovHC' package in R.

* P<0.1; ** P<0.05; *** P<0.01

Table 3. Panel IV regressions of regional productivity

Panel A. First-stage of the panel IV model		
	Dependent variable	
	(1)	(2)
	Share_AI	Share_AI
IV_AIRD_Complementary	0.0062***	0.0064***
	(0.0014)	(0.0014)
Controls	NO	YES
Observations	1302	1302
Adj. R-Squared	0.6652	0.6650
Within R-Squared	0.0212	0.0281
Wald F-statistic	28.073***	28.916***

Panel B. Second-stage of the panel IV model		
	Dependent variable	
	(1)	(2)
	Productivity	Productivity
Share_AI	-6.6541	-5.6858
	(8.5597)	(8.3291)
Controls	NO	YES
Observations	1302	1302
Adj. R-Squared	0.9241	0.9244
Within R-Squared	0.0008	0.0116
Wald F-statistic	28.073***	28.916***

Wu-Hausman	0.4935	0.3552

Notes: * P<0.1; ** P<0.05; *** P<0.01. All models control serial correlation by using clustered standard errors of each TTWA.

4.2 Heterogeneous productivity effects

This study further conducts panel regressions separately for two 3-year periods (2018-2020 and 2021-2023) to distinguish the early stage of AI adoption before and during the Covid-19 crisis from another stage of increasing AI diffusion after the Covid-19 and the public release of ChatGPT in Nov. 2022. Model (1) in Table 4 show an insignificant and negative effect of regional AI skill demand on regional productivity between 2018-2020, while similarly, Model (3) finds an insignificant but positive effect between 2021-2023. These results partly align with company-level findings from an OECD report of Calvino et al. (2026) that the adoption of AI technologies does not significantly affect turnover per employee among firms being surveyed in Great Britain between 2021-2024.

The study also investigates its occupational heterogeneity among job categories or SOC2020 groups in regions at the Top 25th percentile with the greatest share of AI OJAs between 2018-2023. Table 5 shows estimates of the productivity effects of AI skill demand from all OJAs, or only IT jobs, Scientific and quality assurance jobs, Accounting, finance, and consultancy jobs, Engineering jobs, or Marketing, sales, and customer services jobs. Almost all types of AI skill demand show insignificant effects, but the share of AI skill demand from the scientific jobs has a significant and positive correlation with regional productivity. This effect indicates that regional productivity can increase by 0.34% if the regional share of scientific OJAs seeking AI skills increases by 1% in the last year among those Top 25th regions. In contrast, this estimate is insignificant for the rest of regions[5]. Furthermore, Table C.4 in the Appendix C shows

that the demand for managers or professionals using AI skills does not show a significant effect on regional productivity, but the administrative and secretarial occupation has a significantly positive effect. Administrative and secretarial occupations mainly accomplish office-related tasks such as data and document management, communication, and office coordination. These tasks are more exposed to AI technologies or AI tools, which improve the efficiency of production support and service activities (Brynjolfsson et al. 2025; Noy and Zhang, 2023). In sum, these results indicate significant heterogeneity among occupations and regions.

Furthermore, the study examines its region-sectoral heterogeneity among regional specialisations in each industrial sector for all regions in Great Britain in each period (2018-2020 and 2021-2023). Table 6 shows the estimates for the period of 2021-2023, while estimates for the 2018-2020 period are shown with all insignificant effects in Table C.5 in the Appendix C. Results of Table 6 find significant and positive productivity effects of AI skill demand, especially in regions specialised in the professional, scientific, technical activities sector or the financial sector between 2021-2023. A map in Figure 7 illustrates that employment from the professional, scientific, technical activities sector is spatially concentrated in regions such as London, Cambridge, Reading, Salisbury, Oxford, and Manchester in England, Brecon in Wales, and Aberdeen, Thurso, and Edinburgh in Scotland. Leveraging place-based employment capabilities in this professional sector, these regions can improve labour productivity to a greater extent between 2021-2023 when increase the regional share of AI OJAs. Similarly, a map in Figure 8 illustrates that financial employment is more spatially concentrated in some regions, for instance, Edinburgh, London, Bournemouth, Halifax, Skipton, Crewe, and Swindon. These regions can also improve labour productivity more considerably in 2021-2023 if they increase the regional share of AI OJAs. All of these results together support the second hypothesis.

These findings, at a more detailed level, appear to align with the argument about the productivity paradox of intangible capital regarding the adoption of AI skills (Acemoglu et al., 2014; Brynjolfsson et al., 2017, 2021; Calvino et al., 2026; McElheran et al., 2025). The study finds significant productivity effects in regions specialised in the professional and finance sectors for the 2021-2023 period. There could be reinforcing economic disparities between lagging regions and technology- and capital-intensive regions. These heterogeneous effects align with geographical patterns illustrated by Zhang et al. (2025a) and research implications demonstrated by Babina et al. (2024).

These results remain robust against different specifications. First, regression models remove regions including London, Cambridge, Oxford, and Manchester to avoid measurement errors of the productivity metric and to remove outliers of AI adoption. Second, as a robustness test, we also introduce a stricter deduplication process of OJAs and test whether the estimated effects are robust. More specifically, we further remove OJAs with the highly similar job descriptions, even though they have different advertisement IDs and may be posted in different time or location. The correlation between the regional share of AI OJAs and that of deduplicated AI OJAs is up to 0.995. Estimates of the productivity effects are highly similar.[5] Heterogeneity exists among different occupations, periods, and regional sectors.

Table 4. Two-way fixed effect panel regressions for the periods of 2018-2020 and 2021-2023.

	Dependent variable: Productivity	
	GVA per employee	
	(1)	(2)
	2018-2020	2021-2023
Share_AI	-2.16	1.61
	(2.42)	(2.41)
Controls	YES	YES
Year fixed effects	YES	YES
TTWA fixed effects	YES	YES
Summary		
Observations	651	651
P-value	0.00	0.00
R-squared	0.95	0.96
Adjusted R-squared	0.92	0.94
Akaike Inf. Cri.	-2091.6	-2205.6
Bayesian Inf. Crit.	-1066.0	-1180.0

Notes: All models account for TTWA-level serial correlation.

* P<0.1; ** P<0.05; *** P<0.01

Table 5. Panel regressions of Share_AI for each job category in 2018-2023 among Top 25th percentile regions with the highest share of AI OJAs.

	Dependent variable: Productivity					
	GVA per employee					
	(1)	(2)	(3)	(4)	(5)	(6)
Share_AI	-0.97					
	(1.60)					
Share_AI_IT		-0.14				
		(2.93)				
Share_AI_Science			**33.99*** **			
			(11.00)			
Share_AI_Finance				3.87		
				(30.59)		
Share_AI_Engineering					-0.00	
					(1.71)	
Share_AI_Marketing						-10.32
						(10.86)
Controls	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
TTWA fixed effects	YES	YES	YES	YES	YES	YES
Model Summary						

Observations	330	330	330	330	330	330
P-value	0.00	0.00	0.00	0.00	0.00	0.00
R-squared	0.97	0.97	0.97	0.97	0.97	0.97
Adjusted R-squared	0.96	0.96	0.96	0.96	0.96	0.96
Akaike Inf. Cri.	-1167.11	-1166.4	-1177.491	-1166.4	-1166.4	-1167.1
Bayesian Inf. Crit.	-901.2	-900.4	-911.555	-900.5	-900.4	-901.2

Notes: All models account for TTWA-level serial correlation. * P<0.1; ** P<0.05; *** P<0.01

Table 6. Two-way fixed effect panel regressions for the period of 2021-2023.

