Local Heterogeneity in Artificial Intelligence Jobs Over Time and Space

By LEFTERIS ANDREADIS, ELENI KALOTYCHOU, MANOLIS CHATZIKONSTANTINOU, CHRISTODOULOS LOUCA, AND CHRISTOS A. MAKRIDIS* (FORTHCOMING IN AE P&P 2025)

* Lefteris Andreadis, Bank of Greece, El. Venizelou 21, Athina 102 50, Greece (email: lefandreadis@gmail.com); Eleni Kalotychou, Cyprus University of Technology, 30 Arch. Kyprianos Str. 3036, Limassol (email: eleni.kalotychou@cut.ac.cy); Christodoulos Louca, Cyprus University of Technology, 30 Arch. Kyprianos Str. 3036, Limassol (email: christodoulos.louca@cut.ac.cy); Manolis Chatzikonstantinou, Georgetown University in Qatar, Education City – Qatar Foundation, P.O. Box 23689, Doha, Qatar (email: ec1269@georgetown.edu). Christos A. Makridis, Arizona State University, W. P. Carey School of Business, Business Administration, 300 E Lemon St, Tempe, AZ 85287 (email: cmakridi@asu.edu). We thank Ashley Peterson and Chris Compton at Lightcast for their graciousness in sharing the data.

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% to 2.05% of all job postings (Beckett, 2023) with projections indicating that up to 80% of the workforce could see at least 10% of their tasks influenced by AI and large language models (Eloundou et al., 2023). As with other general-purpose technologies (GPTs), such as electricity and the internet (Romer, 1990; Aghion and Howitt, 1992; 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 (Mihet and Philippon, 2019; Brynjolfsson et al., 2021).

Rather than focusing on aggregate macroeconomic effects, Andreadis et al., (2024) focuses on microeconomic dynamics and document substantial variability in AI economic benefits at the local county level, and 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. Specifically, by running a horse-race among demographic, innovation, and industry factors we first find substantial variation in the adoption of AI-related jobs across U.S. counties, with some counties (e.g., Slope County, ND; Santa Clara, CA) 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, MO, and Hughes, SD, reflecting a shift toward suburban and remote-friendly regions, likely driven 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, controlling for county and year fixed effects. 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 economies. The findings are robust to including state × 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, such as AI's regulation (Beraja and Zorzi, 2022), competition (Aghion et al., 2017; Farboodi and Veldkamp, 2021), and economic growth (Aghion et al., 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), entrepreneurship (Gofman and Jin, 2024), financial analysts (Grennan and Michaely, 2020; Abis and Veldkamp, 2024), and fintech innovation (Chen et al., 2019). However, none of these studies focus on the regional economy correlates 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 house prices can stifle AI adoption, explaining why some have moved to more rural areas. Overall, these are consistent with the view that AI can lead to variable economic benefits for municipalities (Andreadis et al., 2024), helping to understand the potentially unequal distribution of technology's economic benefits (Autor, 2015; Acemoglu and Restrepo, 2019).

I. Data and Measurement

A. Job Postings and Artificial Intelligence

We proxy for AI labor investments using data from Lightcast, a leading source with a vast repository of millions of job postings. Their technology extracts information from more than 40,000 online job boards, newspapers and employer websites. Lightcast employs advanced machine learning techniques to streamline the data, eliminating duplicate job postings, whether they are posted multiple times on the same site or across multiple sites, and enriching profiles using standardized information on job titles, company names, skills, and educational requirements.

Lightcast data offer two main advantages: First, they contain a comprehensive occupational taxonomy built hierarchically, with over 1,900+ specialized occupations that are mapped to the Standardized Occupation Classification (SOC) used in the official publications by the BLS. 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 associated with each vacancy and keywords relating to AI. We define AI related jobs by parsing text from job postings, and by linking them with a list of skills that have been associated with the use and development of AI (e.g., Acemoglu et al. (2022), Babina et al. (2023), 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 mention AI skills in a county, and we merge these data with (1-yr lagged) county characteristics, described below:

B. County Demographics

We use the American Community Survey (ACS) from the Census Bureau, specifically each five-year sample for the periods 2013-2022, covering: population, age, education, income, gender, occupation distributions, as well as the median household income for each county. Then, we create year-to-year estimates for each county's share of the workforce with a bachelor's degree, share of black population, and the share of population under poverty. We complement these data with information from the Federal Housing Finance Agency (FHFA) on house prices (see Bogin et al. 2018).

