Artificial Intelligence and Jobs: Evidence from US Commuting Zones*

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Abstract

We study the effect of Artificial Intelligence (AI) on employment across US commuting zones over the period 2000-2020. A simple model shows that AI can automate jobs or complement workers, and illustrates how to estimate its effect by exploiting variation in a novel measure of local exposure to AI: job growth in AI-related professions built from detailed occupational data. Using a shift-share instrument that combines industry-level AI adoption with local industry employment, we estimate robust negative effects of AI exposure on employment across commuting zones and time. We find that AI's impact is different from other capital and technologies, and that it works through services more than manufacturing. Moreover, the employment effect is especially negative for low-skill and production workers, while it turns positive for workers at the top of the wage distribution and for those in STEM occupations. These results are consistent with the view that AI has contributed to the automation of jobs and to widen inequality.

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1 Introduction

Artificial Intelligence (AI) is often viewed as one of the most transformative and disruptive technologies of recent times. Thanks to improvements in machine learning techniques and the growing availability of vast amounts of digital data, the last two decades have witnessed a tremendous increase in the use of AI applications, which include web search engines, targeted advertising, recommendation systems, self-driving cars, generative or creative tools and chatbots. A pressing policy question is how these advances will affect labor markets and especially employment. On the one hand, intelligent tools promise to enhance human capabilities and create new demand for certain skills. For instance, AI can substitute existing capital (Bresnahan, 2021) and boost labor productivity (Brynjolfsson et al., 2023, McKinsey Global Institute, 2017). On the other hand, AI may surpass workers in decision-making tasks and make them redundant. In particular, a widespread concern is that AI-assisted machines can be used to automate more and more jobs (Acemoglu, 2022, Acemoglu and Johnson, 2023). Whether AI will complement or substitute workers is therefore an empirical question, for which there is still little systematic evidence.

In this paper, we study the effect of AI on employment across US Commuting Zones (CZs) over the period 2000-2020. Our analysis covers the years of the rise of the digital economy. All the major companies involved in big data collection were founded by the early 2000s: Amazon (1994), Google (1998), LinkedIn (2003), Facebook (2004), Twitter (2006). There is also evidence that the diffusion of AI technologies speeded up after 2010 (e.g., Taddy, 2018, Alekseeva et al., 2021, Acemoglu et al. 2022). Yet, precise metrics for quantifying AI adoption are at present lacking. To overcome this limitation, we recognize that using AI necessitates skills that only professionals in a narrow range of occupations possess. Taking advantage of a novel section of the O*NET database, we classify AI-related occupations as those whose job postings most frequently require specialized software used for machine learning and data analysis. Then, we detect AI adoption from the growth in the relative importance of these AI-related occupations.

A second challenge in identifying causal effects is that AI adoption might be correlated with other shocks hitting a CZ. For instance, Bonfiglioli et al. (2024) argue that positive shocks can trigger investment in automation and simultanously increase employment. To overcome this problem, we use a shift-share instrument that combines industry-level AI adoption for the US with pre-adoption CZ-level employment shares across industries. Then, guided by a simple model, we identify CZs more exposed to AI as those specialized in industries that experienced faster growth in AI-related occupations. With this data, we can estimate the effect of an increase in AI adoption in a CZ on local employment.

We first document some patterns about the change in the employment share of AI-related occupations across industries, CZs and time. This preliminary analysis confirms that AI-adoption varies significantly and that it has accelerated after 2010. We then estimate the effect of AI-adoption on employment using 2SLS stacked first-differences models for the decades 2000-2010 and 2010-2020. To control for other characteristics of a CZ that may influence AI adoption and employment, we include a wealth of fixed effects and covariates. We also control for other technologies such as ICT and industrial robots, and follow various approaches to account for underlying trends and unobserved shocks. In all cases, we estimate robust negative effects of AI exposure on employment across CZs and time. Interestingly, we find that the 2SLS coefficient is more strongly negative than its OLS counterpart, which is consistent with the view that contemporaneous shocks may induce an upward bias.

Finally, we dig deeper into the effect of AI adoption. We start by comparing AI with other shocks studied in the literature. Then, we explore the mechanisms through which the effect of AI unfolds. Differently from industrial robots, we find that AI adoption is concentrated in the service sector, but it exerts a negative effect on employment both in services and in manufacturing. Within manufacturing, we find that the negative effects are concentrated in sectors that use automation intensively. We also study how the employment response to AI varies by gender, age, skill and occupation. We show that the negative employment effects are largest for low-skill and production workers, while they turn strongly positive for workers in the top decile of the wage distribution and for occupations requiring a STEM degree. We also find that some of the negative effects affect workers in occupations that are not expected to use AI directly. These results suggest that AI adoption may have contributed to the automation of work and to increasing inequality.

This paper is related to the large and growing literature on the labor market effects of new technologies and especially of automation. Our paper shares similarities with Acemoglu and Restrepo (2020), who study the effects of industrial robots across US CZs. We differ in several respects. First, we focus on an entirely different technology, namely, the deployment of AI. Second, we use a novel approach to measuring AI adoption, with a number of important advantages. As a proxy for automation, Acemoglu and Restrepo (2020) follow Graetz and Michaels (2018) in using data from the International Federation of Robotics (IFR), which are available for 19 broad sectors only. Our variable, built from occupations, has instead a much finer variation (188 industries). Moreover, the IFR data are not available at the CZ level, which makes it impossible to test the mechanisms through which US-level exposure operates across localities. In terms of results, we find evidence that AI adoption, similarly to robots, displaces workers. However, we also find that, unlike robots, AI adoption operates mostly through the service sector.

A recent strand of the literature studies the evolution of occupations that are "exposed" to AI. Various measures have been proposed: the AI occupational impact measure by Felten et al. (2018, 2019, 2021); the Suitability for Machine Learning (SML) index by Brynjolfsson et al. (2018, 2019); and Webb's (2020) AI Exposure score. Combining these measures with information from job postings, Acemoglu et al. (2022) find that, consistently with our approach to measuring AI adoption, US establishments with AI-suitable tasks increase their demand for AI-related skills and reduce their overall hiring. Albanesi et al. (2023) study instead the evolution of occupations exposed to AI in a panel of European countries. None of these papers detect a negative relationship between AI exposure and overall employment. This could be because, as emphasized in Pizzinelli et al. (2023), existing classifications identify occupations where AI is likely to be used, not necessarily those that compete with it. On the one hand, AI can sometimes augment rather than substitute workers. For instance, Brynjolfsson et al. (2023) show that generative AI has increased the productivity of customer support agents. On the other hand, we provide evidence that AI also displaces workers with low AI exposure scores, consistent with the view that AI promotes automation in manufacturing.

More recently, Eloundou et al. (2023) study the occupational exposure to large language models (LLM), such as Generative Pretrained Transformers (GPTs). They show that around 80% of the US workforce could have at least 10% of their work tasks affected by the introduction of LLMs. They also find that LLM exposure is lower in manufaturing and span all wage levels. Yet, Acemoglu (2024) argues that the macroeconomic impact of LLMs is likely to be limited in the near future. We differ from all these papers by being agnostic on who should be affected by these new technologies and letting the data detect their effect on employment. Moreover, it is important to stress that our working definition of AI, namely algorithms applied to big data, predates the development of LLMs and encompasses many more applications.

Our paper is the first to identify negative effects of AI adoption on total employment across US CZs. A distinctive feature of our findings is that they capture the overall net impact across occupations and industries. In doing so, they complement recent studies showing that AI has started to displace workers in a number of specific jobs. For instance, Hui, Reshef and Zhou (2023) document a negative impact of generative AI on the employment of free-lancers in an online labor market; Grennan and Michaely (2020) find negative effects for financial analysts;

Armour et al. (2022) find evidence of lawyers being displaced by AI; and Abis and Veldkamp (2024) estimate that changes in data intensity led to a 5% decline in the labor share within the investment management industry. We are also among the first to show that AI adoption increases the demand for top earners. While high-skill jobs are often found to be more exposed to AI, our results suggest that workers at the very top of the wage distribution and those in STEM occupations benefit from these technologies.

Finally, while most of the literature focuses on workers potentially affected by AI, a few recent papers consider instead the jobs that are involved in the creation of AI. Hanson (2022) selects AI-related occupations from keywords such as "computer", "data" or "software" in job titles, while we use specific software requirements included in job postings. Yet, he uses his classification to study a very different question, namely, the determinants of regional specialization in AI-related activities. Alekseeva et al. (2021) provide instead more descriptive evidence on the demand for AI skills in the US across occupations and industries. Babina et al. (2023, 2024) measure firm-level AI investment from worker resumes and job postings. They find that AI-investing firms benefit from increased product innovation but also experience a significant reorganization of their workforce.

The remainder of the paper is organized as follows. Section 2 presents a simple model of the effects of AI on employment to guide the empirical analysis. Section 3 describes the data and the main variables. Section 4 discusses the empirical specification and the identification strategy. Section 5 presents some stylized facts and preliminary evidence. Section 6 contains the main empirical results. Section 7 considers possible threats to identification. Section 8 compares the results to other technologies and explores the adjustment mechanisms. Section 9 concludes.

2 AI and Local Labor Demand

This section presents a simple partial-equilibrium, task-based, model of the effects of AI on the demand for labor across CZs similar to Acemoglu and Restrepo (2020). The role of the model is to show that AI can automate jobs or complement workers, to illustrate how to estimate its effect using variation in local exposure to AI and to clarify how to measure it. The analysis is kept deliberately simple to make the link with the empirical section as transparent as possible.

2.1 A Simple Model of AI and Employment

The economy consists of a set C of commuting zones. Each CZ $c \in C$ has identical preferences over a set I of industries. For simplicity, trade is free across CZs and we denote with p_i the price of the output of industry $i \in I$. Each industry produces output by combining a specific capital with a continuum of tasks indexed by $z \in [0, 1]$, each of which can be performed by AI or labor. The production function for industry i in CZ c is:

$$y_{ci} = \varphi_{ci} \left[\exp \left(\int_0^1 \ln x_{ci}(z) \mathrm{d}z \right) \right]^{\alpha} K_{ci}^{1-\alpha}, \tag{1}$$

where $x_{ci}(z)$ is the output of task z and K_{ci} is CZ c's endowment of the specific capital used in industry i. Differences in the endowment of specific capital generate differences in the industrial composition of employment across CZs.

Denote with η_c and w_c the cost of AI and the wage in CZ c. We assume that $\eta_c < w_c$. We identify the capabilities of AI with the set of tasks it can perform. Workers can perform all tasks. However, since AI is cheaper than labor, workers will not be employed in tasks that can be performed by AI. Assuming that AI can be used in the set of tasks $[0, \kappa_{ic}]$, we have $x_{ci}(z) = A_{ci}/\kappa_{ci}$, where A_{ci} is the AI input used in CZ c in industry i. Labor performs the remaining tasks $[\kappa_{ic}, 1]$, with $x_{ci}(z) = L_{ci}/(1 - \kappa_{ci})$, where L_{ci} is employment in CZ c in industry i. Substituting these quantities into (1), industry output becomes:

$$y_{ci} = \varphi_{ci} \left(\frac{A_{ci}}{\kappa_{ci}} \right)^{\alpha \kappa_{ci}} \left(\frac{L_{ci}}{1 - \kappa_{ci}} \right)^{\alpha(1-\kappa_{ci})} K_{ci}^{1-\alpha}. \tag{2}$$

The demand for AI services and for labor from industry i in CZ c are:

$$\eta_c A_{ci} = \alpha \kappa_{ci} p_i y_{ci}, \tag{3}$$

and

$$w_c L_{ci} = \alpha \left(1 - \kappa_{ci} \right) p_i y_{ci}. \tag{4}$$

Substituting (3)-(4) into (2) yields:

$$y_{ci} = (\varphi_{ci} \alpha)^{\frac{1}{1-\alpha}} p_i^{\frac{\alpha}{1-\alpha}} \left(\frac{1}{\eta_c} \right)^{\frac{\alpha \kappa_{ci}}{1-\alpha}} \left(\frac{1}{w_c} \right)^{\frac{\alpha(1-\kappa_{ci})}{1-\alpha}} K_{ci}.$$

Recall that AI capabilities are defined by the AI share of tasks, κ_{ci}. Accordingly, we measure the arrival of AI with the increase in this share, $d\kappa_{ci} > 0$, starting from an initial equilibrium where $\kappa_{ci} \approx 0$. This seems a natural assumption to study the adoption of an entirely new technology. We also allow the deployment of AI to raise the productivity of existing factors. Hence, we also assume that $d\varphi_{ci}/d\kappa_{ci} = \gamma \geq 0$. This assumption captures phenomena such as the use of AI as a general purpose technology complementing existing factors or the creation of new tasks. These are mechanisms that have been emphasized in part of the literature. In this way, we model in a simple but flexible way the possibility for AI to substitute or augment labor.[1]

Since AI services are cheaper than labor and may raise productivity, industry output necessarily expands with $d\kappa_{ci} > 0$:

$$d \ln y_{ci} = \left(\frac{\alpha \ln \pi_c}{1-\alpha} + \frac{\gamma}{1-\alpha} \right) d\kappa_{ci}, \tag{5}$$

where $\pi_c \equiv w_c/\eta_c > 1$ is the cost saving of AI relative to labor.

The partial-equilibrium effects on labor demand follow from differentiating (4):

$$d \ln(w_c L_{ci}) = -\frac{d\kappa_{ci}}{1-\kappa_{ci}} + d \ln(p_i y_{ci}). \tag{6}$$

This equation illustrates the two key possible effects of AI. The first term captures the negative effect on labor demand when AI displaces workers in some tasks previously performed by humans. The second term is the increase in labor demand when AI raises productivity and hence total revenue of the industry. Eq. (6) clarifies that the displacement effect of AI is the only one responsible for any negative impact on labor demand.

Aggregating the industry-level implications yields the effect on local labor demand:

$$d \ln(w_c L_c) = -\sum_{i \in I} \frac{L_{ci}}{L_c} \frac{d\kappa_{ci}}{1-\kappa_{ci}} + \sum_{i \in I} \frac{L_{ci}}{L_c} d \ln(p_i y_{ci}). \tag{7}$$

2.2 AI and Local Labor Demand: Empirical Specification

Equations (5) and (7) summarize the effects of advances in AI on labor demand, through the displacement of workers and the increase in productivity. In order to derive an estimation equation for employment in the most transparent way, we now make some additional simplifying assumptions. First, we assume that the supply of labor is fully elastic and set the wage

[1] Note that in a Cobb-Douglas production function, factor-augmenting technological progress is always Hicks neutral. Hence, labor-augmenting AI is isomorphic to γ. Alternatively, one could identify technological progress in AI with a decrease in its cost, η_c, and assume $d\kappa_{ci}/d\eta_c < 0$. While it would deliver qualitatively similar results, this approach is somewhat less suited for studying the arrival of AI starting from $\kappa_{ci} \approx 0$.

as the numeraire, $w_c = 1$. For instance, this would be the case if labor is freely mobile across CZs or if there is a binding wage floor. We discuss later what happens when labor supply is not fully elastic.

Second, we assume that AI services are also in fully elastic supply, with $\eta_c = \eta$. In particular, the AI input is a bundle of intermediate inputs I_{ic} (such as computing power and data) and AI-related workers H_{ci} (e.g., programmers and data scientists), which are combined according to the following production function:

$$A_{ci} = \left(\frac{I_{ic}}{\iota_{ci}}\right)^{\iota_{ci}} \left(\frac{H_{ci}}{1-\iota_{ci}}\right)^{1-\iota_{ci}}.$$

In analogy with (2), we can interpret ι_{ci} as the share of tasks performed by algorithms and computers as opposed to programmers in the production of AI, and allow for the possibility that AI also expands the range of tasks assigned to software, $d\iota_{ci}/dA_{ci} > 0$. That is, algorithms may write new and more powerful algorithms.

