AEA Papers and Proceedings 2025, 115: 29–34
https://doi.org/10.1257/pandp.20251001

Local Heterogeneity in Artificial Intelligence Jobs over Time and Space[†]

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We have witnessed a profound technological transformation driven by the rapid adoption of artificial intelligence (AI) over the past decade. Between 2014 and 2022, AI-related job postings surged from 0.5 percent to 2.05 percent of all job postings with projections indicating that up to 80 percent of the workforce could see at least 10 percent of their tasks influenced by AI and large language models (Eloundou et al. 2024). As with other general-purpose technologies (GPTs), such as electricity and the internet (Bresnahan and Trajtenberg 1995), AI and machine learning (ML) systems could drive substantial economic gains. However, their modest observed impact on aggregate productivity has raised skepticism about their transformative benefits (Acemoglu 2024) or suggested that these benefits may require longer time horizons to materialize (Brynjolfsson, Rock, and Syverson 2021).

Rather than focusing on aggregate macroeconomic effects, Andreadis et al. (2024) focus on microeconomic dynamics and document substantial variability in AI economic benefits at the local county level and show that these benefits are mostly over the long run. In this paper, we build on and extend this paper by taking a local approach to understanding the spatial and temporal predictors of AI adoption between 2014 and 2023. First, we document substantial variation in the adoption of AI-related jobs across US counties, with some counties (e.g., Slope County, North Dakota; Santa Clara, California) demonstrating exceptionally high AI job shares due to their established tech ecosystems, while others, primarily rural areas, report no activity. Between 2018 and 2023, the fastest growth in AI-related jobs occurred in some unexpected locations, such as Maries, Missouri, and Hughes, South Dakota, perhaps reflecting a shift toward suburban and remote-friendly regions impacted by the rise of remote work. Most counties experienced modest growth with a median change of 0.088 percentage points during this period.

Second, we identify several key drivers of AI job intensity, including demographics, innovation, and industry factors, after controlling for county and year fixed effects. Specifically, higher shares of STEM degrees, labor market tightness, and patent activity significantly predict greater AI adoption, underscoring the importance of education, innovation, and dynamic labor markets. Conversely, manufacturing intensity is negatively associated with AI intensity, reflecting challenges in integrating AI into traditional industrial locations (Makridis and Mishra 2022). The findings are robust to including *state* $\times$ *year* fixed effects specifications, confirming the stability of these relationships. Importantly, the growth in AI jobs highlights the potential for regional disparities in technological adoption, with suburban and innovation-driven areas benefiting most from the expansion of AI.

Our study contributes to several strands of literature. It adds to the growing body of research examining AI's economic effects, which traditionally focuses on macroeconomic perspectives (Acemoglu 2024; Aghion, Jones, and Jones 2017). Our work is most relevant to studies taking a micro perspective, such as those examining AI's impact on firm growth (Babina et al. 2024) and entrepreneurship (Gofman and Jin 2024). However, none of these studies focus on the regional economy correlates

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[†] Go to https://doi.org/10.1257/pandp.20251001 to visit the article page for additional materials and author disclosure statement(s).

of AI adoption. Our research fills this gap by taking a local labor market approach to studying the rise of AI and its determinants. Our results underscore the importance of local human capital and labor market policy as measured by the share of STEM degrees, bachelor's graduates, labor market tightness, and the turnover rate as robust determinants of AI adoption. We also find that the surge in housing prices can stifle AI adoption, explaining why some have moved to more rural areas. Overall, these results are consistent with the view that AI can benefit municipalities (Andreadis et al. 2024).

I. Data and Measurement

A. *Job Postings and AI*

We proxy for AI labor investments using data from Lightcast, a leading source with a vast repository of millions of job postings. Lightcast data offer two main advantages: First, they contain a comprehensive list of skills and an occupational taxonomy with over 1,900+ specialized occupations that are mapped to the Standardized Occupation Classification (SOC). Second, they have precise location data for job postings, allowing us to link labor demand at a county-level.