C. County Labor and Industry Indicators

We use the number of job advertisements from the Lightcast data along with data on the number of employed, and unemployed workers for each county from the Local Area Unemployment Statistics (LAUS) program of the BLS to create estimates of labor market tightness for each county for the period 2013-2022. Then, we use data from the Quarterly Workforce Indicators (QWI) to get measures of labor market turnover for each county and year, as well as data from the County Business

Patterns (CBP) to measure for each county, the share of establishments that are small, medium or large, and the share of employment in the manufacturing and information sectors.

D. County Innovation Indicators

We use publicly available patent data from the U.S. Patent and Trademark Office (PatentsView) that provide location information for each inventor, and we measure for each county the number of inventors per worker for each county. In addition, we use information provided by the AI patent dataset of the USPTO (see Giczy et al. 2022) to measure for each county the share of published patents that are classified as AI patents. We complement these data with information from the National Center for Education Statistics (IPEDS database) on the number of bachelor's and masters' degrees granted per capita in each county 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%, median = 0.23%). Perhaps surprisingly, at the top of the list is Slope County, North Dakota, with an AI job posting share of 10.0%. Other high-ranking counties include Santa Clara County, California (8.19%), Fairfax County, Virginia (6.97%), San Francisco County, California (6.34%), and Hudson County, New Jersey (6.13%). 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 include Iosco County, Michigan; Lipscomb County, Texas; Kenedy County, Texas; Jim Hogg County, Texas; and Mississippi County, Missouri with an AI job posting share of 0%. These counties are primarily rural and less integrated into the technological workforce, which may account for the lack of AI-related job activity. This variation underscores the localized nature of AI's economic impact and the potential for regional disparities in technological adoption.

Before we continue, we pause to explain the time period of interest in Panel B: 2018-2023. While we have data as early as 2014, the share of AI jobs is much lower during these early years with a very small 0.028 percentage point median change between 2014 and 2018.

Panel B turns towards the percentage point growth in AI job shares from 2018-19 to 2022-23, showing an average increase of 0.278 percentage points and standard deviation of 0.995. This period features both substantial growth and declines, as the changes range from a decrease of 0.29 percentage points (at the 10th percentile) to an increase of 0.93 (at the 90th percentile). Most counties experienced modest changes with the median being a 0.088 change.

From 2018 to 2023, the counties with the fastest growth in AI-related job postings include Maries, MO (12.35 pp), Hughes, SD (10.43 pp), Osage, MI (9.82 pp), Forest, PA (8.99 pp), Nevada (overall) (7.28 pp), Calhoun, IL (7.23 pp), Lynn, TX (6.80 pp), Kalawao, HI (6.67 pp), Lane (6.67 pp), and Kansas (overall) (6.44 pp). 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 be done remotely. The correlation between the rate changes from 2014-18 and 2018-23 is -0.12.

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 county demographic, innovation, and industry characteristics all measured as z-scores, conditional on county and year fixed effects (columns 1-4) and state × year fixed effects (column 5). Standard errors are clustered at the county-level.

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, 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, 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 introduces state-by-year fixed effects as a robustness check given all the time-varying state policy shocks over these years. Most coefficients remain stable. Labor market tightness (0.3156, $p<0.01$), bachelor's share (0.1034, $p<0.05$), and patents per employee (0.0312, $p<0.01$) continue to positively and significantly predict AI intensity. Manufacturing intensity remains a negative and significant factor (-0.0247, $p<0.01$), while ICT sector intensity gains slightly stronger significance (0.0280, $p<0.05$).

