Disclosure Statement for Wenjia Cao

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Sincerely,



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Machine Versus Muscle, Bot Versus Brain: Effects of Artificial Intelligence on Heterogeneous Skill Groups

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Abstract

This paper studies effects of artificial intelligence (AI) on employment and wages for heterogeneous skill groups in the U.S. by introducing and analyzing a task-based framework. I first categorize labor into four skill groups based on skill specializations: (1) abstract and AI-intensive; (2) abstract-intensive but not yet AI-related; (3) routine-intensive; and (4) manual-intensive. The demand for AI skills is then measured by matching phrases for AI-developing skills to descriptions of online job postings. I document a consistent upward trend in the share of AI postings for the high-skilled AI-complement group during my sampling period, 2012-21. There is a strong growth in both employment and wages for abstract and AI-intensive occupations associated with an increasing demand for AI skills, while abstract but not-yet-AI occupations have much smaller growth. Middle-skilled occupations experience wage declines associated with an increase in the standard deviation of the intensity that AI-developing skills are required for job tasks. Employment and wage gaps between abstract and AI-intensive occupations and other skill groups widen as the labor market favors workers with AI skills, consistent with my theoretical model's implications. I also discuss whether AI is possibly a general-purpose technology.

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1 Introduction

The displacement effect of high tech, especially automation and industrial robots, has been intensively studied (e.g., Acemoglu and Autor, 2011; Autor and Dorn, 2013; Acemoglu and Restrepo (2019, 2022a); Faber, Sarto, and Tabellini, 2019; Dauth et al., 2021; Kogan et al., 2021). Previous literature has largely focused on how low- and middle-skilled workers (those who specialize in manual- and routine-intensive occupations, respectively) are replaced by automation and has assumed that high-skilled workers are unlikely to be negatively affected by automation. However, this assumption may not hold in the case of artificial intelligence (AI). AI is an algorithm or a program which aims at recognizing patterns from large datasets and making predictions and rational decisions like humans (Russell and Norvig, 2021).

The biggest difference between AI and industrial automation discussed in this paper is that AI is claimed to be a general-purpose technology (GPT) with profound impacts on technological evolution and the economy (e.g., Dafoe, 2018; Brynjolfsson, Rock, and Syverson, 2019; Cockburn, Henderson, and Stern, 2019; Crafts, 2021; Hötte et al., 2022; Goldfarb, Taska, and Teodoridis, 2023), while industrial automation is not. The latter one specifically substitutes for labor in tasks that follow explicitly defined rules (i.e., routine tasks). Importantly, AI can not only perform more complex and abstract tasks but also increase the productivity of workers who possess AI-developing skills and even create new job opportunities. Yet there is little evidence regarding effects of AI as a GPT on heterogeneous skill groups in the labor market, or how these effects differ from those of traditional high tech that are not considered as GPTs, especially industrial automation. This paper attempts to fill this gap by introducing and analyzing a task-based framework which (1) incorporates both traditional and rapid-growing high tech and (2) categorizes labor into detailed groups based on skill specializations to reflect the complementarity and displacement effects of AI.

This paper focuses on AI-developing skills (e.g., deep learning, machine learning, natural language processing), which are used to improve the performance of AI technologies, predict patterns, and develop AI-powered tools. To explore the relationship between the demand for AI skills and labor market outcomes of heterogeneous skill groups, I first categorize occupations into four skill groups: (1) high-skilled AI-complement group with a concentration on abstract-intensive tasks that require AI skills (e.g., "Software Developers, Applications and Systems Software" and "Aerospace Engineers"); (2) high-skilled, not-yet-AI-complement group that is abstract-intensive but not yet AI-related (e.g., "Chemists and Materials Scientists" and "Lawyers, and Judges, Magistrates, and other Judicial Workers"); (3) middle-skilled group that is routine-intensive (e.g., "Stock Clerks and Order Fillers" and "Automotive Body and Related Repairers"); and (4) low-skilled group that is manual-intensive (e.g., "Waiters and Waitresses").

Since an occupation comprises a tremendous amount of job postings, I directly match phrases for AI-developing skills to the description of postings using online job postings data to define AI postings, i.e., postings that require AI skills. These postings capture AI's complementarity; more employers listing AI skills in job postings indicate a higher demand for people specializing in AI-developing activities. Next, I aggregate AI postings to the occupational level to distinguish between AI-complement and not-yet-AI occupations. Abstract, routine, and manual occupations are then defined using the occupational-level task contents measured by Autor and Dorn (2013). Finally, an occupation exclusively falls into one skill group according to the definition of skill groups introduced above.

I first document a consistent upward trend in the share of AI postings for the high-skilled AI-complement group during my sampling period, 2012-21. These abstract and AI-intensive occupations experience the largest employment growth and wage gains, associated with an increasing share of AI postings at the state-year level, compared to other skill groups. Specifically, a 1 percentage point increase in the AI posting share leads to 50 more employed people per 100,000 population, a 3% increase in mean hourly wages, and a 0.078 percentage point increase in the wage income share for high-skilled AI-complement occupations. I also perform a principal component analysis to measure the intensity that AI-developing skills are required for job tasks. I document a significant and positive relationship between this measure and labor market outcomes for high-skilled AI-complement occupations.

The second result is that although there is significant growth in employment and wages for high-skilled, not-yet-AI occupations, this growth is much smaller than that for the high-skilled AI-complement group. For example, employment growth for the high-skilled, not-yet-AI group is less than half that of the high-skilled AI-complement group. Findings on the high-skilled occupations suggest that AI has differential effects within the high-skilled group. The employment and wage gaps between abstract, AI-intensive occupations and abstract, not-yet-AI occupations widen when AI becomes more ubiquitous.

The third result shows that overall effects of the AI posting share on the employment and wages for middle- and low-skilled occupations are small and negative, but not statistically significant. However, I find that middle-skilled occupations experience a wage decline associated with an increase in the standard deviation of the measure of the intensity with which AI skills are required for job tasks.

These findings imply a "J-shaped" curve of changes in employment or wages by skill level, where employment or wages in both the right and left tails are higher than the middle, and the right tail is exceptionally higher than the left tail. The labor market favors people specializing in AI-developing tasks as AI grows, with the employment and wage gaps between abstract and AI-intensive occupations and other skill groups widening over time.

My empirical analysis further suggests why AI is possibly a general-purpose technology, akin to

the steam engine and electricity. First, AI has a wide range of applications across occupations and sectors. Second, there is an increasing trend in explicitly listing AI skill requirements when employers post new job vacancies, regardless of skill groups or industry sectors. Third, AI tends to impact the whole economy rather than particular occupations or sectors. Although changes in the state-year share of AI postings have strong and differential effects on employment and wages for skill groups, these relationships become insignificant when using the share of AI postings at more granular level, i.e., 2-digit-occupation-by-state-by-year level.[1] This implies that the employment and wage gaps between skill groups are driven by across-group variation, not within-group.

To provide theoretical explanations for my empirical results, I extend task-based models developed in Acemoglu and Autor (2011), Acemoglu and Restrepo (2018a), and Autor et al. (2024). Tasks can be performed by labor or technology (embodied in capital). Instead of general technology, my model specifically considers AI and industrial automation as factors of production by assuming they have different productivities so that AI can compete against labor in more complex and abstract tasks while industrial automation cannot. Labor is categorized into four skill groups based on skill specializations—high-skilled AI-complement, high-skilled not-yet-AI, middle-skilled, and low-skilled—to better explore the differential effects of AI and industrial automation on labor market outcomes of skill groups.

In my model, AI will by assumption displace middle- and high-skilled workers in complex tasks (displacement effect) and in equilibrium expand the set of tasks performed by high-skilled workers (reinstatement effect). In contrast, industrial automation by assumption only has a displacement effect on both low- and middle-skilled workers. The displacement effect driven by AI narrows wage gaps between high-skilled labor and other skill groups, while the displacement effect of industrial automation and the reinstatement effect of AI widen these wage gaps. In addition, this task-based framework explores the differential effects of AI as a labor-augmenting technology by assuming that the growth in AI particularly increases the productivity of high-skilled AI-complement workers. Since these workers specialize in AI-developing activities and can be complemented by AI, the wage gap between high-skilled AI-complement workers and other types of workers widens as AI grows.

A substantial amount of literature has developed theoretical models to study the impacts of technology on labor market outcomes (e.g., Katz and Murphy, 1992; Autor, Levy, and Murnane, 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Acemoglu and Restrepo (2018a,b, 2019); Autor et al., 2024). Although the canonical model (1) explains that changes in factor-augmenting technologies and relative labor supplies are confounding factors of changes in the wage structure and (2) concludes that skill premiums lead to employment and wage inequalities, it fails to provide a reason for why middle-

[1]The 2-digit occupation is the most broad occupation category in the data used in my empirical analysis.

skilled workers experience declines in both wages and employment compared to low- and high-skilled workers (which is referred to as "polarization"). A task-based model has implications on labor market trends and polarization by making a distinction between skills and tasks and allowing labor to have comparative advantages in performing different tasks. The task-based framework introduced in this paper contributes to this body of work by (1) specifically incorporating both industrial automation, which substitutes for low- and middle-skilled workers in simpler and more routine tasks, and AI, which competes against middle- and high-skilled workers in more complex and abstract tasks, and (2) decomposing high-skilled workers into two groups based on the specialization in AI-developing tasks.

This paper also contributes to research focusing on the evolution of work, changes in skill demands, and wage gaps. Using a job postings dataset from 1950 to 2000, Atalay et al. (2020) document an upward-sloping (downward-sloping) trend for the frequency of words related to non-routine (routine) tasks in postings. Similarly, Nedelkoska et al. (2021) find that both male and female workers have switched from performing routine and manual tasks to non-routine cognitive tasks since 1970s. Kogan et al. (2021) show that workers who are exposed to technological innovations have experienced worse labor market outcomes such as employment and wages, while Autor et al. (2024) state that employment and wages increase in occupations exposed to technological innovations with augmentation effects but decrease in those exposed to innovations with displacement effects. Instead of focusing on general technologies or industrial automation that displace labor in routine-intensive tasks, this paper discusses the differential effects of AI, a fast-growing technology that can not only substitute for but also complement higher-skilled labor in performing more abstract tasks, on heterogeneous skill groups.

The most closely related to this paper is Acemoglu et al. (2022). They specifically study the effects of AI on hiring and skill requirements using online job vacancies data. They conclude that recruitment of workers with AI skills increases in establishments highly exposed to AI, while non-AI hiring declines in these establishments. However, the measures of AI they used capture the extent an occupation is exposed to AI, i.e., AI's substitutability. In this paper, I classify job postings into AI and not-yet-AI postings and use AI postings to capture AI's complementarity. New job vacancies that require AI skills indicate that these jobs need to hire people to perform AI-developing tasks, suggesting the demand for AI skills. I also propose an alternative measure that captures the intensity of AI skills required for job applicants when applying for a job.

The rest of this paper proceeds as follows. A task-based framework is introduced in Section 2 which motivates my empirical analysis. Section 3 describes the data used in my empirical analysis and defines skill groups. My empirical strategy and main results are presented in Sections 4 and 5, respectively. Section 6 discusses why AI can be considered as a general-purpose technology. Section 7 concludes.

2 Theoretical Model

In this section, I follow Acemoglu and Autor (2011), Acemoglu and Restrepo (2018a), and Autor et al. (2024) to introduce a task-based model, which motivates my empirical analysis on exploring the influences of AI on labor market outcomes of heterogeneous skill groups.

2.1 Environment

I begin with a unique final good Y produced by combining a unit measure of tasks as follows:

$$Y = \left[\int_{N-1}^{N} y(i)^{\frac{\sigma-1}{\sigma}} di \right]^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where $y(i)$ is the output of task $i \in [N-1, N]$ and $\sigma \in (0, \infty)$ is the elasticity of substitution between tasks. The index i represents the complexity of a task. The higher an index is, the more complex the corresponding task is. Since I assume that Y is the unique final good, Y is set to be the numeraire and its price $P \equiv 1$.

There are five factors of production, high-skilled AI-complement labor (H^{AI}), high-skilled not-yet-AI labor (H^{Non}), middle-skilled or AI-substitutable labor (M), low-skilled labor (L), and technology which embodied in capital (K). Then the production function for task i is:

$$y(i) = \alpha_{H^{AI}}(i) h^{AI}(i) + \alpha_{H^{Non}}(i) h^{Non}(i) + \alpha_M(i) m(i) + \alpha_L(i) l(i) + \alpha_K k(i), \tag{2}$$

where $\alpha_{H^{AI}}(i)$, $\alpha_{H^{Non}}(i)$, $\alpha_M(i)$, $\alpha_L(i)$, and α_K represent the productivity of the corresponding factor of production; $h^{AI}(i)$, $h^{Non}(i)$, $m(i)$, $l(i)$, and $k(i)$ are the total quantities of the corresponding factor used to perform task i. I impose the following assumptions on these productivities:

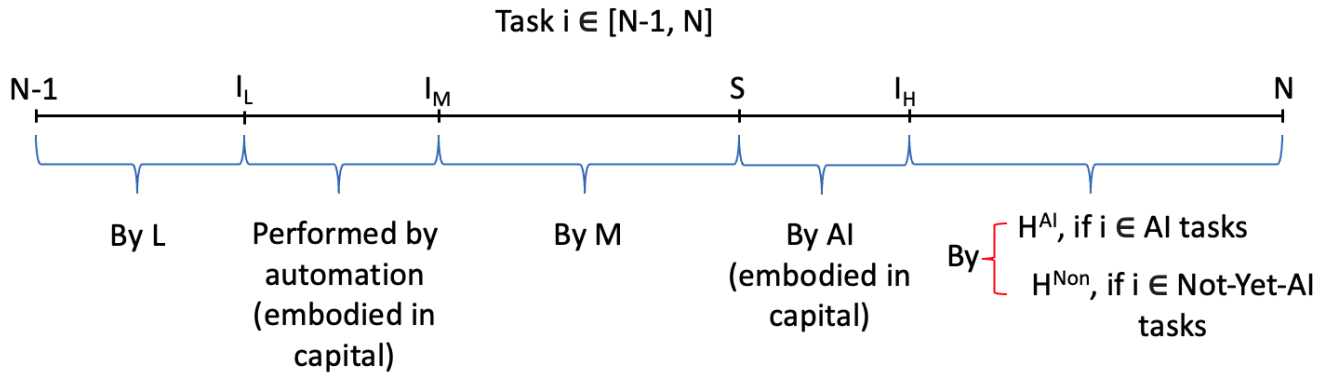
Assumption 1. *$\alpha_{H^j}(i)$, $\alpha_M(i)$, $\alpha_L(i)$, $\frac{\alpha_{H^j}(i)}{\alpha_M(i)}$, and $\frac{\alpha_M(i)}{\alpha_L(i)}$, $j \in \{AI, Non\}$, are continuously differentiable and strictly increasing.*

This assumption implies that (1) labor has higher productivity in more complex tasks (i.e., more abstract tasks) which are represented by a higher index; and (2) higher-skilled workers have comparative advantages over lower-skilled workers in performing more complex tasks.