	Dependent variable: Productivity					
	GVA per employee					
	(1)	(2)	(3)	(4)	(5)	(6)
Share_AI	1.61	3.81	**5.41****	**6.67****	1.80	1.93
	(2.41)	(2.56)	**(2.39)**	**(2.78)**	(2.51)	(2.50)
Share_AI*Emp_ICT		2.08				
		(2.52)				
Share_AI*Emp_Pro			**6.24*****			
			(2.25)			
Share_AI*Emp_Finance				**4.06****		
				(1.65)		
Share_AI*Emp_Manufact					2.73	
					(2.99)	
Share_AI*Emp_Energy						1.48
						(2.36)
Controls	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
TTWA fixed effects	YES	YES	YES	YES	YES	YES
Model Summary						
Observations	651	651	651	651	651	651

P-value	0.00	0.00	0.00	0.00	0.00	0.00
R-squared	0.95	0.96	0.96	0.96	0.96	0.96
Adjusted R-squared	0.92	0.94	0.94	0.94	0.94	0.94
Akaike Inf. Cri.	-2091.6	-2206.3	-2212.6	-2214.7	-2206.4	-2204.5
Bayesian Inf. Crit.	-1066.0	-1176.2	-1182.5	-1184.6	-1176.4	-1174.4

Notes: All models account for TTWA-level serial correlation. * P<0.1; ** P<0.05; *** P<0.01

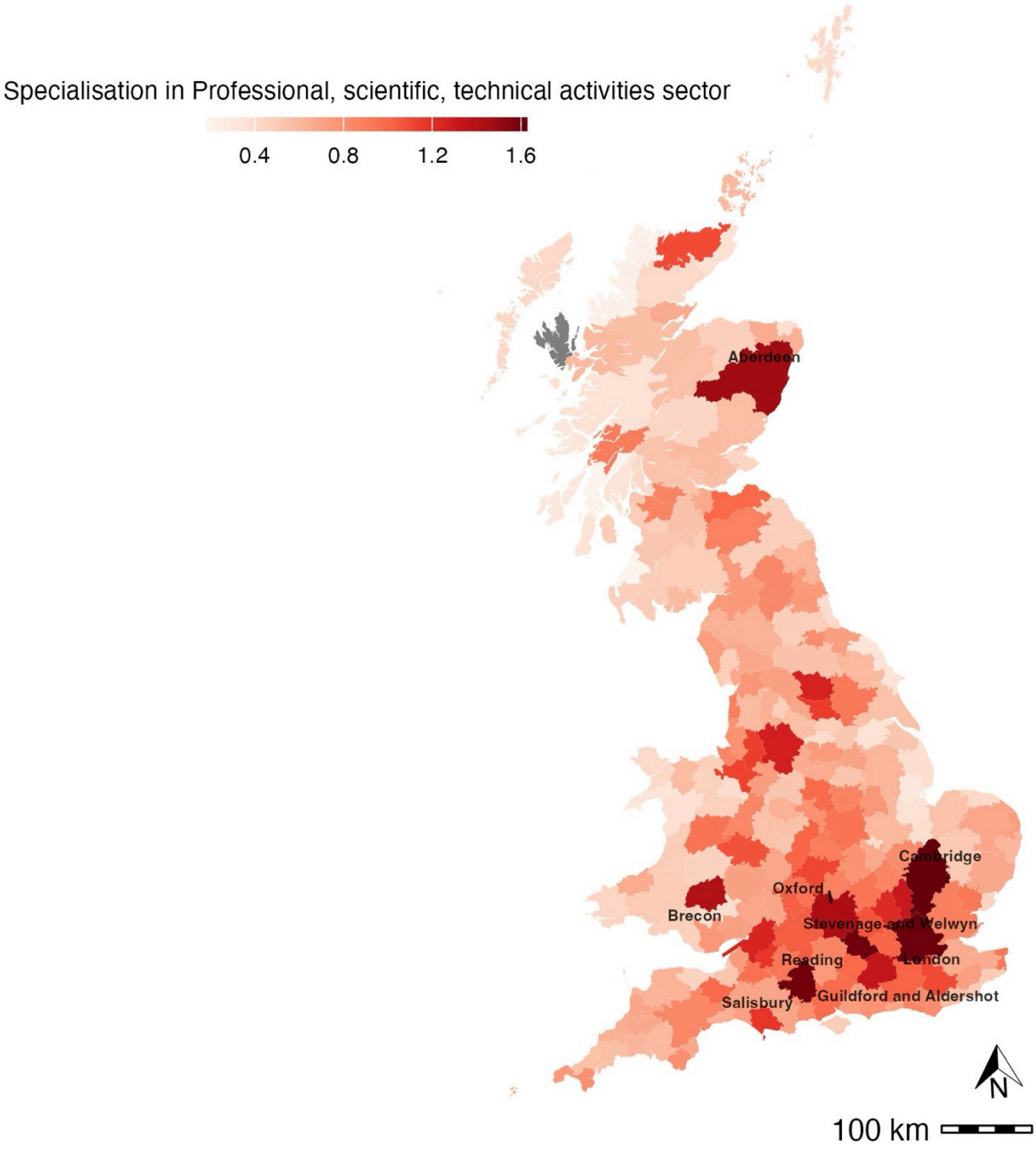


Figure 7. Average regional specialisation in the professional, scientific, technical activities sector in travel to work areas in Great Britain between 2020-2022.