Under these assumptions, we can detect technological progress in AI from the increase in AI-related workers. To see this, start from the first-order condition for H_{ci}:

$$H_{ci} = (1-\iota_{ci})\,\frac{\eta}{w_H} A_{ci},$$

where w_H is the wage of AI-related workers, which we also take as fixed. Differentiating this condition yields:

$$dH_{ci} = \frac{\eta}{w_H}\left(1 - \iota_{ci} - A_{ci}\frac{d\iota_{ci}}{dA_{ci}}\right) dA_{ci}. \tag{8}$$

This equation shows that employment of AI-related workers increases with AI adoption but falls with the automation of AI itself. However, for $\kappa_{ci} \approx 0$, we also have $A_{ci} \approx 0$. Hence, starting from an initial equilibrium with no AI, (8) simplifies to:

$$dH_{ci} = \frac{1}{\nu} dA_{ci} > 0, \tag{9}$$

where $\nu^{-1} \equiv (1-\iota)\,\eta/w_H$ and ι corresponds to $A_{ci} \approx 0$. Equation (9) shows that, starting from zero, AI adoption must necessarily increase the demand for AI-related workers.

Next, differentiating (3) and using (9) yields:

$$d\kappa_{ci} = \frac{1}{\pi}\frac{dA_{ci}}{L_{ci}} = \frac{\nu}{\pi}\frac{dH_{ci}}{L_{ci}}. \tag{10}$$

This equation shows that technological progress in AI in industry i can be measured by the increase in AI employment over raw labor that it generates.

Finally, using $\kappa_{ci} \approx 0$, $w_c = 1$, (5) and (10) into (7) yields:

$$\frac{dL_c}{L_c} = \frac{\nu}{\pi}\left(\frac{\alpha \ln \pi}{1-\alpha} + \frac{\gamma}{1-\alpha} - 1\right)\sum_{i\in I}\frac{L_{ci}}{L_c}\frac{dH_{ci}}{L_{ci}}. \tag{11}$$

Equation (11) shows that the effect of AI can be estimated by regressing changes in employment on changes in AI-related jobs at the CZ level. However, the main concern is that shocks to AI employment in a CZ might be correlated with other local shocks that have a direct effect on employment. For instance, an increase in local demand may trigger AI adoption and simultaneously raise labor demand. Ideally, we want to use changes in AI technology that are exogenous to other labor market shocks in CZ c. To do so, we adopt a classic Bartik design and instrument dH_{ci}/L_{ci} with its national counterpart, dH_i/L_i, where dH_i is the change in AI-related jobs in industry i in the US. We defer a detailed discussion of the identification strategy and the possible threats to identification to Section 4.

Before proceeding, we pause to briefly discuss what happens when labor supply is not fully elastic. In this case, employment in CZ c must satisfy the market-clearing condition $\sum_{i\in I} L_{ci} = L_c$. Adding a labor supply equation of the form $L_c = \eta w_c^{\phi}$, it is possible to solve simultaneously for L_c and w_c. An increase (decrease) in labor demand will then translate into an increase (decrease) in both employment and wages.[2]

3 Data and Variables

Our sample consists of 722 CZs covering the entire mainland of the US.[3] The time period of our analysis spans the last two decades, given that the surge of AI is a recent phenomenon. Specifically, we observe each CZ at the endpoints of each decade, i.e., in the years 2000, 2010 and 2020. We now present the data sources and explain the construction of the main variables. Descriptive statistics are provided in Appendix Tables C1 and C2.

[2] One could also wonder what would happen if the price of output, p_i, was determined at the CZ level, for instance $p_{ci} = By_{ci}^{-1/\epsilon}$ as in an Armington model with a price elasticity of demand equal to ϵ. In this case, prices would fall after an increase in output thereby weakening the productivity effect. Yet, this general-equilibrium effect would not change qualitatively the results derived in this section.

[3] CZs are clusters of counties with strong commuting ties within them and weak commuting ties among them (Tolbert and Sizer, 1996). As such, CZs may approximate local labor markets. The CZs in our sample are the same as in Autor and Dorn (2013), Autor, Dorn and Hanson (2013) and Acemoglu and Restrepo (2020).

3.1 Employment, Population and Other Characteristics of CZs

For each CZ, we measure employment, population and other characteristics using micro-level data from two sources: the decennial Census for the year 2000 and the American Community Survey (ACS) for the years 2010 and 2020. Both data sources are extracted from IPUMS (Ruggles et al., 2023).[4] To increase sample size, we follow Autor, Dorn and Hanson (2013) and Acemoglu and Restrepo (2020) in measuring 2010 variables using pooled five-year ACS data for 2011 (2007-2011). Similarly, we measure 2020 variables from pooled five-year ACS data for 2021 (2017-2021). In Appendix A.1, we show that the results are unchanged if 2020 variables are measured using pooled three-year ACS data for 2019 (2017-2019) to exclude the early phase of the Covid-19 pandemic.

We construct total CZ-level employment using sample weights, considering individuals aged 16+ who are not unpaid family workers, do not reside in institutional group quarters and have reported being employed over the previous year (Autor and Dorn, 2013). In later sections, we consider disaggregations of employment along various dimensions. Specifically, we distinguish between employment in private and public sectors as well as in primary, secondary and tertiary industries. We also disaggregate employment between high- and low-skill workers, production and non-production workers, male and female workers, occupations at different points of the wage distribution, STEM and non-STEM occupations, and by age.[5] Using data from the Census and the ACS, we also construct CZ-level population and numerous proxies for initial demographic and industrial compositions (details in Section 4).

3.2 Measuring AI Adoption within CZs

Precise metrics for quantifying AI adoption are presently lacking. To make progress, we build a novel proxy for AI adoption in each CZ by exploiting a specific feature of AI technologies. Adopting these technologies demands a wide spectrum of specialized software, which is es-

[4]The Census and the ACS are 5% and 1% samples, respectively, of the US population, and are representative at the level of micro-regions known as Public Use Microdata Areas (PUMAs). We map PUMAs to CZs using a crosswalk developed by Autor and Dorn (2013).

[5]The public sector comprises transportation, communication, other public utilities, public administration and armed forces. The private sector is made up of all non-public sector industries. The primary sector comprises agriculture, forestry, fisheries and mining. The secondary sector comprises construction and manufacturing. The tertiary sector consists of the public sector as well as wholesale trade, retail trade, finance, insurance, real estate, business and repair services, personal services, entertainment and recreation services, professional and related services. High-skill workers are those who have completed at least a bachelor's degree, low-skill workers those who have completed less than a bachelor's degree. Production occupations comprise construction, extraction, installation, maintenance, repair and other production occupations. STEM (Science, Technology, Engineering and Math) occupations are those identified by Hanson and Slaughter (2018).

sential for a firm to: execute existing machine learning algorithms, which extract patterns from large datasets by exploiting results from statistics and data science; combine and adapt these algorithms to solve complex problems specific to the needs of the firm; generate, update and assemble the input datasets in real time; train the algorithms and govern their learning process. In turn, operating this specialized software necessitates a distinct set of skills, which are primarily possessed by professionals engaged in a narrow range of occupations pertaining to the domains of computer science, mathematics, statistics and operations research.[6]

Our proxy for AI adoption leverages the specific requirement of specialized software and advanced technical skills that is typical of AI. In a nutshell, we first identify a set of AI-related occupations using data on the software knowledge required to workers in each job. Then, following the theoretical model, we proxy for AI adoption in a CZ using the increase in the relative importance of AI-related occupations in that locality.[7]

To identify AI-related occupations, we take advantage of a novel section of the O*NET database called "Hot Technologies". The latter reports the software requirements that are most frequently included in all current employer job postings in the US. The list of software includes 157 titles, spanning from software with general applications like Microsoft Excel, to advanced programming languages like Python and C++. With the help of computer scientists, we narrow down the list to 54 software that are normally used for data collection and generation; for execution and adaptation of machine learning algorithms; and to feed these algorithms with large (structured and unstructured) datasets. The list of software is reported in Appendix Table C3.

Using the "Hot Technology" section of O*NET, we identify occupations for which each software is "in demand". These are occupations whose job postings typically require the knowledge of a given software. This yields 82 occupations, defined according to the 2018 version of the Standard Occupational Classification (SOC). We refine the list by applying two sequential filters. First, we restrict to occupations for which at least two software are "in demand". This excludes 21 occupations that use a single software in their daily activities. Examples are "Special Effects Artists and Animators", who only use Python, or "Commercial and Industrial Designers", who only use JavaScript. Second, we select occupations that require skills falling within the typical domains of AI. To this purpose, we combine occupational

[6] In line with this view, Acemoglu et al. (2022) document a recent surge in AI-related hiring in the US, and show that establishments whose task structures enable the use of AI have substantially increased their postings of vacancies requiring AI-related skills such as machine learning.

[7] Babina et al. (2023, 2024) follow a similar approach in measuring firm-level AI investment from employee CVs and job postings. Using occupations has the advantage of a broader availablility and applicability. For instance, Babina et al. (2023, 2024) study a sample of around one thousand firms only.

definitions from the SOC with the official crosswalk between the SOC and the Classification of Instructional Programs (CIP), as provided by the National Center for Education Statistics of the US Department of Education. Using this information, we identify occupations with non administrative, supportive or educational roles, whose required skills are provided by academic programs in the following fields: computer and information sciences and support services, mathematics and statistics, and operations research.[8] This filter eliminates occupations like "Economists". While both Python and SQL are "in demand" for this job, the main skills required at this occupation are provided by academic programs in social sciences according to the SOC-CIP crosswalk.

The final list of AI-related occupations comprises 19 titles, which are listed in Table 1. Using correspondence tables from the US Bureau of Labor Statistics, we track these occupations back in time across the revisions of the SOC occurred over the sample period. Then, we use information on each worker's SOC occupation (available in the Census and in the ACS) to match our consistent set of AI-related occupations with the micro-level data. With this information, we measure employment in AI-related occupations in each CZ and year. Finally, following (11), we construct our proxy for AI adoption as follows:

$$AIado_{ct} = \frac{L^{AI}_{c\tau_1} - L^{AI}_{c\tau_0}}{L_{c2000}}, \tag{12}$$

where $L^{AI}_{c\tau_0}$ and $L^{AI}_{c\tau_1}$ denote employment in AI-related occupations in CZ c in the first year (τ_0) and last year (τ_1) of each decade t, while L_{c2000} is total employment (across all occupations) in CZ c in 2000. Hence, for each CZ, $AIado_{ct}$ measures the decadal change in the relative importance of AI-related occupations, as proxied by the employment of these professions relative to initial employment in the CZ.

Before proceeding, we pause to discuss two potential limitations of this variable. First, not all employment in AI-related occupations needs to be devoted to AI adoption. Second, employment growth in AI-related occupations may reflect a wider usage of ICT independently of AI. We believe both issues to have a modest influence on $AIado_{ct}$. On the one hand, the list of AI-related occupations is obtained starting from a restricted set of specialized software, and is further narrowed down by our sequential filters. Second, because ICT have rapidly spread all over the US during previous decades, the scope for further diffusion of ICT over the sample period is likely to be limited.

Nevertheless, we specifically tackle these issues in the empirical analysis. In Appendix

[8]The corresponding CIP codes among the occupations that pass the first filter are: 110101, 110201, 110701, 111006, 143701, 270503 and 520302.

Table 1: AI-Related Occupations

Computer and Information Research Scientists	Mathematicians
Computer Network Architects	Network and Computer Systems Administrators
Computer Network Support Specialists	Operations Research Analysts
Computer Occupations, All Other	Software Developers
Computer Programmers	Software Quality Assurance Analysts and Testers
Computer Systems Analysts	Statistical Assistants
Computer User Support Specialists	Statisticians
Data Scientists	Web and Digital Interface Designers
Database Administrators	Web Developers
Database Architects	

Occupations are classified according to the 6-digit level of the 2018 Standard Occupational Classification.

A.3, we construct $AIado_{ct}$ using a single AI-related occupation, "Data Scientists", whose tasks are limited to the typical domains of AI.[9] The resulting indicator is certainly too narrow to capture the actual size of AI adoption in the US, but the patterns it delivers are identical to those of our broader proxy, both qualitatively and quantitatively. We also show that the results are unchanged when $AIado_{ct}$ is constructed using an alternative classification of AI-related occupations (proposed by Hanson, 2022) based on different selection criteria.[10] Finally, in Section 8, we control for various proxies for ICT exposure. These variables do not affect the main results and, interestingly, they tend to have smaller, and sometimes opposite, effects on employment compared to AI.

4 Empirical Specification and Identification Strategy

In this section, we present the empirical specification and illustrate our identification strategy.

[9] According to the definition provided in the SOC, Data Scientists "develop and implement a set of techniques or analytics applications to transform raw data into meaningful information using data-oriented programming languages and visualization software. Apply data mining, data modeling, natural language processing, and machine learning to extract and analyze information from large structured and unstructured datasets. Visualize, interpret, and report data findings. May create dynamic data reports".

[10] Hanson (2022) defines as AI-related those STEM occupations that are not involved in administrative and supportive roles, are not tied to scientific disciplines that are far removed from AI, and whose associated Census-defined job titles contain at least one term from the group {designer/design, researcher/research, scientist, or statistician/statistical} and one term from the group {computer, data, software}. These criteria deliver a list of five AI-related occupations: "Computer Scientists and Systems Analysts", "Computer Software Engineers", "Network Systems and Data Communication Analysts", "Statisticians" and "Computer Hardware Engineers".

4.1 Regression Equation

Guided by the theoretical model (eq. 11), our empirical analysis relates changes in employment to AI adoption across CZs and time. To this purpose, similarly to Autor, Dorn and Hanson (2013) and Acemoglu and Restrepo (2020), we estimate specifications of the following form:

$$\Delta\left(L/P\right)_{cdt} = \alpha_d + \alpha_t + \beta \cdot AIado_{cdt} + \mathbf{X}^{'}_{cdt} \cdot \boldsymbol{\gamma} + \varepsilon_{cdt}, \tag{13}$$

where c indexes a CZ, d denotes the Census Division to which the CZ belongs, t stands for time, and ε_{cdt} is an error term.[11] We estimate (13) by stacking two first-differences corresponding to changes over 2000-2010 and 2010-2020, the two decades spanned by our sample. The main outcome variable, $\Delta\left(L/P\right)_{cdt}$, is the change in the employment-to-population ratio of CZ c over decade t, analogously to Acemoglu and Restrepo (2020).[12] To shed light on the mechanisms, we also consider alternative outcomes, such as unemployment and non-participation, and we disaggregate employment across different industries. To study heterogeneity, we further split employment across occupations, skill levels, genders and age groups. The main explanatory variable, $AIado_{cdt}$, is the proxy for the adoption of AI technologies in CZ c over decade t introduced in Section 3. Given the definition of $AIado_{cdt}$ in (12), eq. (13) is a changes-on-changes regression.

The specification in (13) includes a wealth of fixed effects and covariates, which control for general-equilibrium effects and other characteristics of the CZ that may influence AI adoption and employment. We control for Census Division fixed effects, α_d, to absorb heterogeneous trends in labor market conditions across groups of contiguous states. We also include decade fixed effects, α_t, to soak up time-varying shocks hitting all CZs simultaneously. Moreover, we control for a large set of covariates, included in the vector $\mathbf{X}_{cdt}$. The latter contains two types of variables. First, it includes several proxies for initial characteristics of each CZ: (i) size, measured by log population; (ii) demographic composition, proxied by the population shares of female, college-educated, white and old individuals (aged 65+); and (iii) composition of economic activities, captured by the share of manufacturing in total employment, the share of females in manufacturing employment, the share of light manufacturing in total manufac-

[11] Census Divisions are defined by the US Census Bureau and subdivide the country into nine groups of states: New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific.