We measure AI labor investments using the skills and keywords relating to AI associated with each vacancy. This list of skills has been associated with the use and development of AI (e.g., Acemoglu et al. 2022; Babina et al. 2024; and Makridis and Alterovitz 2024). Then we create for each county a measure of AI intensity, which is defined as the share of the job posts that mentions AI skills in a county, and we merge these data with (one-year-lagged) county characteristics, described below:

B. *County Demographics*

We use the American Community Survey (ACS) from the Census Bureau, specifically each five-year sample during 2013–2022 to create year-to-year estimates for each county's population, median household income, share of the workforce with a bachelor's degree, share of Black population, and share of the population under poverty. We also use information from the Federal Housing Finance Agency (FHFA) on housing prices (see Bogin, Doerner, and Larson 2019).

C. *County Labor and Industry Indicators*

We use the number of job advertisements from Lightcast data along with data on unemployed workers from the Local Area Unemployment Statistics program of the Bureau of Labor Statistics to create estimates of labor market tightness for each county. We use labor market turnover and the share of establishments that are small, medium, or large along with the share of employment in the manufacturing and information sectors from the County Business Patterns (CBP) and the Quarterly Workforce Indicators (QWI).

D. *County Innovation Indicators*

We use publicly available patent data from the US Patent and Trademark Office (USPTO) (PatentsView) that provide location information for each inventor, and we measure for each county the number of inventors per worker. In addition, we use the AI patent dataset of the USPTO (see Giczy, Pairolero, and Toole 2022) to obtain the share of published patents that is related to AI for each county over time. We complement these data with information from the National Center for Education Statistics (Integrated Postsecondary Education Data System database) on the number of bachelor's and master's degrees granted per capita and the share of STEM-related degrees.

II. Descriptive Patterns

Panel A of Figure 1 displays significant variation in the proportion of AI-related job postings across counties averaged between 2014 and 2023 (average = 0.45 percent and median = 0.23 percent).

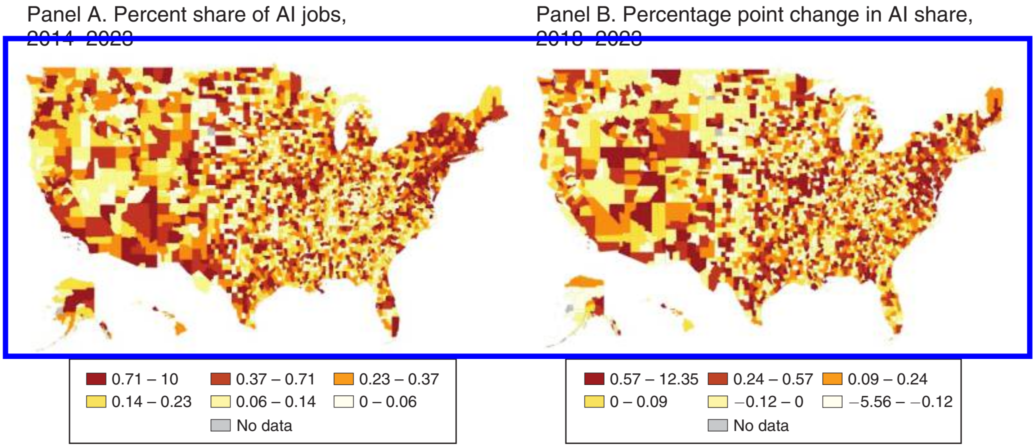

FIGURE 1. SPATIAL HETEROGENEITY IN THE SHARE OF AND CHANGE IN AI JOBS

Notes: Panel A plots the share (average 2014–2023) of job postings related to AI in a county. Panel B plots the percentage point change (2023–2018) in the share of AI jobs.

Perhaps surprisingly, at the top of the list is Slope County, North Dakota, with an AI job posting share of 10.0 percent. Other high-ranking counties include Santa Clara County, California (8.19 percent), Fairfax County, Virginia (6.97 percent), San Francisco County, California (6.34 percent), and Hudson County, New Jersey (6.13 percent). These counties are well-known for their strong connections to technology industries, innovation ecosystems, or proximity to major economic centers. On the other hand, several counties show no recorded AI-related job postings. These counties are primarily rural and less integrated into the technological workforce. This variation shows the localized (not just national) nature of AI's economic impact and the potential for regional disparities in technological adoption.

