INTERNATIONAL MONETARY FUND

The Labor Market Impact of Artificial Intelligence: Evidence from US Regions

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WP/24/199

2024
SEP

WORKING PAPER

 WP/24/199

IMF Working Paper
Research Department

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September 2024

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RECOMMENDED CITATION:

JEL Classification Numbers:	J23, J24, O33, R23
Keywords:	Artificial intelligence; technology; labor; local labor markets; shift share
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* I would like to thank Florence Jaumotte, Giovanni Melina, Alexandre Balduino Sollaci, Yoro Diallo, Florian Misch, Jin Liu, Mohamed Norat, Augustus Panton, Carlo Pizzinelli, Ippei Shibata, Manmohan Singh, Marina Tavares, Alberto Tumino, and seminar participants at the IMF for helpful comments and discussions. The views expressed in this paper are those of the author and should not be attributed to the IMF, its Executive Board, or its management. All errors are my own.

The Labor Market Impact of Artificial Intelligence: Evidence from US Regions*

Yueling Huang†

September 3, 2024

Abstract

This paper empirically investigates the impact of Artificial Intelligence (AI) on employment. Exploiting variation in AI adoption across US commuting zones using a shift-share approach, I find that during 2010-2021, commuting zones with higher AI adoption have experienced a stronger decline in the employment-to-population ratio. Moreover, this negative employment effect is primarily borne by the manufacturing and low-skill services sectors, middle-skill workers, non-STEM occupations, and individuals at the two ends of the age distribution. The adverse impact is also more pronounced on men than women.

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1 Introduction

The rapid and ongoing development in Artificial Intelligence (AI) since the last decade, and in particular the advent of generative AI technologies such as ChatGPT in November 2022, have spurred much debate on the labor market implications of AI. A natural question arises: how does AI affect employment? Theoretically, the answer is ambiguous (Acemoglu and Restrepo (2019), Webb (2020), Acemoglu (2024)). On the one hand, AI can expand the set of automatable tasks, thereby displacing workers. On the other hand, AI can boost productivity and value-added, thereby increasing labor demand in non-automated tasks. AI can also create new tasks and jobs such as machine learning engineer, data engineer, or data scientist. Empirically, most research so far has studied this question at the micro, firm level (Acemoglu et al. (2022b), Copestake et al. (2023), Hui et al. (2023), Abis and Veldkamp (2024), Babina et al. (2024)).

In this paper, I move towards a more macro-level analysis by focusing on local labor markets. I ask two main questions: (i) how does the change in overall employment-to-population during 2010-2021 in commuting zones with higher AI exposure compare relative to commuting zones with lower AI exposure? (ii) is the effect unequally distributed across population subgroups? Specifically, I exploit variation in AI adoption across US commuting zones using a shift-share approach. Throughout the paper, I define AI as one of the following five technologies: machine learning, machine vision, natural language processing, voice recognition software, and automated-guided vehicles (AGVs) (McElheran et al. (2024))[1].

There are two key empirical challenges. First, there is no readily available data of AI adoption at the commuting zone level. To address this constraint, I construct a measure of AI exposure at the level of US commuting zones, combining data on local employment share in 2010 with nationwide industry-level AI adoption data in the US from the Annual Business Survey (ABS) Technology module. The second empirical challenge is the endogeneity of AI exposure. For example, unobserved positive local demand shocks may induce firms to adopt AI and demand more workers, leading to an upward bias in the OLS estimates. Moreover, AI adoption is likely to be anticipated or depends on previous waves of technologies. Commuting zones that have adopted more ICT, software,

[1]The main period of analysis is 2010-2021. Therefore, the paper does not focus on generative AI due to the recency of generative AI technology and limited data availability.

and robotics are also more likely to adopt AI. To the extent that anticipation or past technologies affect employment outcomes, using local industry specialization patterns after the ICT revolution to construct AI exposure may suffer from simultaneity bias. To address these endogeneity concerns, I instrument the AI exposure measure using local employment share in 1990 and industry-level AI adoption in the EU. Under the reasonable assumption that ICT only started to proliferate since the second half of 1990s (Colecchi and Schreyer (2002)), the use of 1990 local employment shares mitigates the anticipation effect of AI arrival and path dependence nature of technological change. I also use 1995 local employment share and average local employment share in 1990-1995 to compute the IV as robustness checks. EU-wide industry-level AI adoption allows to capture global technological advances and isolate US-specific factors. For example, idiosyncratic US-specific factors such as positive US-specific industry demand shocks can increase both AI adoption and local labor demand, resulting in a positive bias of the simple OLS estimate. The first-stage F-statistic shows that the instrument is relevant. Furthermore, I control for a comprehensive set of initial commuting zone characteristics and commuting zone exposures to the concurrent labor market shocks of robotization and import competition. I perform falsification tests that regress *past* changes in overall employment-to-population ratio in 1980-2010 on AI exposure in 2010-2021. The results suggest that once controlling for these commuting zone covariates, AI exposure does not affect employment in 1980-2010. Therefore, long-run common factors are unlikely to be the main drivers for both the change in employment-to-population and AI adoption.

I find that commuting zones with a higher share of AI adopting firms experienced a more significant decline in the overall employment-to-population ratio during 2010-2021. The estimate suggests that a one standard deviation increase in AI exposure leads to 0.976 percentage points lower employment-to-population. Furthermore, the estimated effect implies that employment-to-population in commuting zones at the 75th percentile of AI exposure declines by 1.25 percentage points more than commuting zones at 25th percentile of AI exposure.

The negative effect is heterogeneous. It is primarily borne by the manufacturing and low-skill services sectors, middle-skill workers, non-STEM occupations, and individuals at the two ends of the age distribution. The adverse impact is also more pronounced on men than women. These unequal effects of AI mimic previous waves of labor market shocks, such as routine-biased technological change (Autor et al. (2006), Goos et al. (2014)

for skill group), offshoring (Goos et al. (2014) for skill group), robotization (Acemoglu and Restrepo (2020) for skill group and gender), and import competition (Traiberman (2019) for age). For policymakers, these results underscore the importance of considering unequal distributional consequences of labor market shocks, as well as the need of social safety nets and job retraining programs. The main findings are robust across several alternative specifications, such as using alternative definition of US industry-level AI adoption, constructing AI exposure measure and its IV with local employment shares in alternative years, and using 2019 as the end year to address concerns about the potential employment impact of Covid-19.

Related literature. This paper contributes to several strands of literature. First, the paper directly speaks to the burgeoning debate on the labor market impact of AI. Several studies map measures of AI progress to tasks or human abilities, and then leverage information on the occupational task content to compute occupational exposure to AI (Frey and Osborne (2017), Webb (2020), Felten et al. (2021), Eloundou et al. (2023)). These studies do not take a stand on whether AI is a complement or substitute to human labor, and remain agnostic about the employment impact of AI. Cazzaniga et al. (2024) augment the standard AI occupational exposure score by a potential complementarity index, calculated based on a set of pre-selected occupational characteristics from O*NET. The augmented index is then applied to six countries[2] with good labor market microdata coverage to gauge the occupational exposures to AI in these countries. My paper distinguishes from the above papers, in that it uses AI adoption by firms rather than occupational task content to measure AI exposure. Doing this allows me to directly estimate the employment impact of AI using historical data.

Most empirical works that directly estimate the employment impact of AI are at the firm, or establishment level. The most common ones use vacancy data (Acemoglu et al. (2022b), Copestake et al. (2023), Babina et al. (2024)). The findings are mixed.[3] Hui et al. (2023) examine the short-run employment effect of generative AI using data on freelancers from Upwork and find that generative AI reduces overall labor demand for all

[2]These six countries include two advanced economies (UK and US) and four emerging market economies (Brazil, Colombia, India, South Africa).

[3]Acemoglu et al. (2022b) and Copestake et al. (2023) find negative effect of AI adoption on non-AI jobs and overall hiring in US and India establishments, respectively. However, Babina et al. (2024) show that AI-investing US public firms experience higher growth in sales and employment. They further argue that the positive growth stems from stronger product innovation of AI-investing firms.

types of knowledge workers in the short-term. One exception is Bonfiglioni et al. (2024), who also move towards a more macro-level analysis and focus on local labor markets. They also find a stronger negative impact in more exposed commuting zones. One key distinction between this paper and theirs is the measure of AI exposure. Bonfiglioni et al. (2024) use changes in commuting zone employment share of AI-related professions for AI exposure. There are 19 AI professions, which essentially correspond to "Computer and Mathematical Occupations" in SOC 2018, excluding actuaries. In this paper, I directly leverage information on AI adoption from a nationally representative survey of firms. This measure has several advantages. First, using AI adoption can more intuitively capture the concept of AI exposure when examining the employment impact. There are many non-AI occupations such as managers (Copestake et al. (2023)), economists (Korinek (2023)), financial analysts (Abis and Veldkamp (2024)), even customer support agents (Brynjolfsson et al. (2023)) whose job contents are transformed by AI. It is also very possible that AI production (which heavily relies on computer and mathematical occupations) is geographically concentrated and does not take place in the same local labor market as AI adoption. Second, using AI adoption allows for instrumenting US industry-level adoption with EU data to capture global technological advances, thereby isolating US-specific shocks.

This paper is also related to the extensive literature on the impact of technological change and automation. Theoretically, Acemoglu and Restrepo (2019) highlight the main economic forces through which automation affects employment in a task-based framework. Acemoglu (2024) applies the logic to the context of AI. This paper is an empirical analysis of a different and new technology on local labor markets. It is closely related to Autor et al. (2013), who study the impact of Chinese import competition in 1990-2007 on US commuting zones. In a similar vein, Acemoglu and Restrepo (2020) investigate the employment and wage impact of industrial robots in 1990-2007. In fact, the identification strategy employed in this paper directly borrows from Acemoglu and Restrepo (2020). This paper also explores the distributional impact of AI. It is therefore related to the literature on job polarization (Acemoglu and Autor (2011), Autor et al. (2006), Goos et al. (2014)) and trade (Traiberman (2019)).