[12] While the model yields sharp predictions for non-AI employment, we prefer to focus on total employment to be more general and conservative, also given that AI employment is still small as shown in Section 5. In Appendix A.3, we show that the results are unchanged if we use working-age population (individuals aged 16-64) or labor force as the denominator of the outcome variable in place of overall population. We also find similar patterns when using the log change in employment as the dependent variable.

turing employment, and the employment share of workers in routine-intensive occupations.[13] These variables account for heterogeneous trends across CZs characterized by different initial demographic and industrial structures. Second, the vector $\mathbf{X}_{cdt}$ includes proxies for two main labor market shocks considered in the recent literature: the change in import competition from China (Autor, Dorn and Hanson, 2013) and exposure to industrial robots (Acemoglu and Restrepo, 2020). Both variables are measured in each decade.[14]

The coefficient of interest is β. Our empirical design implies that this coefficient measures the relative difference in the growth of employment relative to population across CZs that have similar initial conditions, face similar trade and automation shocks, but experience different rates of AI adoption over time. Two final considerations are in order. First, by exploiting differences across CZs, our approach isolates the local labor market effects of AI adoption and cannot be used to study US-level general-equilibrium effects. Hence, our results capture variation in employment within AI-adopting firms, but also local spillover effects on other firms that compete or buy services in the same CZ.[15] Second, although the rich set of controls and fixed effects absorb most observable confounders, the OLS estimate of β need not have a causal interpretation, due to unobservable factors that may simultaneously affect AI adoption and employment. We now turn to discussing the key identification concerns and illustrate our strategy to estimate causal effects.

4.2 Identification Strategy

The variation in $AIado_{cdt}$ could reflect CZ-specific unobservables that also influence employment. In particular, demand shocks in a CZ may lead firms to hire more workers and use more AI technologies, inducing a spurious positive correlation between $AIado_{cdt}$ and $\Delta\,(L/P)_{cdt}$. To account for this issue, we construct an instrument that is meant to isolate variation in $AIado_{cdt}$ not due to demand shocks within CZs. Following a long tradition initiated by Bartik (1991) and Blanchard and Katz (1992), and more recently extended to the study of the

[13] Light manufacturing is made up of textile mill products, apparel and other finished textile products, paper and allied products, printing, publishing and allied industries. The employment share of routine-intensive occupations is defined as the share of hours worked in occupations with routine-task intensity at the top tercile of the distribution (Autor and Dorn, 2013) and is constructed using data from the 2000 Census.

[14] Import competition from China is a Bartik measure of changes in imports from China per worker across industries, as in Autor, Dorn and Hanson (2013). Exposure to industrial robots is a Bartik measure of changes in robot density (the number of installed robots per worker) and is constructed as in Acemoglu and Restrepo (2020) using data on robot installments from the IFR.

[15] Both Acemoglu et al. (2022) and Babina et al. (2024) emphasize the effects of AI investment within US firms, establishments and industries. However, our analysis will also find local spillover effects on non-adopting sectors.

effects of Chinese import competition (Autor, Dorn and Hanson, 2013) and robot adoption (Acemoglu and Restrepo, 2020), we use a shift-share (Bartik) instrument, which combines nation-wide industry *shifts* with local industry *shares*. The instrument is constructed as follows:

$$AIexp_{cdt} = \sum_{i=1}^{I} \lambda_{cdi1980} \times \left(\frac{L^{AI}_{i\tau_1} - L^{AI}_{i\tau_0}}{L_{i2000}} \right), \tag{14}$$

where $L^{AI}_{i\tau_0}$ and $L^{AI}_{i\tau_1}$ denote employment of AI-related occupations in industry i, at the national level, in the first year (τ_0) and last year (τ_1) of decade t, respectively; L_{i2000} is total employment in industry i, at the US level, in 2000; and $\lambda_{cdi1980} \equiv \frac{L_{cdi1980}}{L_{cd1980}}$ is industry i's share in total employment of CZ c in 1980.

The intuition behind this instrument is the following. As technological progress lowers the cost of AI and/or increases its productivity, AI adoption grows especially in industries whose activities are more amenable to the use of these technologies. These industry-level AI adoption shifts have asymmetric effects across CZs, depending on historical differences in their industrial specialization, as captured by the employment shares $\lambda_{cdi1980}$. Accordingly, the instrument isolates the variation in AI adoption that stems from the combination of aggregate industry-level developments in AI technologies with pre-determined differences in local industrial compositions. At the same time, the instrument purges away the variation in AI adoption that is due to CZ-specific shocks occurring over the sample period, which may have independent effects on the local labor markets.[16] In the baseline version of the instrument, we measure the employment shares in 1980, i.e., 20 years before the beginning of the sample period. Because AI was largely inexistent at that time, this choice mitigates the concern that the industrial composition of a CZ might have been influenced by the anticipation of AI developments in future decades. We keep the employment shares constant to avoid endogenous and serially correlated changes in $AIexp_{cdt}$ in the context of our stacked first-differences specification.

To compute the industry-level shifts, we use the micro-level data from the Census and the ACS, which contain information on each worker's industry of employment. The employment shares are computed using data from the County Business Patterns, which we slightly aggregate to match the industry detail of the micro-level data. The final sample includes 188 NAICS industries, mostly at the 3- or 4-digit level, spanning all sectors of the economy. It is worth noting that our instrument exploits significantly larger cross-industry variation than the typical Bartik measures used in the recent automation literature. For instance, the

[16] See Autor, Dorn and Hanson (2013) and Acemoglu and Restrepo (2020) for further discussion on the variation exploited by similar shift-share instruments at the CZ level.

proxies for exposure to industrial robots based on data from the IFR aggregate industry-level shifts for 19 broad sectors.

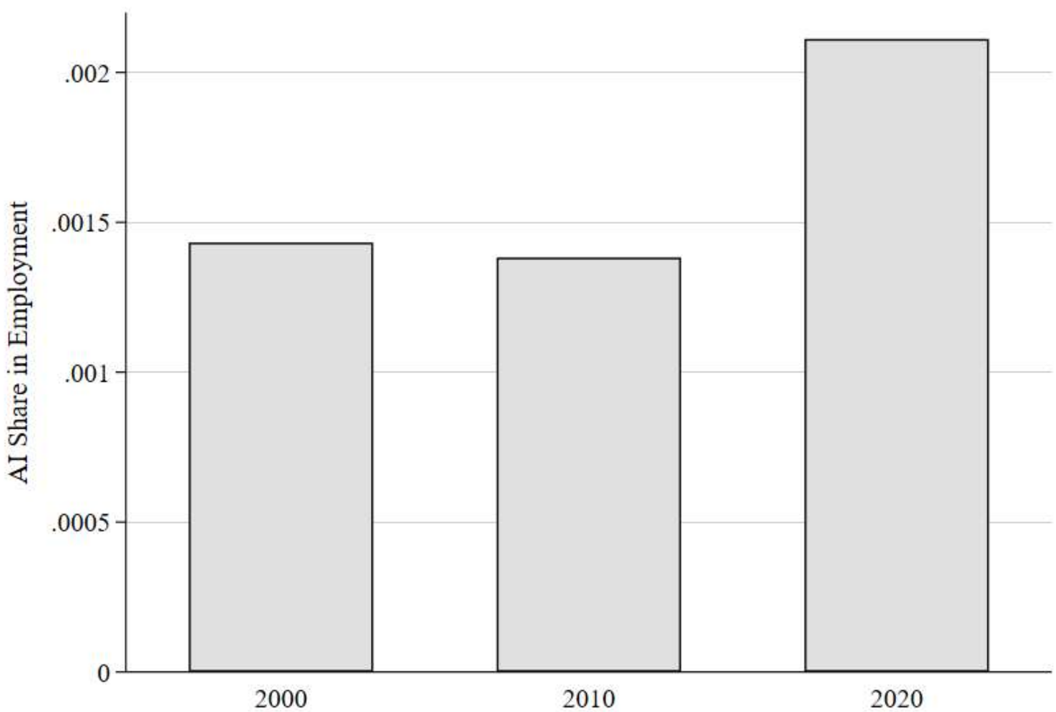
The identifying assumption behind our approach is that the industry-level shifts are exogenous to shocks occurring in individual CZs. We believe this to be a reasonable assumption, given that most CZs are tiny relative to the overall size of the US economy. Moreover, our specification controls for a large set of fixed effects and covariates. Yet, our identification strategy would be endangered in two cases. First, if some contemporaneous shocks remained that correlate with the outcome $\Delta\left(L/P\right)_{cdt}$ and the instrument $AIexp_{cdt}$. Second, if some remaining underlying trends at the CZ-level influenced employment independently of AI. In Section 7, we use various approaches to account for these identification threats and find that they are unlikely to drive the results.

5 Stylized Facts and Preliminary Evidence

We now illustrate the main patterns of AI adoption emerging from our data and provide preliminary evidence on the relationship between AI and employment in the US. Figure 1 plots the nation-wide employment share of AI-related occupations in 2000, 2010 and 2020. This share has remained fairly constant, at around 0.14%, over the 2000s but has rapidly increased thereafter, exceeding 0.2% in 2020. This pattern confirms existing evidence according to which the use of AI was quite limited in the early 2000s but has significantly accelerated after 2010 (e.g., Taddy, 2018, Alekseeva et al., 2021). Our stacked first-differences specification exploits the differential AI adoption between the two decades.

The process of AI adoption is not uniform across industries. Rather, the data reveal a substantial degree of heterogeneity across the 188 industries in our sample, a crucial aspect for the identification strategy. The standard deviation of the industry-level AI adoption shifts is 0.3%, almost five times the mean, and the difference between the industries at the top and bottom percentiles of the distribution is 1.2%. Another distinguishing feature of AI adoption is the type of industries that are most interested by the phenomenon. Table 2 lists the top ten and bottom ten industries in terms of the average shifts over the sample period. The top industries consist of advanced services such as information services; professional, scientific and technical services; business services; and financial services.[17] They also comprise some utilities (electricity) and some of the most advanced branches of the public sector (na-

[17] These patterns are consistent with Acemoglu et al. (2022) who find that information, business services and finance have the greatest number of AI job postings. Other papers have found that AI is particularly important in services, which is not surprising given that these industries generate vast amounts of data.



Source: US Census and American Community Survey. Each bar corresponds to the employment share of AI-related occupations in the US in a given year.

Figure 1: Employment Share of AI-Related Occupations in the US

Table 2: Top and Bottom Industries in Terms of AI Adoption in the US

Top 10 Industries		Bottom 10 Industries	
Computer Systems Design and Related Services	0.0241	Household Appliance Stores	-0.0048
Software Publishers	0.0156	Computer and Peripheral Equipment Manufacturing	-0.0037
Executive Offices and Legislative Bodies	0.0078	Other General Government and Support Activities	-0.0018
Management of Companies and Enterprises	0.0071	Printing and Related Support Activities	-0.0011
Electric Power Generation, Transmission and Distribution	0.0030	Utilities (excl. Electricity)	-0.0009
National Security and International Affairs	0.0030	Commercial and Service Industry Machinery Manufacturing	-0.0007
Scientific Research and Development Services	0.0028	Structural Clay Products	-0.0006
Management, Scientific and Technical Consulting Services	0.0023	Apparel Accessories and Other Apparel	-0.0006
Finance and Insurance	0.0019	Beverage Manufacturing	-0.0006
Other Professional, Scientific, and Technical Services	0.0017	Electronic and Precision Equipment Repair and Maintenance	-0.0005

Industries are classified according to the NAICS classification. The second and fourth columns report the AI adoption shift in each industry (the term in round brackets in eq. 14) averaged between the decades 2000-2010 and 2010-2020.

tional security and international affairs, executive offices and legislative bodies). Conversely, the bottom industries include traditional manufacturing sectors like beverage, apparel and structural clay products, utilities other than electricity, retail services, and the public administration. Interestingly, AI adoption involves different industries compared to the adoption of industrial robots. Indeed, Acemoglu and Restrepo (2020) show that automation is mostly concentrated in manufacturing, especially in highly mechanized industries such as automotive, in the chemical and pharmaceuticals sectors, and in heavy activities such as production of metal products.

We now discuss regional variation. Figure 2a shows the average value of $AIado_{cdt}$, computed between the two decades, in each CZ; Figure 2b displays the corresponding values of $AIexp_{cdt}$. Four main patterns stand out. First, negative values of $AIado_{cdt}$ are very rare (only 6% of CZs), implying that AI adoption has been a widespread phenomenon in the US over the last two decades. Second, because CZs differ in their historical industrial specialization, the cross-industry variation in the shifts translates into significant differences in AI exposure across localities. $AIexp_{cdt}$ is particularly high in some CZs on the West Coast—especially in states like California and Washington—and in South-Central US—e.g., in states like Texas and Arizona. It is also high in CZs comprising large cities on the East Coast and the Great Lakes region, like Boston, New York, Miami, Philadelphia, Washington D.C. and Chicago. On the contrary, $AIexp_{cdt}$ is relatively low in Northern states and in most of the Midwest.

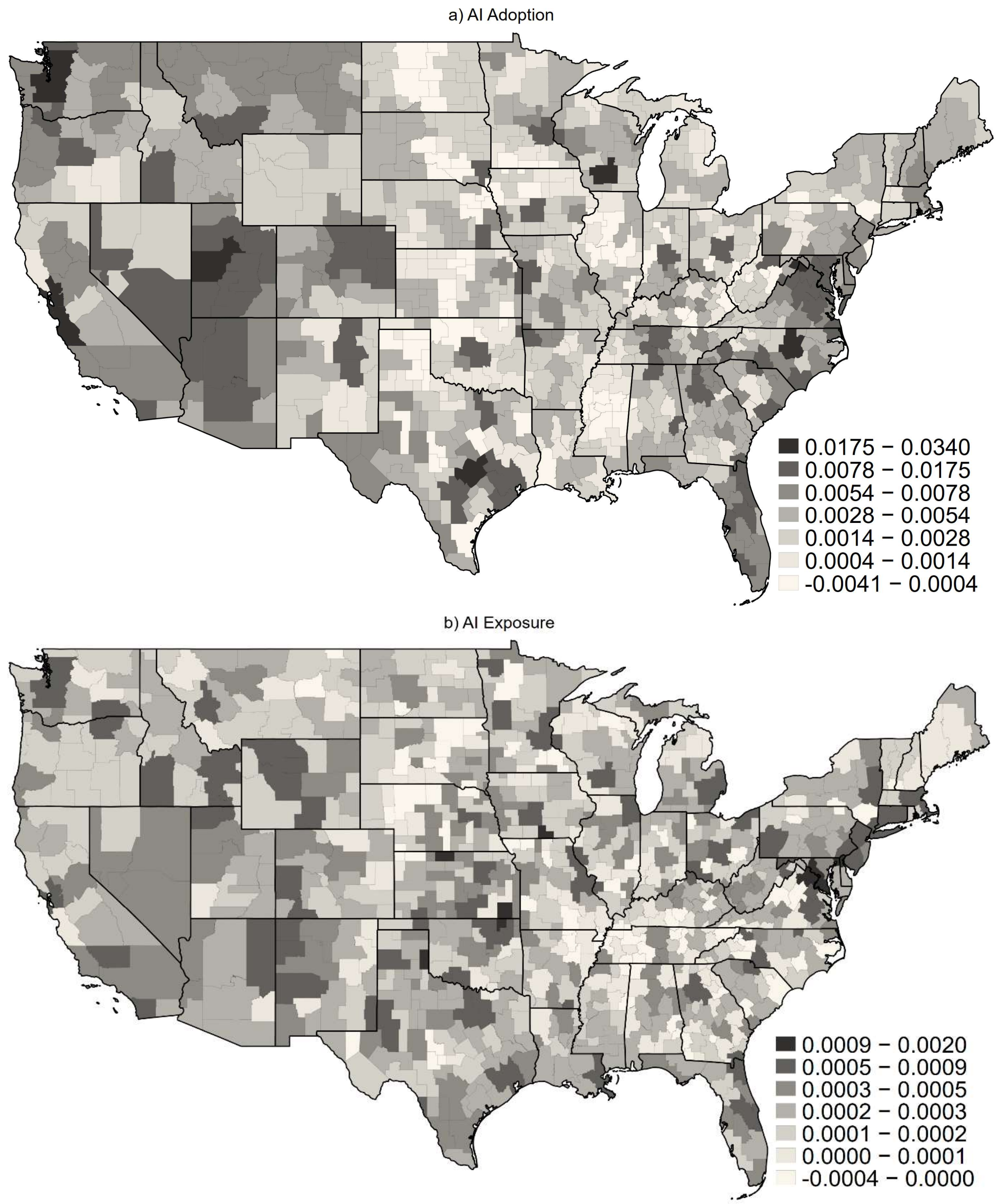
Third, the spatial variation in $AIado_{cdt}$ largely resembles that in $AIexp_{cdt}$. This suggests that the combination of nation-wide industry-level AI adoption shifts with spatial historical differences in industrial structure is a good predictor of actual AI adoption across CZs in the US. Fourth, there are notable exceptions to this pattern. For instance, some CZs in states like Utah, Colorado and Montana score higher in the ranking of $AIado_{cdt}$ than they do in terms of $AIexp_{cdt}$. These are examples of the rise of new high-tech hubs around cities like Salt Lake City, Boulder and Bozeman, which could take advantage of the low cost of living and the proximity to research institutions to compete with premier locations.[18] However, they also illustrate that AI adoption could be driven by CZ-specific factors, independently of actual exposure to these technologies. This is exactly the endogenous variation in AI adoption our identification strategy aims to get rid of.