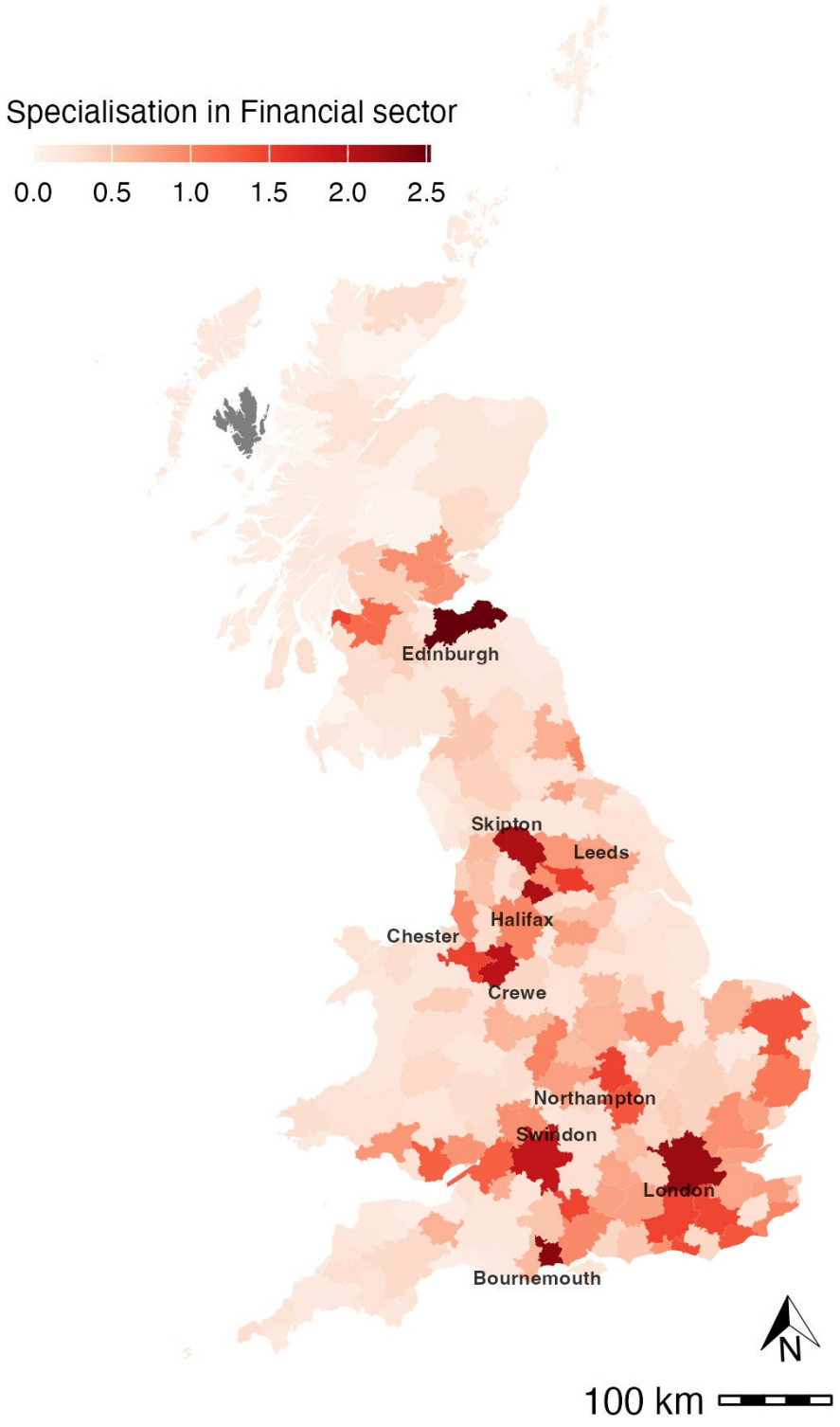


Figure 8. Average regional specialisation in the financial sector in travel to work areas in Great Britain between 2020-2022.

5 Conclusion

This study investigates the effect of regional AI skill demand on regional productivity between 2018 and 2023 in Great Britain through the pathway of diverse AI applications by using panel regressions. The use of relatedness density of regionally specialised skill portfolios to which AI skills are complementary in 2016-2021 as an IV allow us to test the causal interpretation of the results. Based on the literature, this paper proposes two theoretical hypotheses: 1) regions with denser labour demand for AI skills can experience an increase in regional productivity; 2) this productivity effect is heterogeneous across different periods, occupations, and regional sectors. Regression results do not find statistically significant effects to support the first hypothesis. However, the second hypothesis is partly supported by more detailed regression analyses. Results find significant temporal, occupational, and region-sectoral heterogeneity.

As for occupational and regional heterogeneity, regions at the Top 25th percentile with the greatest share of AI skill demand, especially from the scientific and quality assurance jobs or the administrative and secretary occupations, can experience a significant increase in regional productivity between 2018-2023. As for temporal and region-sectoral heterogeneity, broad AI skill demand from all jobs shows a significant and positive effect on regional productivity, especially between 2021-2023 in regions specialised in the professional, scientific, technical activities sector or the financial sector. In contrast, these effects are insignificant between 2018-2020. Research findings indicate reinforcing regional productivity disparities. This uneven geography is significant among regions with differing industrial structures probably along the spatial division of labour among financial professionals, scientific researchers, quality assurance engineers, administrative and secretary employees, and general workers.

From the perspective of regional AI skill demand, this study sheds new light on the discussion of the productivity paradox in economic geography. Like information technology discussed by Brynjolfsson and Hitt (1996) and Acemoglu et al. (2014), AI is producing a similar productivity paradox. More importantly, it potentially increases socio-economic inequalities among workers, sectors, and regions. Indeed, increased intensity of AI skills in regional labour markets may produce greater productivity gains, especially by scientific or technical workers in the professional, scientific, technical activities sector or the financial sector. However, more labour could be demanded and employed to serve and 'feed' a global AI system in which greater productivity gains can be distributed unevenly among various groups of labour and regions (Acemoglu and Restrepo, 2026; Lynch, 2025).

This paper has empirical contributions to the policy debate. Regional policies could facilitate the diverse applications of AI skills across tasks and sectors for growing regional productivity in the future. More importantly, policies should also consider how to re-distribute the productivity gains more equally among regions, sectors, and workers who develop, adopt, and are detrimentally influenced by AI technologies. For instance, governments may promote the AI application which empower and is complementary to workers rather than the adoption of labour-saving AI technologies only for cost-reduction. In addition, more funding could be invested in re-skilling programs helping the local labour force to develop place-based, AI-complementary skills for new jobs and a just human society.

This study is not free from limitations. First, we can only observe the demand for AI skills in regional labour markets rather than the supply of such skills. So, the independent variable does not reflect the actual adoption of AI technologies by companies. In addition, the dataset of online job advertisements as the proxy of skill demand may also not be very

comprehensive and representative with the potential biases towards businesses, professionals, and IT jobs. Yet, the OJA data can capture the majority of the skills that are demanded to implement emerging digital technologies such as AI. The OJA data reflecting the demand for AI skills can reveal an emerging trend of such new skills in regional labour markets as well where the supply of labour is more inelastic and stagnant than the labour demand data. Second, this study does not actually investigate how the adoption of AI technologies influences regional employment. Future research should investigate the effect of AI adoption on regional employment and potential job displacement among various groups of occupations from different sectors in large, industrialised, small, and lagging regions.

Notes

1. UK National AI Strategy is developed and implemented by Department for Science, Innovation and Technology (DSIT). Accessed on 1st Jan. 2026 via https://oecd.ai/en/dashboards/policy-initiatives/national-ai-strategy-5813

2. see pages 431-433 of the Stanford AI 2025 report. Accessed on 1st Sep. 2025 via *https://hai.stanford.edu/assets/files/hai_ai_index_report_2025.pdf*

3. Accessed on 15th June 2025 via *https://lightcast.io/open-skills*

4. The skill range (r) has 1,083 unique skill groups (s) among all OJAs in Great Britain in 2016.

5. Results of these robustness tests can be provided upon a proper request.

Disclosure Statement

The authors declare that they have no known competing financial interests. Considering methodological transparency, the authors disclose the use of Google Gemini 3.1 Pro for coding assistance in R. As for data availability, Adzuna online job listings 2016-2024 is a safeguarded dataset, which can be applied from Adzuna (2025).