Assumption 2. *$\exists I_H \in [N-1, N]$ such that $\frac{\alpha_{H^{AI}}(i)}{\alpha_{H^{Non}}(i)}$ is continuously differentiable and strictly increasing (decreasing) if $i > I_H$ and requires AI skills (is not yet related to AI).*

This assumption indicates that within the group of high-skilled workers, those who possess AI skills have comparative advantages in complex tasks that require AI skills. However, not all complex tasks

Figure 1: The Equilibrium Task Allocation



Notes: L, M, H^{AI}, and H^{Non} represent low-skilled, middle-skilled, high-skilled AI-complement, and high-skilled not-yet-AI labor, respectively. $I_H = \min\{I_{H^{AI}}, I_{H^{Non}}\}$, S, I_M, and I_L are thresholds used to determine the equilibrium.

are AI-related. Other soft skills (e.g., cognitive and social skills) may play a pivotal role in these not-yet-AI complex tasks. Assumption 2 then implies that high-skilled not-yet-AI workers have comparative advantages in these tasks over high-skilled AI-complement workers.

Different from most previous literature that has utilized the supermodular comparative advantage structure across all factors, I follow Acemoglu and Restrepo (2018a) to state that technology can efficiently compete with not only low-skilled labor in simpler tasks but also middle- or high-skilled labor in more complex tasks. I assume that there exists $S \in (N-1, N)$ such that tasks $i \in (N-1, S)$ can be automated with productivity $\alpha_K = 1$, while tasks $i \in (S, N)$ can be performed by AI with productivity $\alpha_K > 1$. This assumption indicates that technology can efficiently perform some simpler tasks that low-skilled labor used to specialize in and some more complex tasks that previously utilized middle- or high-skilled labor.

Assumption 3. *$\exists I_L, I_M \in (N-1, S)$, where $I_L < I_M$, and $I_H \in (S, N)$ such that $\frac{W_{Hj}}{\alpha_{Hj}(I_H)} > \frac{R}{\alpha_K}$, and $\frac{W_M}{\alpha_M(I_M)} > R > \frac{W_L}{\alpha_L(I_L)}$, $j \in \{AI, Non\}$.*

This assumption ensures that it is strictly cheaper to produce (1) tasks $i \in (I_L, I_M]$ by industrial automation than by low-skilled labor and (2) tasks $i \in (S, I_H]$ by AI than by high-skilled labor in equilibrium. The equilibrium is then characterized by using the comparative advantage structure in Assumptions 1 and 2 and the effective cost assumption stated in Assumption 3. In particular, there exist some thresholds, I_H, I_M, I_L, and S, such that low-skilled workers perform tasks $i \in [N-1, I_L]$, middle-skilled workers perform tasks $i \in (I_M, S]$, high-skilled AI-complement workers perform tasks $i \in (I_H, N]$ with AI skill requirements, and high-skilled not-yet-AI workers perform tasks $i \in (I_H, N]$ without any AI skill requirements. Tasks $i \in (I_L, I_M]$ are automated and tasks $i \in (S, I_H]$ are performed by AI. This equilibrium allocation of tasks to factors is depicted in Figure 1 and is formally presented as follows:

Proposition 1. *In any equilibrium, $\exists I_{H^{AI}}$, $I_{H^{Non}}$, I_M, I_L, and S such that $N-1 < I_L < I_M < S < I_H < N$,*

where $I_H = min\{I_{H^{AI}}, I_{H^{Non}}\}$, *and*

(a) for any $i \in (I_L, I_M] \cup (S, I_H]$, $l(i) = m(i) = h^{AI}(i) = h^{Non}(i) = 0$;

(b) for any $i \in [N-1, I_L]$, $m(i) = h^{AI}(i) = h^{Non}(i) = k(i) = 0$;

(c) for any $i \in (I_M, S]$, $l(i) = h^{AI}(i) = h^{Non}(i) = k(i) = 0$;

(d) for any $i \in (I_H, N]$ *and* $i \in$ *AI tasks*, $l(i) = m(i) = h^{Non}(i) = k(i) = 0$;

(e) for any $i \in (I_H, N]$ *and* $i \in$ *not-yet-AI tasks*, $l(i) = m(i) = h^{AI}(i) = k(i) = 0$.

The intuition behind this proposition is that task allocation is determined by cost minimization and the comparative advantage structure introduced in Assumptions 1 and 2. $I_{H^{AI}}$ ($I_{H^{Non}}$) is the threshold where high-skilled AI-complement (high-skilled not-yet-AI) labor and capital can be indifferently used to perform task $i = I_{H^{AI}}$ ($i = I_{H^{Non}}$). Since the sets of tasks that high-skilled AI-complement and high-skilled not-yet-AI workers perform in equilibrium are both complex (represented by a higher index) but have different skill requirements (the former ones require AI skills while the latter ones are not yet AI-related), I am not able to determine which type of tasks is more superior. That is, it is insufficient to say all tasks that high-skilled AI-complement workers specialize in are more complex than those performed by high-skilled not-yet-AI workers or vice versa. Therefore, I set $I_H = \min\{I_{H^{AI}}, I_{H^{Non}}\}$ to distinguish the set of tasks performed by all high-skilled workers but add conditions of different skill requirements when charaterizing the equilibrium (Propositions 1(d) and 1(e)). The differences in how technology affects these two types of workers in the labor market will be discussed later. Given the equilibrium allocation of tasks in Proposition 1, the equilibrium price of task i is shown below:

$$p(i) = \begin{cases} \frac{W_L}{\alpha_L(i)} & \text{if} \quad i \in [N-1, I_L], \\ R & \text{if} \quad i \in (I_L, I_M], \\ \frac{W_M}{\alpha_M(i)} & \text{if} \quad i \in (I_M, S], \\ \frac{R}{\alpha_K} & \text{if} \quad i \in (S, I_H], \\ \frac{W_H^j}{\alpha_{H^j}(i)} & \text{if} \quad i \in (I_H, N] \text{ and } j \in \{AI, Non\}, \end{cases} \tag{3}$$

where $W_{H^{AI}}$, $W_{H^{Non}}$, W_M, and W_L are the economy-wide wages for high-skilled AI-complement, high-skilled not-yet-AI, middle-skilled or AI-substitutable, and low-skilled labor. R is the rental rate of capital.

From equation (1), the quantity of task i can be derived as

$$y(i) = Yp(i)^{-\sigma}. \tag{4}$$

Combining Proposition 1 with equations (3) and (4), I can obtain the demand for each factor in task i as

$$
\begin{aligned}
k(i) &= Y\alpha_K^{-1}p(i)^{-\sigma}, \text{ if } i \in (I_L, I_M] \cup (S, I_H] \\
l(i) &= Y\alpha_L(i)^{-1}p(i)^{-\sigma}, \text{ if } i \in [N-1, I_L] \\
m(i) &= Y\alpha_M(i)^{-1}p(i)^{-\sigma}, \text{ if } i \in (I_M, S] \\
h^j(i) &= Y\alpha_{H^j}(i)^{-1}p(i)^{-\sigma}, \text{ if } i \in (I_H, N] \text{ and } j \in \{AI, Non\}.
\end{aligned} \tag{5}
$$

Then the factor markets clear in the equilibrium:

$$
K = Y\mathrm{A}_K R^{-\sigma}, \quad L = Y\mathrm{A}_L W_L^{-\sigma}, \quad M = Y\mathrm{A}_M W_M^{-\sigma}, \quad H^j = Y\mathrm{A}_{H^j} W_{H^j}^{-\sigma}, \quad j \in \{AI, Non\}, \tag{6}
$$

where

$$
\begin{aligned}
&\mathrm{A}_K = (I_M - I_L) + (I_H - S)\alpha_K^{\sigma-1}, \quad \mathrm{A}_L = \int_{N-1}^{I_L} \alpha_L(i)^{\sigma-1}di, \quad \mathrm{A}_M = \int_{I_M}^{S} \alpha_M(i)^{\sigma-1}di, \\
&\mathrm{A}_{H^{AI}} = \int_{I_H}^{N} \mathbf{1}\{i \in \text{AI tasks}\}\alpha_{H^{AI}}(i)^{\sigma-1}di, \quad \mathrm{A}_{H^{Non}} = \int_{I_H}^{N} \mathbf{1}\{i \in \text{not-yet-AI tasks}\}\alpha_{H^{Non}}(i)^{\sigma-1}di,
\end{aligned} \tag{7}
$$

can be viewed as the "allocation share" of each factor. Factor prices satisfy the ideal-price condition:

$$
\mathrm{A}_{H^{AI}} W_{H^{AI}}^{1-\sigma} + \mathrm{A}_{H^{Non}} W_{H^{Non}}^{1-\sigma} + \mathrm{A}_M W_M^{1-\sigma} + \mathrm{A}_L W_L^{1-\sigma} + \mathrm{A}_K R^{1-\sigma} = 1. \tag{8}
$$

Proposition 2. *The equilibrium factor prices and output can be expressed as:*

$$
R = Y^{\frac{1}{\sigma}}\mathrm{A}_K^{\frac{1}{\sigma}}K^{-\frac{1}{\sigma}}, \quad W_L = Y^{\frac{1}{\sigma}}\mathrm{A}_L^{\frac{1}{\sigma}}L^{-\frac{1}{\sigma}}, \quad W_M = Y^{\frac{1}{\sigma}}\mathrm{A}_M^{\frac{1}{\sigma}}M^{-\frac{1}{\sigma}}, \quad W_{H^j} = Y^{\frac{1}{\sigma}}\mathrm{A}_{H^j}^{\frac{1}{\sigma}}(H^j)^{-\frac{1}{\sigma}}, \quad j \in \{AI, Non\}, \tag{9}
$$

and

$$
Y = \left[\mathrm{A}_{H^{AI}}^{\frac{1}{\sigma}}(H^{AI})^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_{H^{Non}}^{\frac{1}{\sigma}}(H^{Non})^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_M^{\frac{1}{\sigma}}M^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_L^{\frac{1}{\sigma}}L^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_K^{\frac{1}{\sigma}}K^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}. \tag{10}
$$

This proposition provides intuitions for the "allocation share" of each factor defined in equation (7). These "allocation shares" can be viewed as the distribution parameters in the equilibrium output in equation (10). They indicate how different factors are allocated in producing the final good, Y.

2.2 Relationship between Labor Market Outcomes and High Tech

In this section, I discuss the relationship between labor market outcomes (e.g., employment, relative wages) of different skill groups and AI or industrial automation. I follow Acemoglu and Restrepo (2019) to define the following effects: (1) the displacement effect means capital substitutes for labor

in production; (2) the reinstatement effect means the set of tasks performed by labor is expanded; and (3) the productivity effect means technology increases productivity in production. Proposition 3 explores the displacement effect and the reinstatement effect of AI or industrial automation. Propositions 4 and 5 study effects on relative wages. Proposition 6 explores the productivity effect of AI on the income distributed to high-skilled AI-complement labor or capital. Only the inequalities that can be tested in my empirical analysis are presented. Additional inequalities and proofs can be found in Appendix A.

Proposition 3 (Displacement and reinstatement effects of AI or industrial automation).

(1) AI can displace workers in some complex tasks, $\frac{d\mathrm{A}_{H^j}}{dI_H} < 0$, $\frac{d\mathrm{A}_K}{dI_H} > 0$, $\frac{d\mathrm{A}_M}{dS} > 0$, $\frac{d\mathrm{A}_K}{dS} < 0$.

(2) AI can expand the set of tasks performed by high-skilled workers, $\frac{d\mathrm{A}_{H^j}}{dN} > 0$.

(3) Industrial automation primarily takes over simpler tasks, $\frac{d\mathrm{A}_M}{dI_M} < 0$, $\frac{d\mathrm{A}_K}{dI_M} > 0$.

Note that $j \in \{AI, Non\}$.

The growth in AI (represented by an increase in I_H) reduces the share of tasks specialized by high-skilled workers (A_{H^j}, $j \in \{AI, Non\}$) because AI becomes more efficient in production and can take over some complex tasks previously performed by high-skilled workers. AI also has a displacement effect on middle-skilled workers. A decrease in S means that some tasks that previously used middle-skilled workers switch to utilize AI (captured by a decrease in A_M or an increase in A_K).

An increase in I_M means improvements in industrial automation, which reduces the share of tasks performed by middle-skilled workers (A_M) but increases that of capital (A_K). This can be viewed as a direct displacement effect of industrial automation on middle-skilled workers and an indirect displacement effect of AI since improvements in AI may also stimulate developments in industrial automation.