Figure 3 illustrates the empirical strategy and provides a preliminary, visual, representation of the main results. The figure contains four scatterplots. In each of them, the hollow circles correspond to CZ$\times$decade pairs, for a total of 1,444 observations. Plot a) illustrates the relationship between $\Delta\left(L/P\right)_{cdt}$ and $AIado_{cdt}$. The relationship is negative (coeff. -0.345, s.e. 0.062), implying that a higher AI adoption is associated with a relatively faster decline in employment as a share of population. Plot b) shows the first-stage relationship between $AIado_{cdt}$ and $AIexp_{cdt}$. The plot underscores the strong predictive power of our instrument in explaining AI adoption (coeff. 7.782, s.e. 0.616). Plot c) displays the reduced-form relationship between $\Delta\left(L/P\right)_{cdt}$ and $AIexp_{cdt}$. The strong negative association between the two variables (coeff. -12.889, s.e. 1.015) suggests that a higher AI exposure is related to a significantly larger reduction in the employment-to-population ratio. Plot d) finally shows the relationship between $\Delta\left(L/P\right)_{cdt}$ and $\widehat{AIado}_{cdt}$, the fitted value of AI adoption from the first-stage regression. The association between the two variables is strongly negative (coeff. -1.656, s.e. 0.130), suggesting that variation in AI adoption, driven by variation in exposure to AI, has a strong negative effect on employment as a share of population. Interestingly, the relationship in Plot d) is stronger than its counterpart in Plot a), consistent with demand shocks inducing an upward bias in the OLS estimates.

6 Baseline Results

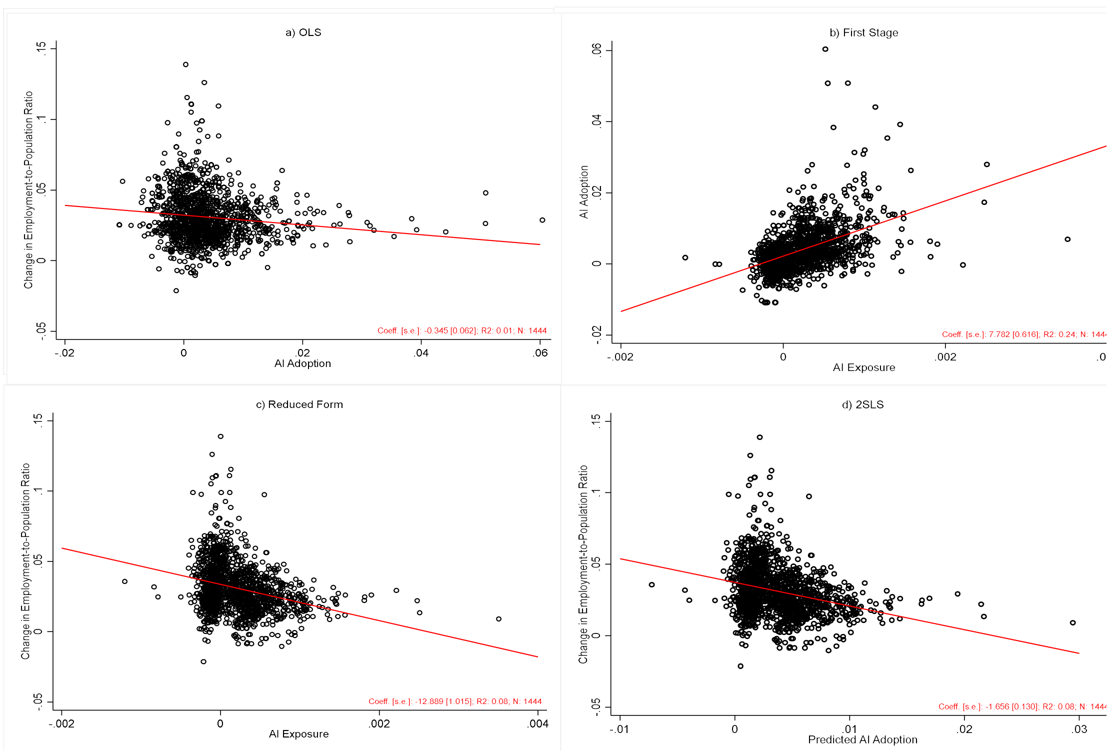
Table 3 shows the baseline estimates of (13). Standard errors are corrected for clustering at the state level to account for residual correlation across CZs within each state, and observations are weighted by the initial-period share of each CZ in total population. The first four columns correspond to a parsimonious specification including only Census Division and decade fixed effects. Column (1) reports the OLS estimate of β, which is negative and very precisely estimated (coeff. -0.253, s.e. 0.080), confirming that AI adoption and changes in the employment-to-population ratio are negatively correlated. Columns (2) and (3) show, respectively, the first-stage and reduced-form coefficients on the instrument $AIexp_{cdt}$. The

[18] Other dark spots in the map also correspond to locations hosting large federal government facilities. It is reassuring that our map looks remarkably similar to the geographical distribution of AI investments based on job postings reported in the Appendix of Babina et al. (2024).



Source: US Census and American Community Survey. The top map plots the average value of $AIado_{cdt}$ (see eq. 12) in each CZ between the decades 2000-2010 and 2010-2020. The bottom map plots the corresponding values of $AIexp_{cdt}$ (see eq.14).

Figure 2: AI Adoption and AI Exposure in US Commuting Zones



The sample consists of 722 CZs observed over two decades, 2000-2010 and 2010-2020. In each plot, an observation is a CZ x decade pair. *AI Adoption* and *AI Exposure* are defined in eq. (12) and (14), respectively. *Predicted AI Adoption* is the fitted value of *AI Adoption* from the first-stage regression in Plot b).

Figure 3: AI Adoption, AI Exposure and Employment in US Commuting Zones

Table 3: Baseline Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	First Stage	Reduced Form	Second Stage	OLS	First Stage	Reduced Form	Second Stage
$AIado_{cdt}$	-0.253***			-0.671***	-0.238**			-1.594***
	[0.080]			[0.157]	[0.104]			[0.377]
$AIexp_{cdt}$		9.695***	-6.507***			9.599***	-15.298***	
		[1.128]	[1.447]			[1.813]	[3.279]	
Census Division FE	yes	yes	yes	yes	yes	yes	yes	yes
Decade FE	yes	yes	yes	yes	yes	yes	yes	yes
Control Variables	no	no	no	no	yes	yes	yes	yes
Kleibergen–Paap F-stat.	-	-	-	73.8	-	-	-	28.0
Obs.	1444	1444	1444	1444	1444	1444	1444	1444
R2	0.33	0.58	0.33	-	0.42	0.63	0.45	-

The sample consists of 722 CZs observed over two decades, 2000-2010 and 2010-2020. Each observation is a CZ x decade pair. The subscripts c, d and t denote CZs, Census Divisions and decades, respectively. The dependent variable is the change in the employment-to-population ratio in each CZ over each decade. $AIado_{cdt}$ and $AIexp_{cdt}$ are the measures of AI adoption and AI exposure defined in eq. (12) and (14) respectively. *Control variables* include the following initial characteristics of each CZ: log population; the population shares of female, college-educated, white and old individuals (age 65+); the share of manufacturing in total employment; the share of females in manufacturing employment; the share of light manufacturing in total manufacturing employment; and the employment share of workers in routine-intensive occupations. *Control variables* also include the change in import competition from China and exposure to industrial robots in each CZ over each decade. Observations are weighted by the initial-period share of each CZ in total population. Standard errors are corrected for clustering at the state level. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively.

first-stage estimate is positive, large and highly statistically significant (coeff. 9.695, s.e. 1.128), confirming the strong predictive power of the instrument.[19] At the same time, the reduced-form estimate is negative and very precisely estimated (coeff. -6.507, s.e. 1.447), confirming that a higher exposure to AI is associated with a relatively larger reduction in employment as a share of population. The results in columns (2) and (3) imply a negative 2SLS estimate of β (coeff. -0.671, s.e. 0.157), as shown in column (4). Also in this case, the 2SLS coefficient is more negative than its OLS counterpart, consistent with OLS estimates being upward biased due to unobserved CZ-specific shocks.

The last four columns of Table 3 report estimates from our preferred specification, which includes the full list of controls described in Section 4. The results are confirmed, suggesting that our evidence depends neither on initial differences in CZ characteristics nor on other important shocks occurred over the sample period, namely, the increase in Chinese import competition and the diffusion of industrial robots. The 2SLS coefficient reported in column (8) implies that a 1 standard deviation (s.d.) higher $AIado_{cdt}$ causes a reduction in $\Delta\left(L/P\right)_{cdt}$ by 1 percentage point (p.p.), roughly 0.56% of a s.d.. To have a sense of the magnitude of the effect, if the CZ with average AI adoption over the sample period (0.004) had hypothetically had no AI adoption at all, its employment-to-population ratio would have grown by 0.6 p.p.

[19] The Kleibergen-Paap F-statistic equals 73.8 and thus exceeds the value of 10 normally considered as a rule-of-thumb threshold for instrument relevance.

more, i.e., 20% faster than observed growth. While these numbers cannot be interpreted as a counterfactual exercise, because nation-wide effects are differenced out, they nevertheless suggest that AI adoption has contributed to slowing down job creation in the US over the last two decades.

In the Appendix, we submit the baseline estimates to an extensive sensitivity analysis. We show that the results are not driven by influential observations in $\Delta\left(L/P\right)_{cdt}$ or $AIado_{cdt}$, and that they are insensitive to excluding the years of the Covid-19 pandemic from the construction of the main variables (Appendix A.1). The evidence is also unchanged across alternative ways of correcting the standard errors for clustering, as well as when using the Borusyak et al. (2022) inference approach in the presence of shift-share instruments (Appendix A.2). Finally, the baseline findings are preserved across alternative ways of constructing the main variables. These include: (i) computing $AIado_{cdt}$ and $AIexp_{cdt}$ using different definitions of AI-related occupations, namely, only "Data Scientists" and Hanson's (2022) classification; (ii) using employment shares for 1990 rather than 1980 in the construction of $AIexp_{cdt}$; (iii) adjusting $AIado_{cdt}$ and $AIexp_{cdt}$ for differences in industries' growth rates; and (iv) defining the outcome variable as the log change in employment, as the change in employment relative to labor force or working-age population, or as the change in private sector employment over population (Appendix A.3).

7 Threats to Identification

Identification requires that, after controlling for Census Division fixed effects, decade fixed effects, initial characteristics of CZs and shocks to trade and automation, no unobservable remains that correlates with the instrument and influences employment across localities. As mentioned in Section 4, the exclusion restriction is threatened by two types of confounders: underlying trends and contemporaneous shocks that might affect local labor markets independently of AI adoption. We now use alternative approaches for accommodating the possible influence of these confounders and study how the coefficient β is affected.

In Table 4, we deal with contemporaneous shocks. To start with, we allow for the possibility that CZs with similar changes in employment or similar AI adoption might be hit by similar unobservable shocks, e.g., to technology, demand, or related to the business cycle. To accommodate these shocks, we divide CZs into ten bins corresponding to the deciles of $\Delta\left(L/P\right)_{cdt}$ or $AIado_{cdt}$ over 2000-2020. We then interact a dummy for each bin with decade dummies. We add these interactions either individually (columns 1 and 2) or jointly (column 3). These interactions absorb shocks hitting all CZs with comparable changes in the key

Table 4: Threats to Identification: Contemporaneous Shocks

	(1) Bins of Δ(L/P)	(2) Bins of AIado	(3) Bins of Δ(L/P) and AIado	(4) No CZs with Top AIado	(5) Leave-One-Out AIexp	(6) No Ind. with Top Shifts	(7) Bartik for Δ Ind. Emp.
2nd Stage Regression							
$AIado_{cdt}$	-1.131***	-2.965***	-2.421***	-2.536*	-2.222*	-1.945***	-1.345***
	[0.229]	[0.940]	[0.810]	[1.274]	[1.132]	[0.656]	[0.320]
1st Stage Regression							
$AIexp_{cdt}$	9.276***	4.520***	4.462***	4.754***	0.031***	8.402***	10.610***
	[1.345]	[1.217]	[1.330]	[1.047]	[0.009]	[2.235]	[2.214]
Kleibergen–Paap F-stat.	47.5	13.8	11.3	20.6	12.3	14.1	22.9
Obs.	1444	1444	1444	1286	1444	1444	1444

The sample consists of 722 CZs observed over two decades, 2000-2010 and 2010-2020. Each observation is a CZ x decade pair. The subscripts c, d and t denote CZs, Census Divisions and decades, respectively. The dependent variable is the change in the employment-to-population ratio in each CZ over each decade. $AIado_{cdt}$ and $AIexp_{cdt}$ are the measures of AI adoption and AI exposure defined in eq. (12) and (14), respectively. In column (5), $AIexp_{cdt}$ is constructed excluding the CZ to which this variable refers. In column (6), $AIado_{cdt}$ and $AIexp_{cdt}$ are constructed excluding industries whose shifts (the round bracket terms of eq. 14) fall in the top decile of the distribution. All specifications include Census Division fixed effects, decade fixed effects and the control variables used in Table 3. The specification in column (1) controls for full sets of interactions between decade dummies and dummies for deciles of the change in the employment-to-population ratio over 2000-2020. The specification in column (2) controls for full sets of interactions between decade dummies and dummies for deciles of $AIado_{cdt}$ over 2000-2020. The specification in column (3) jointly includes the two sets of interactions used in columns (1) and (2). The specification in column (4) excludes CZs falling in the top decile of the distribution of $AIado_{cdt}$ in a given decade. The specification in column (7) includes a Bartik measure of the change in log industry employment. Observations are weighted by the initial-period share of each CZ in total population. Standard errors are corrected for clustering at the state level. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively.

variables. Accordingly, identification exploits the remaining variation across CZs falling in the same bin within each decade. In column (4), we take a complementary approach and exclude CZs with the highest values of $AIado_{cdt}$. These are CZs falling in the top decile of the distribution in a given decade. The coefficient β remains negative, precisely estimated and in the same ballpark as the baseline estimates across all specifications.

A related concern is that the industry shifts that make up the instrument might be driven by shocks occurring in individual CZs. If these shocks also affected the local labor market, the exclusion restriction would be violated. We believe this concern to be assuaged by the small size of most CZs relative to the US as a whole. Nevertheless, in column (5), we estimate (13) using a "leave-one-out" instrument, in which the industry-level shifts are computed after excluding the CZ to which the instrument refers. The main results are preserved also in this case.

Unobserved shocks may also play out at the industry level. For example, industries with large AI adoption might experience other shocks that are relevant to the labor market of some CZs. Our specification already controls for some of the main shocks, by means of Bartik measures of changes in Chinese import penetration and in robot density. Moreover, in the next section, we will enrich the specification with Bartiks for different forms of technical change, and the results will turn out to be insensitive to these additional controls. Nevertheless, we now use two complementary approaches to further address concerns with industry-specific shocks.