Methodologically, this paper is an application of shift share design (Bartik instruments) that exploits regional variation to infer causal relationships. The use of Bartik instruments (Bartik (1991)) has a long history in empirical research. More recently, several works formalize the econometric foundation of Bartik instruments (Adão et al. (2019), Goldsmith-Pinkham et al. (2020), Breuer (2022), Borusyak et al. (2022)). Nakamura and Steinsson (2018) discuss the use of cross-regional variation to estimate relative regional effects and then infer aggregate, macroeconomic effects from regional estimates. One application related to this topic is Acemoglu and Restrepo (2020), who use commuting zone variation in industrial robots adoption to estimate relative regional effects, and then infer the effects of industrial robots on *aggregate* employment and hourly wage from regional estimates using a multi-region, general equilibrium model.

The rest of the paper is organized as follows. Section 2 introduces the data sources. Section 3 describes the empirical strategy. Section 4 presents the main findings and discusses robustness checks. Section 5 concludes.

2 Data Sources

2.1 AI Adoption Data

For industry-level AI adoption, I use data from the Annual Business Survey (ABS) in the United States and its European counterpart, the ICT Usage in Enterprises. The main purpose of using the European data is to isolate US-specific shocks and construct an instrument for US AI adoption, so that the AI adoption "shock" captures global technological advances[4].

Annual Business Survey (ABS). The ABS is an annual survey on US businesses and business owners. The survey introduces a new technology module for the years 2018, 2019, and 2021. The module is conducted by the US Census Bureau in partnership with the National Center for Science and Engineering Statistics (NCSES). The data is publicly available at the 2-digital NAICS level, 3-digit NAICS for manufacturing, and 4-digit

[4] I choose to use AI adoption in the EU for two reasons. First, industry-level AI adoption data is scant. While it would be interesting to obtain data from other large AI-adopting countries, such as China, such data is not easy to acquire. Second, since we are talking about AI adoption (rather than AI production or innovation), Europe still ranks highly in this regard, as indicated by the IMF AI preparedness index (`https://www.imf.org/external/datamapper/datasets/AIPI`). To alleviate the concern that shocks to some commuting zones (e.g., Silicon Valley) may affect global trends of AI adoption in certain industries, I conduct an additional test by excluding the top 1% commuting zone in terms of AI exposure. The results remain robust (Table 2).

NAICS for professional, scientific and technical services. Acemoglu et al. (2022a) and Hubmer and Restrepo (2022) use the 2019 module to study automation at the firm level. In this paper, I use the data in 2021, the latest year available. Specifically, the dataset reports the number of firms that use a given AI technology at the industry level. There are five different AI technologies in the ABS: machine learning, machine vision, natural language processing, voice recognition software, and automated-guided vehicles (AGVs) (McElheran et al. (2024)). Together with information on the total number of firms by industry, I calculate the percentage of firms in a given industry that adopt a given AI technology, and then take the average industry-level adoption rate across AI technologies to obtain the baseline industry-level measure of adoption in AI overall.

ICT Usage in Enterprises. The European Commission collects annual data from national statistical institutes of EU member countries on ICT (Information and Communication Technologies) usage and e-commerce in enterprises. The data is publicly available under NACE Rev. 2 industry classification. I use the percentage of enterprises that use at least one of the following AI technologies (text mining, speech recognition, natural language processing, machine learning, AI-based software robotic process automation, and autonomous robots/vehicles/drones) in 2021 as the baseline measure of industry AI adoption in the EU.

The ABS and the ICT Usage of Enterprises use different industry classification schemes. Appendix A.1 and the fourth column of Appendix A.2 list the final industry classification for the US and the EU. There are 47 industries in the ABS and 27 industries in the ICT Usage in Enterprises data[5]. Both datasets cover manufacturing as well as services.

2.2 Commuting Zone Level Data

There are two main sources of commuting zone level data: the American Community Survey (ACS) and the County Business Patterns (CBP). Both datasets are aggregated to the commuting zone level using the crosswalks of Autor and Dorn (2013). There are 722 commuting zones in total.

American Community Survey (ACS). I use the ACS 5% sample from IPUMS (Rug-

[5] As the EU adoption data is mainly used to construct the IV, I do not need to impose any assumptions on the mapping between US and EU industries. The first-stage F statistic suggests that the IV is relevant, so having coarser industry in the EU data is less concerning.

gles et al. (2024)) to compute commuting zone characteristics such as population, employment, demographics (e.g., share of female population, share of population aged 65 and above, share of white/black/American Indian or Alaskan native/Asian population, share of population with college degrees and above, share of foreign born), industry and occupation compositions. Specifically, I use the crosswalks of Autor and Dorn (2013) to map counties (for the year 1980) or PUMAs (Public Use Microdata Areas, for the years 1990 and beyond) to commuting zones. I drop individuals in the military. The main outcome variable is employment-to-population, defined as the number of employed working-age individuals (aged 16-65), divided by the total working-age population, using census weights.

County Business Patterns (CBP). I use county-level industry employment from the CBP to obtain local employment share. I use the local employment share to construct Bartik-style commuting zone exposure to AI, detailed in Section 3.1 below. I also use the CBP to compute commuting zone Bartik exposure to industrial robot penetration and Chinese import competition during 2010-2021.

2.3 Additional Data Sources

One identification challenge is to ensure that commuting zones with higher AI exposure are comparable to those with lower AI exposure. Differences in initial conditions across commuting zones may affect both AI adoption and employment outcomes. For example, local labor market trends may differ by the share of foreign born for reasons other than AI due to cultural differences - foreign borns are more likely to be employed. If commuting zones with a higher share of foreign born are more likely to adopt AI, the estimates will be upward biased without controlling for the initial share of foreign born. Therefore, I compute a wide range of initial commuting zone demographic characteristics and industrial structure from the ACS. Section 3.1 provides a comprehensive list of controls in the regression analysis.

Another type of confounding factor is concurrent labor market shocks during 2010-2021 (the period of analysis). For example, Acemoglu and Restrepo (2020) document that robotization reduces the employment-to-population ratio. If commuting zones with higher AI adoption are also more exposed to robotization, the estimated effect cannot be attributable to AI adoption alone. Using data on industrial robots from the International Federation of Robotics (IFR), I follow Acemoglu and Restrepo (2020) to compute Bartik exposure to robotics in 2010-2021. Similarly, I compute Bartik exposure to Chinese import competition in 2010-2021 using data from CEPII BACI (Gaulier and Zignago (2010)), which provides information on bilateral trade flows at the HS 6-digit product level.

In Section 4.1, I perform falsification tests and provide support that after controlling for a wide range of commuting zone covariates, AI adoption in 2010-2021 does not affect *past* changes in the employment-to-population ratio in 1980-2010. This implies that commuting zones with low vs. high AI exposures are reasonably similar to begin with.

3 Empirical Strategy

3.1 Empirical Specification

The main goal of the empirical analysis is to estimate the impact of AI on employment. The empirical strategy borrows from Acemoglu and Restrepo (2020). In particular, I exploit commuting zone level variation in AI adoption to estimate its local employment effect. The baseline empirical specification is:

$$\Delta_{2010}^{2021} Y_i = \alpha_{d(i)} + \beta AIExposure_i + \gamma X_i + \epsilon_i \tag{1}$$

where i denotes commuting zones, $d(i)$ refers to the census division of commuting zone i. $\alpha_{d(i)}$ is the census division fixed effect. Y_i refers to labor market outcomes in commuting zone i, such as the overall employment-to-population ratio, or the employment-to-population ratio by subgroups (e.g, occupation, industry). The dependent variable is the long difference of Y_i between 2010 and 2021. I set 2010 as the start year. The underlying assumption is that there was no AI adoption in 2010[6]. To alleviate concerns that 2021 may be related to Covid-19 and affects employment patterns in a special way, I also explore the long-differences using 2019 as an alternative for the end year in Appendix E.

The coefficient of interest is β, which captures the effect of commuting zone level AI exposure on local labor market outcomes. I provide more details on the construction of $AIExposure_i$ during 2010-2021 in Section 3.2 below. The baseline specification controls

[6]The Electronic Frontier Foundation (EFF) published measurements on the progress of AI research (`https://www.eff.org/ai/metrics`) until 2019. The measurement covers a range of AI applications, and there has been little progress in 2010/2011. Felten et al. (2021) chooses 10 AI applications from the AI Progress Measurement to calculate occupational exposure to AI. This is also the start year chosen in Babina et al. (2024), who study the impact of AI investment on firm growth in 2010-2018.

for commuting zone level covariates X_i that may potentially influence the change in labor market outcomes between 2010 and 2021. These covariates are initial demographic characteristics (i.e, log of population size, share of female population, share of population aged above 65, share of white/black/American Indian or Alaskan native/Asian population, share of foreign born, share of college-educated workers), initial industrial structure (i.e, manufacturing share, light manufacturing share), initial share of routine occupations to proxy for exposure to routine-biased technological change[7], initial share of high offshorability occupations[8], as well as Bartik exposures to robotization and Chinese import competition.

3.2 Commuting Zone Level Exposure to AI

Ideally, to determine the causal effect of AI exposure on local employment, $AIExposure_i$ should be exogenous. However, there are several challenges in measuring $AIExposure_i$. First, there is no readily available data of AI adoption at the county (and therefore commuting zone) level. Second, AI adoption is unlikely to be exogenous because of unobserved local demand shocks, anticipation of AI arrival, and the path dependent nature of technological change.