Table 2 examines factors influencing changes in county AI shares from the 2017-18 and 2022-23 averages. Columns 1-3 separately analyze demographic, innovation, and 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. We find that 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, 2023).

REFERENCES

Abis, S., & Veldkamp, L. (2023). The changing economics of knowledge production. Review of Financial Studies.

Acemoglu, D. (2024). The simple macroeconomics of AI. Working Paper.

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. Journal of Economic Perspectives, 33(2), 3–30.

Andreadis, L., Chatzikonstantinou, M., Kalotychou, E., Louca, C., & Makridis, C. A. (2024). The local effects of artificial intelligence labor investments: Evidence from the municipal bond market. SSRN Working Paper.

Aghion, P., & Howitt, P. (1992). A model of growth through creative destruction. Econometrica, 60(2), 323–351.

Aghion, P., Jones, B. F., & Jones, C. I. (2017). Artificial intelligence and economic growth. NBER Working Paper.

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. Journal of Economic Perspectives, 29(3), 3–30.

Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. Journal of Financial Economics, 151(103745).

Beckett, E. (2023). Demand for AI skills continues climbing. Lightcast.

Beraja, M., & Zorzi, N. (2022). Inefficient automation. National Bureau of Economic Research.

Bogin, A., Doerner, W., & Larson, W. (2019). Local house price dynamics: New indices and stylized facts. Real Estate Economics, 47(2), 365-398.

Bresnahan, T., & Trajtenberg, M. (1995). General-purpose technologies ‘engines of growth’? Journal of Econometrics, 61(1), 83–108.

Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity J-curve: How intangibles complement general-purpose technologies. American Economic Journal: Macroeconomics, 13(1), 333–372.

Chen, M. A., Wu, Q., & Yang, B. (2019). How valuable is FinTech innovation? The Review of Financial Studies, 32(5), 2062–2106.

Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2024). GPTs are GPTs: Labor market impact potential of LLMs. Science, 384(6702), 1306–1308.

Farboodi, M., & Veldkamp, L. (2021). A model of the data economy. National Bureau of Economic Research.

Giczy, A. V., Pairolero, N. A., & Toole, A. A.

(2022). Identifying artificial intelligence (AI) invention: A novel AI patent dataset. The Journal of Technology Transfer, 47(2), 476-505.

Gofman, M., & Jin, Z. (2024). Artificial intelligence, education, and entrepreneurship. The Journal of Finance, 79(1), 631–667.

Grennan, J., & Michaely, R. (2020). Artificial intelligence and high-skilled work: Evidence from analysts. Swiss Finance Institute Research Paper(20-84).

Kline, P., & Moretti, E. (2013). People, places, and public policy: Some simple welfare economics of local economic development programs. Annual Review of Economics, 5, 629–662.

Mihet, R., & Philippon, T. (2019). The economics of big data and artificial intelligence. International Finance Review, 20.

Romer, P. M. (1990). Endogenous technological change. Journal of Political Economy, 98(5, Part 2), S71–S102.

U.S. Census Bureau, American Community Survery accessed on July 1, 2024 < https://www.census.gov/data/datasets/time-series/econ/acs/acs-datasets.html>.

U.S. Census Bureau, American Community Survery accessed on July 1, 2024 < https://www.census.gov/programs-surveys/cbp/data/datasets.html>.

U.S. Census Bureau, Quarterly Workforce Indicators (2013-2024). Washington, DC: U.S. Census Bureau, Longitudinal-Employer Household Dynamics Program , accessed on 11/29/2024 at https://qwiexplorer.ces.census.gov.

U.S. Department of Education, National Center for Education Statistics, Integrated Postsecondary Education Data System (IPEDS), 2013-2022. Retrieved on 11/29/2024.

U.S. Patent and Trademark Office. “Data Download Tables.” PatentsView. Accessed [11/29/2024].https://patentsview.org/ download/data-download-tables.