In a first exercise, presented in column (6), we construct both $AIado_{cdt}$ and $AIexp_{cdt}$ excluding industries whose AI adoption shifts fall in the top decile of the distribution. The coefficient of interest remains close to the baseline estimate. This exercise also serves an additional purpose. As shown in Table 2, the industries with the largest shifts include some of the sectors where most AI is likely to be produced, such as information services; computer, scientific, professional and technical services; and the branches of the public sector related to public defense and national security. Accordingly, excluding these industries better isolates the effect of AI *adoption* from that of AI *production*.[20]

In a second exercise, illustrated in column (7), we augment the specification with a Bartik measure of changes in log industry employment. This variable serves as a synthetic proxy for all factors leading to differential changes in employment across industries. One such factor is that industries have different sensitivities to the business cycle. As a result, local labor markets may be exposed differently to the business cycle, depending on the industrial composition of each CZ. Nevertheless, controlling for this Bartik measure is largely inconsequential for the results.

We now discuss underlying trends. The specification controls for linear trends both across Census Divisions—through Census Division fixed effects, α_d—and across CZs with similar initial characteristics within each Census Division—through the start-of-period controls included in the vector $\mathbf{X}_{cdt}$. In Table 5, we allow for richer sets of fixed effects to accommodate underlying trends more flexibly. In column (1), we replace the Census Division fixed effects with state fixed effects, thereby allowing for heterogeneous linear trends across individual states rather than across groups of them. The coefficient of interest is essentially unchanged. In column (2), we go one step further by taking advantage of our stacked first-differences design, which allows us to include CZ fixed effects. In this case, identification exclusively relies on the variation in $\Delta\left(L/P\right)_{cdt}$ and $AIado_{cdt}$ within each CZ between the two decades. This specification fully exploits the acceleration in AI adoption occurred after 2010, but it is extremely demanding, because the sample comprises only two observations for each CZ.[21] The estimate of β is largely unaffected, suggesting that our results largely reflect the changes in the rates of AI adoption occurred over time within individual CZs. In a last exercise,

[20] Goldsmith-Pinkham et al. (2020) discuss identification using shift-share instruments under the assumption of exogeneity of the industry shares. We believe that the alternative assumption of shift exogeneity, which underlies the Borusyak et al. (2022) approach, is more consistent with our identification strategy discussed in Section 4.2. Nevertheless, the exercise in column (6) gets close in spirit to Goldsmith-Pinkham et al. (2020), as long as the industries with the largest AI adoption shifts also play a significant role in the shift-share instrument $AIexp_{cdt}$.

[21] Controlling for CZ fixed effects also accounts for possible mean reversion after the bust of the digital technology bubble.

Table 5: Threats to Identification: Underlying Trends

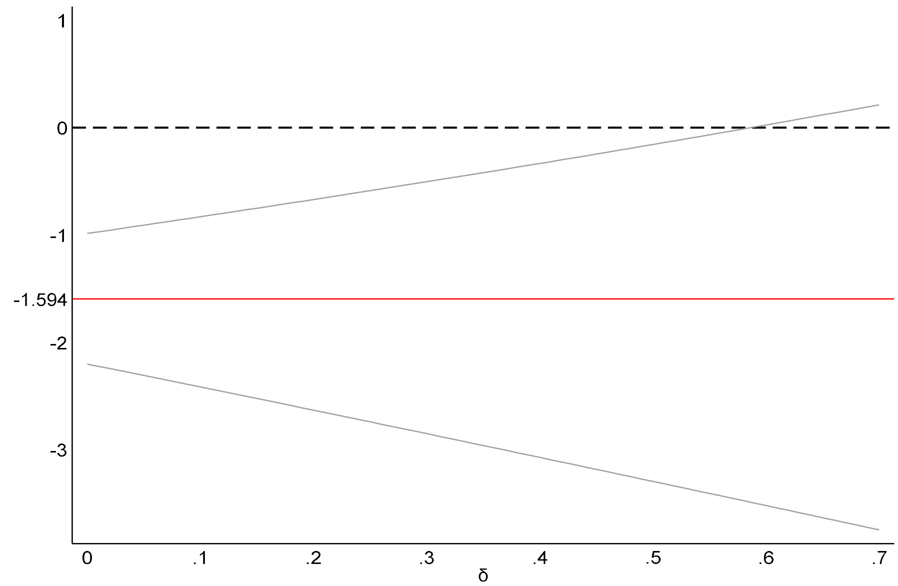
	(1) State Fixed Effects	(2) CZ Fixed Effects	(3) Cens. Div. x Decade FE	(4) State x Decade FE	(5) Past Δ(L/P) as Dep. Var.	(6) Past Δ(L/P) as Control
2nd Stage Regression						
$AIado_{cdt}$	-1.529***	-1.299***	-1.400***	-1.202***	0.253	-1.494***
	[0.389]	[0.438]	[0.317]	[0.330]	[0.171]	[0.363]
1st Stage Regression						
$AIexp_{cdt}$	10.398***	15.997***	9.591***	9.898***	9.599***	9.515***
	[1.924]	[2.281]	[1.836]	[2.229]	[1.813]	[1.798]
Kleibergen–Paap F-stat.	29.2	48.9	27.3	19.7	28.0	28.0
Obs.	1444	1444	1444	1440	1444	1444

The sample consists of 722 CZs observed over two decades, 2000-2010 and 2010-2020. Each observation is a CZ x decade pair. The subscripts c, d and t denote CZs, Census Divisions and decades, respectively. Except for column (5), the dependent variable is the change in the employment-to-population ratio in each CZ over each decade; in column (5), the dependent variable is the change in the employment-to-population ratio in each CZ over the pre-sample decades 1980-1990 and 1990-2000. $AIado_{cdt}$ and $AIexp_{cdt}$ are the measures of AI adoption and AI exposure defined in eq. (12) and (14), respectively. All specifications include Census Division fixed effects, decade fixed effects and the control variables used in Table 3. The specifications in columns (1)-(4) control for state fixed effects, CZ fixed effects, Census Division x decade fixed effects and state x decade fixed effects, respectively. The specification in column (6) controls for the change in the employment-to-population ratio in each CZ over the pre-sample decades 1980-1990 and 1990-2000. Observations are weighted by the initial-period share of each CZ in total population. Standard errors are corrected for clustering at the state level. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively.

we replace the Census Division and decade fixed effects with Census Division×decade fixed effects (column 3) and state×decade fixed effects (column 4), thereby allowing for non-linear trends. The main results are preserved.

In the remainder of this section, we use two additional approaches to further raise trust in our 2SLS estimates. In column (5) of Table 5, we implement a falsification test by regressing changes in the employment-to-population ratio prior to the beginning of the sample (over 1980-1990 and 1990-2000) on current AI adoption (in 2000-2010 and 2010-2020). We include the same controls as in the baseline specification, and instrument $AIado_{cdt}$ using $AIexp_{cdt}$. If current AI adoption explained past changes in employment, our evidence could reflect labor market trends that antedate the rise of AI, or long-lasting CZ characteristics that jointly affect innovation and employment. Reassuringly, however, the coefficient on $AIado_{cdt}$ is very small and statistically not significant. In column (6), we include the pre-sample change in the employment-to-population ratio among the controls. Consistently with column (5), this variable has no bearing on the coefficient β. Overall, these results help strengthening the view that our evidence captures the effects of current AI adoption rather than other time-varying confounders.

In a second approach, we change perspective and start from the premise that the instrument might be correlated with the error term due to some confounding factor. Then, following



The figure plots 90% confidence intervals around the baseline 2SLS coefficient on $AIado_{cdt}$ (Table 3, column 8) for different priors about a potential violation of the exclusion restriction. Priors are described by the parameter δ reported on the horizontal axis: $\delta=0$ implies that the exclusion restriction is satisfied; $\delta=x>0$ corresponds to a violation of the exclusion restriction such that a change in $AIexp_{cdt}$ by 1 interquartile range has a direct effect on the employment-to-population ratio equal to a change in $AIado_{cdt}$ by x interquartile ranges. The confidence intervals are based on standard errors corrected for clustering at the state level.

Figure 4: Threats to Identification: Sensitivity of Inference to Violations of the Exclusion Restriction

Conley, Hansen and Rossi (2012), we study how strong a violation of the exclusion restriction would have to be for inference on β to become uninformative about the causal effect of AI adoption. We illustrate the approach of Conley, Hansen and Rossi (2012) in Appendix B. Here, we present the main results, which are summarized in Figure 4. The latter plots the 90% confidence interval around β corresponding to different violations of the exclusion restriction, as captured by the parameter δ. When $\delta = 0$, we are in the benchmark case in which the exclusion restriction is satisfied. When $\delta > 0$, instead, the exclusion restriction is violated. Specifically, $\delta = x > 0$ corresponds to a violation such that a change in $AIexp_{cdt}$ by one interquartile range has a direct effect on $\Delta\left(L/P\right)_{cdt}$ equal to a change in $AIado_{cdt}$ by x interquartile ranges.

When $\delta = 0$, the confidence interval around β is $[-2.202, -0.985]$. As δ departs from this benchmark, the confidence interval progressively widens. However, thanks also to the strong predictive power of the instrument, the reduction in precision is slow and the confidence interval starts including zero only when $\delta \approx 0.6$. Hence, for our parameter of interest to become uninformative, the direct effect of $AIexp_{cdt}$ on $\Delta\left(L/P\right)_{cdt}$ would have to be at least 60% as large as the effect of a commensurate exogenous change in $AIado_{cdt}$. Such a change is twice the median value of $AIado_{cdt}$ in our sample. More concretely, it roughly corresponds to the difference in average AI adoption between the CZ of Los Angeles and that of New Albany. Overall, these figures suggest that even substantial relaxations of the exclusion restriction would leave inference informative about the employment effect of AI adoption.

8 Additional Evidence

In this section, we delve deeper into the effect of AI adoption. We start by comparing AI with other shocks studied in the literature. Then, we explore the mechanisms through which the effect of AI unfolds. Finally, we study how the employment response to AI adoption varies by gender, age, skill and occupation.

8.1 AI Adoption and Other Shocks

Our model shows that AI adoption affects labor demand in two ways: by replacing workers in some tasks (displacement effect) and by increasing efficiency (productivity effect). Accordingly, the effects of AI adoption should differ from those of other shocks that do not have a displacement effect. We now compare AI adoption with various shocks of this type. The results are reported in Table 6. In columns (1)-(6), we augment (13) with proxies for different shocks; in column (7), we include all these proxies together. The specification in column (1) includes a proxy for capital deepening, which is a Bartik measure of the change in capital intensity (capital-to-labor ratio) across industries.[22] The coefficient β is largely unchanged, suggesting that the results are not capturing the effect of capital deepening. At the same time, the coefficient on the new control is very small and positive, consistent with the effect of capital deepening being different from that of AI.

Next, we study the implications of ICT. In columns (2)-(4), we add three Bartik measures of changes in (i) software, (ii) computer and (iii) communication equipment intensities, respectively. In all specifications, the effect of AI adoption remains very close to the baseline estimate. This reassures against the concern that $AIado_{cdt}$ might capture the effect of computers, software and other high-tech capital. Also in this case, the coefficients on the new controls are small and, when they are precisely estimated, their sign is positive. This pattern suggests that AI adoption has different labor demand consequences compared to ICT.[23]

[22] This and the other Bartik measures used in Table 6 are constructed using data from the Production Accounts Tables of the US Bureau of Economic Analysis.

[23] This finding is consistent with Gaggl and Wright (2017) and Blanas, Gancia and Lee (2019), who find positive associations between ICT and labor demand.

Table 6: Controls for Other Shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2nd Stage Regression							
$AIado_{cdt}$	-1.597***	-1.590***	-1.575***	-1.744***	-1.675***	-1.833***	-2.185***
	[0.377]	[0.376]	[0.377]	[0.428]	[0.379]	[0.503]	[0.660]
$CapInt_{cdt}$	0.000*						0.000**
	[0.000]						[0.000]
$SoftInt_{cdt}$		-0.000					-0.001*
		[0.000]					[0.000]
$CompInt_{cdt}$			-0.001				0.003
			[0.001]				[0.002]
$CommInt_{cdt}$				0.003**			0.003
				[0.001]			[0.002]
VA_{cdt}					0.088***		0.084***
					[0.021]		[0.023]
$Offsh_{cdt}$						0.060*	0.084*
						[0.035]	[0.045]
1st Stage Regression							
$AIexp_{cdt}$	9.603***	9.593***	9.468***	8.987***	9.636***	7.984***	7.011***
	[1.818]	[1.812]	[1.778]	[1.803]	[1.821]	[1.886]	[1.879]
Kleibergen–Paap F-stat.	27.9	28.0	28.3	24.8	28.0	17.9	13.9
Obs.	1444	1444	1444	1444	1444	1444	1444

The sample consists of 722 CZs observed over two decades, 2000-2010 and 2010-2020. Each observation is a CZ x decade pair. The subscripts c, d and t denote CZs, Census Divisions and decades, respectively. The dependent variable is the change in the employment-to-population ratio in each CZ over each decade. $AIado_{cdt}$ and $AIexp_{cdt}$ are the measures of AI adoption and AI exposure defined in eq. (12) and (14), respectively. $CapInt_{cdt}$, $SoftInt_{cdt}$, $CompInt_{cdt}$ and $CommInt_{cdt}$ are Bartik measures of the change in, respectively, the capital-to-labor ratio, the software capital-to-labor ratio, the computer capital-to-labor ratio and the communication equipment-to-labor ratio, across industries. VA_{cdt} is a Bartik measure of the change in log industry value added. $Offsh_{cdt}$ is the initial employment share of offshorable occupations in each CZ. All specifications include Census Division fixed effects, decade fixed effects and the control variables used in Table 3. Observations are weighted by the initial-period share of each CZ in total population. Standard errors are corrected for clustering at the state level. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively.

In column (5), we consider other productivity-enhancing shocks. To remain agnostic about the precise nature of the shock, we add a broad proxy, which is obtained as a Bartik measure of the change in log industry value added. This proxy enters with a positive and statistically significant coefficient, but its inclusion is inconsequential for the coefficient of interest. Hence, AI adoption differs from productivity-enhancing shocks, and has distinct effects on the labor market.[24] Finally, in column (6), we compare AI adoption with offshoring. To this purpose, we add the initial employment share of offshorable occupations, constructed using data from Autor and Dorn (2013). The coefficient β is largely unchanged. Moreover, while offshoring could also displace workers, the results show that AI adoption has markedly different labor market effects.[25]

8.2 Channels

So far, our evidence highlights a negative impact of AI adoption on employment within CZs. We now explore some of the mechanisms underlying this effect. The results are reported in Table 7. We start by studying which sectors contribute the most to the overall effect. As shown in Section 5, the leading industries in terms of AI adoption belong to the service sector, while manufacturing is still lagging behind. It is conceivable, therefore, that AI adoption in services might currently have larger effects on labor demand than AI adoption in manufacturing. To study the role of the two sectors, we split both $AIado_{cdt}$ and $AIexp_{cdt}$ in two separate variables, constructed as in (12) and (14) on the subsets of manufacturing and non-manufacturing industries, respectively. We then estimate (13) using the sector-specific variables in place of the aggregate variables. The results are reported in column (1) for manufacturing and in column (2) for non-manufacturing. Consistently with the different speed of AI diffusion in the two sectors, the estimates show that the service sector makes up the lion's share of the overall effect.

A related issue has to do with the sectors that experience the largest changes in employment as a consequence of AI adoption. The previous results do not imply that the effect is entirely concentrated in the service sector, because industries are linked to each other by upstream or downstream relationships and because workers may move across sectors in response to shocks. To investigate the employment effects in different sectors, we divide the numerator of the dependent variable into employment in primary, secondary and tertiary industries. We

[24] The Bartik variables included in columns (1)-(5) also mitigate the concern that aggregate technological developments in specific industries might have differential effects across CZs depending on their industrial structure.

[25] See Bonfiglioli et al. (2022) for more evidence on the relationship between automation and offshoring.