Different from industrial automation which mainly brings displacement effects to middle-skilled labor, the growth in AI expands the set of tasks that high-skilled workers can perform by creating new tasks that require high-skilled labor (an increase in N) or changing task content in favor of high-skilled labor over AI. This is referred to as the reinstatement effect of AI (Acemoglu and Restrepo, 2019).

Proposition 4 (Relationship between relative wages and AI or industrial automation).

(1) The displacement effect of AI narrows wage gaps, $\frac{d(\frac{W_{H^j}}{W_L})}{dI_H} < 0$, $\frac{d(\frac{W_{H^j}}{W_M})}{dI_H} < 0$.

(2) The reinstatement effect of AI widens wage gaps, $\frac{d(\frac{W_{H^j}}{W_L})}{dN} > 0$, $\frac{d(\frac{W_{H^j}}{W_M})}{dN} > 0$, $\frac{d(\frac{W_M}{W_L})}{dN} > 0$.

(3) The displacement effect of industrial automation widens wage gaps, $\frac{d(\frac{W_{H^j}}{W_M})}{dI_M} > 0$, $\frac{d(\frac{W_M}{W_L})}{dI_M} > 0$.

Note that $j \in \{AI, Non\}$.

The main takeaway from this proposition is that the displacement effect of AI (an increase in I_H) narrows wage gaps between high-skilled group and middle- or low-skilled group ($\frac{W_{H^j}}{W_M}$ and $\frac{W_{H^j}}{W_L}$), while

the displacement effect of industrial automation (an increase in I_M) or the reinstatement effect of AI (an increase in N) widens these wage gaps. An increase in I_H leads to a reduction in the share of tasks performed by high-skilled workers, further resulting in lower wagebills for these workers. Since wages for workers from other skill groups are assumed to be not affected under this scenario, the wage gap between high-skilled labor and middle- or low-skilled labor becomes smaller. In contrast, AI can also create tasks that require skills possessed by high-skilled labor or change task contents in favor of high-skilled labor rather than AI. In this way, the wage gap between high- and middle-skilled labor ($\frac{W_{H^j}}{W_M}$) or between high- and low-skilled labor ($\frac{W_{H^j}}{W_L}$) widens associated with the growth in AI.

Since the reinstatement effect of AI on wage gaps between high-skilled group and other groups is in the opposite direction of the displacement effect of AI, which effect is dominant is indeterminate. However, my empirical findings will shed light on which effect is dominant for different skill groups.

Proposition 5 (Relationship between relative wages and labor-augmenting AI). *The growth in AI widens the wage gap between the high-skilled AI-complement group and other skill groups by increasing the productivity of labor possessing AI skills.*

$$\frac{d(\frac{W_{H^{AI}}}{W_L})}{d\alpha_{H^{AI}}(i)} > 0, \quad \frac{d(\frac{W_{H^{AI}}}{W_M})}{d\alpha_{H^{AI}}(i)} > 0, \quad \frac{d(\frac{W_{H^{AI}}}{W_{H^{Non}}})}{d\alpha_{H^{AI}}(i)} > 0. \tag{11}$$

Different from industrial automation which is assumed to be only factor-augmenting in my model and mainly displaces labor, AI not only substitutes for but also complements labor. I view AI as a factor- and labor-augmenting technology since it can increase the productivity of both capital and workers with AI skills. Since high-skilled AI-complement workers possess AI skills and utilize AI to complement their work, AI is assumed to raise the productivity of high-skilled AI-complement workers ($\alpha_{H^{AI}}(i)$) but not other skill groups in this model. As the performance of AI improves, high-skilled AI-complement workers earn more due to an increase in their productivity. As a result, the wage gap between these workers and other skill groups (low-skilled, middle-skilled, or high-skilled not-yet-AI workers) widens.

Proposition 6 (Income allocated to high-skilled AI-complement labor and AI technologies).

(1) An increase in the productivity of high-skilled AI-complement labor widens the gap between the income allocated to this skill group and that allocated to capital, $\frac{d(\frac{H^{AI}W_{H^{AI}}}{KR})}{d\alpha_{H^{AI}}(i)} > 0$.

(2) The relationship between the productivity of AI technologies and this income allocation gap depends on whether the factors are complements or substitutes: if $\sigma \in (0,1)$, $\frac{d(\frac{H^{AI}W_{H^{AI}}}{KR})}{d\alpha_K} > 0$; *if* $\sigma = 1$, $\frac{d(\frac{H^{AI}W_{H^{AI}}}{KR})}{d\alpha_K} = 0$; *if* $\sigma \in (1,\infty)$, $\frac{d(\frac{H^{AI}W_{H^{AI}}}{KR})}{d\alpha_K} < 0$.

(3) *If factors are complements,* $\sigma \in (0,1]$*, the productivity effect of high-skilled AI-complement labor dominates the productivity effect of AI technologies,* $|\frac{d(\frac{H^{AI}W_{H^{AI}}}{KR})}{d\alpha_{H^{AI}}(i)}| > |\frac{d(\frac{H^{AI}W_{H^{AI}}}{KR})}{d\alpha_K}|$*; if factors are substitutes,* $\sigma \in (1,\infty)$*, it is indeterminate which effect dominates,* $|\frac{d(\frac{H^{AI}W_{H^{AI}}}{KR})}{d\alpha_{H^{AI}}(i)}| \gtreqless |\frac{d(\frac{H^{AI}W_{H^{AI}}}{KR})}{d\alpha_K}|$.

The takeaway of this proposition is that if factors are complements, an increase in the productivity of either high-skilled AI-complement labor or AI technologies embodied in capital widens the gap between the income allocated to high-skilled AI-complement labor and capital. If factors are substitutes, then an increase in the productivity of high-skilled AI-complement labor (AI technologies) has a positive (negative) effect on this income allocation gap. In this case, it is indeterminate which effect dominates.

In summary, my task-based framework implies that AI has a reinstatement effect by creating new tasks that demand high-skilled labor. It also indicates that the growth in AI widens both the wage gap between high-skilled AI-complement group and other skill groups, and the income allocation gap between high-skilled AI-complement labor and capital. In addition, I discuss the relationships between (1) the reinstatement and displacement effects of AI, and (2) the productivity effect of high-skilled AI-complement labor and the productivity effect of AI technologies.

3 Data and Construction of Skill Groups

Section 3.1 describes the datasets I use. Section 3.2 introduces how I define skill groups. Section 3.3 presents summary statistics of job postings and labor market outcomes by skill group.

3.1 Data

Online Job Postings. I use the online job postings data from LinkUp. LinkUp has web scraped over 200 million daily online job postings directly from over 60,000 employer websites worldwide since 2007. Postings with missing information on either the posted time, geographic locations, occupational codes, or job descriptions (i.e., the raw text of a posting) are dropped. Since only around 2% of collected postings in the U.S. were posted on and before 2010, my sample comprises postings between 2011 and 2022 in the U.S. These restrictions leave me with a total sample of around 125 million postings.

Occupational Descriptions. Since it is difficult for LinkUp, as well as other web-scraping companies, to scrape and collect *every single* online posting, I use the Occupational Information Network (O*NET) database as a complement of LinkUp data for this paper. Among all occupational features provided by O*NET, occupational tasks, technology skills, detailed work activities, and knowledge information are adopted to define skill groups. These features provide descriptions of tasks that are usually performed

for an occupation and list skills, softwares, and knowledge that are commonly required by this occupation. One disadvantage of using the O*NET database over the job postings data is that the available occupational descriptions provided by O*NET are time-invariant. Although the O*NET occupational codes have changed periodically, to the best of my knowledge, the detailed descriptions of occupational features for older versions are not available. Therefore, researchers are not able to track how occupational features have changed within and across occupations over time by only using the O*NET database.

Employment and Wages. The individual-level data on labor market outcomes is from the American Community Survey (ACS) Public Use Microdata Sample (PUMS) data (IPUMS-ACS hereafter) between 2012-21. For my analysis, I restrict to individuals aged 18 to 64 and drop all unemployed individuals with no work experience in the last 5 years or earlier and individuals who never worked. Individuals whose occupation that is not on the list of my proposed skill groups, which will be introduced in the Section 3.2, are also dropped. I then calculate occupational-level employment per 100,000 capita, share of employment, mean hourly wage (all wages are in 2019 U.S. dollars), and share of wage income to explore the relationship between these labor market outcomes and AI.[2]

3.2 Defining Skill Groups

This section describes how I define the following skill groups: (1) high-skilled AI-complement occupations that have a concentration of abstract and AI-related tasks; (2) high-skilled, not-yet-AI occupations that focus on abstract tasks which are not yet AI-related; (3) middle-skilled occupations that consist of routine tasks; and (4) low-skilled occupations that comprise manual tasks. To categorize occupations into these four groups, I first define AI postings (Section 3.2.1) and AI occupations (Section 3.2.2) which are those with a specilization in AI-developing activities. Abstract, routine, and manual occupations are then defined based on the occupational-level task contents measured by Autor and Dorn (2013) (Section 3.2.3). Occupations are classified into one of these skill groups in Section 3.2.4.

3.2.1 Defining AI Postings

The phrases for AI-developing skills I used to define AI postings are from LeCun, Bengio, and Hinton (2015), Zhang et al. (2022), and topics of top journals and conferences in the field of AI (e.g., Institute of

[2]IPUMS-ACS has not collected the exact number of weeks worked during the calendar year before each Census year (the reference period) until 2019 (the "WKSWORK1" variable). However, it provides the interval of weeks worked during the reference period (the "WKSWORK2" variable) for my sampling period, 2012-21. Thus, I treat the midpoint of each interval to be the number of weeks worked to calculate mean hourly wage. In addition, neither the total number of hours (the "HRSWORK1" variable) nor the interval (the "HRSWORK2" variable) that the respondent was at work during the previous week between 2012-21 is provided by IPUMS-ACS. Thus, the "UHRSWORK" variable which represents the number of hours per week that the respondent usually worked, if the person worked during the previous year, is adopted to calculate mean hourly wage.

Table 1: Phrases for AI Skills and Applications

Category	Phrases
Narrow AI	artificial intelligence, augmented reality (AR), autonomous driving, big data, computer graphics, computer vision, data mining, deep learning, machine learning, matlab, multimedia, natural language processing (NLP), neural network, pattern recognition, python, pytorch, robotic, tensorflow, virtual reality (VR), voice recognition, 3D modeling
Broad AI	All phrases in the Narrow AI category + cloud computing, cognitive science, computational biology, computational intelligence, computer-aided design/drafting (CAD), cybernetics, geographic information system (GIS), image processing, phenotype, remote sensing, symbolic inference

Notes: The set of phrases in the narrow AI category is a subset of phrases in the broad AI category.

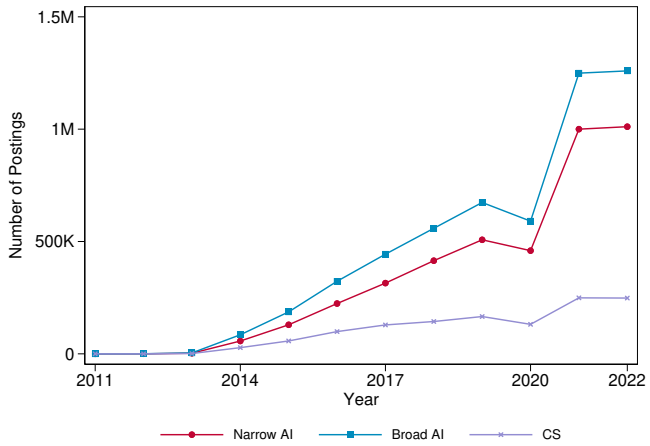
Electrical and Electronics Engineers (IEEE) and Association for Computing Machinery (ACM)), which are listed in Table 1. These phrases are then divided into two categories: (1) the narrow definition of AI or "narrow AI", which refers to AI itself, the major subfields of AI, commonly used programming languages for AI, and AI-powered technologies; and (2) the broad definition of AI or "broad AI", which includes not only all phrases in the "narrow AI" category but also more general computer science (CS) skills and applications that are, to some extent, AI-related.

I then directly match the chosen AI phrases to the raw text of online job postings. Including a chosen AI phrase in the job description means that this posting explicitly requires this AI skill when hiring people to fill this position. If a job description includes any chosen AI phrase from the narrow (broad) AI category, then this posting will be defined as a narrow (broad) AI posting. I further define CS postings as those with at least one CS phrase but no narrow AI phrase included in job descriptions.[3] Figure 2 presents the number and share of narrow AI, broad AI, and CS postings between 2011-22 in the U.S. There was an overall increasing trend for both narrow and broad AI postings, while the share of CS postings remained constant between 2014-22. The number of AI postings dropped from 2019-20 but dramatically increased from 2020-21, which could be due to the COVID-19 pandemic. Although AI and CS postings account for a small share of postings in LinkUp data, this share increased from around 0.15% to 4.58% for narrow AI postings, from 0.28% to 5.70% for broad AI ones, and from 0.13% to 1.11% for CS ones during 2011-22. Note that both the number and share of broad AI postings are higher than either narrow AI or CS ones because phrases that are used to define narrow AI/CS postings also belong to the broad AI category. Appendix Figures B.1 and B.2 further show trends of AI and CS postings by the Bureau of Labor Statistics (BLS) regions.[4] All eight regions have similar trends in the number of AI postings but are different in magnitude. The Western region experienced the largest AI job vacancies

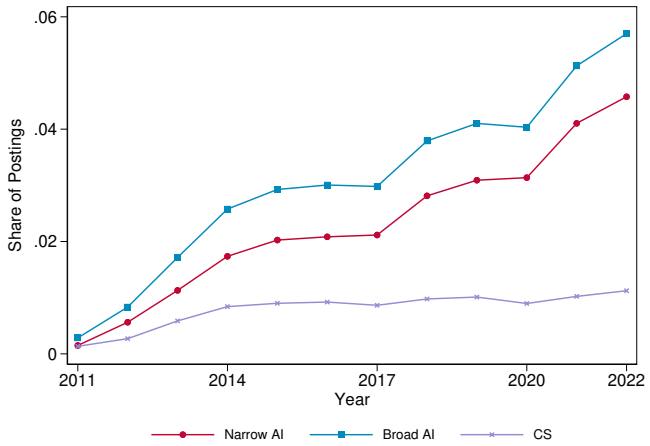
[3]CS phrases refer to those that belong to the broad AI category but not the narrow AI category as listed in Table 1.
[4]Guam, Puerto Rico, and Virgin Islands are dropped from my sample.