Before we continue, we pause to explain the period 2018–2023 shown in panel B. While our data start in 2014, the share of AI jobs is low during the early years of our sample period, with only a 0.028 percentage point median change between 2014 and 2018. Accordingly, to get a more representative view of the growth in AI job shares, in Panel B, we report the percentage point growth in AI job shares from 2018–2019 to 2022–2023. During this period, there is an average increase of 0.278 percentage points and a standard deviation of 0.995. In addition, this period features both substantial growth and declines, as the changes range from a decrease of 0.29 percentage points (at the tenth percentile) to an increase of 0.93 (at the ninetieth percentile). Most counties experienced modest changes with the median being a 0.088 change.

From 2018 to 2023, the areas with the fastest growth in AI-related job postings include Maries, Missouri (12.35 percentage points), Hughes, South Dakota (10.43 percentage points), Osage, Michigan (9.82 percentage points), Forest, Pennsylvania (8.99 percentage points), Nevada overall (7.28 percentage points), Calhoun, Illinois (7.23 percentage points) and Lynn, Texas (6.80 percentage points). These counties may appear counterintuitive considering the conventional wisdom that AI jobs are most plentiful in areas like San Francisco, Boston, and New York! However, the growth in AI jobs, particularly following the lockdowns, has been in more suburban areas as these jobs can often be done remotely, and, therefore, people move to areas with a lower cost of living.

III. Spatial Correlates of AI Jobs

Table 1 presents the results of regressions analyzing the determinants of AI job posting shares across counties from 2014 to 2023 as a function of demographic, innovation, and industry characteristics

Table 1— The Correlates of the Share of AI Jobs

Model	(1)	(2)	(3)	(4)	(5)
Bachelor's share, z-score	0.1906			0.1814	0.1034
	(0.0513)			(0.0505)	(0.0459)
House price growth, z-score	−0.0144			−0.0141	−0.0156
	(0.0080)			(0.0079)	(0.0074)
Labor market tightness, z-score	0.2780			0.2765	0.3156
	(0.0583)			(0.0585)	(0.0643)
Patents per employee, z-score		0.0232		0.0294	0.0312
		(0.0090)		(0.0113)	(0.0138)
STEM degrees share, z-score		0.0686		0.0475	0.0375
		(0.0238)		(0.0205)	(0.0184)
ICT sector intensity, z-score			0.0121	0.0257	0.0280
			(0.0144)	(0.0135)	(0.0136)
Manufacturing intensity, z-score			−0.0630	−0.0333	−0.0247
			(0.0113)	(0.0108)	(0.0111)
Turnover rate, z-score			0.0345	0.0188	0.0154
			(0.0137)	(0.0137)	(0.0132)
Fixed effects	County, year	County, year	County, year	County, year	County, state-year
Observations	24,645	24,645	24,645	24,645	24,645
R^2	0.69739	0.68013	0.67989	0.69828	0.71558

Notes: The tables report the demographic, innovation, and industry determinants of the share of AI jobs. Standard errors are clustered at the county level.

all measured as z-scores to ensure comparability, conditional on county and year fixed effects (columns 1–4) and *state* $\times$ *year* fixed effects (column 5). For brevity, rows with controls having insignificant coefficients are not reported.

We begin by examining the effects of demographic characteristics in column 1. The share of individuals with a bachelor's degree is strongly and positively associated with AI intensity (0.1906, $p < 0.01$), indicating that counties with more highly educated populations tend to exhibit greater AI-related job activity. Other demographic variables, such as the share of Black population and poverty share or median income are not statistically significant. Population size shows a positive but insignificant relationship with AI intensity.

Column 2 focuses on innovation characteristics. Labor market tightness emerges as a key driver, with a positive and highly significant coefficient (0.2780, $p < 0.01$). STEM degrees' share and patents per employee also show positive and significant associations, highlighting the importance of technical education and local innovation capacity in fostering AI job growth. AI patents' share and degrees awarded per capita are not significant, suggesting that general innovation activity may matter more than AI-specific metrics.