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Appendix A. Keywords of AI Skills

AI_General_Skills = ['Artificial intelligence', 'Machine learning', 'Natural language processing', 'NLP', 'Computer vision', 'Neural networks', 'Robotics', 'AI ethics', 'Autonomous driving', 'Generative AI', 'Generative artificial intelligence', 'Image recognition']

AI_Specific_Skills = ["ethical AI", "data sovereignty", "AI security", "agentic systems", "AI/ML inference", "AIOps", "AI personalization", "AI testing", "artificial general intelligence", "automated data cleaning", "Azure Cognitive Services", "Baidu", "cognitive automation", "cognitive computing", "computational intelligence", "Cortana", "Data Version Control", "Edge Intelligence", "embedded AI", "expert systems", "explainable AI", "intelligent control", "intelligent systems", "interactive kiosk", "IPSoft Amelia", "knowledge distillation", "knowledge engineering", "knowledge-based configuration", "knowledge-based systems", "knowledge representation", "multi-agent systems", "neuro-symbolic AI", "Open Neural Network Exchange", "OpenAI Gym", "operationalizing AI", "PineCone", "Qdrant", "reasoning systems", "swarm intelligence", "synthetic data generation", "Watson Conversation", "Watson Studio", "Weka Weaviate", "advanced driver-assistance systems", "autonomous cruise control systems", "autonomous system", "autonomous vehicles", "dynamic routing", "guidance navigation and control systems", "LiDAR", "light detection and ranging", "object tracking", "OpenCV", "path analysis", "path finding", "remote sensing", "scene understanding", "unmanned aerial systems", "Adobe Sensei", "ChatGPT", "CrewAI", "DALL-E image generator", "generative adversarial networks", "Google Bard", "image inpainting", "image super-resolution", "LangGraph", "large language modeling", "LLM", "Microsoft Copilot", "multimodal learning", "multimodal models", "prompt engineering", "retrieval-augmented generation", "Stable Diffusion", "text summarization", "text to speech", "variational autoencoders", "AdaBoost", "adversarial machine

learning", "Apache MADlib", "Apache Mahout", "Apache SINGA", "Apache Spark", "association rule learning", "attention mechanisms", "AutoGen", "automated machine learning", "autonomic computing", "AWS SageMaker", "Azure Machine Learning", "bagging techniques", "Bayesian belief networks", "Boltzmann Machine", "Chi-Squared Automatic Interaction Detection", "Classification and Regression Tree", "cluster analysis", "collaborative filtering", "concept drift detection", "confusion matrix", "cyber-physical systems", "Dask", "data classification", "Dbscan", "decision models", "decision-tree learning", "dimensionality reduction", "distributed machine learning", "Dlib", "embedded intelligence", "ensemble methods", "evolutionary programming", "expectation maximization algorithm", "feature engineering", "feature extraction", "feature learning", "feature selection", "federated learning", "game AI", "Gaussian process", "genetic algorithm", "Google AutoML", "Google Cloud ML Engine", "gradient boosting", "H2O.ai", "hidden Markov model", "hyperparameter optimization", "incremental learning", "inference engine", "k-means clustering", "kernel methods", "Kubeflow", "LIBSVM", "loss functions", "Markov chain", "matrix factorization", "meta learning", "Microsoft Cognitive Toolkit", "MLflow", "MLOps", "mlpack", "ModelOps", "Naive Bayes Classifier", "neural architecture compression", "neural architecture search", "objective function", "Oracle Autonomous Database", "Perceptron", "Predictionio", "predictive modeling", "programmatic media buying", "Pydata", "PyTorch", "PyTorch Lightning", "Random Forest Algorithm", "recommender systems", "Scikit-Learn", "semi-supervised learning", "soft computing", "sorting algorithm", "supervised learning", "support vector machines", "t-SNE", "t-distributed Stochastic Neighbor Embedding", "test datasets", "topological data analysis", "Torch", "training datasets", "transfer learning", "transformer", "unsupervised learning", "Vowpal Wabbit", "Xgboost", "Theano", "AI copywriting", "Amazon Alexa", "Amazon Textract",

"ANTLR", "Apache OpenNLP", "BERT", "chatbot", "computational linguistics", "conversational AI", "DeepSpeech", "dialog systems", "fastText", "fuzzy logic", "handwriting recognition", "Hugging Face", "intelligent agent", "intelligent virtual assistant", "Kaldi", "language model", "latent Dirichlet allocation", "Lexalytics", "machine translation", "Microsoft LUIS", "natural language generation", "natural language programming", "natural language toolkits", "natural language understanding", "natural language user interface", "nearest neighbour algorithm", "Nuance Mix", "optical character recognition", "screen reader", "semantic analysis", "semantic kernel", "semantic search", "sentence transformers", "sentiment analysis", "Seq2Seq", "Shogun", "small language model", "speech recognition", "speech synthesis", "statistical language acquisition", "summarization methods", "text mining", "text retrieval systems", "tokenization", "Vespa", "voice assistant technology", "voice interaction", "voice user interface", "word embedding", "Word2Vec", "Apache MXNet", "artificial neural networks", "Caffe2", "Chainer", "convolutional neural networks", "Cudnn", "deep learning", "Deeplearning4j", "deep reinforcement learning", "evolutionary acquisition of neural topologies", "Fast.AI", "graph neural networks", "Keras", "Long Short-Term Memory", "neural ordinary differential equations", "OpenVINO", "PaddlePaddle", "Pybrain", "recurrent neural network", "residual networks", "sequence-to-sequence models", "spiking neural networks", "TensorFlow", "advanced robotics", "bot framework", "cognitive robotics", "motion planning", "Nvidia Jetson", "OpenAI Gym environments", "reinforcement learning from human feedback", "robot framework", "robot operating systems", "robotic automation software", "robotic liquid handling systems", "robotic programming", "robotic systems", "servomotor", "SLAM algorithms", "Simultaneous Localization and Mapping", "3D reconstruction", "activity recognition", "contextual image classification", "Deck.gl", "digital image processing", "digital twin technology", "eye tracking",

"face detection", "facial recognition", "general-purpose computing on graphics processing units", "gesture recognition", "image analysis", "image captioning", "image matching", "image recognition", "image segmentation", "image sensor", "ImageNet", "instance segmentation", "machine vision", "MNIST", "motion analysis", "object recognition", "OmniPage", "pose estimation", "RealSense", "thermal imaging analysis", "Parsing","Visual Odometry",'Predictive Text','Word Recognition','Knowledge Graph','Document Classification','Obstacle Avoidance','Bayes Classifier','RDF','Buildbot','VisualVM','Automated Machinery','Robotc','Mechanical Reasoning','Autonomous Underwater Vehicle','Fingerprint Recognition','Regular Expressions','Automation','Structured Text','Semantics','Unstructured Data', "Visual Recognition","Named Entity Recognition", "Generative Design","Text Processing","Decision Tree Learning", 'Three Degrees Of Freedom','Six Degrees Of Freedom', 'Object Detection', "Backpropagation", "Text Classification", "Feature Detection", "Decision Trees", "Image Processing", "WordNet","Robotic Components","Knowledge Discovery","Information Extraction","Pattern Recognition", "Ontologies","Data Mining","LSTM","Relation Extraction","Support Vector Machine" , "Data Mining Methods","Speech Processing","Automatic Target Recognition","Image Generation" , "Automated Reasoning","Robots.txt", "Visual Objects","Text Extraction", "Semantic Web", "Conditional Random Fields","Relationship Extraction", "Artificial Consciousness", "Amazon Polly", "Bonsai", "AI Agents","AI Alignment", "AI Innovation","AI Research","AI Safety", "AWS Bedrock","AWS Certified Machine Learning Specialty", "Aforge","Agentic AI", "Amazon Forecast","Amazon Personalize","Amazon Transcribe", "Autoencoders", "Automated Planning And Scheduling","Automation Systems","Automation Systems Design","Azure AI Studio", "Azure OpenAI", "Building Automation Software", "CatBoost", "ChatGPT Integration",