US Exposure to AI. To address the first challenge, I compute a Bartik-style measure of AI exposure in the US in 2010-2021, $USExposure_i$:

$$USExpsoure_i = \sum_j \frac{L_{ij2010}}{L_{i2010}} \Delta_{2010}^{2021} AIAdoption_j^{US} \tag{2}$$

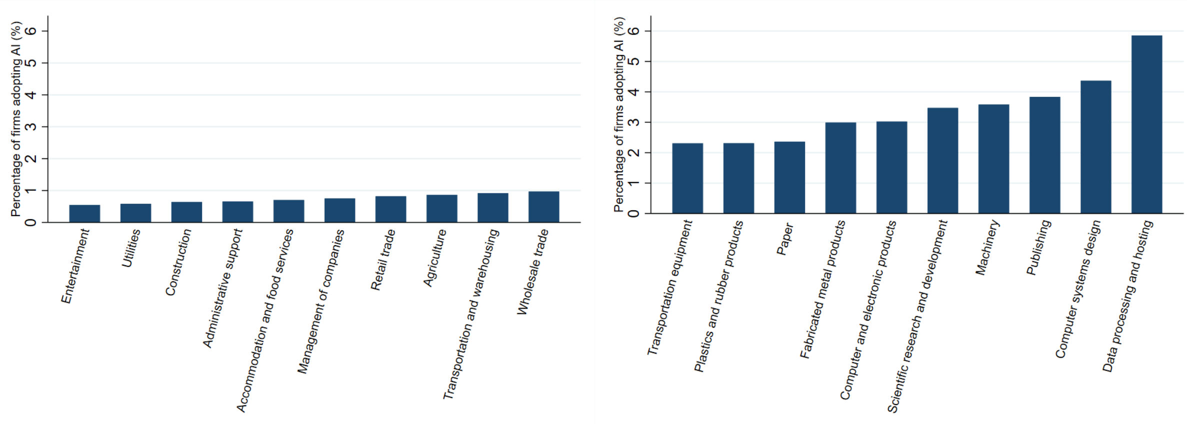
which is a weighted sum of nationwide industry-specific change in AI adoption in 2010-2021 in the US from the ABS[9], $\Delta_{2010}^{2021} AIAdoption_j^{US}$ ("shift"). Weights are computed as the local employment share of industry j in commuting zone i, $\frac{L_{ij2010}}{L_{i2010}}$ ("share"). Autor et al. (2013) use a similar measure for commuting zone exposure to Chinese import competition in 1990-2007 and Acemoglu and Restrepo (2020) for exposure to industrial robots in 1990-2007.

[7]Acemoglu and Autor (2011) calculate routine task scores from data on occupation task content from O*NET. I define routine occupations as occupations with a routine task score above the 66th percentile, as in Autor and Dorn (2013).

[8]Data on offshorability of occupations is from Autor and Dorn (2013). I define offshorable occupations as occupations with an offshorability score above the 66th percencile.

[9]I leverage the industry AI adoption data in 2021, so the implicit assumption is that AI adoption in the US is zero across all industries in 2010.

Figure 1 depicts the top and bottom 10 industries of AI adoption in the US. The baseline measure of industry-level AI adoption is the average percentage of adopting firms across the five different AI technologies (AGV, machine learning, voice recognition, speech recognition, text mining). I also present robustness results using the maximum adoption rate across the five AI technologies for a given industry as an alternative measure for industry-level AI adoption in Appendix D. Not surprisingly, the data processing, hosting, and related services industry, an industry in the information sector, has the highest AI adoption rate at 6%. The second and third industries of AI adoption are computer systems design and publishing. There are also several manufacturing industries with high AI adoption, such as machinery, computer and electronic products, paper products, plastic and rubber products, and transportation equipment. Scientific research and development is also intensive in AI adoption.



(a) bottom 10 industries

(b) top 10 industries

Figure 1: Bottom and Top 10 Industries of AI Adoption in the US

Sources: ABS (2021) and author's calculations.

Notes: Each blue bar represents the average percentage of adopting firms across the five different AI technologies (AGV, machine learning, voice recognition, speech recognition, text mining) for the bottom 10 industries (Panel (a)) and top 10 industries (Panel (b)) in the US. Industry classification is according to Appendix A.1.

However, neither the share nor the shift component of $USExposure_i$ is likely to be exogenous. Local employment share in 2010 can incorporate the anticipation effect of AI arrival, resulting in simultaneity bias. Similarly, technological change can be fairly path dependent. Commuting zones that have adopted more ICT, software, and robotics since the 1990s are also more likely to adopt AI. To the extent that anticipation or past technologies affect employment outcomes, using local industry specialization patterns after the proliferation of ICT to construct AI exposure may suffer from simultaneity bias. As for the shift component, idiosyncratic US-specific factors such as US-specific industry demand shocks can increase both AI adoption and local labor demand, resulting in a positive bias of the simple OLS estimate.

Instrumental Variable. I construct the following instrumental variable (IV) for $USExposure_i$, denoted as $EUExposure_i$:

$$EUExpsoure_i = \sum_j \frac{L_{ij1990}}{L_{i1990}} \Delta_{2010}^{2021} AIAdoption_j^{EU} \tag{3}$$

This IV is in the same spirit as in Acemoglu and Restrepo (2020), who use 1970 local employment share interacted with EU industry-level industrial robot penetration to instrument for 1990 US robot penetration. I use the local employment share in 1990 to mitigate concerns of AI anticipation and path dependence of technological change. This is because in 1990, technologies such as ICT and robotization are only at burgeoning stages at best[10]. I also perform robustness checks using local employment shares in 1995 and average local employment shares in 1990-1995. For the shift component, I use industry-level AI adoption in the EU to capture global technological advances, similar to Autor et al. (2013) and Acemoglu and Restrepo (2020). Figure 2 shows a strong positive relationship between industry-level AI adoption in the US versus the EU, suggesting that EU AI adoption is a relevant instrument for US AI adoption[11]. Moreover, as shown in Table 1, the F-statistic is 58.2, well above 10, indicating that $EUExposure_i$ is a strong instrument.

AI Exposure vs. AI Adoption. To clarify, I use the terms "AI exposure" and "AI adoption" interchangeably when referring to *commuting zone level* AI exposure. I only

[10]I do not choose earlier periods such as 1980 due to the concern that local employment share in 2010 may have changed too much, resulting in the problem of weak instrument.

[11]The scales of US and EU adoption are different, because the two measures use different definitions. The baseline definition for industry-level AI adoption in the US data is the average industry-level adoption rate across five AI technologies (machine learning, machine vision, natural language processing, voice recognition software, and AGVs). The definition for industry-level AI adoption in the EU data is the percentage of enterprises that use at least one of the following AI technologies (text mining, speech recognition, natural language processing, machine learning, AI-based software robotic process automation, and autonomous robots/vehicles/drones).

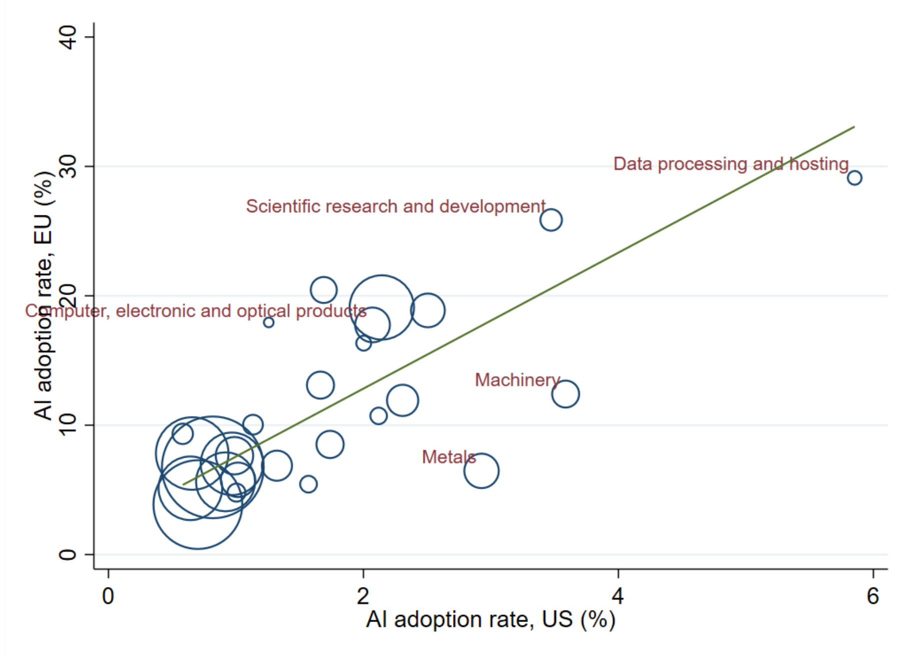
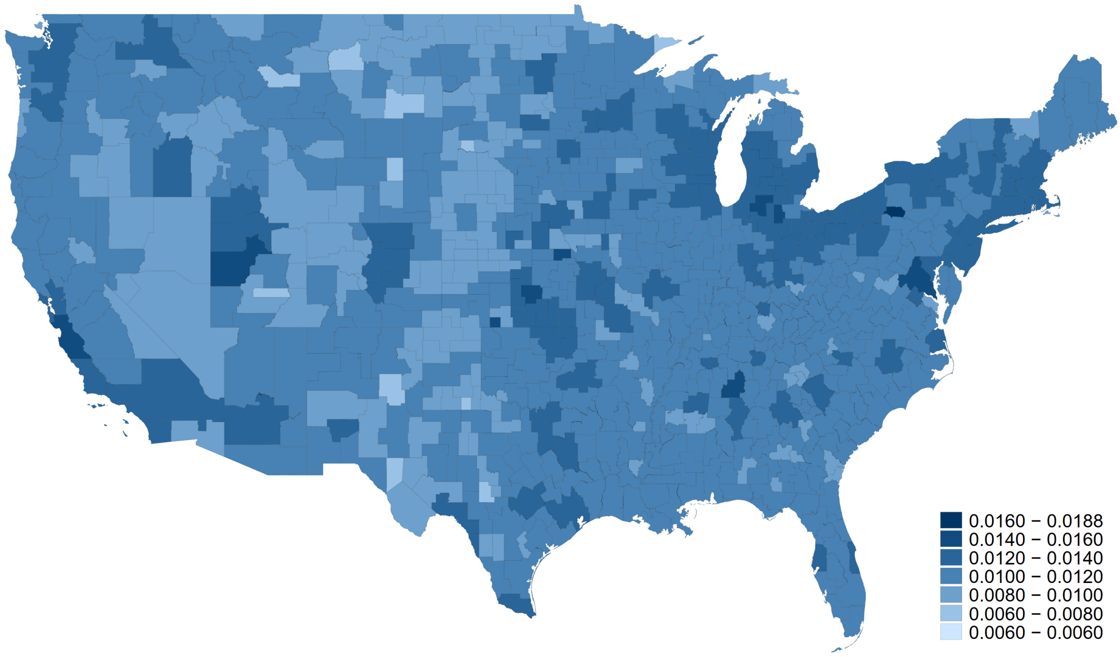