Figure 2: AI/CS Postings in the U.S. in LinkUp Data, 2011-22

(a) Number of AI/CS Postings



(b) Share of AI/CS Postings



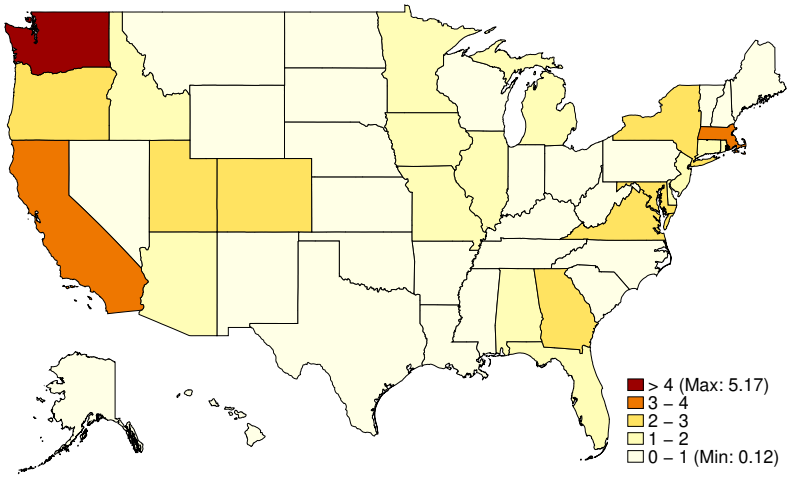
while the Mountain-Plains region had the smallest number of AI postings. The share of AI postings was relatively high in the New England, New York/New Jersey, Mid-Atlantic, and Western regions. All eight regions had a relatively small number and share of CS postings with a constant trend.

The geographic distribution of the narrow AI posting share from 2011-14, 2015-18, and 2019-22 is presented in Figure 3. The darker a state's color is, the more narrow AI vacancies were posted in that state. During 2011-14, only Washington was in the darkest color with the highest share of narrow AI postings, followed by California and Massachusetts. From 2015-18, both Washington and California were in the darkest red with a few more states in orange and yellow. After 2019, the narrow AI posting share in both the West Coast and the Northeast was the highest in the U.S. Almost all states were in orange or yellow, implying a growth in the narrow AI posting share nationwide over time. Note that the scales also increased over 2011-22. The minimum and maximum share increased from 0.12% to 0.96% and from 5.17% to 8.52%, respectively. These facts indicate spatial and temporal patterns of AI postings; the share of narrow AI postings changed differentially across states and consistently increased over time. The share of broad AI postings have similar patterns displayed in Appendix Figure B.3.

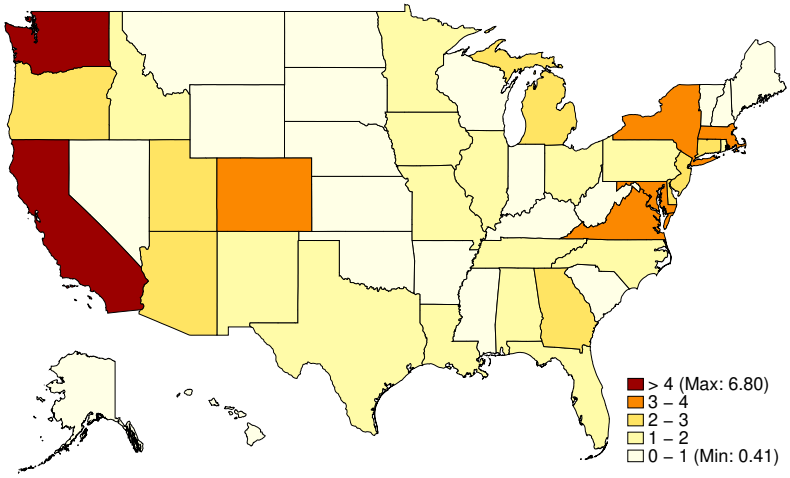
Compared to the online job postings data from Lightcast, formerly known as Burning Glass Technologies, which has been widely used in economic research (e.g., Deming and Noray (2018, 2020); Bloom et al., 2020; Alekseeva et al., 2021; Acemoglu et al., 2022; Dillender and Forsythe, 2022; Hemelt et al., 2023), LinkUp data has been less utilized. To test the validity of using LinkUp data to examine the relationship between changes in online job postings and labor market outcomes, I compare the annual share of AI postings in the U.S. separately computed using LinkUp and Lightcast data as displayed in Appendix Figure B.4. The share from Lightcast data is presented on the x axis and that from LinkUp data is on the

Figure 3: Geographic Distribution of the Narrow AI Posting Share in LinkUp Data

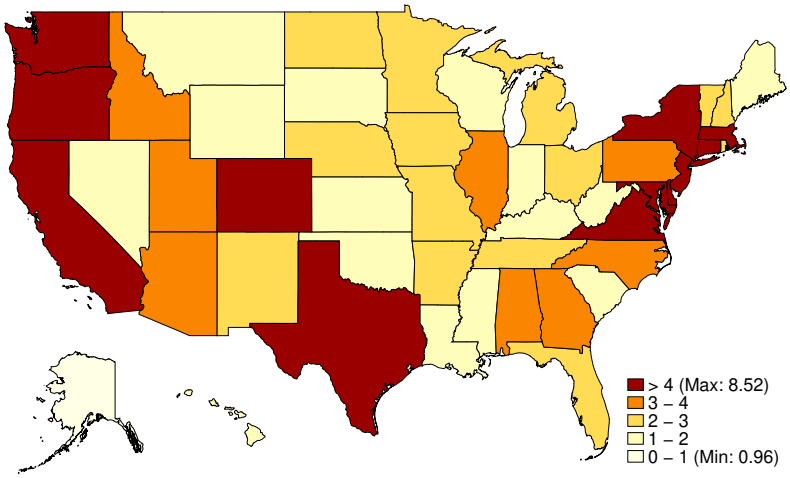
(a) 2011-14



(b) 2015-18



(c) 2019-22



Notes: Scales are in percentage point.

y axis.[5] Each marker represents the annual share of postings in one of the following AI subcategories proposed by Zhang et al. (2022): artificial intelligence, autonomous driving, machine learning, natural language processing, neural networks, robotics, and visual image recognition. Most markers locate on or close to the 45 degree line, implying a high similarity between LinkUp and Lightcast data.[6] Specifically, the correlation between the overall share of AI postings in LinkUp and Lightcast data is 0.9490.[7]

3.2.2 Defining AI Occupations

Since each occupation comprises a substantial amount of job postings, an AI occupation, $AIocc_{j,c,\tau}$, is:

$$AIocc_{j,c,\tau} = \begin{cases} 1 & , \text{ if } \%AIpost_{j,c,\tau} > \frac{1}{N}\sum_{j\in\mathcal{J}} \%AIpost_{j,c,\tau} \\ 0 & , \text{ if } \%AIpost_{j,c,\tau} \leq \frac{1}{N}\sum_{j\in\mathcal{J}} \%AIpost_{j,c,\tau}, \end{cases} \tag{12}$$

where j, $\mathcal{J}$, and N denote an occupation, the set of all occupations, and the number of all occupations. $\%AIpost_{j,c,\tau}$ is the share of AI postings in category $c \in \{\text{Narrow AI, Broad AI}\}$ of occupation j in the U.S. during the time period $\tau \in \{2011-14, 2015-18, 2019-22\}$. If the AI posting share of an occupation is greater than the chosen threshold, the mean of shares across all occupations during a time period, this occupation is treated as an AI occupation. Similar to the occupational classification systems that are updated periodically, my proposed AI occupation indicators are time-variant to capture how AI technologies and the demand for AI skills have changed over time. The time-invariant indicators are also constructed by using the share of AI postings over 2011-22 for a robustness check.

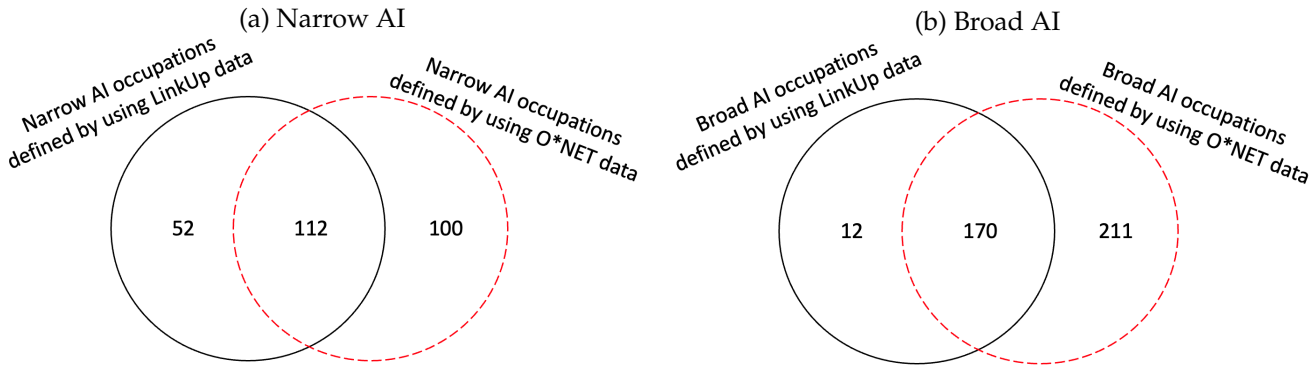
To test the validity of my choice of threshold in defining AI occupations, I cross-check AI occupations defined by using LinkUp data with those constructed by using O*NET data. To make the results comparable across datasets, I match the same set of AI phrases listed in Table 1 to tasks, technology skills, detailed work activities, and knowledge information of each occupation provided by O*NET (Appendix Figure B.5 shows an example of these features). If the description of any of the above features is matched to at least one chosen AI phrase, the corresponding occupation will be defined as an AI occupation. Among 901 occupations represented by 2019 O*NET-SOC code in my sample, (1) 164 are narrow AI occupations defined by using LinkUp data and 212 are defined by using O*NET data with an overlap

[5] Since Lightcast data is non-public, I use the monthly share of AI postings from 2010-20 in the U.S., made publicly available by Zhang et al. (2022) and the Stanford Institute for Human-Centered Artificial Intelligence (HAI) at https://aiindex.stanford.edu/ai-index-report-2022/, to compute the annual share of AI postings in Lightcast data.

[6] The share of postings in robotics differs from that of the other subcategories, possibly because the phrases used to define robotics postings in this paper and in Zhang et al. (2022) are different. While I directly match "Robotic" to descriptions of LinkUp online job postings, Zhang et al. (2022) list phrases such as "Motoman Robot Programming", "Robot Framework", "Robotic Systems", and "Robot Programming" as AI skills in the robotics category.

[7] This correlation within each of the seven subcategories is: 0.9698 (artificial intelligence), 0.6649 (autonomous driving), 0.9581 (machine learning), 0.8236 (NLP), 0.9660 (neural networks), 0.6459 (robotics), and 0.6797 (visual image recognition).

Figure 4: Comparison between AI Occupations Defined by Using LinkUp and O*NET Data



Notes: The black solid circle in each venn diagram represents the set of AI occupations defined by using LinkUp data with narrow AI (Subfigure 4a) or broad AI (Subfigure 4b) definition discussed in Section 3.2.1, while the red dashed circle represents the set of AI occupations defined by using O*NET data. The overlapping area represents occupations that are defined as AI occupations in both datasets. The numbers shown in each venn diagram represent the total number of occupations that belong to one of the above sets.

of 112 occupations; (2) 182 are broad AI occupations defined by using LinkUp data and 393 are defined by using O*NET data with an overlap of 170 occupations (shown in Figure 4). Due to the advantages and disadvantages of both LinkUp and O*NET data discussed in Section 3.1, I treat the overlapping occupations as the narrow/broad AI occupations in my main analysis.

3.2.3 Defining Abstract, Routine, and Manual Occupations

The next step is to categorize occupations into high-, middle-, and low-skilled groups, which are respectively proxied by abstract, routine, and manual occupations. I define these three types of occupations based on abstract, routine, and manual task contents measured by Autor and Dorn (2013):

$$OccType_j = x \text{ if } T^x_{j,1980} = max\, \mathbf{T}_{j,1980}, \text{ for } x \in \{Abstract, Routine, Manual\}, \tag{13}$$

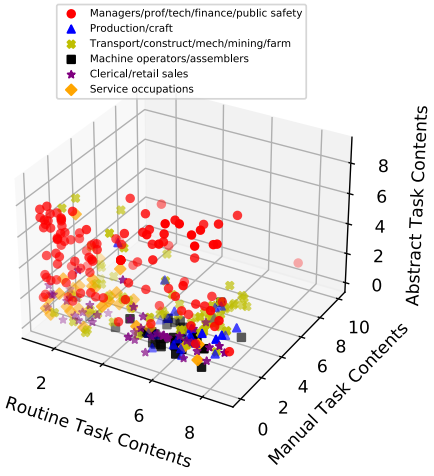
where $\mathbf{T}_{j,1980} \equiv \{T^{Abstract}_{j,1980}, T^{Routine}_{j,1980}, T^{Manual}_{j,1980}\}$ and j denotes an occupation.[8] $OccType_j$ represents the indicator for the type (i.e., abstract, routine, and manual) that occupation j belongs to. $T^{Abstract}_{j,1980}$, $T^{Routine}_{j,1980}$, and $T^{Manual}_{j,1980}$ are the abstract, routine, and manual task inputs in each occupation j measured in 1980 by Autor and Dorn (2013) with a range between 0 and 10. Based on equation (13), each occupation falls into only one category.[9] Note that since Autor and Dorn (2013) use task inputs in 1980, which is the starting

[8] An occupation in equation (13) is represented by occ1990dd occupation classification constructed by Dorn (2009). I map occ1990dd to 2010 Census Occupational Classification using the crosswalk provided by Autor (2015) to merge the occupation indicators with the data on employment and wages.