"ChatGPT Prompt", "Decision-Matrix Method", "Few Shot Learning", "Fuzzy Set", "Generative AI Agents", "Genetic Programming", "GitHub Copilot", "Google Assistant", "Google Colaboratory", "Haystack", "Human AI Interaction", "Intelligent Automation", "Intelligent Character Recognition", "Intertec Superbrain", "Isaac SDK", "K-Nearest Neighbors Algorithm", "LangChain", "Language Models", "LightGBM","Linear Prediction", "ML.NET" , "Machine Learning Algorithms", "Machine Learning Methods", "Machine Learning Model Monitoring And Evaluation", "Machine Learning Model Training", "Markov Decision Process", "Markov Process","Meta-Learning", "Microsoft Delve", "Multimodal Learning", "NeuroSolutions", "Nuance Nina Virtual Assistant", "OPS5", "Open Mind Common Sense", "Orthogonal Projections", "Partially Observable Markov Decision Process", "Particle Swarm Optimization", "Pattern Mining", "Probably Approximately Correct Learning", "PyCaret", "Q Learning", "Quote Generators", "Recurrent Neural Networks", "RLHF", "ResNet", "Residual Networks", "Retrieval Augmented Generation", "S Voice", "SAS Certified ModelOps Specialist", "Sequence Detector", "Sframe", "Skflow", "SpamBayes", "Systems Automation", "Vertex AI", "Weaviate", "Weka", "Wit.ai", "XLISP", "Zero Shot Learning", 'Amazon Comprehend', 'Amazon Lex', 'Artificial Linguistic Internet Computer Entity', 'Dialogflow', 'Disambiguation', 'Doc2vec', 'GPT-3', 'Generative Grammar', 'GluonNLP', 'Grammatical Framework', 'Language Identification', 'Lemmatization', 'Lexical Analysis', 'Lingpipe', 'N Gram', 'NLTK', 'NetBase Quid', 'Parser Generators', 'Part-of-Speech Tagging', 'Porter Stemmer', 'Question Answering', 'Refal', 'Relationship Extraction', 'Semantic Analysis', 'Semantic Reasoner', 'Sirikit', 'Speech Enhancement', 'Speech Technology', 'Stemming', 'SyntaxNet', 'Tilde', 'Voice Technology', 'Sphero', 'SCARA Robot', 'SACA Certified Industry 4.0 Associate Robot System Operations', 'Robotic Machines','Robot End Effector', 'Remotely Operated Underwater Vehicle', 'Paint Robot',

'PX4 Autopilot', 'Motion Estimation', 'Mobile Robot Programming Toolkit', 'Mobile Robot Navigation', 'Microsoft Robotics Developer Studio', 'Linear Encoder', 'Lego Mindstorms NXT', 'Inverse Kinematics', 'Industrial Robotics', 'Forward Kinematics', 'Flownet', 'Automated Guided Vehicle Operation and Maintenance', 'Automated Guided Vehicle', 'Unmanned Ground Vehicles', 'ArduPilot', 'Autopilot System']

Appendix B Variable construction

Table B.1. Description of variables

Variables	Definition	Data	References
Productivity (Dependent)	Gross Value Added (GVA) per unit of total employment (E) in each TTWA in each year t between 2018-2023.	Office for National Statistics (ONS)	Tranos et al. (2021); Apostol & Hernández-Rodríguez (2025)
Share_AI (Independent)	The share of online job adverts requiring AI skills, such as machine learning, computer vision, natural language processing and so on in each TTWA in the last year t-1 between 2017-2022.	Adzuna Labour Market Data	Zhang, Tranos, and Zhu (2025)
Share_AI_IT, Share_AI_Science, Share_AI_Finance, Share_AI_Engineering, Share_AI_Marketing	The share of AI online job adverts (from only IT jobs, Scientific & quality assurance jobs, Accounting & finance jobs, Engineering jobs, or Marketing, sales & customer services jobs) in each TTWA in the last year t-1. The dataset of Adzuna OJAs provides an entry column named job categories. There are 30 types of jobs including Information		

(Independent variables)	Technology (IT), Scientific & Quality Assurance (QA) jobs, and so on.		
Share_AI_Manager, Share_AI_Profession, Share_AI_Associate_Pro, Share_AI_Administrative, Share_AI_Skilled_trades	The share of AI OJAs from each of the broad groups: Managers, directors and senior officials, Professional occupations, Associate professional occupations, Administrative and secretarial occupations, or Skilled trades occupations in each TTWA in the last year t-1.		Draca et al. (2024)
IV_AIRD_Complementary (Instrumental variable)	AI Relatedness density of complementary skills in each TTWA indicates a share: the sum of the probability of cooccurrence in all OJAs between AI skills and each non-AI-IT-math skill in which the region (TTWA) is specialised, over the sum of the AI-cooccurrence probability for every skill in the year of 2016 in Great Britain. Complementary skills include the skills to which AI is complementary, but they are not IT and Mathematical modeling skills (Lightcast,	ONS & NOMIS	Apostol & Hernández-Rodríguez (2025); Mäkelä & Stephany (2024)

	2025). The combination between AI skills and the AI-complementary skills lays the foundation of adopting AI methods/skills in various application domains, for instance, law, customer services, marketing, finance and consulting, and manufacturing.		
IV_AI_Knowledge_Hubs (Instrumental variable for robustness tests)	The multiplication of the average number of AI academic publications during 1988-1993 in each region with the yearly national growth rate of the AI publications in 2001, 2002, … , 2006. An academic publication is identified as an AI publication if its all fields include at least one AI keywords which are ‘Artificial intelligence', 'Machine learning', 'Computer vision', 'Natural language processing', 'Neural network', 'Deep learning', and 'Generative AI'.	The Lens (2026)	Hunt et al. (2024)
Broadband	The median of broadband upload speed	Speedchecker Ltd (https://www.	Tranos et al.