Table 7: Channels

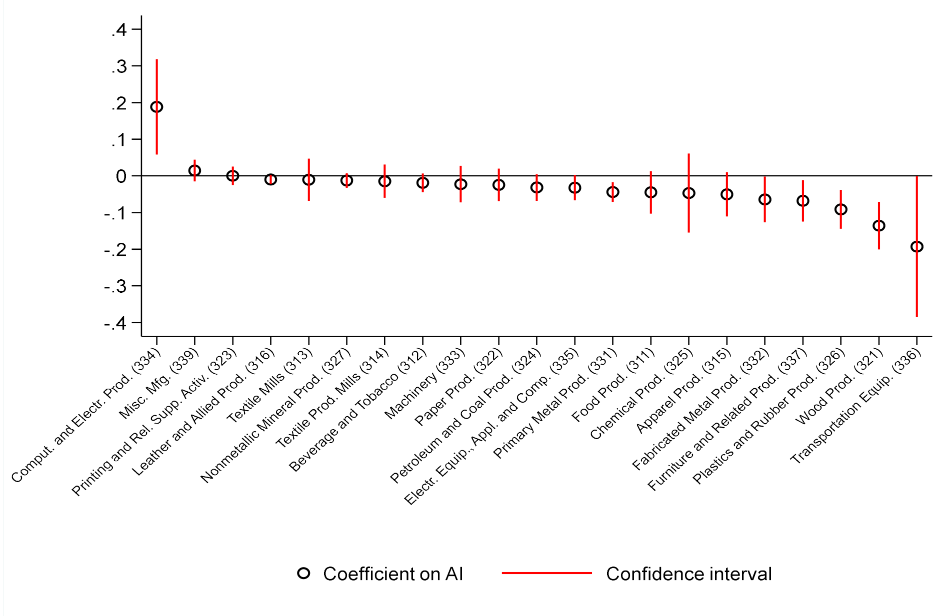
	(1) AIado and AIexp for Mfg	(2) AIado and AIexp for Nmfg	(3) Primary Sector Emp.	(4) Secondary Sector Emp.	(5) Mfg Sector Emp.	(6) Tertiary Sector Emp.	(7) Unemployment	(8) Not in Labor Force
2nd Stage Regression								
$AIado_{cdt}$	1.127	-1.405***	0.252**	-0.866***	-0.725***	-0.979***	0.390*	1.203***
	[1.878]	[0.422]	[0.101]	[0.259]	[0.253]	[0.291]	[0.211]	[0.241]
1st Stage Regression								
$AIexp_{cdt}$	2.296***	5.089***	9.599***	9.599***	9.599***	9.599***	9.599***	9.599***
	[0.650]	[1.269]	[1.813]	[1.813]	[1.813]	[1.813]	[1.813]	[1.813]
Kleibergen–Paap F-stat.	12.5	16.1	28.0	28.0	28.0	28.0	28.0	28.0
Obs.	1444	1444	1444	1444	1444	1444	1444	1444

The sample consists of 722 CZs observed over two decades, 2000-2010 and 2010-2020. Each observation is a CZ x decade pair. The subscripts c, d and t denote CZs, Census Divisions and decades, respectively. In columns (1)-(2), the dependent variable is the change in the employment-to-population ratio in each CZ over each decade. In columns (3)-(6), the dependent variables are the changes in primary sector employment, secondary sector employment, manufacturing sector employment and tertiary sector employment, respectively, as a share of population in each CZ over each decade. In columns (7)-(8), the dependent variables are the changes in the number of unemployed workers and in the number of individuals out of the labor force, respectively, relative to population in each CZ over each decade. $AIado_{cdt}$ and $AIexp_{cdt}$ are the measures of AI adoption and AI exposure defined in eq. (12) and (14), respectively. In columns (1)-(2), these variables are constructed on the subsets of manufacturing and non-manufacturing industries, respectively. All specifications include Census Division fixed effects, decade fixed effects and the control variables used in Table 3. Observations are weighted by the initial-period share of each CZ in total population. Standard errors are corrected for clustering at the state level. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively.

also consider employment in manufacturing, which makes up the secondary sector together with the construction industry. We then estimate (13) using employment in each branch of the economy, relative to population, as the dependent variable. The results are reported in columns (3)-(6). The largest effect is found in the tertiary sector, which accounts for roughly 60% of the impact of AI adoption on overall employment. In addition, negative effects are evident also in the secondary sector, primarily in manufacturing, which accounts for 45% of the aggregate impact. Finally, the results show a small positive effect on employment in the primary sector, which probably absorbs a small fraction of workers laid off from the other branches.

These results reveal that AI adoption has repercussions not only on the sectors where it is most prevalent, i.e., services, but also on other branches of the economy where the use of these technologies is still limited, especially manufacturing. An interpretation of these findings is that the proximity of AI-adopting firms favors the automation of a larger number of tasks in other firms. This could happen, for instance, as a result of the deployment of more sophisticated, AI-assisted, machines, or because AI simplifies the integration of additional automated stages of production within firms. In turn, a wider use of automation could generate negative consequences for employment in highly automation-intensive sectors, regardless of their actual direct adoption of AI.

To explore this interpretation, we focus on the manufacturing sector and estimate (13) using employment in each 3-digit NAICS industry, relative to population, as the dependent variable. The estimates of β obtained from these regressions are displayed in Figure 5, along with their 90% confidence intervals. Consistently with the view that AI fosters automation,



Each hollow circle corresponds to the 2SLS coefficient on $AIado_{cdt}$ from a separate regression, where the dependent variable is the change in employment, as a share of population, in a given 3-digit NAICS manufacturing industry (as indicated on the horizontal axis) in each CZ over each decade. The sample consists of 722 CZs observed over two decades, 2000-2010 and 2010-2020. Each observation is a CZ x decade pair. $AIado_{cdt}$ and the instrument $AIexp_{cdt}$ are the measures of AI adoption and AI exposure defined in eq. (12) and (14), respectively. All specifications include Census Division fixed effects, decade fixed effects and the control variables used in Table 3. Observations are weighted by the initial-period share of each CZ in total population. Confidence intervals are at the 90% level and refer to standard errors corrected for clustering at the state level.

Figure 5: AI Adoption and Employment in Individual Manufacturing Industries

the largest negative effects of AI adoption are found on employment in highly automation-intensive industries, such as transportation equipment, wood and furniture, plastics and rubber, and fabricated metal products (Acemoglu and Restrepo, 2020). By contrast, AI adoption has virtually no impact on employment in traditional manufacturing industries, where the potential for automation remains limited. The only positive effect of AI adoption is found in the computer and electronics products industry, which produces goods that are highly complementary to these technologies.

In the last two columns of Table 7, we finally study what happens to displaced workers that are not re-employed. To this purpose, we analyze the responses of unemployment and non-participation to AI adoption, by estimating (13) using two different dependent variables: unemployment as a share of population (column 7) and the share of population out of the labor force (column 8). The results indicate that AI adoption raises both unemployment and non-participation. However, non-participation absorbs a much larger share of the overall reduction in employment compared to unemployment (75% vs. 25%). This fraction includes both workers who temporarily leave the labor force to update their skills and discouraged workers who drop out of the labor force. In the next section, we study heterogeneity in the

Table 8: Heterogeneity: Gender and Age

	(1) Male Emp.	(2) Female Emp.	(3) Emp. 16-24 Yrs	(4) Emp. 25-44 Yrs	(5) Emp. 45+ Yrs
2nd Stage Regression					
$AIado_{cdt}$	-0.928***	-0.665***	-0.296*	-1.401***	0.103
	[0.260]	[0.181]	[0.166]	[0.366]	[0.207]
1st Stage Regression					
$AIexp_{cdt}$	9.599***	9.599***	9.599***	9.599***	9.599***
	[1.813]	[1.813]	[1.813]	[1.813]	[1.813]
Kleibergen–Paap F-stat.	28.0	28.0	28.0	28.0	28.0
Obs.	1444	1444	1444	1444	1444

The sample consists of 722 CZs observed over two decades, 2000-2010 and 2010-2020. Each observation is a CZ x decade pair. The subscripts c, d and t denote CZs, Census Divisions and decades, respectively. In columns (1)-(2), the dependent variables are the changes in the employment of males and females, respectively, as a share of population in each CZ over each decade. In columns (3)-(5), the dependent variables are the changes in the employment of workers aged 16-24, 25-44 and 45+, respectively, as a share of population in each CZ over each decade. $AIado_{cdt}$ and $AIexp_{cdt}$ are the measures of AI adoption and AI exposure defined in eq. (12) and (14), respectively. All specifications include Census Division fixed effects, decade fixed effects and the control variables used in Table 3. Observations are weighted by the initial-period share of each CZ in total population. Standard errors are corrected for clustering at the state level. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively.

effect of AI adoption, with the aim of shedding light on the possible winners and losers from this new technology.

8.3 Heterogeneity

In columns (1) and (2) of Table 8, we investigate how the effect of AI adoption varies by gender. We find negative effects on both male employment and female employment as a share of population. While the coefficient is somewhat larger for men, the difference is not statistically significant. Hence, the results do not clearly point to a strong gender bias in the effect of AI adoption.

Different conclusions are reached regarding other dimensions of heterogeneity. A first aspect to play a role is age. Columns (3)-(5) report the effects of AI adoption on employment for three groups of workers: younger (aged 16-24), middle-age (aged 25-44) and older (aged 45+) workers. The largest negative effect is found for middle-age workers, which account for almost 88% of the effect on overall employment. The impact of AI adoption is also negative, albeit much smaller, on younger workers, while it is small and imprecisely estimated on older workers. One possible interpretation of these results is that younger workers are better equipped to cope with the challenges posed by AI, as they are capable of swiftly updating their skills. Older workers are instead shielded from the AI shock possibly due to their tendency to hold more stable jobs.

A second important dimension of heterogeneity is education. As shown in columns (1) and (2) of Table 9, the negative effect of AI adoption is concentrated on low-skill workers. Conversely, for high-skill workers, the coefficient is positive, albeit imprecisely estimated. However, an important message of Table 9 is that the role of education is not uniform across individuals. Rather, as shown below, education interacts both with the occupation in which workers are employed and with the nature of the educational degree they hold. To study the role of occupations, in columns (3)-(6), we distinguish high- and low-skill workers depending on whether they are employed in a production or non-production occupation. For production workers, the effect of AI adoption is always negative, regardless of their educational level. On the contrary, for non-production workers, the effect of AI adoption is negative only among low-skill individuals.

In columns (7) and (8), we provide evidence on the role of different educational degrees. To this purpose, we divide high-skill workers into those employed in STEM occupations, which necessitate degrees in scientific fields, and those employed in non-STEM occupations. The effect of AI adoption is positive and highly statistically significant for STEM workers. By contrast, it is negative and only marginally not significant for non-STEM employees (p-value 0.106). The two effects combine to produce the positive but imprecisely estimated coefficient for high-skill workers shown in column (1). These results suggest a specific aspect of upskilling in a period of rising deployment of AI. Specifically, higher education may not fully equip workers to reap the benefits of AI unless it is oriented towards the type of scientific fields made more valuable by these technologies.

We now turn to a related dimension of heterogeneity, namely, job polarization. It is well documented that, both in the US and in other industrialized countries employment has shrunk among occupations in the middle of the wage distribution and expanded in those at the upper and lower tails. The most accredited explanation for this hollowing-out is routine-biased technical change. Our interest is to study whether AI adoption has contributed to job polarization over the last two decades.[26] The previous results suggest that this might not have been the case: as previously shown, the effects of AI adoption on overall employment are different from those of software and computers, the main culprits of job polarization

[26] Job polarization has proceeded over the period of our analysis. Between 2000 and 2020, the average employment share of occupations in the third (middle) quintile of the initial wage distribution has declined by -1.45 p.p., while it has increased in all other quintiles.

Table 9: Heterogeneity: Skills and Occupations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	HS Emp.	LS Emp.	HS-NP Emp.	HS-P Emp.	LS-NP Emp.	LS-P Emp.	HS-STEM Emp.	HS-NSTEM Emp.
2nd Stage Regression								
$AIado_{cdt}$	0.048	-1.641***	0.115	-0.067***	-1.021***	-0.621***	0.577***	-0.530
	[0.326]	[0.450]	[0.326]	[0.023]	[0.340]	[0.206]	[0.042]	[0.321]
1st Stage Regression								
$AIexp_{cdt}$	9.599***	9.599***	9.599***	9.599***	9.599***	9.599***	9.599***	9.599***
	[1.813]	[1.813]	[1.813]	[1.813]	[1.813]	[1.813]	[1.813]	[1.813]
Kleibergen–Paap F-stat.	28.0	28.0	28.0	28.0	28.0	28.0	28.0	28.0
Obs.	1444	1444	1444	1444	1444	1444	1444	1444

The sample consists of 722 CZs observed over two decades, 2000-2010 and 2010-2020. Each observation is a CZ x decade pair. The subscripts c, d and t denote CZs, Census Divisions and decades, respectively. The dependent variables are the changes in the employment of high-skill workers (column 1), low-skill workers (column 2), high-skill/non-production workers (column 3), high-skill/production workers (column 4), low-skill/non-production workers (column 5), low-skill/production workers (column 6), high-skill/STEM workers (column 7) and high-skill/non-STEM workers (column 8), respectively, as a share of population in each CZ over each decade. $AIado_{cdt}$ and $AIexp_{cdt}$ are the measures of AI adoption and AI exposure defined in eq. (12) and (14), respectively. All specifications include Census Division fixed effects, decade fixed effects and the control variables used in Table 3. Observations are weighted by the initial-period share of each CZ in total population. Standard errors are corrected for clustering at the state level. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively.

according to the literature (e.g., Autor and Dorn, 2013).

To provide direct evidence, in columns (1)-(5) of Table 10, we estimate (13) using employment in occupations at each quintile of the initial wage distribution, as a share of population, as the dependent variable. The results are inconsistent with a contribution of AI adoption to job polarization. Indeed, there is no evidence of a U-shaped pattern in the estimated coefficients. Rather, the coefficients follow a seemingly monotonic trend: they are strongly negative for the bottom two quintiles, mildly negative for the third and fourth quintiles, and strongly positive at the top of the distribution.

These results suggest that AI adoption poses threats to low- and medium-wage workers while offering new opportunities to high-wage individuals. At first glance, this seems at odds with the perception that AI should destroy high-paid jobs, as it is used to perform complex tasks. This perception overlooks the fact that AI adoption also necessitates sophisticated skills, which are typically possessed by highly educated individuals, who normally are among the highest paid ones. The previous results on STEM vs. non-STEM workers are consistent with this view.

To provide additional evidence in this direction, we now delve deeper into the effect on the fifth quintile of the initial wage distribution. We divide this quintile into two groups of occupations: those belonging to the top 10 percentiles and those belonging to the remaining percentiles, from the 80th to the 89th. We compute the change in employment as a share of population for each group of occupations and use these variables as outcomes to estimate

Table 10: Heterogeneity: Initial Wage Distribution

	(1) Emp. 1st Quintile	(2) Emp. 2nd Quintile	(3) Emp. 3rd Quintile	(4) Emp. 4th Quintile	(5) Emp. 5th Quintile	(6) Emp. 90-100 Percentiles	(7) Emp. 80-89 Percentiles
2nd Stage Regression							
$AIado_{cdt}$	-0.750*	-0.916***	-0.262**	-0.283**	0.616***	1.040***	-0.423**
	[0.415]	[0.213]	[0.122]	[0.137]	[0.199]	[0.140]	[0.178]
1st Stage Regression							
$AIexp_{cdt}$	9.599***	9.599***	9.599***	9.599***	9.599***	9.599***	9.599***
	[1.813]	[1.813]	[1.813]	[1.813]	[1.813]	[1.813]	[1.813]
Kleibergen–Paap F-stat.	28.0	28.0	28.0	28.0	28.0	28.0	28.0
Obs.	1444	1444	1444	1444	1444	1444	1444

The sample consists of 722 CZs observed over two decades, 2000-2010 and 2010-2020. Each observation is a CZ x decade pair. The subscripts c, d and t denote CZs, Census Divisions and decades, respectively. The dependent variables are the changes in employment, as a share of population, for occupations in the first quintile (column 1), second quintile (column 2), third quintile (column 3), fourth quintile (column 4), fifth quintile (column 5), percentiles 90 to 100 (column 6) and percentiles 80 to 89 (column 7) of the initial wage distribution in each CZ over each decade. $AIado_{cdt}$ and $AIexp_{cdt}$ are the measures of AI adoption and AI exposure defined in eq. (12) and (14), respectively. All specifications include Census Division fixed effects, decade fixed effects and the control variables used in Table 3. Observations are weighted by the initial-period share of each CZ in total population. Standard errors are corrected for clustering at the state level. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively.