Figure 2: Correlation of Industry-Level AI Adoption in US vs. EU

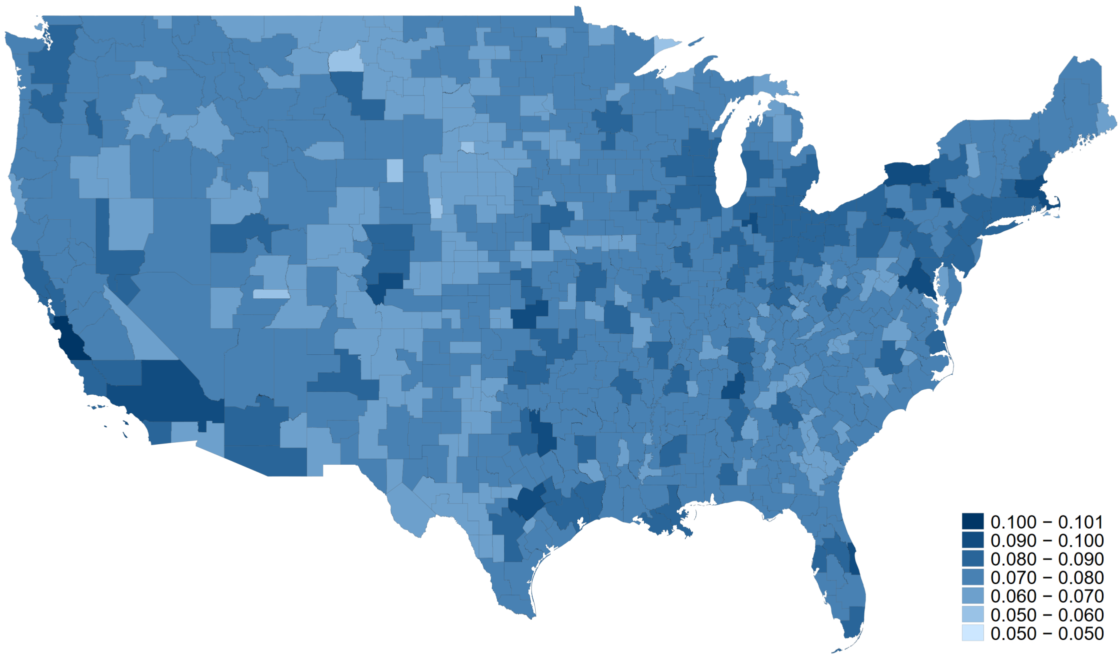
Sources: ABS (2021), Eurostat (2021), BLS OEWS (2010), and author's calculations.
Notes: Each blue circle represents an industry according to the industry classification in Appendix A.2. The x-axis is AI adoption in the US. The y-axis is AI adoption in the EU. The green line is the linear regression fit, with coefficient of 5.255 and standard error of 0.874. The size of the blue circle is the US industry share in 2010.

use the term "AI adoption" (but not "AI exposure") when referring to *industry-level* AI adoption, as AI adoption is the main variable that is used in the "shift" component of commuting zone level AI exposure measures ($USExposure_i$, $EUExposure_i$).

AI Exposure by Commuting Zone. Figure 3 plots the geographic distribution of AI exposure across US commuting zones. Darker color indicates that the commuting zone is more exposed to AI. Consistent with intuition, San Francisco, Los Angeles, San Antonio, Seattle, Pittsburgh, New York, Washington D.C., and Boston have high exposure to AI under both $USExposure_i$ and $EUExposure_i$.



(a) $USExposure_i$



(b) $EUExposure_i$

Figure 3: AI Exposure by US Commuting Zone

Sources: ABS (2021), Eurostat (2021), CBP (1990, 2010), and author's calculations.

Notes: Each cell represents a commuting zone. Darker color indicates a higher value for $USExposure_i$ (Panel (a)) or $EUExposure_i$ (Panel (b)).

3.3 Instrumental Variable Approach

Given specification (1) and the IV, the main empirical approach of the paper is a two-stage least-squares (2SLS) regression. The first stage is:

$$USExposure_i = \tilde{\alpha}_{d(i)} + \tilde{\beta} EUExposure_i + \tilde{\gamma} X_i + \tilde{\epsilon}_i \tag{4}$$

The second stage is:

$$\Delta_{2010}^{2021} Y_i = \alpha_{d(i)} + \beta US\widehat{Exposure}_i + \gamma X_i + \epsilon_i \tag{5}$$

where $US\widehat{Exposure}_i$ is the first-stage estimate from equation (4). Each regression is weighted by commuting zone population in 2010. Standard errors are clustered at the state-level to account for potential serial correlation in the error term within state.

4 Results

4.1 Effect on the Overall Employment-to-Population Ratio

Table 1 presents the second-stage estimates β from equation (5), which explores the impact of AI exposure on overall employment-to-population ratio at the commuting zone level. I find that commuting zones with higher AI exposure have experienced a stronger decline in the employment-to-population ratio during 2010-2021.

The baseline IV uses local employment share in 1990, as shown in equation (3). Under the reasonable assumption that ICT have not yet proliferated[12], I also use local employment share in 1995 and average local employment share in 1990-1995 to compute the IV for robustness. I refrain from using later years such as the 2000s due to concerns that ICT and robotization have become more prevalent by then, resulting in an invalid instrument. The first stage F-statistic is consistently above 50, indicating that the IV is relevant.

Column (1) is the baseline specification, where I use 1990 as the local employment share to compute the IV, and examine the effect of AI exposure on change in employment-to-population ratio in 2010-2021. The estimate suggests that a one standard deviation increase in AI exposure implies 0.976 percentage points lower employment-to-population

[12] Colecchi and Schreyer (2002) show that the rate of growth in IT equipment in the 1990s doubled with respect to the 1980s in the US. ICT investment accelerated particularly in the second half of the 1990s.

ratio. Furthermore, the estimate also implies that the employment-to-population ratio in commuting zones at the 75th percentile of AI exposure declines by 1.25 percentage points more than commuting zones at 25th percentile of AI exposure. Column (2) presents the second-stage estimate using 1995 local employment share to compute the IV. Similarly, column (3) uses average local employment share in 1990-1995 to compute the IV, so that I do not rely on the local employment share in any particular year. The estimated effects of AI exposure on change in employment-to-population ratio in 2010-2021 from both specifications remain significantly negative.

I first perform a falsification test, where I regress *past* changes in the overall employment-to-population ratio in 1980-2010 on *future* AI exposure in 2010-2021. The coefficients are insignificant in columns (4)-(6). These results suggest that after controlling for initial commuting zone characteristics, concurrent labor market shocks, and census division fixed effects, AI exposure in 2010-2021 only affects outcomes for the period 2010-2021, but not for the earlier period of 1980-2010. Hence, long-run common factors are unlikely to drive both the change in employment-to-population and AI adoption.

One potential concern is that shocks to some commuting zones (e.g., Silicon Valley) may affect global trends of AI adoption in certain industries, undermining the exogeneity of EU adoption. To address this concern, I remove the top 1% of commuting zones in terms of AI exposure ($USExposure_i$). Table 2 reports the results. The negative effect on the employment-to-population ratio remains robust.

The baseline outcome variable is the employment-to-population ratio. However, one potential concern is that if the commuting zones that are early adopters of AI are also the richest in the country, their population may have increased by more than the national average over time. As a result, the employment-to-population ratio could have decreased for reasons other than AI exposure. I show that the negative effect in the employment-to-population ratio is indeed driven by the negative effect on employment (the numerator). Specifically, I use the change in the log of overall employment *level* in 2010-2021 as the main outcome variable and include changes in the log of working-age population as an additional control. Table 3 shows that conditional on changes in working-age population, commuting zones with higher exposure to AI experience stronger declines in the employment level.