(Control)	in TTWAs in the year of t-1.	broadbandspeedchecker.co.uk/)	(2025)
Emp_ICT (Control)	It indicates the level of regional employment specialisation in the ICT sector in each year t-1. This variable is measured by dividing the regional share of ICT employment over the national share of ICT employment, similar to a location quotient (or revealed comparative advantage) index.	ONS & NOMIS	Babina et al. (2024); Capello and Lenzi (2024); Tranos et al. (2021)
Emp_Pro (Control)	It indicates the level of regional employment specialisation in the Professional, scientific, technical activities sector in each year t-1.		
Emp_Finance (Control)	It indicates the level of regional employment specialisation in the financial sector in each year t-1.		
Emp_Manufacturing (Control)	It indicates the level of regional employment specialisation in the manufacturing sector in each year t-1.		

Emp_Energy (Control)	It indicates the level of regional employment specialisation in the Electricity, gas, steam and air conditioning supply sector in each year t-1.		
Emp_Diversity (Control)	The inverse of aggregated Herfindahl–Hirschman index (HHI) values of all employees working in each sector in TTWAs in year t-1 between 2017-2022.		Tranos et al. (2021)
Large_Com (Control)	The share of large companies with more than 250 employees in each region in each year t-1.		Babina et al. (2024); Calvino et al. (2026)

Appendix C. Robustness tests

Additional instrumental variable

Except for those AI skill demand from the application side, AI academic knowledge can also be adapted and materialised to develop new AI methods or algorithms, for instance, in biomedical research and development (Zhang et al., 2025b), or to educate generations of AI human capital (Babina et al. 2024). AI academic knowledge is mainly created by academic researchers publishing papers or books in any AI sub-field (Buarque et al. 2020), such as machine learning, computer vision, natural language processing, generative AI, and so forth.

For robustness tests, this study adds another IV, which is constructed based on Hunt et al. (2024). In the U.S., commuting zones closer to any AI knowledge cluster with more than 1,000 academic papers published before 2007 have a significantly greater growth of not only AI research jobs but also AI application jobs during 2007-2019 (Hunt et al., 2024). More importantly, this additional IV is a 'Shift-Share' Bartik IV, following Bonfiglioli et al. (2025) building an AI exposure IV by multiplying the regional share of industrial employment in 1980 with the national growth rate of AI-exposed employment in each industry in each year between 2000-2020. In our study, $IV_AI_Knowledge_Hubs_{\mathrm{it-17}}$ is computed by multiplying the average number of AI academic publications between 1988-1993 in each region with the national yearly multiplier (rate) of AI academic publications in each year during 2001-2006 (see Equation (B.1)). We identify an AI academic publication if its all fields such as title, keywords, or abstract mention at least one AI keyword including 'Artificial intelligence', 'Machine learning', 'Computer vision', 'Natural language processing', 'Neural network', 'Deep learning', and 'Generative AI'.[1] The number of academic publications published by each UK university in each region is retrieved from the Lens (2026). Following Bonfiglioli et al. (2025), this IV has asymmetric

effects on the regional share of AI skill demand across regions over time, depending on historical differences in their AI academic knowledge production, as captured by the average number of AI publications in the early stage of the AI Winter (1988-1993). In the entire AI winter (1987-2000), both businesses and governments in the UK had limited funding for AI-related research, technology innovation, products, or AI-empowered systems.[2] As the national interests in AI gradually grew again during the 2000s, we expect that those AI knowledge hubs with continuous academic research during the AI winter should produce more AI papers along the national trend.

$$IV_AI_Knowledge_Hubs_{\mathrm{it}-17} = Ave_AI_Papers_i^{1988_1993} * \frac{\sum_i AI_Papers_{\mathrm{it}-17}}{\sum_i AI_Papers_{\mathrm{it}-18}} \quad \text{(B.1)}$$

where $Ave_AI_Papers_i^{1988_1993}$ is the average yearly number of AI academic publications in each region (i) between 1988-1993. $\sum_i AI_Papers_{\mathrm{it}-17}$ refers to the total number of AI publications in the UK in each year in 2001-2006, while $\sum_i AI_Papers_{\mathrm{it}-18}$ is the total number of AI publications in the last year during 2000-2005.

This $IV_AI_Knowledge_Hubs_{\mathrm{it}-17}$ captures partly the AI knowledge hubs, which were driven by research interests, without much influence by market investment or governmental funding considering that this was the AI winter period. In addition, AI-related academic knowledge in these hubs was created during the AI winter, and we do not expect this AI knowledge to have any applied usage such as patents or products. Therefore, the AI knowledge hubs are not influenced by and do not influence regional productivity gains directly, which aligns with the first IV condition of exclusion. However, such regions with high concentration of AI academic knowledge could also influence regional productivity in the long term based through

attracting ICT investment and professional workers and providing digital skills training. Such a scenario would be in line with regional path dependence argumentation.

To satisfy the second condition of IV independence, regression models control sectoral employment diversity and regional employment specialisations in each sector, especially the ICT sector and professional, scientific, technical activities sector. In this way, the IV of AI knowledge hubs does not influence regional productivity through other pathways like Jacobian externalities or regional concentration of ICT-related and professional labour. In addition, the models control broadband speed and the regional share of large companies to consider the roles of capital investment in the economic development of knowledge-intensive regions. By doing so, the IV also does not operate through other pathways of attracting tangible investment in the future. At last, the models also control the regional fixed effect. In this way, we ensure that this IV can influence regional productivity only through the single pathway of increasing AI skill demand rather than regional path dependence.

At last, this IV also satisfies the third condition of relevance. Theoretically speaking, complex knowledge and technologies are spatially concentrated in cities or regions (Balland et al., 2020). For instance, AI-related human capital with vital, tacit knowledge of AI is educated and cultivated in AI-related knowledge-intensive regions. Geographic barriers can prevent companies in distant regions from successfully recruiting this AI talent. Without the influx of AI-related human capital, companies located in other regions face significant difficulties in adopting AI, scaling AI skill demand, employing AI workers, and establishing new AI companies. So, companies with AI skill demand should also be located in these knowledge-intensive regions. It is efficient for local companies and workers geographically close to the AI knowledge hubs to access cutting-edge information, form productive partnerships, and reduce risks of integrating

immature technologies such as AI in application (Hunt et al., 2024). This type of local spillover effect can justify that the regional level of AI academic knowledge is significantly correlated to the future growth of AI-related OJAs (Hunt et al., 2024). In sum, this second IV can promote regional productivity only through the pathway of transforming AI academic knowledge to increase AI OJAs.

Based on this IV, Figure C.1 illustrates its spatially dispersed geographies of AI academic publications with different clusters, such as the London-Oxbridge triangle, Bristol-Cardiff-Exeter in the Southwest, Manchester-Sheffield-Leicester in the middle, and Edinburgh-Glasgow-Aberdeen in Scotland. This spatial pattern differs from that of regional productivity shown in Figure 2 (corr.=0.191). Figure C.2 shows correlations between IVs and the independent or dependent variable, indicating that both IVs are highly correlated with the share of AI OJAs but have low correlations with regional productivity. Table B.1 in the Appendix B describes this alternative IV in detail. Table C.1 shows descriptive statistics of this IV, and Table C.2 presents estimated effects for robustness tests. The estimated productivity effect of regional AI skill demand in Table C.2 remains robust and insignificant, which is similar to Table 3.