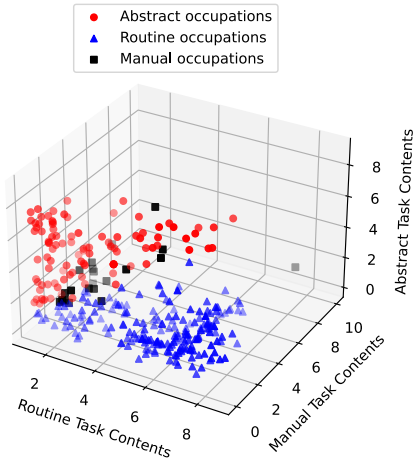
[9] There is no occupation that has the highest value of task inputs with ties in Autor and Dorn (2013)'s data.

Figure 5: Occupational Task Contents

(a) By Autor and Dorn (2013)'s Occupation Group



(b) By Abstract, Routine, and Manual Occupation



Notes: Each marker represents an occupation using the occ1990dd occupation classification constructed by Dorn (2009). According to https://www.ddorn.net/data.htm, "the occ1990dd occupation classification aggregates U.S. Census occupation codes to a balanced panel of occupations for the 1980, 1990, and 2000 Census, as well as the 2005-2008 ACS". There are 330 occupations in Autor and Dorn (2013)'s data. The abstract, routine, and manual task contents have a range between 0 and 10.

year of their sample, my indicators for abstract, routine, and manual occupations are static over time.

Figure 5 shows a 3D visualization of each occupation's task contents. Each marker represents an occupation and the style of the marker distinguishes which group this occupation belongs to. Figure 5a displays occupational task contents by Autor and Dorn (2013)'s occupation group, while Figure 5b divides occupations into abstract, routine, and manual ones constructed using equation (13). Since these figures present three dimensions, they should be viewed as 3D boxes instead of 2D surfaces. The darker the color of and the more solid a marker is, the closer this marker is located to readers (i.e., the closer this marker is located to the space with a *high* value in routine task contents and a *low* value in manual task contents, regardless of the abstract task contents which are represented by the vertical axis or the z axis); the lighter the color of and the more transparent a marker is, the further this marker is located to readers (i.e., the closer this marker is located to the space with a *low* value in routine task contents and a *high* value in manual task contents). Managers/prof/tech/finance/public safety occupations have a high abstract task intensity, while production/craft and machine operators/assemblers specialize in routine tasks. Manual-intensive occupations are mainly transport/construct/mech/mining/farm and service occupations. Undoubtedly, in Figure 5b, the red circles that represent abstract occupations locate in the upper surface of the 3D box with a *high* value in abstract task inputs but a *low* value in both routine and manual task inputs. Routine occupations, represented by blue triangles, have the highest concentration

in routine tasks, while manual occupations labelled by black squares specialize in manual tasks.

3.2.4 Categorizing Occupations into Skill Groups

The final step is to categorize occupations into one of the four skill groups as follows:

$$SkillGroup_{j,c,\tau} = \begin{cases} \text{High-skilled AI-complement} & , \text{ if } OccType_j = Abstract \ \& \ AIocc_{j,c,\tau} = 1 \\ \text{High-skilled not-yet-AI} & , \text{ if } OccType_j = Abstract \ \& \ AIocc_{j,c,\tau} = 0 \\ \text{Middle-skilled} & , \text{ if } OccType_j = Routine \\ \text{Low-skilled} & , \text{ if } OccType_j = Manual, \end{cases} \tag{14}$$

where j, $c \in \{\text{Narrow AI, Broad AI}\}$, and τ denote an occupation, the narrow or broad AI definition, and a time period (2011-14, 2015-18, or 2019-22), respectively. Although the indicators for occupation type, $OccType_j$, are time-invariant, the skill group indicators, $SkillGroup_{j,c,\tau}$, change across time periods because the indicator for AI occupations, $AIocc_{j,c,\tau}$, is time-variant. Note that an occupation is exclusively categorized into one skill group.

Table 2 lists occupations with the highest and lowest number of narrow AI postings. Most occupations in Panel A with a high number of AI postings are from high-skilled AI-complement group, while most occupations without any AI posting in Panel B are middle-skilled (i.e., routine-intensive). Appendix Table B.1 shows a similar pattern by ranking occupations using the narrow AI posting share. Appendix Table C.1 provides a full list of all 4-digit occupations by skill group.

3.3 Facts about Skill Groups

Table 3 summarizes the 30 high-skilled AI-complement occupations, 110 high-skilled not-yet-AI ones, 257 middle-skilled ones, and 31 low-skilled ones in my sample.[10] Note that the skill group indicators in Table 3 are static to better compare statistics over time.[11] Panel B of Table 3 shows a large difference in AI and CS postings between the high-skilled AI-complement group and other skill groups. Occupations that are abstract and AI-intensive, on average, have more AI and CS postings than others. On average, 15.5% of job postings for high-skilled AI-complement occupations are narrow AI postings, 24.1% are broad AI postings, and 8.6% are CS postings. Note that the number (share) of CS postings, on average, is

[10] For the consistency in occupation code, my main analysis use OCC2010 coding system, which is a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification, because my data on employment and wages adopts OCC2010 system. Since LinkUp and O*NET use 2019 O*NET-SOC code, I crosswalk 6-digit 2019 O*NET-SOC to 4-digit OCC2010 as explained in Appendix C to construct a skill group indicator for each 4-digit OCC2010.

[11] Since only 7 out of 428 OCC2010 have their skill group indicator changed across time periods as shown in Appendix Table C.1, the statistics are robust to using the time-variant skill group indicators.

Table 2: Occupations Ranked by the Number of Narrow AI Postings, 2021

OCC2010	Occupation title	Skill group	#Narrow AI postings
	Panel A. Occupations with the Top 15 #AI Postings		
1020	Software Developers, Applications and Systems Software	H^{AI}	596,312
1100	Network and Computer Systems Administrators	H^{AI}	148,016
1000	Computer Scientists and Systems Analysts/Network Systems Analysts/Web Developers	H^{AI}	84,249
710	Management Analysts	H^{AI}	44,886
730	Other Business Operations and Management Specialists	H^{AI}	36,653
30	Managers in Marketing, Advertising, and Public Relations	H^{AI}	33,622
3130	Registered Nurses	M	27,952
1550	Engineering Technicians, Except Drafters	M	24,981
1430	Industrial Engineers, Including Health and Safety	H^{AI}	23,077
800	Accountants and Auditors	H^{Non}	22,401
1410	Electrical and Electronics Engineers	H^{AI}	17,778
3500	Licensed Practical and Licensed Vocational Nurses	M	17,157
1240	Mathematicians and Statisticians	H^{AI}	13,771
1460	Mechanical Engineers	H^{AI}	13,115
120	Financial Managers	H^{Non}	12,035
	Panel B. Occupations with the Bottom 15 #AI Postings		
3700	First-Line Supervisors of Correctional Officers	L	0
5630	Weighers, Measurers, Checkers, and Samplers, Recordkeeping	M	0
3800	Bailiffs, Correctional Officers, and Jailers	L	0
7540	Locksmiths and Safe Repairers	M	0
6240	Carpet, Floor, and Tile Installers and Finishers	M	0
6700	Elevator Installers and Repairers	M	0
6400	Insulation Workers	M	0
3730	First-Line Supervisors of Protective Service Workers, All Other	H^{Non}	0
6460	Plasterers and Stucco Masons	M	0
6710	Fence Erectors	M	0
4500	Barbers	M	0
8450	Upholsterers	M	0
4540	Tour and Travel guides	M	0
6740	Rail-Track Laying and Maintenance Equipment Operators	M	0
5410	Reservation and Transportation Ticket Agents and Travel Clerks	M	0

Notes: The number of narrow AI postings in this table is calculated at the 4-digit-occupation-by-year level. There is a tie in the lowest number of narrow AI postings, with 64 occupations having no narrow AI posting. 15 out of 64 occupations are randomly chosen and listed in Panel B. H^{AI}, H^{Non}, M, and L represent high-skilled AI-complement, high-skilled not-yet-AI, middle-skilled, and low-skilled occupation group, respectively.

the difference between the number (share) of broad and narrow AI postings. This is because CS postings are defined as those whose job descriptions include phrases that belong to broad AI category but not narrow AI category. That is, narrow AI phrases and CS phrases are not only two subsets of broad AI phrases but also mutually exclusive. Panel C presents summary statistics on labor market outcomes for the four skill groups. On average, there are more people employed in high-skilled not-yet-AI occupations (0.34% or 335 per 100,000 capita), while high-skilled AI-complement occupations experience the highest mean hourly wage (44.3 in 2019 U.S. dollars) and the share of wage income (0.41%).

By collapsing the occupation-by-state-by-year data to the skill-group-by-year level, Figure 6 displays plots of employment per 100,000 capita (Figure 6a), the employment share (Figure 6b), mean houly wage (Figure 6c), the wage income share (Figure 6d), the narrow AI posting share (Figure 6e) and CS posting

Table 3: Summary Statistics, 2012-21

	Skill group:			
	High-skilled AI-complement group	**High-skilled not-yet-AI group**	**Middle-skilled group**	**Low-skilled group**
	Panel A. Skill Group Indicators			
#4-Digit occ.	30	110	257	31
	Panel B. Job Postings			
#Narrow AI postings	101.697	6.936	10.269	1.962
	(748.411)	(28.554)	(64.013)	(15.364)
#Broad AI postings	125.916	13.014	14.626	3.197
	(812.833)	(50.407)	(69.350)	(20.965)
#CS postings	24.219	6.078	4.358	1.235
	(97.897)	(34.073)	(19.606)	(8.812)
%Narrow AI postings	0.155	0.034	0.053	0.019
	(0.223)	(0.101)	(0.144)	(0.092)
%Broad AI postings	0.241	0.093	0.116	0.037
	(0.275)	(0.192)	(0.231)	(0.129)
%CS postings	0.086	0.060	0.064	0.018
	(0.188)	(0.163)	(0.177)	(0.091)
Obs.	23,180	38,472	40,308	4,932
	Panel C. Labor Market Outcomes			
Emp. per 100,000 capita	232.128	335.016	234.737	289.895
	(324.312)	(544.575)	(428.403)	(550.691)
%Emp.	0.0023	0.0034	0.0024	0.0029
	(0.0032)	(0.0054)	(0.0043)	(0.0055)
Mean hourly wage	44.297	32.477	21.958	25.600
	(25.188)	(31.697)	(18.350)	(31.603)
%Wage income	0.0041	0.0045	0.0017	0.0022
	(0.0056)	(0.0082)	(0.0034)	(0.0046)
Obs.	13,591	51,672	113,244	13,631

Notes: Standard deviations are shown in parentheses. Occupation is represented by OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. Each observation in Panel B is a 2-digit-occupation-by-state-by-year cell, while each observation in Panel C is at the 4-digit-occupation-by-state-by-year level. This is because the job posting data from LinkUp is collected at the 6-digit 2019 O*NET-SOC level. Since (1) there is a one-to-one matching between 2-digit Census occupation group and 2-digit O*NET-SOC and (2) there is neither a direct matching between 4-digit OCC2010 and 6-digit 2019 O*NET-SOC nor a one-to-one matching between these two occupational classification, the job postings data is collapsed to the 2-digit O*NET-SOC level first and then merged to IPUMS-ACS labor market outcome data. The skill group indicator in this table is static to make summary statistics comparable over time. The statistics remain consistent when switching to the time-variant skill group indicator, since only 7 (out of 428) 4-digit OCC2010 occupations have their skill group indicator changed across time periods as shown in Appendix Table C.1. Only statistics on %employment and %wage income in Panel C are in four decimal places to better compare the magnitudes of statistics across skill groups.

share (Figure 6f), where the skill groups are defined using the narrow AI definition. The plots generated using the broad AI definition are presented in Appendix Figure B.6.

Among all skill groups, middle-skilled group experienced the highest employment, while both high-skilled AI-complement and low-skilled groups employed the smallest number of people between 2012 and 2021. These findings suggest an inverted U-shaped employment distribution by skill level. These trends were relatively constant over time in the U.S.

The mean hourly wage for the high-skilled AI-complement group was the highest from 2012-21, more than double that of middle- or low-skilled groups. Thus, the high-skilled AI-complement (low-skilled) group can be considered as the highest (lowest) wage group. In addition, the highest wage income share was allocated to high-skilled not-yet-AI group, followed by middle-skilled group. This could be driven by the large employment in these two skill groups and the relative high mean hourly wage for high-skilled not-yet-AI group. Although there was an upward trend in mean hourly wage for all four skill groups, only high-skilled AI-complement group experienced a growth in the wage income share (from 11% to 15%). Middle-skilled group, in contrast, had a decline in the wage income share (from 38% to 34%). These findings can be viewed as a sign of capital redistribution over time.

Undoubtedly, as displayed in Figure 6e, high-skilled AI-complement group experienced the highest share of narrow AI postings during 2012-21. More importantly, this share increased dramatically over time. Notably, this share in 2021 was more than three times larger than that in 2012. Shares of narrow AI postings from other three skill groups were smaller than 1% but slightly increased over time, indicating an increasing demand for narrow AI skills in all occupations rather than for a specific skill group. These increasing trends in AI posting shares reflects the reinstatement effect of AI discussed in Proposition 3. Nonetheless, the share of CS postings remained consistently small for all skill groups.