	1990 Share	1995 Share	1990-1995 Average	1990 Share	1995 Share	1990-1995 Average
	2010-2021	2010-2021	2010-2021	1980-2010	1980-2010	1980-2010
	(1)	(2)	(3)	(4)	(5)	(6)
$USExposure$	-7.511**	-5.699*	-8.375***	2.217	-1.199	0.716
	(3.067)	(2.979)	(3.129)	(4.739)	(5.402)	(5.075)
Observations	722	722	722	722	722	722
R-squared	0.28	0.30	0.26	0.56	0.55	0.55
First-stage coefficient	0.075***	0.084***	0.086***	0.075***	0.084***	0.086***
	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)
First-stage F-statistic	58.2	52.8	57.3	58.2	52.8	57.3

Table 1: Effect of AI on Employment-to-Population Ratio: 2SLS Estimates

Notes: The table reports the second stage estimates β from equation (5). The dependent variable is the change in the employment-to-population ratio in 1980-2010 (for columns (4)-(6)) and 2010-2021 (for columns (1)-(3)). Columns (1) and (4) use local employment share in 1990 to compute the IV $EUExposure_i$. Columns (2) and (5) use local employment share in 1995 to compute the IV $EUExposure_i$. Columns (3) and (6) use the average local employment share in 1990-1995 to compute the IV $EUExposure_i$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

4.2 Heterogeneity

In this section, I examine the effect of AI exposure on changes in employment by various subgroups, such as the broad sector, occupation, education, age, and gender. The goal is to explore potential heterogeneous effects of AI adoption and investigate the subgroups that contribute to the negative impact of AI exposure on employment. There are four main findings. First, the manufacturing and low-skill services sectors are negatively affected. Second, similar to routine-biased technological change, one of the main drivers behind job polarization[13] in the 1990s (Autor et al. (2006), Goos et al. (2014)), the negative impact of AI exposure also falls mainly on middle-skill workers. Third, AI exposure reduce the employment-to-population ratio of individuals at the two ends of the age distribution (those aged 16-25 and above 46). Fourth, the adverse impact is more pronounced on men than women.

Broad sector. Table 4 shows the second-stage estimates of AI exposure on changes in sectoral employment-to-population ratio during 2010-2021. The results reported here

[13] Job polarization is a labor market phenomenon in the US and EU since the 1990s where middle-skill occupations are in decline in terms of employment and wage.

	1990 Share 2010-2021 (1)	1995 Share 2010-2021 (2)	1990-1995 Average 2010-2021 (3)	1990 Share 1980-2010 (4)	1995 Share 1980-2010 (5)	1990-1995 Average 1980-2010 (6)
$USExposure$	-8.968**	-6.345	-10.054***	2.409	-2.533	-0.024
	(4.156)	(3.912)	(4.225)	(6.220)	(7.361)	(6.900)
Observations	714	714	714	714	714	714
R-squared	0.24	0.29	0.22	0.55	0.55	0.55
First-stage coefficient	0.060***	0.066***	0.067***	0.060***	0.066***	0.067***
	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)
First-stage F-statistic	41.5	43.1	43.0	41.5	43.1	43.0

Table 2: Effect of AI on Employment-to-Population Ratio (Excluding Top 1% $USExposure_i$): 2SLS Estimates

Notes: The table reports the second stage estimates β from equation (5). The dependent variable is the change in the employment-to-population ratio in 1980-2010 (for columns (4)-(6)) and 2010-2021 (for columns (1)-(3)). The sample excludes commuting zones with top 1% $USExposure_i$. Columns (1) and (4) use local employment share in 1990 to compute the IV $EUExposure_i$. Columns (2) and (5) use local employment share in 1995 to compute the IV $EUExposure_i$. Columns (3) and (6) use the average local employment share in 1990-1995 to compute the IV $EUExposure_i$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

use the baseline IV, where local employment shares are from 1990. Manufacturing, and especially low-skill services, stand out as the sectors contributing to the negative impact of AI exposure on employment. The effect on agriculture is mildly positive, consistent with the finding in Bonfiglioni et al. (2024). One possible explanation could be that workers in low-skill services and manufacturing switch into agriculture, as the agriculture sector has a relatively low skill requirement.

Occupation. Table 5 explores the impact of AI exposure on employment for two classifications of occupation groups: whether the occupation is STEM or not (Columns (1)-(2)), and whether the occupation is high-skill, middle-skill, or low-skill (Columns (3)-(5)). The estimates suggest that the negative employment impact is due to non-STEM and middle-skill occupations. This is finding is consistent with the firm-level evidence documented in Babina et al. (Forthcoming). They find that firms with higher initial shares of more educated workers tend to invest more in AI, which in turn shift these AI-investing firms towards a more educated and more specialized workforce in STEM fields and IT skills.

	1990 Share 2010-2021 (1)	1995 Share 2010-2021 (2)	1990-1995 Average 2010-2021 (3)	1990 Share 1980-2010 (4)	1995 Share 1980-2010 (5)	1990-1995 Average 1980-2010 (6)
$USExposure$	-10.970**	-8.759*	-12.351***	2.162	-3.237	-0.269
	(4.856)	(4.701)	(4.951)	(7.190)	(8.245)	(7.605)
Observations	722	722	722	722	722	722
R-squared	0.95	0.95	0.95	0.99	0.98	0.99
First-stage coefficient	0.075	0.084	0.086	0.075	0.084	0.086
First-stage F-statistic	59.5	53.2	58.0	59.4	54.2	59.5

Table 3: Effect of AI on Log Employment Level: 2SLS Estimates

Notes: The table reports the second stage estimates β from equation (5). The dependent variable is the change in the change in log employment level in 1980-2010 (for columns (4)-(6)) and 2010-2021 (for columns (1)-(3)). In addition, the right-hand side also controls for the change in log working age population in 1980-2010 (for columns (4)-(6)) and 2010-2021 (for columns (1)-(3)). Columns (1) and (4) use local employment share in 1990 to compute the IV $EUExposure_i$. Columns (2) and (5) use local employment share in 1995 to compute the IV $EUExposure_i$. Columns (3) and (6) use the average local employment share in 1990-1995 to compute the IV $EUExposure_i$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

	Agriculture (1)	Manufacturing (2)	Construction (3)	Low-Skill Services (4)	High-Skill Services (5)
$USExposure$	0.914**	-5.118*	1.047	-5.292***	0.939
	(0.460)	(2.782)	(1.091)	(2.039)	(1.635)
Observations	722	722	722	722	722

Table 4: Effect of AI on Employment-to-Population Ratio by Broad Sector: 2SLS Estimates

Notes: The table reports the second stage estimates β from equation (5), with, using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in sectoral employment-to-population ratio in 2010-2021. Manufacturing includes manufacturing and mining. Low-skill services are wholesale trade, retail trade, utilities, transportation, information, real estate, administrative support and waste management, arts and entertainment, accommodation and food services, and other services. High-skill services are finance and insurance, professional scientific and technical services, management of companies and enterprises, education, health, and social assistance. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

	Non-STEM	STEM	Low-Skill	Middle-Skill	High-Skill
	(1)	(2)	(3)	(4)	(5)
$USExposure$	-6.997***	-0.514	-0.230	-4.936*	-2.345
	(2.881)	(1.049)	(0.980)	(2.559)	(1.701)
Observations	722	722	722	722	722

Table 5: Effect of AI on Employment-to-Population Ratio by Occupation: 2SLS Estimates

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in occupational (STEM vs. non-STEM occupations; low, middle, high-skill occupations) employment-to-population ratio in 2010-2021. The list of STEM occupations are from O*NET. High-skill occupations are management, business and financial occupations, professionals, and technicians. Middle-skill occupations are office and administration, sales, construction and extraction, mechanics and repairers, production, transportation and material moving. Low-skill occupations are personal services and agriculture occupations. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Education. I compute the employment-to-population ratio by four education groups: below high school, high school graduate, some college, college and above. The estimates in Table 6 suggest that the employment of individuals with middle levels of education, namely those with some college education (but not reaching Bachelors degree) and in particular high school graduates, are negatively affected by AI exposure. Together with the previous finding that middle-skill occupations drive the negative employment impact of AI, these results indicate that similar to routine-biased technological change, one of the main drivers behind job polarization in the 1990s, the negative impact of AI exposure also falls primarily on middle-skill workers.

Age. I divide the working-age population by 10-year age bins (16-25, 26-35, 36-45, 46-55, 56-65) and calculate their respective employment-to-population ratios. Columns (1)-(5) in Table 7 show that the negative impact of AI on employment falls primarily on individuals at the two ends of the age distribution: the very young (aged 16-25) and older workers (aged above 46). Intuitively, the low employment-to-population ratio of young individuals can be attributed to two reasons. First, as technological change tends to replace simple tasks, more individuals aged 16-25 stay in school for longer to acquire more

	Below High School	High School	Some College	College and Above
	(1)	(2)	(3)	(4)
$USExposure$	-2.598	-9.723***	-6.216*	-0.550
	(5.850)	(3.935)	(3.729)	(2.401)
Observations	722	722	722	722

Table 6: Effect of AI on Employment-to-Population Ratio by Education: 2SLS Estimates

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by education levels (below high school, high school, some college, college and above) in 2010-2021. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

technical skills and remain competitive in the labor market. Second, young individuals who are already in the labor force are less likely to have attended college, and therefore tend to work in lower skill occupations, which are more at risk of displacement under technological change. Older workers (those aged 46 and above) are negatively hit by AI as their skills may have become obsolete upon the arrival of new frontier technologies and these workers are also less adaptable to learn new technologies (Cazzaniga et al. (2024)). Older workers also have a higher opportunity cost to switch jobs because of the large amount of *specific* human capital they have accumulated over time. The higher switching cost and lower job mobility is also found among older workers in the context of import competition (Traiberman (2019)) or trade liberalization (Dix-Carneiro (2014)).