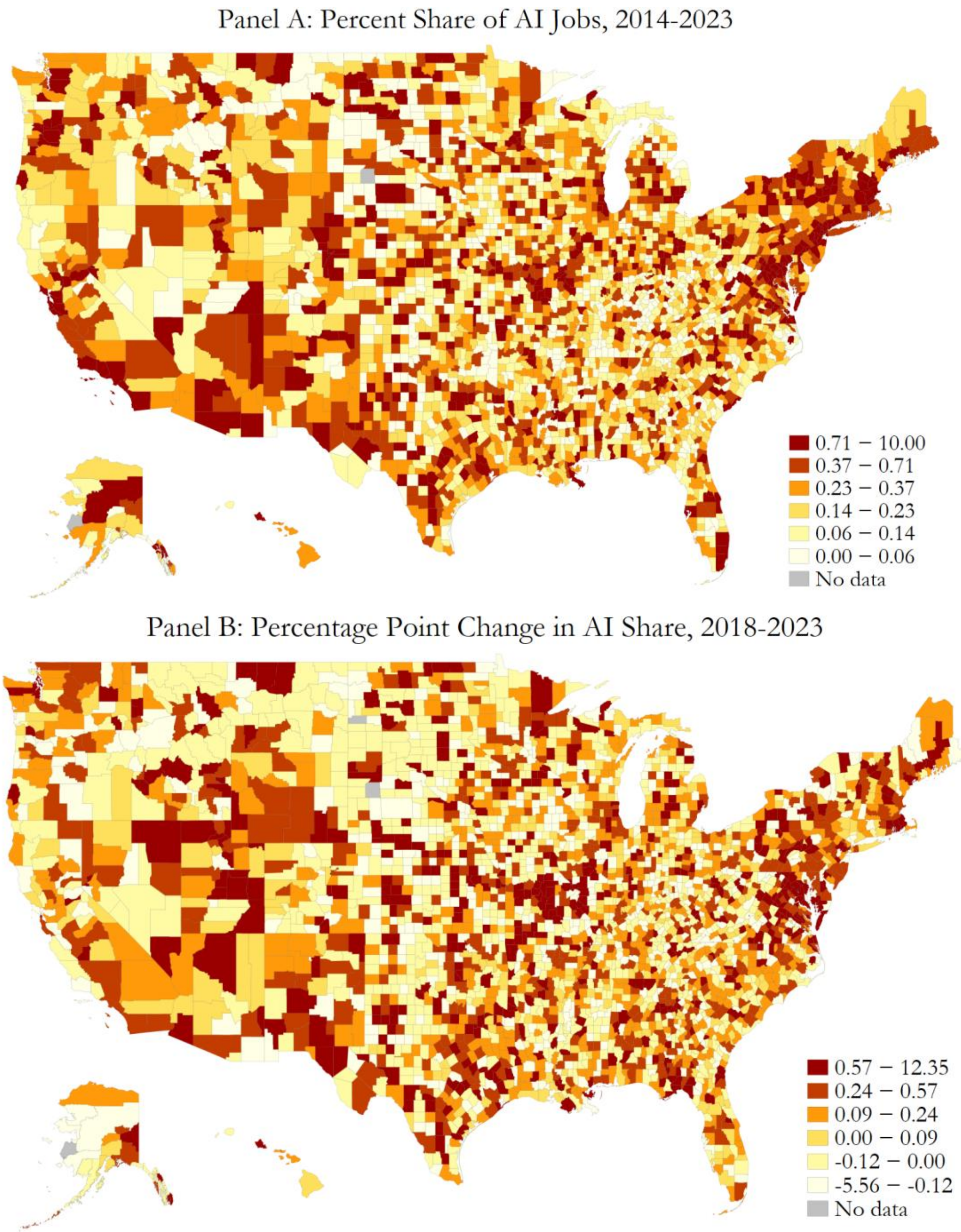

FIGURE 1. SPATIAL HETEROGENEITY IN THE SHARE OF AND CHANGE IN ARTIFICIAL INTELLIGENCE JOBS
THE STYLE IS NAMED FIGURE TITLE

Note: Source: Lightcast. Panel AI plots the proportion of AI job postings in a county averaged across 2014 and 2023. Panel B plots the percentage point change in the share of AI jobs between the 2022-23 and 2018-19 averages.