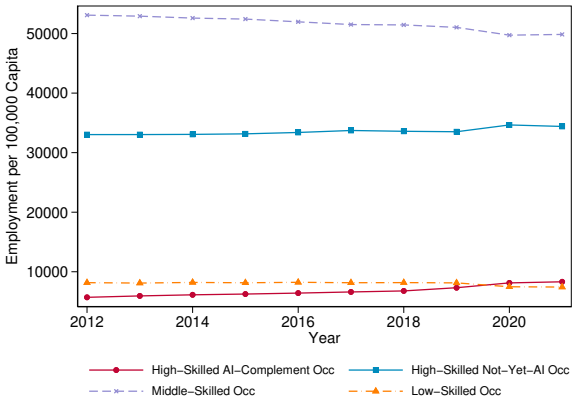
4 Empirical Strategy

To explore the relationship between changes in demand for AI skills and labor market outcomes of heterogeneous skill groups, I adopt the following specification:

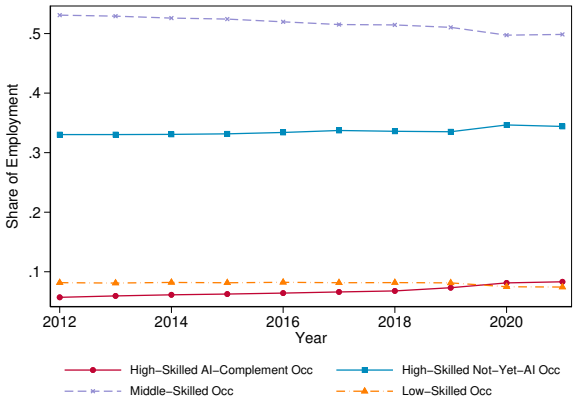
$$\begin{aligned} y_{o4,s,t} =& \alpha + \beta_0 \%AIpost_{s,t} + \sum_{k \in \{H^{AI}, H^{Non}, M\}} \tau_k \mathbf{1}\{SkillGroup_{o4} = k\} \\ &+ \sum_{k \in \{H^{AI}, H^{Non}, M\}} \beta_k \%AIpost_{s,t} \times \mathbf{1}\{SkillGroup_{o4} = k\} \\ &+ \mathbf{X}_{s,t}\mathbf{\Phi} + \delta_s + \theta_t + \varepsilon_{o4,s,t}, \end{aligned} \tag{15}$$

Figure 6: Plots of Skill-Group-By-Year Employment, Wages, and Postings, 2012-21

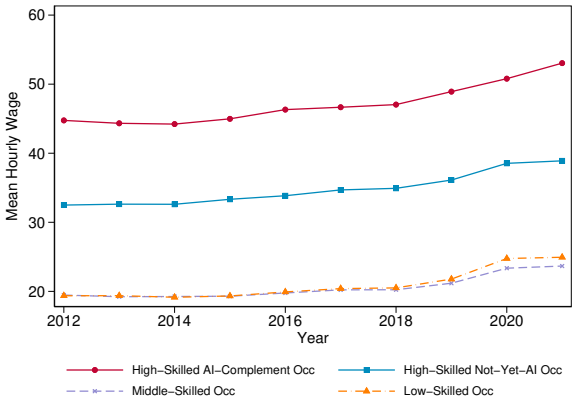
(a) Employment per 100,000 Capita



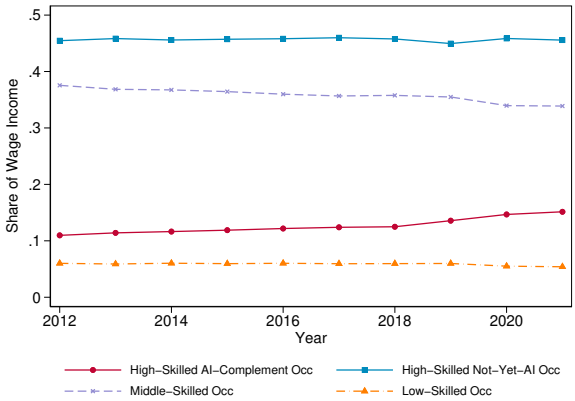
(b) Share of Employment



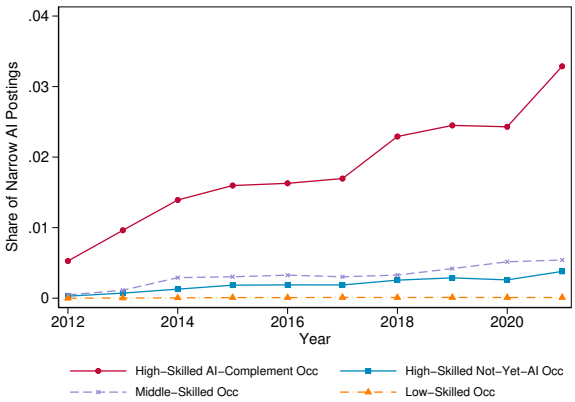
(c) Mean Hourly Wage



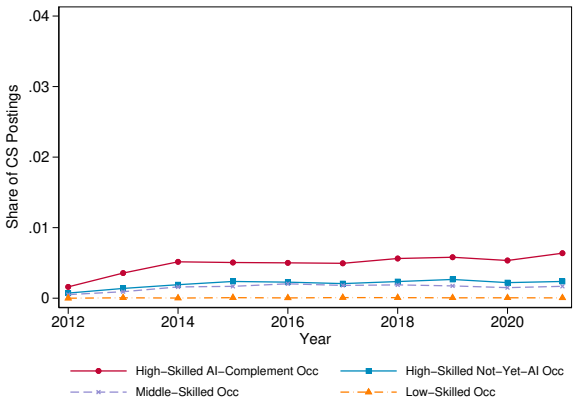
(d) Share of Wage Income



(e) Share of Narrow AI Postings



(f) Share of CS Postings



Notes: Narrow AI definition is used when defining skill groups and computing %AI postings. The skill group indicators in these figures are time-invariant to make statistics comparable across time. The statistics remain consistent when switching to the time-variant skill group indicators, since only 7 (out of 428) 4-digit OCC2010 occupations have their skill group indicators changed across time periods as shown in Appendix Table C.1.

where $o4$, s, and t denote 4-digit OCC2010 occupation, state, and year, respectively.[12] $y_{o4,s,t}$ is one of the following labor market outcomes: (1) the employment per 100,000 capita; (2) the share of employment; (3) the log mean hourly wage; and (4) the share of wage income, all measured at 4-digit-occupation-by-state-by-year level. $\%AIpost_{s,t}$ is the share of narrow AI postings in state s and year t, which captures changes in demand for AI-developing skills and serves as the proxy for growth in AI.[13] This share is multiplied by 100; thus the unit of measurement is a percentage point (pp). $\mathbf{1}\{SkillGroup_{o4} = k\}$ refers to the binary indicator for skill group $k \in \{H^{AI}, H^{Non}, M\}$ that an occupation $o4$ belongs to, as defined by using narrow AI postings. The chosen excluded group is low-skilled group; thus only three groups are included in the set of skill group indicators k. By interacting AI posting shares with skill group dummies, equation (15) can capture the differential effects on skill groups. $\mathbf{X}_{s,t}$ contains state-year control variables that may affect individuals' labor market outcomes: the unemployment rate; the sex ratio; the share of population who have a Bachelor's degree or higher; and the share of population who are White, Black, Asian, or Hispanic. Standard errors, $\varepsilon_{o4,s,t}$, are clustered at the 4-digit-occupation-by-state-by-year level.

Equation (15) includes skill-group, state, and year fixed effects. The skill-group fixed effect, denoted by $\mathbf{1}\{SkillGroup_{o4} = k\}$, accounts for unobserved differences in labor market performance across skill groups. δ_s denotes a state fixed effect which absorbs state-specific time-invariant differences in outcomes. θ_t is a year fixed effect which accounts for general time trends that are constant across states and broad occupation categories. The underlying identification assumption of my approach is that there are no changes in unobserved determinants of labor market outcomes at the skill-group-by-year level that are correlated with changes in AI postings. One threat to this assumption is the possibility of contemporaneous shocks that affect both the AI growth and skill groups' labor market performances. I estimate specifications that interact the skill-group fixed effects with year fixed effects to account for any unobservable time trends in how a skill group responds or is exposed to AI.

Since skill groups are constructed based on 4-digit occupation codes, the set of 2-digit occupation groups is not a subset of skill groups, and vice versa. That is, as presented in Appendix Tables C.2-C.4, (1) a skill group consists of 4-digit occupations from different 2-digit occupation groups and (2) 4-digit occupations from the same 2-digit group can be classified to different skill groups. Thus, the identification could be threatened if there are labor market trends at the 2-digit-occupation level. To address this concern, I include a 2-digit-occupation fixed effect which controls for differences in unobserved determinants of labor market performances across broad occupation categories.[14]

[12] The 4-digit code is the most detailed occupation classification in the OCC2010 coding system.

[13] Results on borad AI postings will be presented in robustness checks.

[14] Since the 2-digit occupation group is not a subset of skill groups and vice versa, including both skill-group and 2-digit-occupation fixed effects does not lead to collinearity.

Taking the above factors into account, my main specification is as follows:

$$\begin{aligned} y_{o4,s,t} =& \alpha + \beta_0 \%AIpost_{s,t} + \sum_{k \in \{H^{AI}, H^{Non}, M\}} \tau_k \mathbf{1}\{SkillGroup_{o4} = k\} \\ &+ \sum_{k \in \{H^{AI}, H^{Non}, M\}} \beta_k \%AIpost_{s,t} \times \mathbf{1}\{SkillGroup_{o4} = k\} \\ &+ \mathbf{X}_{s,t}\mathbf{\Phi} + \delta_s + \theta_t + \gamma_{o2} + \mu_{k,t} + \varepsilon_{o4,s,t}, \end{aligned} \tag{16}$$

where γ_{o2} and $\mu_{k,t}$ are 2-digit-occupation and skill-group-by-year fixed effects, respectively. The coefficients of interest are β_0 and β_k, which capture the relationship between changes in online job postings that require AI-developing skills and labor market outcomes of heterogeneous skill groups. Specifically, β_0 is the change in labor market outcomes of the low-skilled group associated with a 1pp difference in the share of AI postings. β_k is the gap in labor market outcomes between skill group k (high-skilled AI-complement, high-skilled not-yet-AI, or middle-skilled) and the low-skilled group when the share of AI postings changes by 1pp. Thus, $\beta_0 + \beta_k$ is the total change in the outcome variable of skill group k associated with a 1pp difference in the share of AI postings at the state-year level.

5 Results

5.1 Main Results

5.1.1 AI and Employment

Table 4 shows the relationship between narrow AI posting shares and employment. Specifically, columns 1-3 focus on employment per 100,000 capita while columns 4-6 look at the employment share. Note that the skill groups are constructed using the narrow AI definition. Column 1 presents estimates from a simple Ordinary Least Squares (OLS) regression on the share of AI postings itself and skill group indicators. It estimates the overall effect of AI postings on all occupations. The coefficient on the share of AI postings, -10.5, indicates a significant decline in the number of employed people associated with a 1pp increase in the AI posting share, regardless of which skill group this occupation belongs to.

Column 2 interacts the AI posting share with skill group indicators and includes state, year, and skill-group fixed effects to explore effects of the demand for AI skills on heterogeneous skill groups. The estimate of the interaction term between the AI posting share and the high-skilled AI-complement group dummy is 57.9, implying that, compared with the low-skilled group, a 1pp increase in state-year AI posting shares leads to roughly 58 more people employed in abstract and AI-intensive occupations

Table 4: Effects of Demand for AI Skills on Employment, 2012-21

	Dep. Var.:					
	Employment per 100,000 capita			Share of employment[1]		
	(1)	(2)	(3)	(4)	(5)	(6)
%AI postings[2]	-10.5***	-10.8	-6.2	-0.010***	-0.011	-0.006
	(1.5)	(10.5)	(8.3)	(0.026)	(0.002)	(0.008)
%AI postings ×						
High-skilled AI-complement occ		57.9***	55.8***		0.058***	0.056***
		(15.5)	(14.9)		(0.016)	(0.015)
High-skilled not-yet-AI occ		23.0*	20.1**		0.023*	0.020**
		(12.4)	(10.1)		(0.012)	(0.010)
Middle-skilled occ		11.1	2.9		0.011	0.003
		(11.6)	(9.0)		(0.012)	(0.009)
Skill group =						
High-skilled AI-complement occ	-77.7	-187.9	-333.4*	-0.078	-0.188	-0.333*
	(110.6)	(124.7)	(187.6)	(0.111)	(0.125)	(0.188)
High-skilled not-yet-AI occ	40.4	-5.2	-209.5	0.040	-0.005	-0.209
	(112.4)	(131.2)	(184.7)	(0.112)	(0.131)	(0.185)
Middle-skilled occ	-61.5	-84.5	-192.2	-0.062	-0.084	-0.192
	(104.3)	(124.5)	(181.4)	(0.104)	(0.124)	(0.181)
Observations	192,008	192,008	192,008	192,008	192,008	192,008
State FE		✓	✓		✓	✓
Year FE		✓	✓		✓	✓
Skill-group FE	✓	✓	✓	✓	✓	✓
2-digit-occ FE			✓			✓
Skill-group FE × year FE			✓			✓
R-squared	0.012	0.018	0.129	0.012	0.018	0.129

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The unit of the share of employment is a percentage point.

[2] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

per 100,000 capita. This effect is larger than that for the high-skilled not-yet-AI group, indicating an employment gap within high-skilled occupations.