Gender. Columns (6) and (7) in Table 7 summarize the findings on male and female employment. Both gender groups experienced a stronger decline in employment in more AI-exposed commuting zones during 2010-2021. However, the negative impact on male employment is more pronounced than female employment. Cazzaniga et al. (2024) argue that although women are more likely to be employed in high AI exposure occupations[14], these occupations also tend to be more complementary to AI. Therefore, AI also presents greater opportunities for women. The complementary nature of occupations held by women may be the reason for the relatively smaller adverse employment impact of AI on women than men.

[14] AI occupation exposure (AIOE) is from Felten et al. (2021). An occupation with a higher AIOE score implies that this occupation requires more abilities on which AI technologies have made more progress.

	16-25 (1)	26-35 (2)	36-45 (3)	46-55 (4)	56-65 (5)	Male (6)	Female (7)
$USExposure$	-11.519**	-2.962	-5.576	-7.746**	-7.969*	-9.191**	-5.581*
	(5.606)	(3.423)	(4.007)	(3.750)	(4.108)	(4.214)	(3.089)
Observations	722	722	722	722	722	722	722

Table 7: Effect of AI on Employment-to-Population Ratio by Age and Gender: 2SLS Estimates

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by 10-year age bin (16-25, 26-35, 36-45, 46-55, 56-65) or gender (male, female) in 2010-2021. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Use 1995 local share or 1990-1995 average local share in IV. I perform robustness checks by using 1995 local employment share and 1990-1995 average local employment share to compute the IV. Results are in Appendix B and Appendix C. The findings are robust. The negative employment effect is primarily borne by manufacturing and low-skill services, middle-skill workers, non-STEM occupations, and individuals at the two ends of the age distribution. The adverse impact is also more pronounced on men than women.

4.3 Robustness

I conduct three robustness exercises. First, as mentioned in Section 3.2, I use the maximum adoption rate across the five AI technologies for a given industry as an alternative measure of US industry-level AI adoption $AIAdoption_j^{US}$ (Appendix D). Second, I use 2019 as the end year of the long-difference to mitigate the concern that employment patterns in 2021 may be related to Covid-19 (Appendix E). Third, I use local employment shares in 2005 instead of 2010 for $USExposure_i$ (Appendix F) to mitigate potential AI anticipation or mean reversion from the 2007-2009 Great Recession. The findings are very consistent across these alternative specifications.

5 Conclusion

Rapid and ongoing development in AI since the last decade, and in particular the advent of generative AI technologies such as ChatGPT in November 2022, have spurred much debate on the labor market implications of AI. Most empirical research has studied this question at the micro, firm level. This paper moves towards a more macro-level analysis by focusing on local labor markets. In particular, I exploit variation in AI adoption across US commuting zones using a shift-share approach to investigate the employment impact of AI in 2010-2021. To overcome the lack of data on commuting zone level AI adoption, I construct a measure of commuting zone AI exposure in the US using data on local employment share in 2010 and nationwide industry-level AI adoption. To mitigate potential positive bias due to factors such as unobserved local demand shocks, anticipation of AI, and path dependency of AI with previous waves of technological changes in ICT, I instrument the exposure measure using data on local employment share in 1990 and industry-level AI adoption in the EU. Moreover, I control for a comprehensive set of initial commuting zone characteristics and commuting zone exposures to the concurrent labor market shocks of robotization and import competition.

I find that commuting zones with a higher share of AI adopting firms experienced a more significant decline in the overall employment-to-population ratio during 2010-2021. The estimated effect implies that the employment-to-population ratio in commuting zones at the 75th percentile of AI exposure declines by 1.25 percentage points more than commuting zones at 25th percentile of AI exposure.

I further explore potential heterogeneous effects of AI adoption and investigate the subgroups that contribute to the negative impact of AI exposure on employment. I find that this negative employment effect is primarily borne by the manufacturing and low-skill services sectors, middle-skill workers, non-STEM occupations, and individuals at the two ends of the age distribution. The adverse impact is also more pronounced on men than women. These unequal effects of AI are similar to previous waves of labor market shocks, such as routine-biased technological change (Autor et al. (2006), Goos et al. (2014) for skill group), offshoring (Goos et al. (2014) for skill group), robotization (Acemoglu and Restrepo (2020) for skill group and gender), and import competition (Traiberman (2019) for age). For policymakers, these results underscore the importance of considering unequal distributional consequences of labor market shocks, as well as the need of social safety nets and job retraining programs.

Currently, there are two main constraints in the research of the labor market impact of AI. First, reliable data is scant, in particular large-scale, up-to-date micro-level *panel* data on AI adoption[15]. The ABS does not extend to the generative-AI era, proliferated by the launch of ChatGPT in 2022. It is therefore still too early to explore the effects of generative AI systematically. Second, the direction of AI technological change is rapid and highly uncertain. This uncertainty poses a challenge to researchers.

There are several avenues for future research. First, in ongoing work, building a fully-specified general equilibrium model to properly account for cross-region spillovers is important to gauge aggregate effects from regional estimates provided in this paper (Nakamura and Steinsson (2018)). Second, AI production can be quite different from AI usage or adoption, which is the focus of this paper. Local labor markets can specialize in or outsource AI production. Investigating the geographical specialization in the AI "value chain", spanning from AI production to AI usage is also a fruitful dimension for research. Third, the empirical analysis can be extended to other outcome variables, such as wage, housing prices, and political views.

[15] The panel dimension allows researchers to exploit the time variation.

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Online Appendix

A Industry Classification

A.1 Industry Classification in the ABS

Industry	Description	NAICS
1	Agriculture, forestry, fisheries	11
2	Mining, extraction, and support activities	21
3	Utilities	22
4	Construction	23
5	Food, beverages, tobacco	311-312
6	Textile, apparel, leather products	313-316
7	Wood products	321
8	Paper products	322
9	Printing and related support activities	323
10	Coke and refined petroleum products	324
11	Chemicals and chemical products	325
12	Rubber and plastic products	326
13	Nonmetallic mineral products	327
14	Basic metals	331
15	Fabricated metal products	332
16	Machinery	333
17	Computer and electronic products	334
18	Electrical equipment, appliances, and components	335
19	Transportation equipment	336
20	Furniture and related products	337
21	Miscellaneous manufacturing	339
22	Wholesale trade	42
23	Retail trade	44
24	Transportation and storage	48
25	Accommodation and food services	72
26	Publishing	511
27	Telecommunications	517

28	Data processing, hosting, and related services	518
29	Other information	519
30	Finance and insurance	52
31	Real estate	53
32	Legal services	5411
33	Accounting, tax preparation, bookkeeping, and payroll services	5412
34	Architectural, engineering, and related services	5413
35	Specialized design services	5414
36	Computer systems design	5415
37	Management, scientific, and technical consulting services	5416
38	Scientific research and development services	5417
39	Advertising, public relations, and related services	5418
40	Other professional, scientific and technical services	5419
41	Management of companies and enterprises	55
42	Administrative and support service	56
43	Education	61
44	Health care	621
45	Social assistance	624
46	Arts, entertainment, and recreation	71
47	Other services	81

A.2 Crosswalk of NAICS and NACE Rev. 2

Industry	Description	NAICS	NACE Rev. 2
1	Food, beverages, tobacco	311-312	C10-C12
2	Textile, wearing apparel, leather and related products	313	C13-15
3	Wood products, paper products, printing and related support activities	321-323	C16-C18
4	Coke and refined petroleum products	324	C19
5	Chemicals and chemical products	325 (ex. 3254)	C20
6	Basic pharmaceutical products and pharmaceutical preparations	3254	C21
7	Rubber and plastic products, other non-metallic mineral products	326-327	C22-C23
8	Basic metals and fabricated metal products, except machinery and equipment	331-332	C24-C25
9	Computer, electronic and optical products	334, 339	C26
10	Electrical equipment	335	C27
11	Machinery and equipment n.e.c.	333	C28
12	Motor vehicles, trailers and semi-trailers, other transport equipment	336	C29-C30
13	Furniture and related products	337	C31-C33
14	Utilities, water supply and waster management	22	D, E
15	Construction	23	F
16	Wholesale trade	42	G46
17	Retail trade	44	G47
18	Transportation and storage	48	H
19	Accommodation and food service	72	I
20	Publishing activities	511, 519	J58-J60
21	Telecommunications	517	J61
22	Computer programming, data processing, hosting and related activities	518	J62-J63
23	Real estate	53	L68
24	Legal and accounting activities, activities of head offices, management consultancy activities,	5411-5416	M69-M71

	architectural and engineering activities,		
	technical testing and analysis		
25	Scientific research and development	5417	M72
26	Advertising, public relations, and related services	5418-5419	M73-M75
	Other professional, scientific, technical activities		
27	Administrative and support service	56	N

B Heterogeneous Effects with 1995 Local Share in IV

This section presents the second-stage estimates of heterogeneous effects of employment by subgroups using 1995 local share to calculate the IV $EUExposure_i$.