Column 3 examines industry characteristics. Manufacturing intensity is negatively associated with AI intensity (−0.0630, $p < 0.01$), suggesting that counties with a stronger manufacturing presence may face challenges in AI adoption. In contrast, information and communications technology (ICT) sector intensity is positively related to AI intensity but only marginally significant. The presence of a higher share of large establishments does not play a significant role, while the turnover rate shows a weak positive association.

Column 4 integrates all controls with county and year fixed effects and serves as the baseline model. The coefficients for key predictors, such as bachelor's share (0.1814, $p < 0.01$), labor market tightness (0.2765, $p < 0.01$), patents per employee (0.0294, $p < 0.01$), and STEM degrees share (0.0475, $p < 0.05$), remain economically and statistically significant. Manufacturing intensity continues to show a significant negative relationship (−0.0333, $p < 0.01$), while ICT sector intensity gains significance (0.0257, $p < 0.10$). Column 5 adds state fixed effects as a robustness check with stable coefficients and significance for the same variables.

Table 2 examines factors influencing percentage point changes in county AI shares from the 2017–2018 and 2022–2023 averages. Columns 1–3 separately analyze demographic, innovation, and

Table 2—The Correlates of the Percentage Point Change in the Share of AI Jobs

Model	(1)	(2)	(3)	(4)	(5)
Bachelor's share, z-score in 2017	0.0022			−0.0035	−0.0044
	(0.0027)			(0.0032)	(0.0029)
Income, log z-score in 2017	0.0784			0.0695	0.0614
	(0.0382)			(0.0391)	(0.0442)
Tightness, z-score in 2017	0.0744			0.0732	0.0726
	(0.0215)			(0.0237)	(0.0352)
STEM degrees share, z-score in 2017		0.0742		0.0539	0.0455
		(0.0151)		(0.0163)	(0.0184)
Large establishments, % z-score in 2017			0.0411	−0.0158	−0.0165
			(0.0183)	(0.0219)	(0.0198)
ICT sector intensity, % z-score in 2017			0.0401	0.0137	0.0219
			(0.0153)	(0.0170)	(0.0182)
Manufacturing intensity, % z-score in 2017			−0.0447	−0.0128	0.0001
			(0.0166)	(0.0181)	(0.0203)
Turnover rate, % z-score in 2017			−0.0556	−0.0419	−0.0389
			(0.0222)	(0.0233)	(0.0271)
Fixed effects	No	No	No	No	State
Observations	2,473	2,473	2,473	2,473	2,473
R^2	0.02126	0.01929	0.01554	0.03147	0.08165

Notes: The tables report the demographic, innovation, and industry determinants of the change in AI shares in a county. Standard errors are clustered at the county level.

industry factors. Bachelor's share and income are not significant drivers of change, but labor market tightness (0.0744, $p < 0.01$) and STEM degrees share (0.0742, $p < 0.01$) show strong positive effects. Manufacturing intensity is negatively associated (-0.0448, $p < 0.01$).

Column 4 includes all controls, confirming the positive role of STEM degrees (0.0539, $p < 0.01$) and labor tightness (0.0732, $p < 0.05$), while turnover rate becomes significant (-0.0556, $p < 0.01$). Column 5 adds state fixed effects as a robustness check with stable results for tightness, STEM degrees, and turnover rate.

Overall, STEM degrees, and tight labor markets drive AI job growth, while manufacturing intensity and labor turnover rates show negative effects.

IV. Conclusion

Despite the rapid expansion of AI-related jobs at a national level, there is substantial county-level variation. Counties with stronger innovation ecosystems, higher STEM degree attainment, and tighter labor markets have seen greater AI job growth, whereas manufacturing-heavy regions and areas with high labor turnover have faced challenges in integrating AI. These findings point to the role of place-based policies to attract and retain top-tier talent for economic development (Kline and Moretti 2014).

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