Column 3 estimates equation (16). By further controlling for 2-digit-occupation and skill-group-by-year fixed effects, the comparison is now among 4-digit occupations in the same 2-digit occupation group and the same skill group across states and over time. Estimates are similar with column 2; now, compared with low-skilled occupations, employment in high-skilled AI-complement and high-

skilled not-yet-AI occupations grows by 56 and 20, respectively, per 100,000 capita when AI posting shares increase by 1pp. The overall effects for high-skilled AI-complement and high-skilled not-yet-AI occupations are 50 and 14 more employed people. However, employment for neither middle- nor low-skilled occupations is significantly impacted by changes in the share of AI postings. Estimates in columns 4-6 show a similar relationship between employment shares and AI. These findings support Proposition 3 in Section 2.2, which implies that the reinstatement effect of AI brings a significant employment growth for high-skilled AI-complement occupations.

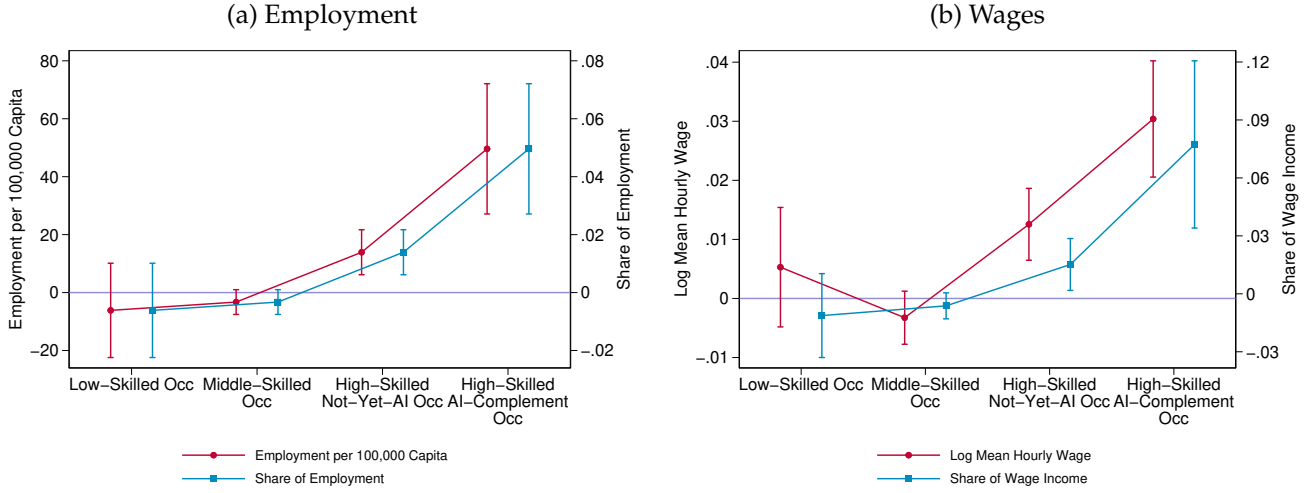
I also plot estimates from my main specification for all four skill groups in Figure 7a. The red line represents estimates from the regression of employment per capita, while the blue line presents estimates from the regression of the employment share. The right tail of both curves is noticeably higher than the left tail. These results document large employment gaps between occupations that are high in abstract and AI-intensive tasks and other skill groups. It is worth noting that there is also an employment gap within abstract-intensive occupations, depending on whether tasks of an occupation require AI-developing skills. These patterns are consistent with findings of Alekseeva et al. (2021) who document a dramatic increase in hiring people with AI skills. Similarly, Felten, Raj, and Seamans (2019) show an employment growth in high wage occupations associated with AI. This is consistent with my finding that high-skilled AI-complement occupations experience an employment growth as the share of AI postings increases. In my paper, high-skilled AI-complement occupations can be considered as high wage occupations because they have the highest mean hourly wage as shown in Figure 6c. In addition, Felten, Raj, and Seamans (2019) do not find a significant relationship between AI and employment growth for low wage occupations, which is also consistent with my results.

5.1.2 AI and Wages

Table 5 shows relationships between AI and wages for heterogeneous skill groups, with columns 1-3 and columns 4-6 presenting results from regressions of log mean hourly wage and the wage income share.

The OLS estimates in column 1 indicate that as AI posting shares increase, the mean hourly wage for all types of occupations significantly increases by 2.7%. After controlling for a full set of fixed effects in column 3, high-skilled AI-complement occupations experience a 2.5% wage growth associated with a 1pp increase in AI posting shares, relative to low-skilled occupations. The overall effect for high-skilled AI-complement occupations is a 3% wage growth. Estimates for other skill groups are much smaller in magnitude and even negative for middle-skilled occupations, but none of them are statistically significant. Estimates on skill group indicators show an interesting finding: mean hourly

Figure 7: Overall Effects of Demand for AI Skills on Labor Market Outcomes, 2012-21



Notes: The coefficient estimates plotted in each subfigure show overall effects of changes in share of narrow AI postings on labor market outcomes. They are obtained by respectively regressing employment per 100,000 capita, share of employment (in percentage point), log mean hourly wages, and share of wage income (in percentage point) on the interaction term between share of narrow AI postings and skill group dummies, using the main specification with a full set of fixed effects (i.e., state, year, skill-group, 2-digit-occupation, and skill-group-by-year fixed effects) included. I also plot the corresponding 95% confidence intervals in each subfigure.

wage for abstract and AI-intensive group is 44.1% higher than the baseline group, the low-skilled group, when the state-year AI posting share is 0. This wage gap widens when AI becomes more ubiquitous. While Proposition 4 discusses that the reinstatement (displacement) effect of AI widens (narrows) wage gaps, my empirical findings on wages further argue that the reinstatement effect of AI on high-skilled labor dominates the displacement effect as AI favors high-skilled workers with AI skills. Moreover, the finding on the wage gap between the high-skilled AI-complement group and other skill groups supports Proposition 5, which indicates a relative wage gain for workers specializing in abstract and AI-intensive tasks as AI increases their productivity.

In addition to mean hourly wage, I explore how AI affects the wage income share which can be viewed as a proxy for the total capital distributed to a skill group. Estimates in column 6 of Table 5 show that a 1pp increase in AI posting shares is associated with an overall growth of 0.078pp (0.015pp) in wage income share for high-skilled AI-complement (high-skilled not-yet-AI) occupations. The overall effects for middle- and low-skilled occupations are negative (-0.006pp and -0.011pp) but are not statistically significant. As AI develops, high-skilled AI-complement workers become more productive since they are supposed to use AI-developing skills to complement their work. Then more income will be distributed to this skill group, which is reflected by the relatively larger increase in its wage income share. The finding that the overall effects on the wage income share across all skill groups sum to more than 0 sheds

Table 5: Effects of Demand for AI Skills on Wages, 2012-21

	Dep. Var.:					
	Log mean hourly wage			Share of wage income[1]		
	(1)	(2)	(3)	(4)	(5)	(6)
%AI postings[2]	0.027***	0.006	0.005	-0.028	-0.011	-0.011
	(0.001)	(0.005)	(0.005)	(0.020)	(0.012)	(0.011)
%AI postings ×						
High-skilled AI-complement occ		0.012**	0.025***		0.080***	0.089***
		(0.006)	(0.007)		(0.024)	(0.026)
High-skilled not-yet-AI occ		0.004	0.007		0.020	0.026*
		(0.005)	(0.006)		(0.015)	(0.014)
Middle-skilled occ		-0.007	-0.009		0.010	0.005
		(0.005)	(0.005)		(0.013)	(0.012)
Skill group =						
High-skilled AI-complement occ	0.673***	0.651***	0.441***	0.152	0.001	-0.151
	(0.080)	(0.080)	(0.104)	(0.111)	(0.114)	(0.166)
High-skilled not-yet-AI occ	0.289***	0.284***	0.126	0.223**	0.182	-0.029
	(0.084)	(0.085)	(0.096)	(0.110)	(0.126)	(0.159)
Middle-skilled occ	-0.076	-0.062	-0.088	-0.056	-0.076	-0.169
	(0.078)	(0.078)	(0.092)	(0.083)	(0.105)	(0.141)
Observations	187,960	187,960	187,960	192,008	192,008	192,008
State FE		✓	✓		✓	✓
Year FE		✓	✓		✓	✓
Skill-group FE	✓	✓	✓	✓	✓	✓
2-digit-occ FE			✓			✓
Skill-group FE × year FE			✓			✓
R-squared	0.195	0.205	0.340	0.053	0.058	0.158

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
[1] The unit of the share of wage income is a percentage point.
[2] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

light on Proposition 6, suggesting that the effect of an increase in productivity of labor specializing in abstract and AI-intensive tasks outweighs the effect of an increase in capital's productivity.[15]

Similar with employment, I document wage gaps between high-skilled AI-intensive occupations

[15]Suppose the total income that can be allocated to each factor in the production is fixed. Then changes in the share of wage income for labor and capital should sum up to 0. Since my empirical results indicate that the overall effects across all four skill groups are positive, then there should be a negative correlation between the demand for AI skills and the income allocated to capital.

and other skill groups. Figure 7b shows a "J-shaped" curve of changes in mean hourly wage associated with AI by skill group: (1) both the left and right tails are higher than the middle; and (2) the right tail is extremely higher than the left tail. These findings imply that as AI grows, wages for labor specializing in abstract and AI-intensive tasks increase dramatically compared to labor specializing in other types of tasks. Conversely, middle-skilled occupations experience the largest wage decline among all four skill groups. These findings on wages are consistent with Felten, Raj, and Seamans (2019) who conclude that wages for high wage occupations are increased by AI and Alekseeva et al. (2021) who document wage premia for AI skills. In contrast to Webb (2019) who argues that AI is predicted to narrow the wage gap between the 90^{th} and 10^{th} percentile of the wage distribution, I find that the wage gap between high-skilled AI-complement and low-skilled occupations widens as demand for AI skills increases.

5.2 Robustness

The main results in Section 5.1 show employment and wage gaps between the abstract and AI-intensive occupations and other skill groups. The underlying assumption of these results is that, given the controls of my specification, labor outcomes are unrelated to unobserved heterogeneity at the skill-group-by-state-by-year level that are correlated with AI or other technological changes (e.g., more general computer science). This section presents several robustness checks to test this assumption. Since main results on employment per capita and the employment share are comparable, this section focuses on employment per capita and wages, while robustness checks for the employment share are presented in Appendix B.

First, I test the potential endogeneity issue by adopting a shift-share instrumental variable (SSIV) (Goldsmith-Pinkham, Sorkin, and Swift, 2020). The share of AI postings could be endogenous to the supply of AI skills in the local labor market and the extent to which local firms are developing or adopting AI technologies. The former one is likely to be positively correlated with the AI posting share. If a local labor market has a large supply of workers with AI-developing skills, employers may specify more AI skills when posting job vacancies. The correlation between the latter one and the AI posting share is likely to be unclear. On the one hand, if more firms start to develop AI models or AI-powered tools, the demand for AI skills will increase. On the other hand, it is possible that, as AI grows, AI-substituting technologies have more capabilities in performing tasks that were previously completed by high-skilled labor. The more AI-substituting technologies firms adopt, the less AI hiring is. Due to the lack of firm-level data on what kinds of AI technologies firms develop or adopt which could be used as a possible instrument, I construct a "leave-one-out" SSIV by interacting local employment shares and industry-specific AI posting shares to instrument for the AI posting share. The "leave-one-

out" estimator is adopted to address the finite sample bias issue (Angrist, Imbens, and Krueger, 1999; Goldsmith-Pinkham, Sorkin, and Swift, 2020). This "leave-one-out" SSIV for state s and year t is:

$$AIpost\ share\ IV_{s,t} = \sum_{o2} E_{o2,s,2011} \frac{\sum_{s' \neq s} \sum_{o4} \#AIpost_{o4,o2,s',t}}{\sum_{s' \neq s} \sum_{o4} \#post_{o4,o2,s',t}}, \tag{17}$$

where $o2$ is the 2-digit 2010 Census OCC code. $E_{o2,s,2011} = \frac{emp_{o2,s,2011}}{\sum_{o2'} emp_{o2',s,2011}}$ represents the start-of-period share of employment in broad occupation category $o2$ in state s.

Columns 1 and 2 of Table 6 present the results on employment per capita from my main specification and the "leave-one-out" SSIV, respectively. Although the SSIV estimates in column 2 become much larger in magnitude but less precise compared with OLS estimates in column 1, the relative comparison between skill groups still holds. The effect of the AI posting share for abstract and AI-intensive occupations (112) is almost three times larger than that for abstract, not-yet-AI occupations (47). Another difference between OLS and SSIV estimates is that SSIV estimates show a significant employment decline for low-skilled occupations (-92). These estimates show widened employment gaps between skill groups compared with OLS estimates, especially the gap between abstract, AI-intensive occupations and other skill groups. I also re-conduct SSIV analyses by changing the 2-digit occupation group, $o2$, in equation (17) to 4-digit occupation, 4-digit North American Industry Classification System (NAICS) code, or an alternative occupational classification constructed by clustering occupations based on skill similarity using a machine learning algorithm.[16] Estimates are presented in Appendix Tables B.2 and B.3, which reassure a consistent pattern in employment gaps between skill groups.

Columns 3 and 4 of Table 6 focus on log mean hourly wage, while columns 5 and 6 turn to the wage income share. Similar with the comparison between columns 1 and 2, SSIV estimates on the interaction term between the AI posting share and skill group dummies are about double of OLS estimates when focusing on wages. Different from OLS estimates in column 3, SSIV estimates in column 4 indicate a significant mean hourly wage gain for high-skilled not-yet-AI occupations (0.029), although this wage gain is smaller than that for high-skilled AI-complement occupations (0.050). In addition, low-skilled occupations experience a significant decline in the wage income share (-0.101) after adopting a SSIV approach shown in column 6. Estimates from using SSIVs summing over different occupation groups are presented in Appendix Tables B.4 and B.5. Regardless of which SSIV being used, the significant wage gaps between high-skilled AI-complement occupations and other skill groups always exist.

The second concern is that the main results could be driven by more general CS skills, rather than the AI-developing skills captured in narrow AI postings. To address this concern, I additionally control for

[16] Details on how I propose this alternative occupational classification will be explained in Section 6.2.