B.1 Broad Sector

	Agriculture	Manufacturing	Construction	Low-Skill Services	High-Skill Services
	(1)	(2)	(3)	(4)	(5)
$USExposure$	0.866*	-4.069*	1.671	-6.058***	1.890
	(0.489)	(2.321)	(1.162)	(1.712)	(1.496)
Observations	722	722	722	722	722

Table A.3: Effect of AI on Employment-to-Population Ratio by Broad Sector: 1995 Share in IV

Notes: The table reports the second stage estimates β from equation (5), with, using 1995 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in sectoral employment-to-population ratio in 2010-2021. Manufacturing includes manufacturing and mining. Low-skill services are wholesale trade, retail trade, utilities, transportation, information, real estate, administrative support and waste management, arts and entertainment, accommodation and food services, and other services. High-skill services are finance and insurance, professional scientific and technical services, management of companies and enterprises, education, health, and social assistance. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

B.2 Occupation

	Non-STEM	STEM	Low-Skill	Middle-Skill	High-Skill
	(1)	(2)	(3)	(4)	(5)
$USExposure$	-6.045**	-0.346	-0.394	-4.020	-1.285
	(2.821)	(1.019)	(1.239)	(2.491)	(1.750)
Observations	722	722	722	722	722

Table A.4: Effect of AI on Employment-to-Population Ratio by Occupation: 1995 Share in IV

Notes: The table reports the second stage estimates β from equation (5), using 1995 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in occupational (STEM vs. non-STEM occupations; low, middle, high-skill occupations) employment-to-population ratio in 2010-2021. The list of STEM occupations are from O*NET. High-skill occupations are management, business and financial occupations, professionals, and technicians. Middle-skill occupations are office and administration, sales, construction and extraction, mechanics and repairers, production, transportation and material moving. Low-skill occupations are personal services and agriculture occupations. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

B.3 Education

	Below High School	High School	Some College	College and Above
	(1)	(2)	(3)	(4)
$USExposure$	-5.527	-8.665**	-3.586	0.272
	(6.209)	(3.502)	(3.815)	(2.494)
Observations	722	722	722	722

Table A.5: Effect of AI on Employment-to-Population Ratio by Education: 1995 Share in IV

Notes: The table reports the second stage estimates β from equation (5), using 1995 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by education levels (below high school, high school, some college, college and above) in 2010-2021. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

B.4 Age and Gender

	16-25	26-35	36-45	46-55	56-65	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$USExposure$	-11.499**	-1.458	-6.657*	-6.620*	-0.826	-6.613*	-4.596
	(5.260)	(3.860)	(3.789)	(3.853)	(3.980)	(3.758)	(3.273)
Observations	722	722	722	722	722	722	722

Table A.6: Effect of AI on Employment-to-Population Ratio by Age and Gender: 1995 Share in IV

Notes: The table reports the second stage estimates β from equation (5), using 1995 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by 10-year age bins (16-25, 26-35, 36-45, 46-55, 56-65) or gender (male, female) in 2010-2021. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

C Heterogeneous Effects with 1990-1995 Average Local Share in IV

This section presents the second-stage estimates of heterogeneous effects of employment by subgroups using average 1990-1995 local share to calculate the IV $EUExposure_i$.

C.1 Broad Sector

	Agriculture	Manufacturing	Construction	Low-Skill Services	High-Skill Services
	(1)	(2)	(3)	(4)	(5)
$USExposure$	0.878*	-4.976*	1.260	-6.432***	0.895
	(0.453)	(2.605)	(1.126)	(1.743)	(1.484)
Observations	722	722	722	722	722

Table A.7: Effect of AI on Employment-to-Population Ratio by Broad Sector: 1990-1995 Average Share in IV

Notes: The table reports the second stage estimates β from equation (5), with, using 1990-1995 average local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in sectoral employment-to-population ratio in 2010-2021. Manufacturing includes manufacturing and mining. Low-skill services are wholesale trade, retail trade, utilities, transportation, information, real estate, administrative support and waste management, arts and entertainment, accommodation and food services, and other services. High-skill services are finance and insurance, professional scientific and technical services, management of companies and enterprises, education, health, and social assistance. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

C.2 Occupation

	Non-STEM	STEM	Low-Skill	Middle-Skill	High-Skill
	(1)	(2)	(3)	(4)	(5)
$USExposure$	-7.781***	-0.594	-0.559	-5.090**	-2.726
	(2.838)	(1.096)	(1.124)	(2.504)	(1.814)
Observations	722	722	722	722	722

Table A.8: Effect of AI on Employment-to-Population Ratio by Occupation: 1990-1995 Average Share in IV

Notes: The table reports the second stage estimates β from equation (5), using 1990-1995 average local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in occupational (STEM vs. non-STEM occupations; low, middle, high-skill occupations) employment-to-population ratio in 2010-2021. The list of STEM occupations are from O*NET. High-skill occupations are management, business and financial occupations, professionals, and technicians. Middle-skill occupations are office and administration, sales, construction and extraction, mechanics and repairers, production, transportation and material moving. Low-skill occupations are personal services and agriculture occupations. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

C.3 Education

	Below High School	High School	Some College	College and Above
	(1)	(2)	(3)	(4)
$USExposure$	-7.109	-10.546***	-5.820	-1.555
	(5.782)	(3.703)	(3.873)	(2.553)
Observations	722	722	722	722

Table A.9: Effect of AI on Employment-to-Population Ratio by Education: 1990-1995 Average Share in IV

Notes: The table reports the second stage estimates β from equation (5), using 1990-1995 average local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by education levels (below high school, high school, some college, college and above) in 2010-2021. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

C.4 Age and Gender

	16-25	26-35	36-45	46-55	56-65	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$USExposure$	-13.546***	-3.810	-7.546*	-9.109**	-4.921	-9.945***	-6.534**
	(5.441)	(3.609)	(3.967)	(3.972)	(3.898)	(4.099)	(3.309)
Observations	722	722	722	722	722	722	722

Table A.10: Effect of AI on Employment-to-Population Ratio by Age and Gender: 1990-1995 Average Share in IV

Notes: The table reports the second stage estimates β from equation (5), using 1990-1995 average local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by 10-year age bins (16-25, 26-35, 36-45, 46-55, 56-65) or gender (male, female) in 2010-2021. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

D Alternative Measure of Industry-Level AI Adoption

This section presents the second-stage estimates using the maximum over AI technologies for $AIAdopt_j^{US}$.

D.1 Overall employment-to-population ratio

	1990 Share 2010-2021 (1)	1995 Share 2010-2021 (2)	1990-1995 Average 2010-2021 (3)	1990 Share 1980-2010 (4)	1995 Share 1980-2010 (5)	1990-1995 Average 1980-2010 (6)
$USExposure$	-3.785**	-2.897*	-4.325***	1.117	-0.610	0.370
	(1.628)	(1.584)	(1.740)	(2.403)	(2.746)	(2.622)
Observations	722	722	722	722	722	722
R-squared	0.20	0.25	0.16	0.55	0.55	0.55
First-stage coefficient	0.149	0.165	0.166	0.149	0.165	0.166
First-stage F-statistic	33.2	29.2	30.7	33.2	29.2	30.7

Table A.11: Effect of AI on Employment-to-Population Ratio: Use Maximum for $AIAdoption_j^{US}$

Notes: The table reports the second stage estimates β from equation (5). The dependent variable is the change in the employment-to-population ratio in 1980-2010 (for columns (4)-(6)) and 2010-2021 (for columns (1)-(3)). Columns (1) and (4) use local employment share in 1990 to compute the IV $EUExposure_i$. Columns (2) and (5) use local employment share in 1995 to compute the IV $EUExposure_i$. Columns (3) and (6) use the average local employment share in 1990-1995 to compute the IV $EUExposure_i$. $USExposure_i$ is computed using the maximum over AI technologies for $AIAdopt_j^{US}$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

D.2 Broad Sector

	Agriculture	Manufacturing	Construction	Low-Skill Services	High-Skill Services
	(1)	(2)	(3)	(4)	(5)
$USExposure$	0.461*	-2.579*	0.527	-2.667**	0.473
	(0.243)	(1.472)	(0.551)	(1.048)	(0.827)
Observations	722	722	722	722	722

Table A.12: Effect of AI on Employment-to-Population Ratio by Broad Sector: Use Maximum for $AIAdoption_j^{US}$

Notes: The table reports the second stage estimates β from equation (5), with, using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in sectoral employment-to-population ratio in 2010-2021. Manufacturing includes manufacturing and mining. Low-skill services are wholesale trade, retail trade, utilities, transportation, information, real estate, administrative support and waste management, arts and entertainment, accommodation and food services, and other services. High-skill services are finance and insurance, professional scientific and technical services, management of companies and enterprises, education, health, and social assistance. $USExposure_i$ is computed using the maximum over AI technologies for $AIAdopt_j^{US}$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

D.3 Occupation

	Non-STEM	STEM	Low-Skill	Middle-Skill	High-Skill
	(1)	(2)	(3)	(4)	(5)
$USExposure$	-3.526**	-0.259	-0.116	-2.487*	-1.182
	(1.509)	(0.534)	(0.495)	(1.327)	(0.871)
Observations	722	722	722	722	722

Table A.13: Effect of AI on Employment-to-Population Ratio by Occupation: Use Maximum for $AIAdoption_j^{US}$

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in occupational (STEM vs. non-STEM occupations; low, middle, high-skill occupations) employment-to-population ratio in 2010-2021. The list of STEM occupations are from O*NET. High-skill occupations are management, business and financial occupations, professionals, and technicians. Middle-skill occupations are office and administration, sales, construction and extraction, mechanics and repairers, production, transportation and material moving. Low-skill occupations are personal services and agriculture occupations. $USExposure_i$ is computed using the maximum over AI technologies for $AIAdopt_j^{US}$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

D.4 Education

	Below High School	High School	Some College	College and Above
	(1)	(2)	(3)	(4)
$USExposure$	-1.309	-4.900**	-3.132	-0.277
	(2.971)	(2.050)	(1.903)	(1.209)
Observations	722	722	722	722
R-squared	0.25	0.26	0.25	0.24

Table A.14: Effect of AI on Employment-to-Population Ratio by Education: Use Maximum for $AIAdoption_j^{US}$

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by education levels (below high school, high school, some college, college and above) in 2010-2021. $USExposure_i$ is computed using the maximum over AI technologies for $AIAdopt_j^{US}$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

D.5 Age and Gender

	16-25	26-35	36-45	46-55	56-65	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$USExposure$	-5.804**	-1.493	-2.810	-3.904*	-4.016*	-4.631**	-2.812*
	(2.871)	(1.744)	(2.079)	(2.030)	(2.145)	(2.180)	(1.628)
Observations	722	722	722	722	722	722	722

Table A.15: Effect of AI on Employment-to-Population Ratio by Age and Gender: Use Maximum for $AIAdoption_j^{US}$

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by 10-year age bins (16-25, 26-35, 36-45, 46-55, 56-65) or gender (male, female) in 2010-2021. $USExposure_i$ is computed using the maximum over AI technologies for $AIAdopt_j^{US}$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

E Alternative End Year for the Long-Difference

This section presents the second-stage estimates of AI exposure on employment changes during 2010-2019 rather than 2010-2021.