Notes

1 To identify AI papers, this study prepares a vector of broad AI keywords based on the Stanford AI 2025 report (see pages 442 and 431-433). The main aim is to capture any research topic broadly related to AI in academic publications. Accessed on 1st Jan. 2026 via https://hai.stanford.edu/assets/files/hai_ai_index_report_2025.pdf

2 An entry of the AI winter on Wikipedia. Accessed on 23rd April 2026 via https://en.wikipedia.org/wiki/AI_winter

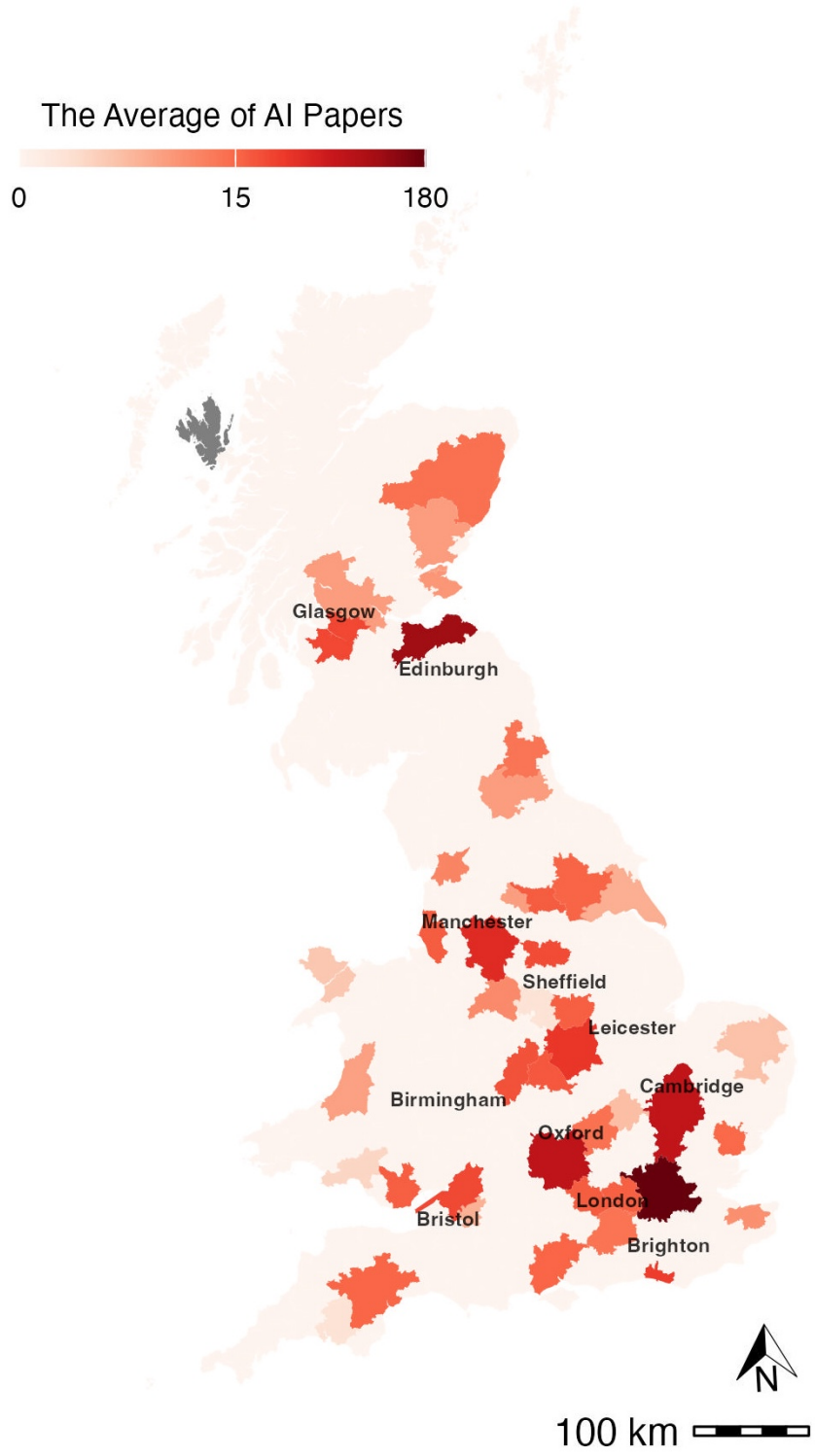


Figure C.1. The average of the weighted number of AI publications in AI knowledge hubs (the average of IV_AI_Knowledge_Hubs) between 2001-2006

(Sources: the Lens (2026))