(13). The properties of the 2SLS estimator imply that the coefficients on $AIado_{cdt}$ from these two regressions add up to the overall coefficient for the fifth quintile, reported in column (5) of Table 10. The results are presented in columns (6) and (7). The estimates show that the positive effect of AI adoption on the fifth quintile of the initial wage distribution is entirely concentrated among the highest-earning occupations.

To conclude, we consider another dimension of occupational heterogeneity, which helps relate our work to other recent studies on the employment effects of AI. As discussed in the Introduction, some contributions analyze the evolution of employment in occupations that are "exposed" to AI, using exposure measures based on the suitability of each occupation's tasks to the use of these technologies (see, e.g., Albanesi et al., 2023). These studies do not find strong evidence of a negative relationship between AI exposure and employment. The difference between our results and theirs can be attributed to three factors. First, these studies are mostly based on correlations. As argued above, the correlation between AI adoption and employment is likely influenced by other shocks that affect both variables simultaneously (see, e.g., Table 3). Second, the measures of exposure proposed by these studies are meant to identify occupations that use AI. As such, they may sometimes end up identifying occupations that are complementary to it. Third, our previous findings show that some workers are affected by AI adoption even if they hold jobs where AI is not directly used (see Figure 5). The measures of AI exposure used in these studies may fail to identify some

Table 11: Heterogeneity: Webb's (2020) Measure of Occupational Exposure to AI

	(1) Emp. 1st Quartile	(2) Emp. 2nd Quartile	(3) Emp. 3rd Quartile	(4) Emp. 4th Quartile	(5) Emp. 1st Quartile	(6) Emp. 2nd Quartile	(7) Emp. 3rd Quartile	(8) Emp. 4th Quartile
OLS Regression								
$AIado_{cdt}$	0.262***	-0.350***	0.015	-0.432***				
	[0.084]	[0.058]	[0.056]	[0.072]				
2nd Stage Regression								
$AIado_{cdt}$					0.205	-0.868***	-0.065	-0.811***
					[0.489]	[0.248]	[0.152]	[0.176]
1st Stage Regression								
$AIexp_{cdt}$					9.599***	9.599***	9.599***	9.599***
					[1.813]	[1.813]	[1.813]	[1.813]
Kleibergen–Paap F-stat.	-	-	-	-	28.0	28.0	28.0	28.0
Obs.	1444	1444	1444	1444	1444	1444	1444	1444

The sample consists of 722 CZs observed over two decades, 2000-2010 and 2010-2020. Each observation is a CZ x decade pair. The subscripts c, d and t denote CZs, Census Divisions and decades, respectively. The dependent variables are the changes in employment, as a share of population, for occupations in the first quartile (columns 1 and 5), second quartile (columns 2 and 6), third quartile (columns 3 and 7) and fourth quartile (columns 5 and 8) of Webb's (2020) measure of occupational exposure to AI. $AIado_{cdt}$ and $AIexp_{cdt}$ are the measures of AI adoption and AI exposure defined in eq. (12) and (14), respectively. All specifications include Census Division fixed effects, decade fixed effects and the control variables used in Table 3. Observations are weighted by the initial-period share of each CZ in total population. Standard errors are corrected for clustering at the state level. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively.

of these occupations.

In Table 11, we provide evidence consistent with this interpretation. We divide occupations into quartiles based on Webb's (2020) AI exposure measure.[27] Then, we estimate (13) using employment at occupations in each quartile of the distribution, relative to population, as the dependent variable. We report both OLS estimates (columns 1-4) and 2SLS estimates (columns 5-8) of the coefficients β obtained from these regressions. As expected, the effect of AI adoption is strongly negative on occupations in the top quartile of AI exposure. However, we also find that the effect is non-monotonic across quartiles. Interestingly, it is negative and highly significant also on occupations in the second quartile. While these occupations have a relatively low AI exposure according to Webb's (2020) measure, the negative impact of AI adoption on them suggests that they may include jobs that are suitable for automation. Finally, Table 11 shows that the OLS coefficients are higher than their 2SLS counterparts across all quartiles of AI exposure. This pattern confirms that simple correlations may fail to detect negative effects of AI on employment, as they tend to be upward biased due to other contemporaneous shocks.

[27] To construct this measure, Webb (2020) identifies patents related to AI as those using specific keywords, such as "neural network", in their titles or abstracts. Then, he develops an algorithm that identifies occurrences of similar verb-noun pairs both in the patents' titles and in the task descriptions of each occupation. Finally, he obtains a measure of AI exposure for each occupation as an average of these common occurrences across the occupations' tasks, weighted by the importance of each task for the occupation. Webb's (2020) measure is not available for all occupations, which explains why the coefficients reported in Table 11 for the four quartiles of AI exposure do not perfectly add up to those shown in columns (5) and (8) of Table 3 for overall employment.

9 Conclusions

Recent improvements in the field of AI have triggered much hype. The ongoing debate highlights the fact that AI is a flexible technology with the potential of turning dreamlike scenarios or nightmares into reality. Nobody can predict the direction that future innovations and applications will take. However, to inform policy decisions, it is important to understand the consequences that these technologies have had so far. The goal of this paper has been to study the effect of AI adoption on labor demand as measured by changes in employment. Since the deployment of AI can potentially increase productivity but also automate work, its impact on employment is a still unanswered empirical question.[28]

Using data across US CZs over the period 2000-2020, a novel measure of AI adoption based on the growth of AI-related jobs and a shift-share empirical strategy to identify causal effects, we were able to estimate robust negative effects of AI exposure on employment. We also found that AI's impact is different from other forms of capital and technologies, such as robots or ICT, and that it works through services more than manufacturing. Moreover, the employment effect is especially negative for low-skill and production workers, while it turns positive for workers at the top of the wage distribution and for those employed in STEM occupations. Overall, these results are consistent with the view that AI, so far, has contributed to the automation of jobs and to widen inequality. Finally, while the focus of this paper has been on employment so as to best capture displacement effects, AI adoption is likely to have affected wages as well. In the interest of space, we left a detailed analysis of this possibility to future research.

We conclude by discussing some policy implications of our findings. The existing literature has already pointed out that automation, in the form of industrial robots, is partly to blame for falling manufacturing employment (e.g., Acemoglu and Restrepo 2020, Dauth et al. 2021, Bonfiglioli et al. 2022 and 2024). Our alarming result is that service employment, which constitutes the lion's share in developed countries, may not be immune to automation through AI. It is therefore crucial that governments put in place measures aimed at alleviating adverse labor-market consequences. Since the negative effects are concentrated among low-skill workers, a first remedy could be to help employees acquire new skills. Moreover, our results on STEM vs. non-STEM workers suggest that investments in education should be targeted towards scientific fields. Facilitating job-to-job transitions and improving the flexibility of the labor market can also ease reallocation costs. Since top earners seem to actually

[28] See Varian (2018) and Acemoglu (2022) for a discussion of policy questions pertaining to other aspects of AI.

benefit from these new technologies, appropriate transfer schemes could also be used to ensure that the gains are more broadly shared. Finally, incentive schemes could be designed to redirect innovation towards applications aimed at improving human capabilities rather than labor savings. To this end, collecting better data and developing methodologies to identify the complementarities between AI applications and jobs seem an important step for future research.

Appendix A Robustness Checks

In this Appendix, we study the robustness of the baseline results along three dimensions: the presence of influential observations; the use of different corrections for the standard errors; and the adoption of alternative definitions for the main variables.

A.1 Outliers

The first six columns of Table A1 report 2SLS estimates of β obtained by estimating (13) on different sub-samples, which exclude extreme observations in $\Delta\,(L/P)_{cdt}$ or $AIado_{cdt}$. We drop observations for which $\Delta\,(L/P)_{cdt}$ is above or below the sample mean by more than two standard deviations (column 1) or for which $\Delta\,(L/P)_{cdt}$ falls in the top or bottom 1% (column 2) or 5% (column 3) of the distribution. We use the same approaches to exclude extreme observations in $AIado_{cdt}$ (columns 4-6). In all cases, the coefficient β remains negative and very precisely estimated. Excluding extreme observations either leaves the point estimate close to the baseline or makes it larger, suggesting that the results are not driven by outliers.

So far, we have used pooled five-year ACS data for 2021 (2017-2021) to construct observations for 2020. This approach follows Acemoglu and Restrepo (2020), who use ACS data for 2012-2016 to construct their 2014 observations. Moreover, it ensures that the 2020 observations in our sample are built analogously to their 2010 counterparts, which are based on pooled five-year ACS data for 2011 (2007-2011). However, the years 2020 and 2021 coincide with the early phase of the Covid-19 pandemic which, besides affecting the labor market, might have influenced firms' decisions to adopt AI. To mitigate the concern that the results might be driven by the Covid-19 pandemic, we exclude 2020 and 2021, and construct 2020 observations for $\Delta\,(L/P)_{cdt}$, $AIado_{cdt}$ and $AIexp_{cdt}$ using pooled three-year ACS data for 2019 (2017-2019). Reassuringly, the coefficient β presented in column (7) is essentially identical to the baseline estimate.

A.2 Inference

In Figure A1, we plot the baseline coefficient β along with confidence intervals corresponding to alternative corrections for the standard errors. Confidence interval (1), labeled "Baseline", is based on standard errors corrected for clustering at the state level. Confidence intervals (2)-(5) are based on standard errors corrected for clustering at the CZ level; the Census Division level; the state-year level; and the Census Division-year level. These clustering structures allow for correlation in the residuals within each CZ over time; across all CZs

Table A1: Robustness Checks: Outliers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Excluding Outliers in Δ(L/P)			Excluding Outliers in AIado			Excl. Covid-19 Pandemic
	2std from Mean	1% Tails	5% Tails	2std from Mean	1% Tails	5% Tails	
2nd Stage Regression							
$AIado_{cdt}$	-1.119***	-1.533***	-1.125***	-2.940***	-2.395***	-3.190***	-1.606***
	[0.333]	[0.370]	[0.334]	[0.642]	[0.616]	[0.777]	[0.464]
1st Stage Regression							
$AIexp_{cdt}$	9.306***	9.556***	9.237***	7.169***	7.467***	5.752***	8.345***
	[1.958]	[1.852]	[1.999]	[1.150]	[1.076]	[1.096]	[1.941]
Kleibergen–Paap F-stat.	22.6	26.6	21.3	38.9	48.1	27.5	18.5
Obs.	1386	1414	1295	1387	1409	1298	1444

The sample consists of 722 CZs observed over two decades, 2000-2010 and 2010-2020. Each observation is a CZ x decade pair. The subscripts c, d and t denote CZs, Census Divisions and decades, respectively. The dependent variable is the change in the employment-to-population ratio in each CZ over each decade. $AIado_{cdt}$ and $AIexp_{cdt}$ are the measures of AI adoption and AI exposure defined in eq. (12) and (14), respectively. The specifications in columns (1)-(3) exclude observations for which the change in the employment-to-population ratio is above or below the sample mean by more than two standard deviations (column 1) or falls in the top or bottom 1% (column 2) or 5% (column 3) of the distribution. The specifications in columns (4)-(6) exclude the corresponding observations of $AIado_{cdt}$. In column (7), the 2020 observations of $AIado_{cdt}$, $AIexp_{cdt}$ and the employment-to-population ratio in each CZ are constructed using pooled three-year ACS data for 2019 (2017-2019) rather than pooled five-year ACS data for 2021 (2017-2021). All specifications include Census Division fixed effects, decade fixed effects and the control variables used in Table 3. Observations are weighted by the initial-period share of each CZ in total population. Standard errors are corrected for clustering at the state level. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively.

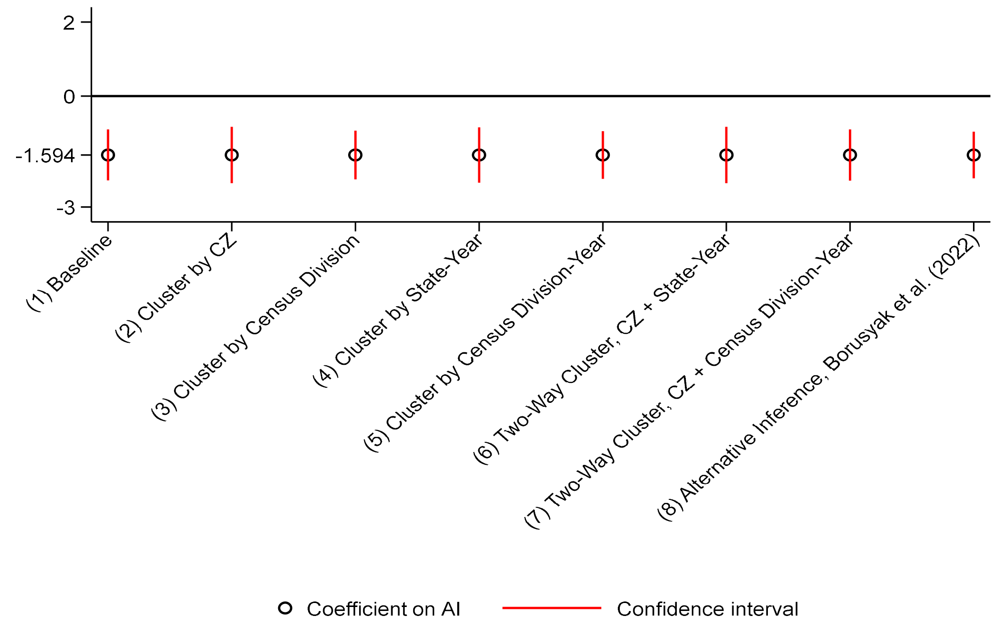
within the same Census Division and over time; and across all CZs within the same state, or within the same Census Division, in a given year. Confidence intervals (6) and (7) combine the latter two clustering structures with clustering at the CZ level (two-way clustering) to allow for residual correlation both across CZs and over time within a CZ. Finally, confidence interval (8) is based on Borusyak et al.'s (2022) inference approach. The latter takes account of the fact that, with a shift-share instrument, standard inference may be invalid because observations with similar industry shares may have correlated residuals.[29] Reassuringly, all confidence intervals are very similar to the baseline one, suggesting that the results are not sensitive to the specific approach used for inference.

A.3 Variables Definitions

In Table A2, we consider alternative ways of defining the main variables. We start by tackling the concern that our definition of AI-related occupations might be too broad, including work unrelated to AI. To this purpose, we construct both $AIado_{cdt}$ and $AIexp_{cdt}$ using a narrow set of AI-related occupations, which only includes "Data Scientists". Employment in this occupation has started to increase only recently and is still very low (0.01% at the national level in 2020). Nevertheless, the estimate of β reported in column (1) is negative and very precisely estimated also in this case. Quantitatively, the effect is essentially identical to the baseline: a 1 s.d. higher $AIado_{cdt}$ would cause a fall in $\Delta (L/P)_{cdt}$ of 1 p.p., or 0.56% of its s.d..

Next, we use a different classification of AI-related occupations, proposed by Hanson (2022). We construct both $AIado_{cdt}$ and $AIexp_{cdt}$ using the five occupations encompassed by

[29] See also Adao et al. (2019).