Table 1: The Correlates of the Share of Artificial Intelligence Jobs

Dependent Variable:	AI intensity				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Bachelors' share, z-score	0.1906***			0.1814***	0.1034**
	(0.0513)			(0.0505)	(0.0459)
Black pop, z-score	-0.0285			-0.0021	0.0369
	(0.1379)			(0.1365)	(0.1160)
Poverty share, z-score	0.0308			0.0315	-0.0032
	(0.0295)			(0.0291)	(0.0265)
log(Population), z-score	0.3942			0.3375	0.2820
	(0.3850)			(0.3896)	(0.4757)
House Price Growth, z-score	-0.0144*			-0.0141*	-0.0156**
	(0.0080)			(0.0079)	(0.0074)
log(Median Income), z-score	-0.0168			-0.0197	0.0042
	(0.0503)			(0.0498)	(0.0472)
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)
AI patents' share, z-score		0.0115		0.0075	0.0036
		(0.0075)		(0.0057)	(0.0054)
Degrees awarded per capita, z-score		0.0239		0.0251	0.0255
		(0.0261)		(0.0223)	(0.0234)
Stem Degrees' share, z-score		0.0686***		0.0475**	0.0375**
		(0.0238)		(0.0205)	(0.0184)
Large Establishments, z-score			0.0054	-0.0080	-0.0048
			(0.0245)	(0.0232)	(0.0236)
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					
Year	Yes	Yes	Yes	Yes	
County	Yes	Yes	Yes	Yes	Yes
State Year					Yes
Fit statistics					
Observations	24,645	24,645	24,645	24,645	24,645
R^2	0.69739	0.68013	0.67989	0.69828	0.71558
Within R^2	0.05653	0.00272	0.00199	0.05931	0.06252

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes.—Sources: Lightcast, American Community Survey, Quarterly Workforce Indicators, 2016-2023. The table reports the coefficients associated with regressions of the share of AI jobs in a county on Demographic Characteristics, Innovation Characteristics, and Industry Characteristics. Observations are unweighted and standard errors are clustered at the county-level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 2: The Correlates of the Change in the Share of Artificial Intelligence Jobs

Dependent Variable:	Change in AI intensity				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Constant	0.3288***	0.3244***	0.3236***	0.3188***	
	(0.0164)	(0.0150)	(0.0153)	(0.0169)	
Bachelors,% z-score in 2017	0.0196			-0.0322	-0.0401
	(0.0250)			(0.0292)	(0.0263)
Black, % z-score in 2017	0.0060			0.0117	0.0233
	(0.0178)			(0.0191)	(0.0249)
Poverty, % z-score in 2017	0.0627*			0.0271	0.0541
	(0.0331)			(0.0365)	(0.0497)
Pop. Growth	-0.6522			0.0717	1.525
	(1.580)			(1.633)	(1.798)
House Price Growth z-score in 2017	-0.0171			-0.0135	0.0066
	(0.0166)			(0.0167)	(0.0225)
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)
Patents per employee z-score in 2017		0.0091		-0.0139	-0.0024
		(0.0141)		(0.0154)	(0.0128)
AI Patents' Share z-score in 2017		0.0173		0.0064	0.0128
		(0.0154)		(0.0160)	(0.0159)
Degrees awarded per capita, z-score in 2017		0.0260		0.0312	0.0216
		(0.0173)		(0.0203)	(0.0216)
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					
state					Yes
Fit statistics					
Observations	2,473	2,473	2,473	2,473	2,473
R^2	0.02126	0.01929	0.01554	0.03147	0.08165
Within R^2					0.02513

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes.—Sources: Lightcast, American Community Survey, Quarterly Workforce Indicators, 2016-2023. The table reports the coefficients associated with regressions of the change in share of AI jobs in a county from 2017-18 (average) to 2022-23 (average) on Demographic Characteristics, Innovation Characteristics, and Industry Characteristics. Observations are unweighted and standard errors are clustered at the county-level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.