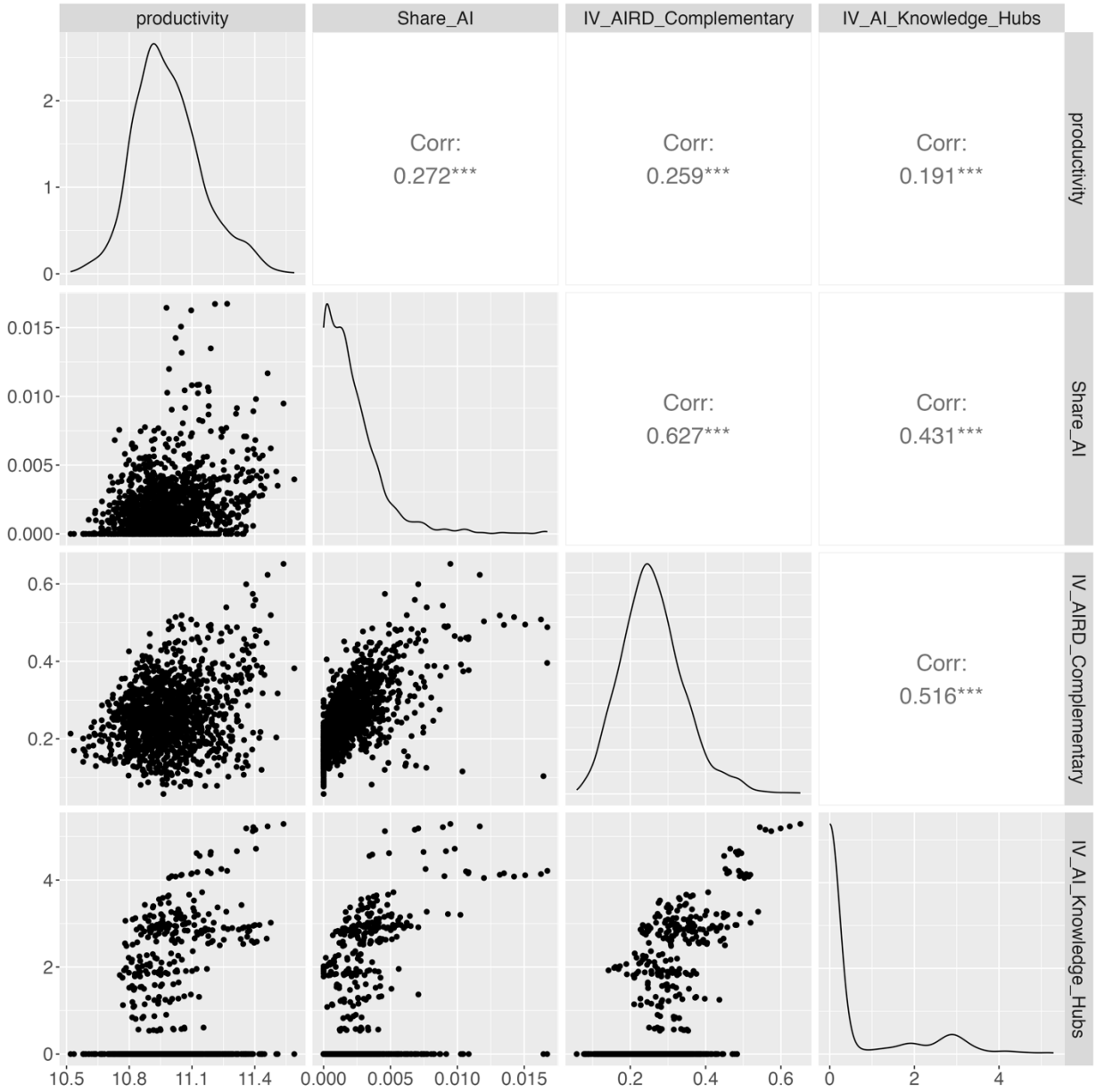


Figure C.2. Correlation between variables (Dependent, Independent, and IVs)

Table C.1. Descriptive statistics of other control variables

Statistic	N	Mean	St. Dev.	Min	Max
IV_AI_Knowledge_Hubs (log+1)	1,302	0.5061	1.1112	0.0000	5.2885

Table C.2. Panel models using two IVs, 2018-2023

Panel A. First-stage of the panel IV model		
	Dependent variable	
	(1)	(2)
	Share_AI	Share_AI
IV_AIRD_Complementary	0.0056***	0.0057***
	(0.0014)	(0.0014)
IV_AI_Knowledge_Hubs	0.0069***	0.0069***
	(0.0022)	(0.0022)
Controls	NO	YES
Observations	1302	1302
Adj. R-Squared	0.6691	0.6690
Within R-Squared	0.0337	0.0405
Wald F-statistic	22.548***	22.954***

Panel B. Second-stage of the panel IV model		
	Dependent variable	
	(1)	(2)
	Productivity	Productivity
Share_AI	-1.0249	-0.9274
	(6.8940)	(6.6959)
Controls	NO	YES
Observations	1302	1302
Adj. R-Squared	0.9241	0.9244

Within R-Squared	0.00003	0.0110
Wald F-statistic	22.548***	22.954***
Wu-Hausman	0.0079	0.0073
Sargan	1.9060	1.4461

Notes: * P<0.1; ** P<0.05; *** P<0.01. All models control serial correlation by using clustered standard errors of each TTWA region. The Sargan statistic of the Model (1) has the p value up to 0.17, while that of Model (2) is 0.23.

UK's Standard Occupational Classification 2020 (SOC 2020) broad major groups

Table C.3 Descriptive statistics of each variable

Statistic	N	Mean	St. Dev.	Min	Max
Share_AI_Manager	1,302	0.0001	0.00025	0.0000	0.0050
Share_AI_Profession	1,302	0.0012	0.0016	0.0000	0.0137
Share_AI_Associate_Pro	1,302	0.0002	0.0003	0.0000	0.0062
Share_AI_Administrative	1,302	0.00002	0.00006	0.0000	0.0009
Share_AI_Skilled_trades	1,302	0.0003	0.00047	0.0000	0.0046

Table C.3 show descriptive statistics of the share of AI OJAs from each broad occupation group over total OJAs in each TTWA in each year. These statistics show that the most AI OJAs are posted in the professional occupations, while the least is from the group of administrative and secretarial occupations. Table C.4 as follows show each corresponding estimate of the share of AI OJAs from each occupation group among the Top 25th percentile regions with the most AI OJAs. All estimates in this Table are insignificant, but only the administrative and secretarial occupations show a significantly positive effect on regional productivity. Regional productivity increases by 1.11% if this occupational group has an 1% increase in the share of AI OJAs. This positive estimate indicates that the labour markets with the most AI skill demand, especially from the administrative and secretarial occupations, have significantly higher labour productivity. These occupations mainly accomplish office-related tasks such as data and document management, communication, and office coordination. These tasks are more exposed to AI technologies or AI tools, which improve the efficiency of production support such as customer service management or data management (Brynjolfsson et al. 2025; Noy and Zhang, 2023).

Table C.4. Panel regressions of Share_AI for each SOC2020 in 2018-2023 among Top 25th percentile regions with the highest share of AI OJAs.

	Dependent variable: Productivity					
	GVA per employee					
	(1)	(2)	(3)	(4)	(5)	(6)
Share_AI	-0.97					
	(1.60)					
Share_AI_Manager		-4.67				
		(8.67)				
Share_AI_Profession			-1.36			
			(1.93)			
Share_AI_Associate_Pro				2.53		
				(8.40)		
Share_AI_Administrative					**111.1****	
					(51.87)	
Share_AI_Skilled_trades						4.46
						(4.73)
Controls	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
TTWA fixed effects	YES	YES	YES	YES	YES	YES
Model Summary						

Observations	330	330	330	330	330	330
P-value	0.00	0.00	0.00	0.00	0.00	0.00
R-squared	0.97	0.97	0.97	0.97	0.97	0.97
Adjusted R-squared	0.96	0.96	0.96	0.96	0.96	0.96
Akaike Inf. Cri.	-1167.11	-1166.9	-1167.2	-1166.5	-1174.2	-1167.2
Bayesian Inf. Crit.	-901.2	-901.0	-901.2	-900.6	-908.3	-901.2

Notes: All models account for TTWA-level serial correlation. * P<0.1; ** P<0.05; *** P<0.01

Table C.5. Two-way fixed effect panel regressions for the period of 2018-2020.

	Dependent variable: Productivity					
	GVA per employee					
	(1)	(2)	(3)	(4)	(5)	(6)
Share_AI	-2.16	-0.85	-1.36	-2.12	-2.35	-2.19
	(2.42)	(3.51)	(3.39)	(3.77)	(2.42)	(2.33)
Share_AI*Emp_ICT		1.80				
		(3.47)				
Share_AI*Emp_Pro			1.94			
			(5.68)			
Share_AI*Emp_Finance				0.06		
				(3.07)		
Share_AI*Emp_Manufact					3.51	
					(3.84)	
Share_AI*Emp_Energy						-0.08
						(3.17)
Controls	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
TTWA fixed effects	YES	YES	YES	YES	YES	YES
Model Summary						
Observations	651	651	651	651	651	651
P-value	0.00	0.00	0.00	0.00	0.00	0.00

R-squared	0.95	0.95	0.95	0.95	0.95	0.95
Adjusted R-squared	0.92	0.92	0.92	0.92	0.92	0.92
Akaike Inf. Cri.	-2091.6	-2090.2	-2089.9	-2089.6	-2091.4	-2089.6
Bayesian Inf. Crit.	-1066.0	-1060.2	-1059.8	-1059.5	-1061.3	-1059.5

Notes: All models account for TTWA-level serial correlation. * P<0.1; ** P<0.05; *** P<0.01