Hollow circles correspond to the baseline 2SLS coefficient on $AIado_{cdt}$ (Table 3, column 8). Confidence interval (1) refers to standard errors corrected for clustering at the state level. Confidence intervals (2)-(7) correspond to standard errors corrected using the alternative clustering schemes indicated on the horizontal axis. Confidence interval (8) is based on Borusyak et al.'s (2022) inference approach. All confidence intervals are at the 90% level.

Figure A1: Robustness Checks: Inference

this classification, and estimate (13) using the new variables.[30] The coefficient β presented in column (2) is very close to the estimate obtained with our classification. The size of the effect is such that a 1 s.d. higher $AIado_{cdt}$ would cause a fall in $\Delta\left(L/P\right)_{cdt}$ of 0.9 p.p., or 0.51% of its s.d.. These results suggest that our evidence is unlikely to be an artifact of the criteria used for identifying AI-related occupations.

We now turn to alternative ways of constructing the AI adoption measure and the instrument. In column (3), we build $AIexp_{cdt}$ using industry shares for 1990 rather than 1980. It is reassuring that β hardly changes, suggesting that $AIexp_{cdt}$ exploits long-lasting differences in the industrial specialization of CZs, rather than period-specific developments in their industrial structure that could result from transitory shocks. In column (4), we adjust $AIado_{cdt}$ for cross-industry differences in the growth rate of employment within each CZ. We similarly adjust $AIexp_{cdt}$ for cross-industry differences in the growth rate of employment at the national level. While the first-stage relationship is slightly weaker, the main results are qualitatively unchanged and quantitatively stronger. This suggests that our evidence is

[30] Hanson's (2022) definition of AI-related occupations comprises "Computer Scientists and Systems Analysts", "Computer Software Engineers", "Network Systems and Data Communication Analysts", "Statisticians" and "Computer Hardware Engineers". See footnote 10 in the main text for additional details.

Table A2: Robustness Checks: Variables Definitions

	(1) Only Data Scientists	(2) Hanson's AI-Related Occ.	(3) Ind. Shares for 1990	(4) Adj. for Ind. Growth	(5) Emp./Working-Age Population	(6) Emp./Labor Force	(7) Log Emp.	(8) Private Sector Emp.	(9) Public Sector Emp.
2nd Stage Regression									
$AIado_{cdt}$	-17.340***	-1.434***	-1.138***	-3.443**	-1.623***	-0.479**	-2.143***	-1.593***	-0.000
	[4.395]	[0.336]	[0.289]	[1.466]	[0.378]	[0.233]	[0.510]	[0.425]	[0.194]
1st Stage Regression									
$AIexp_{cdt}$	12.286***	10.000***	8.620***	1.288***	9.599***	9.599***	8.337***	9.599***	9.599***
	[1.835]	[1.592]	[2.225]	[0.458]	[1.813]	[1.813]	[1.467]	[1.813]	[1.813]
Kleibergen–Paap F-stat.	44.8	39.4	15.0	7.9	28.0	28.0	32.3	28.0	28.0
Obs.	1444	1444	1444	1444	1444	1444	1444	1444	1444

The sample consists of 722 CZs observed over two decades, 2000-2010 and 2010-2020. Each observation is a CZ x decade pair. The subscripts c, d and t denote CZ, Census Divisions and decades, respectively. The dependent variable is: the change in the employment-to-population ratio in each CZ over each decade (columns 1-4); the change in employment relative to working-age population (column 5) or relative to labor force (column 6) in each CZ over each decade; the log change in employment in each CZ over each decade (column 7); and the change in private sector employment (column 8) or public sector employment (column 9) relative to population in each CZ over each decade. $AIado_{cdt}$ and $AIexp_{cdt}$ are the measures of AI adoption and AI exposure defined in eq. (12) and (14), respectively. In column (1), $AIado_{cdt}$ and $AIexp_{cdt}$ are based on a narrow definition of AI-related occupations, which only includes "Data Scientists". In column (2), $AIado_{cdt}$ and $AIexp_{cdt}$ are based on an alternative definition of AI-related occupations proposed by Hanson (2022). In column (3), $AIexp_{cdt}$ is constructed using CZ-level industry shares for 1990 rather than 1980. In column (4), $AIado_{cdt}$ and $AIexp_{cdt}$ are adjusted for cross-industry differences in employment growth rates at the CZ and national level, respectively. All specifications include Census Division fixed effects, decade fixed effects and the control variables used in Table 3. The specification in column (7) also includes the log change in population. Observations are weighted by the initial-period share of each CZ in total population. Standard errors are corrected for clustering at the state level. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively.

not driven by changes in industries' relative size but reflects variation in AI intensity within industries.

Finally, we consider alternative definitions of the main outcome. So far, we have used total population as the denominator of $\Delta\left(L/P\right)_{cdt}$, following Acemoglu and Restrepo (2020). This normalization may raise the concern that the results might not properly account for demographic trends, which are not fully reflected in total population. Accordingly, in columns (5) and (6), we estimate (13) using working-age population and labor force, respectively, as the denominator of $\Delta\left(L/P\right)_{cdt}$. The main evidence is preserved. In column (7), we follow a complementary approach and estimate (13) for the log change in employment, adding the log change in population among the controls. The coefficient implies that a 1 s.d. higher $AIado_{cdt}$ would lower employment growth by 1.3%. In columns (8) and (9), we revert to the employment-to-population ratio as the dependent variable but split the numerator into private and public sector employment. The results show that the effect of AI adoption is entirely concentrated in the private sector, where the bulk of the phenomenon is currently taking place.

Appendix B The Conley, Hansen and Rossi (2012) approach

In this Appendix, we illustrate the main idea behind the approach of Conley, Hansen and Rossi (2012) using our set-up. Consider the following version of (13):

$$\Delta\left(L/P\right)_{cdt} = \alpha_d + \alpha_t + \beta \cdot AIado_{cdt} + \mathbf{X}'_{cdt} \cdot \boldsymbol{\gamma} + \lambda \cdot AIexp_{cdt} + \varepsilon_{cdt},$$

where λ is a parameter measuring the size of a violation of the exclusion restriction. The baseline results presented in the text are based on the standard IV assumption that $\lambda = 0$. However, if the exclusion restriction was not satisfied, i.e., if $\lambda \neq 0$, inference on β could still be performed, using alternative priors about λ and conditional on this parameter. This can be done by estimating the following specification

$$\Delta \left(L/P\right)_{cdt} - \lambda \cdot AIexp_{cdt} = \alpha_d + \alpha_t + \beta \cdot AIado_{cdt} + \mathbf{X}_{cdt}^{'} \cdot \boldsymbol{\gamma} + \varepsilon_{cdt}$$

with 2SLS, instrumenting $AIado_{cdt}$ with $AIexp_{cdt}$. Varying the prior about λ allows assessing how inference on β would be influenced by different degrees of violation of the exclusion restriction. Because the sensitivity of the 2SLS estimator to violations of the exclusion restriction inversely depends on the strength of the instrument, the same value of λ induces a smaller decrease in precision the stronger is the first-stage relationship.

We set λ to be a function of a parameter δ, which we progressively raise (by intervals of 0.01 starting from 0) to generate increasingly larger violations of the exclusion restriction. Specifically, we set $\lambda \equiv -1.594 \times 11 \times \delta$, where -1.594 is the baseline 2SLS estimate of β and the interquartile range of $AIado_{cdt}$ is approximately 11 times that of $AIexp_{cdt}$. For each value of λ, we estimate the confidence interval of β for both the lower and the upper end of the support $[-\lambda, \lambda]$, and compute the final confidence interval as the union of the two confidence intervals.[31]

Appendix C Data Appendix

[31]Besides this "union of confidence intervals" approach, Conley, Hansen and Rossi (2012) discuss other strategies that use more prior information about λ. By imposing additional parametric restrictions, these alternative approaches tend to yield narrower confidence intervals around the treatment parameter, and thus may be less conservative.

Table C1: Summary Statistics on Outcomes

	Obs.	Mean	Median	Std. Dev.
$\Delta(L/P)_{cdt}$	1444	0.0309	0.0279	0.0178
$\Delta(L/P)_{cdt}$ (pre-sample: 1980-1990, 1990-2000)	1444	0.0055	0.0056	0.0136
$\Delta(L/P)_{cdt}$ (excluding 2020 and 2021)	1444	0.0316	0.0292	0.0174
$\Delta(L/P)_{cdt}$ (private sector)	1444	0.0269	0.0246	0.0196
$\Delta(L/P)_{cdt}$ (public sector)	1444	0.0040	0.0037	0.0113
$\Delta(L/P)_{cdt}$ (primary sector)	1444	0.0018	0.0022	0.0127
$\Delta(L/P)_{cdt}$ (secondary sector)	1444	-0.0101	-0.0069	0.0233
$\Delta(L/P)_{cdt}$ (manufacturing sector)	1444	-0.0123	-0.0086	0.0216
$\Delta(L/P)_{cdt}$ (tertiary sector)	1444	0.0393	0.0368	0.0254
$\Delta(L/P)_{cdt}$ (high-skill)	1444	0.0349	0.0339	0.0177
$\Delta(L/P)_{cdt}$ (low-skill)	1444	-0.0041	-0.0070	0.0269
$\Delta(L/P)_{cdt}$ (high-skill, non-production)	1444	0.0338	0.0327	0.0174
$\Delta(L/P)_{cdt}$ (high-skill, production)	1444	0.0011	0.0010	0.0023
$\Delta(L/P)_{cdt}$ (low-skill, non-production)	1444	0.0088	0.0071	0.0283
$\Delta(L/P)_{cdt}$ (low-skill, production)	1444	-0.0128	-0.0111	0.0180
$\Delta(L/P)_{cdt}$ (high-skill, STEM)	1444	0.0027	0.0025	0.0050
$\Delta(L/P)_{cdt}$ (high-skill, non-STEM)	1444	0.0322	0.0318	0.0161
$\Delta(L/P)_{cdt}$ (male)	1444	0.0137	0.0137	0.0129
$\Delta(L/P)_{cdt}$ (female)	1444	0.0172	0.0159	0.0147
$\Delta(L/P)_{cdt}$ (age 16-24)	1444	0.0013	0.0016	0.0119
$\Delta(L/P)_{cdt}$ (age 25-44)	1444	-0.0134	-0.0115	0.0342
$\Delta(L/P)_{cdt}$ (age 45+)	1444	0.0430	0.0473	0.0422
$\Delta(L/P)_{cdt}$ (1st quintile of initial wage distribution)	1444	0.0098	0.0089	0.0300
$\Delta(L/P)_{cdt}$ (2nd quintile of initial wage distribution)	1444	0.0082	0.0084	0.0128
$\Delta(L/P)_{cdt}$ (3rd quintile of initial wage distribution	1444	0.0000	-0.0002	0.0126
$\Delta(L/P)_{cdt}$ (4th quintile of initial wage distribution)	1444	0.0061	0.0051	0.0124
$\Delta(L/P)_{cdt}$ (5th quintile of initial wage distribution)	1444	0.0054	0.0046	0.0208
$\Delta(L/P)_{cdt}$ (percentiles 90-100 of initial wage distribution)	1444	-0.0047	-0.0052	0.0143
$\Delta(L/P)_{cdt}$ (percentiles 80-89 of initial wage distribution)	1444	0.0101	0.0088	0.0093
$\Delta(L/P)_{cdt}$ (percentiles 95-100 of initial wage distribution)	1444	-0.0018	-0.0020	0.0067
$\Delta(L/P)_{cdt}$ (percentiles 80-94 of initial wage distribution)	1444	0.0071	0.0061	0.0156
$\Delta(L/P)_{cdt}$ (1st quartile of Webb's AI exposure)	1444	-0.0348	-0.0287	0.0398
$\Delta(L/P)_{cdt}$ (2nd quartile of Webb's AI exposure)	1444	-0.0158	-0.0132	0.0273
$\Delta(L/P)_{cdt}$ (3rd quartile of Webb's AI exposure)	1444	-0.0421	-0.0416	0.0142
$\Delta(L/P)_{cdt}$ (4th quartile of Webb's AI exposure)	1444	-0.0178	-0.0164	0.0123
$\Delta(L/WAP)_{cdt}$	1444	0.0468	0.0454	0.0182
$\Delta(L/LF)_{cdt}$	1444	0.0070	0.0088	0.0159
$\Delta \ln L_{cdt}$	1444	0.0606	0.0512	0.0858
$\Delta(U/P)_{cdt}$	1444	-0.0054	-0.0072	0.0153
$\Delta(NILF/P)_{cdt}$	1444	-0.0255	-0.0223	0.0226

All statistics are computed on a sample of 722 CZs observed over two decades, 2000-2010 and 2010-2020. The subscripts c, d and t denote CZs, Census Divisions and decades, respectively. L, U, LF, $NILF$, P and WAP denote employment, unemployment, labor force, not in labor force, population and working-age population, respectively.

Table C2: Summary Statistics on AI adoption and AI exposure

	Obs.	Mean	Median	Std. Dev.
AI Adoption				
$AIado_{cdt}$	1444	0.0038	0.0026	0.0063
$AIado_{cdt}$ (excluding 2020 and 2021)	1444	0.0029	0.0022	0.0050
$AIado_{cdt}$ (data scientists only)	1444	0.0003	0.0001	0.0006
$AIado_{cdt}$ (Hanson's AI-related occupations)	1444	0.0041	0.0027	0.0067
$AIado_{cdt}$ (manufacturing industries)	1444	-0.0001	0.0000	0.0012
$AIado_{cdt}$ (non-manufacturing industries)	1444	0.0039	0.0029	0.0059
$AIado_{cdt}$ (adjusted for industry employment growth)	1444	0.0010	0.0012	0.0053
$AIado_{cdt}$ (excluding top decile industries)	1444	0.0033	0.0024	0.0061
AI Exposure				
$AIexp_{cdt}$	1444	0.0002	0.0002	0.0004
$AIexp_{cdt}$ (excluding 2020 and 2021)	1444	0.0002	0.0001	0.0004
$AIexp_{cdt}$ (data scientists only)	1444	0.0000	0.0000	0.0000
$AIexp_{cdt}$ (Hanson's AI-related occupations)	1444	0.0002	0.0002	0.0004
$AIexp_{cdt}$ (manufacturing industries)	1444	0.0000	0.0000	0.0004
$AIexp_{cdt}$ (non-manufacturing industries)	1444	0.0004	0.0003	0.0006
$AIexp_{cdt}$ (adjusted for industry employment growth)	1444	0.0006	0.0002	0.0031
$AIexp_{cdt}$ (excluding top decile industries)	1444	0.0001	0.0001	0.0003
$AIexp_{cdt}$ (1990 industry shares)	1444	0.0003	0.0002	0.0005
$AIexp_{cdt}$ (leave-one-out)	1444	0.0017	-0.0026	0.0650

All statistics are computed on a sample of 722 CZs observed over two decades, 2000-2010 and 2010-2020.$AIado_{cdt}$ and $AIexp_{cdt}$ are the measures of AI adoption and AI exposure defined in eq. (12) and (14), respectively.

Table C3: Software used to Identify the AI-Related Occupations

Amazon Redshift	GitHub	Oracle PL/SQL
Amazon Simple Storage Service S3	Go	PHP
Amazon Simple Storage Service S4	JavaScript	Perl
Amazon Web Services AWS CloudFormation	JavaScript Object Notation JSON	PostgreSQL
Amazon Web Services AWS software	Jenkins CI	Python
Ansible Software	Kubernetes	Ruby
Apache Hadoop	Microsoft .NET Framework	Scala
Apache Hive	Microsoft Azure software	Selenium
Apache Kafka	Microsoft PowerShell	ServiceNow
Apache Spark	Microsoft SQL Server	Splunk Enterprise
Atlassian Confluence	Microsoft SQL Server Reporting Services SSRS	Spring Boot
Atlassian JIRA	MongoDB	Spring Framework
Bash	NoSQL	Structured query language SQL
C	Node.js	Transact-SQL
C#	Objective C	TypeScript
C++	Oracle Database	UNIX
Docker	Oracle Java	Vue.js
Git	Oracle Java 2 Platform Enterprise Edition J2EE	jQuery

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