E.1 Overall employment-to-population ratio

	1990 Share 2010-2021 (1)	1995 Share 2010-2021 (2)	1990-1995 Average 2010-2021 (3)	1990 Share 1980-2010 (4)	1995 Share 1980-2010 (5)	1990-1995 Average 1980-2010 (6)
$USExposure$	-7.060**	-6.450**	-8.240***	2.217	-1.199	0.716
	(3.088)	(2.918)	(3.129)	(4.739)	(5.402)	(5.075)
Observations	722	722	722	722	722	722
R-squared	0.37	0.38	0.35	0.56	0.55	0.55
First-stage coefficient	0.075	0.084	0.086	0.075	0.084	0.086
First-stage F-statistic	58.2	52.8	57.3	58.2	52.8	57.3

Table A.16: Effect of AI on Employment-to-Population Ratio: 2019 as End Year

Notes: The table reports the second stage estimates β from equation (5). The dependent variable is the change in the employment-to-population ratio in 1980-2010 (for columns (4)-(6)) and 2010-2019 (for columns (1)-(3)). Columns (1) and (4) use local employment share in 1990 to compute the IV $EUExposure_i$. Columns (2) and (5) use local employment share in 1995 to compute the IV $EUExposure_i$. Columns (3) and (6) use the average local employment share in 1990-1995 to compute the IV $EUExposure_i$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

E.2 Broad Sector

	Agriculture	Manufacturing	Construction	Low-Skill Services	High-Skill Services
	(1)	(2)	(3)	(4)	(5)
$USExposure$	1.160**	-5.771**	1.482	-4.773***	0.842
	(0.474)	(2.504)	(1.107)	(1.561)	(1.590)
Observations	722	722	722	722	722

Table A.17: Effect of AI on Employment-to-Population Ratio by Broad Sector: 2019 as End Year

Notes: The table reports the second stage estimates β from equation (5), with, using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in sectoral employment-to-population ratio in 2010-2019. Manufacturing includes manufacturing and mining. Low-skill services are wholesale trade, retail trade, utilities, transportation, information, real estate, administrative support and waste management, arts and entertainment, accommodation and food services, and other services. High-skill services are finance and insurance, professional scientific and technical services, management of companies and enterprises, education, health, and social assistance. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

E.3 Occupation

	Non-STEM	STEM	Low-Skill	Middle-Skill	High-Skill
	(1)	(2)	(3)	(4)	(5)
$USExposure$	-6.259**	-0.801	0.550	-5.114**	-2.496
	(2.909)	(0.808)	(1.098)	(2.347)	(1.529)
Observations	722	722	722	722	722

Table A.18: Effect of AI on Employment-to-Population Ratio by Occupation: 2019 as End Year

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in occupational (STEM vs. non-STEM occupations; low, middle, high-skill occupations) employment-to-population ratio in 2010-2019. The list of STEM occupations are from O*NET. High-skill occupations are management, business and financial occupations, professionals, and technicians. Middle-skill occupations are office and administration, sales, construction and extraction, mechanics and repairers, production, transportation and material moving. Low-skill occupations are personal services and agriculture occupations. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

E.4 Education

	Below High School (1)	High School (2)	Some College (3)	College and Above (4)
$USExposure$	-0.320	-7.005**	-7.569**	-2.139
	(5.776)	(3.416)	(3.726)	(2.413)
Observations	722	722	722	722

Table A.19: Effect of AI on Employment-to-Population Ratio by Education: 2019 as End Year

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by education levels (below high school, high school, some college, college and above) in 2010-2019. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

E.5 Age and Gender

	16-25 (1)	26-35 (2)	36-45 (3)	46-55 (4)	56-65 (5)	Male (6)	Female (7)
$USExposure$	-11.104**	-4.588	-3.180	-7.393*	-7.938**	-7.685**	-6.242**
	(5.448)	(3.017)	(3.977)	(4.131)	(3.914)	(3.859)	(3.171)
Observations	722	722	722	722	722	722	722

Table A.20: Effect of AI on Employment-to-Population Ratio by Age and Gender: 2019 as End Year

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by 10-year age bins (16-25, 26-35, 36-45, 46-55, 56-65) or gender (male, female) in 2010-2019. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

F Alternative Share for $USExposure$

This section presents the second-stage estimates using 2005 local employment share to compute $USExpsoure_i$.

F.1 Overall employment-to-population ratio

	1990 Share 2010-2021 (1)	1995 Share 2010-2021 (2)	1990-1995 Average 2010-2021 (3)	1990 Share 1980-2010 (4)	1995 Share 1980-2010 (5)	1990-1995 Average 1980-2010 (6)
$USExposure$	-7.109**	-5.160*	-7.840***	2.098	-1.086	0.671
	(2.899)	(2.712)	(2.946)	(4.479)	(4.892)	(4.751)
Observations	722	722	722	722	722	722
R-squared	0.27	0.30	0.25	0.55	0.55	0.55
First-stage coefficient	0.080	0.092	0.092	0.080	0.092	0.092
First-stage F-statistic	57.5	69.4	56.6	57.5	69.4	56.6

Table A.21: Effect of AI on Employment-to-Population Ratio: 2005 Share in $USExposure$

Notes: The table reports the second stage estimates β from equation (5). The dependent variable is the change in the employment-to-population ratio in 1980-2010 (for columns (4)-(6)) and 2010-2021 (for columns (1)-(3)). $USExposure$ uses 2005 local employment share. Columns (1) and (4) use local employment share in 1990 to compute the IV $EUExposure_i$. Columns (2) and (5) use local employment share in 1995 to compute the IV $EUExposure_i$. Columns (3) and (6) use the average local employment share in 1990-1995 to compute the IV $EUExposure_i$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

F.2 Broad Sector

	Agriculture	Manufacturing	Construction	Low-Skill Services	High-Skill Services
	(1)	(2)	(3)	(4)	(5)
$USExposure$	0.865**	-4.845*	0.991	-5.009**	0.889
	(0.429)	(2.629)	(1.030)	(2.028)	(1.573)
Observations	722	722	722	722	722

Table A.22: Effect of AI on Employment-to-Population Ratio by Broad Sector: 2005 Share in $USExposure$

Notes: The table reports the second stage estimates β from equation (5), with, using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in sectoral employment-to-population ratio in 2010-2021. $USExpsoure_i$ uses 2005 local employment share. Manufacturing includes manufacturing and mining. Low-skill services are wholesale trade, retail trade, utilities, transportation, information, real estate, administrative support and waste management, arts and entertainment, accommodation and food services, and other services. High-skill services are finance and insurance, professional scientific and technical services, management of companies and enterprises, education, health, and social assistance. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

F.3 Occupation

	Non-STEM	STEM	Low-Skill	Middle-Skill	High-Skill
	(1)	(2)	(3)	(4)	(5)
$USExposure$	-6.623**	-0.486	-0.217	-4.672*	-2.220
	(2.725)	(0.992)	(0.926)	(2.516)	(1.545)
Observations	722	722	722	722	722

Table A.23: Effect of AI on Employment-to-Population Ratio by Occupation: 2005 Share in $USExposure$

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in occupational (STEM vs. non-STEM occupations; low, middle, high-skill occupations) employment-to-population ratio in 2010-2021. $USExpsoure_i$ uses 2005 local employment share. The list of STEM occupations are from O*NET. High-skill occupations are management, business and financial occupations, professionals, and technicians. Middle-skill occupations are office and administration, sales, construction and extraction, mechanics and repairers, production, transportation and material moving. Low-skill occupations are personal services and agriculture occupations. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

F.4 Education

	Below High School	High School	Some College	College and Above
	(1)	(2)	(3)	(4)
$USExposure$	-2.459	-9.203**	-5.884	-0.520
	(5.484)	(3.920)	(3.693)	(2.260)
Observations	722	722	722	722

Table A.24: Effect of AI on Employment-to-Population Ratio by Education: 2005 Share in $USExposure$

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by education levels (below high school, high school, some college, college and above) in 2010-2021. $USExpsoure_i$ uses 2005 local employment share. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

F.5 Age and Gender

	16-25	26-35	36-45	46-55	56-65	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$USExposure$	-10.903*	-2.804	-5.278	-7.332**	-7.543**	-8.699**	-5.283*
	(5.653)	(3.220)	(3.599)	(3.336)	(3.843)	(4.134)	(2.795)
Observations	722	722	722	722	722	722	722

Table A.25: Effect of AI on Employment-to-Population Ratio by Age and Gender: 2005 Share in $USExposure$

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by 10-year age bins (16-25, 26-35, 36-45, 46-55, 56-65) or gender (male, female) in 2010-2021. $USExpsoure_i$ uses 2005 local employment share. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

PUBLICATIONS

The Labor Market Impact of Artificial Intelligence: Evidence from US Regions

Working Paper No. WP/2024/199