Table 6: Effects of Demand for AI Skills—Adopting SSIV, 2012-21

	Dep. Var.:					
	Emp. per 100,000 capita		Log mean hourly wage		Share of Wage Income[1]	
	Main spec. (1)	SSIV (2)	Main spec. (3)	SSIV (4)	Main spec. (5)	SSIV (6)
%AI postings[2]	-6.1	-92.3***	0.005	0.010	-0.011	-0.101***
	(8.3)	(19.8)	(0.005)	(0.014)	(0.011)	(0.025)
%AI postings ×						
High-skilled AI-complement occ	55.8***	112.1***	0.025***	0.050***	0.089***	0.158***
	(14.9)	(27.1)	(0.007)	(0.010)	(0.026)	(0.040)
High-skilled not-yet-AI occ	20.1**	47.0**	0.007	0.029***	0.026*	0.056**
	(10.1)	(19.9)	(0.006)	(0.010)	(0.014)	(0.027)
Middle-skilled occ	2.9	10.5	-0.009	0.005	0.005	0.014
	(9.0)	(18.0)	(0.005)	(0.009)	(0.012)	(0.022)
Skill group =						
High-skilled AI-complement occ	-333.4*	-361.1*	0.441***	0.431***	-0.151	-0.184
	(187.6)	(190.3)	(0.104)	(0.104)	(0.166)	(0.168)
High-skilled not-yet-AI occ	-209.4	-220.8	0.126	0.117	-0.029	-0.042
	(184.7)	(188.0)	(0.096)	(0.096)	(0.159)	(0.163)
Middle-skilled occ	-192.2	-194.6	-0.088	-0.094	-0.169	-0.172
	(181.4)	(184.8)	(0.092)	(0.092)	(0.141)	(0.145)
Observations	192,008	192,008	187,960	187,960	192,008	192,008
State FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓	✓	✓
R-squared	0.129	0.122	0.340	0.339	0.158	0.152
Cragg-Donald Wald F statistic		2,594.341		2,454.979		2,594.341

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
[1] The unit of the share of wage income is a percentage point.
[2] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

the share of CS postings using the same specification as in my baseline model. Table 7 shows estimates from regressions of employment per capita and wages. Columns 1, 3, and 5 show estimates from my main specification, while columns 2, 4, and 6 show estimates obtained from additionally controlling for the CS posting share. Estimates on the interaction between the share of AI postings and skill group dummies from this robustness check represent effects of the demand for AI skills residualized on the demand for CS skills. They are very similar to estimates from the main specification, implying that my main results are not likely to be driven by the demand for CS skills.[17]

[17] I also construct SSIVs for the CS posting share using equation (17) by replacing AI postings with CS postings. Appendix

Table 7: Effects of Demand for AI Skills—Controlling for CS Skills, 2012-21

	Dep. Var.:					
	Emp. per 100,000 capita		Log mean hourly wage		Share of Wage Income[1]	
	Main spec.	Controlling for CS	Main spec.	Controlling for CS	Main spec.	Controlling for CS
	(1)	(2)	(3)	(4)	(5)	(6)
%AI postings[2]	-6.1	-3.3	0.005	0.004	-0.011	-0.012
	(8.3)	(7.3)	(0.005)	(0.006)	(0.011)	(0.010)
%AI postings ×						
High-skilled AI-complement occ	55.8***	50.1***	0.025***	0.034***	0.089***	0.086***
	(14.9)	(14.0)	(0.007)	(0.008)	(0.026)	(0.025)
High-skilled not-yet-AI occ	20.1**	17.5*	0.007	0.013*	0.026*	0.030**
	(10.1)	(9.1)	(0.006)	(0.007)	(0.014)	(0.014)
Middle-skilled occ	2.9	1.2	-0.009	-0.008	0.005	0.006
	(9.0)	(7.8)	(0.005)	(0.006)	(0.012)	(0.011)
%CS postings[3]		-20.6		0.006		0.000
		(16.4)		(0.017)		(0.016)
%CS postings ×						
High-skilled AI-complement occ		34.6*		-0.057**		0.013
		(19.2)		(0.023)		(0.027)
High-skilled not-yet-AI occ		16.0		-0.033*		-0.021
		(17.9)		(0.019)		(0.019)
Middle-skilled occ		10.3		-0.004		-0.006
		(17.7)		(0.018)		(0.017)
Skill group =						
High-skilled AI-complement occ	-333.4*	-339.6*	0.441***	0.452***	-0.151	-0.153
	(187.6)	(189.5)	(0.104)	(0.104)	(0.166)	(0.167)
High-skilled not-yet-AI occ	-209.5	-212.1	0.126	0.132	-0.029	-0.026
	(184.7)	(186.7)	(0.096)	(0.097)	(0.159)	(0.161)
Middle-skilled occ	-192.2	-193.8	-0.088	-0.087	-0.169	-0.168
	(181.4)	(183.4)	(0.092)	(0.093)	(0.141)	(0.143)
Observations	192,008	192,008	187,960	187,960	192,008	192,008
State FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓	✓	✓
R-squared	0.129	0.129	0.340	0.340	0.158	0.158

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The unit of the share of wage income is a percentage point.

[2] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

[3] Phrases that belong to broad AI category but not narrow AI category are used to compute %CS postings at the state-year level. %CS postings is in percentage point.

Appendix Tables B.10 and B.11 reassure that my main results are not driven by CS skills through controlling for exposure to software and robots using the measures constructed by Webb (2019). These measures capture the capabilities in software and robots for performing an occupation's tasks. After controlling for software and robot exposure, estimates are almost the same with those from my main specification. Appendix Tables B.12 and B.13 further show adding CS skills to the set of AI phrases does not increase predictability of how AI impacts the labor market. That is, replacing narrow AI phrases with broad AI phrases leads to noisy estimates. In addition, estimates on broad AI posting shares become smaller compared with estimates on narrow AI posting shares, indicating that broad AI definition does not capture the true demand for AI-developing skills well.

I also conduct robustness checks on the choice of threshold for defining AI occupations. Instead of using the binary AI occupation indicator defined by equation (12) to categorize high-skilled occupations into AI-complement and not-yet-AI ones, I decompose high-skilled occupations into five groups using narrow AI posting share quintiles. Thus, there are seven skill groups in total: five groups within high-skilled occupations, middle- and low-skilled groups. Table 8 presents estimates from interacting the AI posting share with the new skill group indicators, with the low-skilled group being the baseline group as in my main analysis. These estimates are also plotted in Figure 8. There is a monotonic trend in effects of AI postings on employment and wages for high-skilled occupations that fall into the top four AI posting share quintiles. High-skilled occupations in the top quintile always have the highest gain in both employment and wages associated with an increase in the demand for AI skills. Low-skilled occupations (the first row of Table 8) have the largest decline in employment and the wage income share (i.e., the estimate is the smallest in magnitude and negative).[18]

Another test to check the threshold for AI occupations is to measure the variation of AI-developing skills being listed in job postings across occupations (denoted as "AI Skill Prevalence Score" hereafter). To construct this measure, I perform a principal component analysis (PCA) on the matrix of frequencies of a narrow AI phrase being listed in job postings across all occupations and years.[19] The AI Skill Prevalence

Tables B.6-B.9 present estimates from instrumenting both AI posting shares and CS posting shares. Each table focuses on one of the four labor market outcomes. Estimates from adopting any kind of SSIV except the SSIV summing across 2-digit occupation group in column 2 of Appendix Tables B.6-B.9 reassuare that my main results are not driven by CS skills. Regardless of the magnitude and significance level of estimates on CS posting shares, estimates on AI posting shares are similar with my main results. Estimates in column 2 are boosted up, especially for regressions of employment, because regressions used in column 2 fit the data poorly implied by the negative R-squared and extremely small F statistic.

[18]These results are robust to using the SSIV approach, with estimates presented in Appendix Tables B.14-B.17.

[19]Each element in this matrix represents how many times a narrow AI phrase listed in Table 1 shows up in all postings of an occupation in a specific year. This matrix uses this frequency for all occupations between 2012 and 2021. Then a static componet loading is calculated for each narrow AI skill using PCA, which captures the importance or weight of a narrow AI phrase in constructing the AI Skill Prevalence Score. Python allows users to choose the number of components to keep. Thus, the multi-dimensional matrix is projected to a one-dimensional space by PCA to construct this single measurement.

Table 8: Effects of Demand for AI Skills—Using AI Posting Share Quintiles, 2012-21

	Dep. Var.:		
	Emp. per 100,000 capita	Log mean hourly wage	Share of Wage Income[1]
	(1)	(2)	(3)
%AI postings[2]	-6.2	0.005	-0.011
	(8.3)	(0.005)	(0.011)
%AI postings ×			
High-skilled occ × AI occ (q5)	48.9***	0.025***	0.076***
	(13.0)	(0.006)	(0.022)
High-skilled occ × AI occ (q4)	38.3***	0.013**	0.055**
	(13.3)	(0.006)	(0.023)
High-skilled occ × AI occ (q3)	10.1	0.004	0.008
	(10.3)	(0.007)	(0.013)
High-skilled occ × AI occ (q2)	-6.3	0.006	-0.008
	(13.5)	(0.008)	(0.017)
High-skilled occ × AI occ (q1)	11.1	-0.012	0.015
	(10.1)	(0.015)	(0.012)
Middle-skilled occ	2.9	-0.009	0.005
	(9.0)	(0.005)	(0.012)
Skill group =			
High-skilled occ × AI occ (q5)	-349.6*	0.334***	-0.172
	(187.0)	(0.105)	(0.164)
High-skilled occ × AI occ (q4)	-175.1	0.189*	0.050
	(191.1)	(0.103)	(0.173)
High-skilled occ × AI occ (q3)	70.5	0.149	0.364
	(256.2)	(0.121)	(0.301)
High-skilled occ × AI occ (q2)	13.3	0.061	0.062
	(212.0)	(0.117)	(0.213)
High-skilled occ × AI occ (q1)	-383.2**	0.045	-0.319**
	(182.7)	(0.133)	(0.153)
Middle-skilled occ	-186.6	-0.081	-0.159
	(181.9)	(0.093)	(0.141)
Observations	192,008	187,960	192,008
State FE	✓	✓	✓
Year FE	✓	✓	✓
Skill-group FE	✓	✓	✓
2-digit-occ FE	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓
R-squared	0.143	0.339	0.175

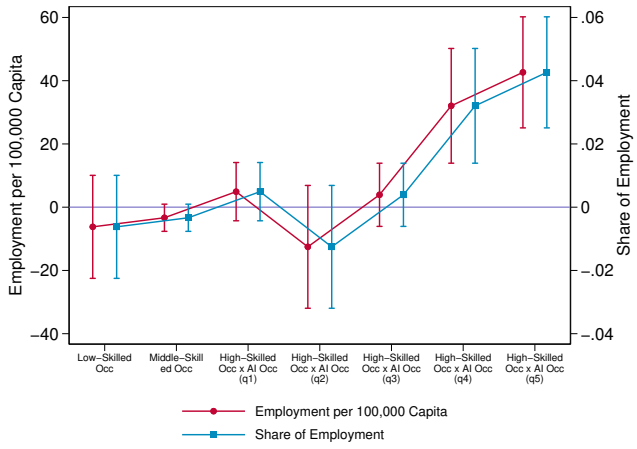
Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The unit of the share of wage income is a percentage point.

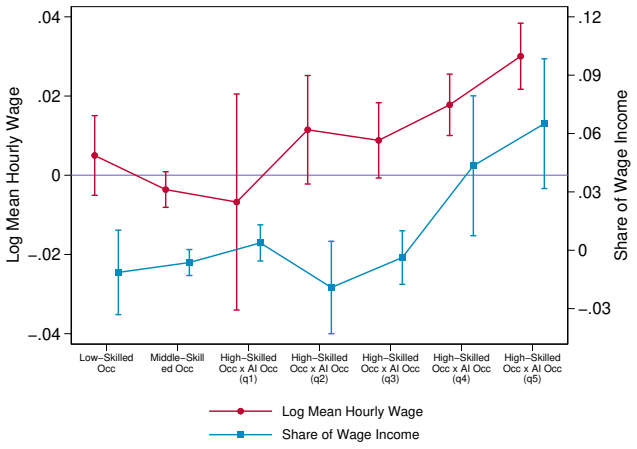
[2] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

Figure 8: Overall Effects of Demand for AI Skills by AI Posting Share Quintile, 2012-21

(a) Employment



(b) Wages



Notes: The coefficient estimates plotted in each subfigure show overall effects of changes in share of narrow AI postings on labor market outcomes for each skill group. Instead of the four skill groups in my main specification, the high-skilled occupations are decomposed into five groups using narrow AI posting share quintiles. Thus, there are seven skill groups in total. Estimates are obtained by respectively regressing employment per 100,000 capita, share of employment (in percentage point), log mean hourly wages, and share of wage income (in percentage point) on the interaction term between share of narrow AI postings and skill group dummies, using the main specification with a full set of fixed effects (i.e., state, year, skill-group, 2-digit-occupation, and skill-group-by-year fixed effects) included. I also plot the corresponding 95% confidence intervals in each subfigure.

Score indicates the intensity that AI-developing skills are required for performing tasks of an occupation. The higher this score is, the more AI-intensive activities an occupation involves. Appendix Table B.18 presents the component loadings of all narrow AI skills used. Of all skills, "python", "machine learning", and "big data" play the most important roles in the AI Skill Prevalence Score.

Figure 9 plots the average AI Skill Prevalence Score over time.[20] The AI Skill Prevalence Score, on average, increased over time, with a big jump between 2012-15 (Figure 9a). This big jump is driven by high-skilled AI-complement occupations, which have a much higher AI Skill Prevalence Score on average compared with the other three skill groups (Figure 9b). To make trends in this measure by skill group comparable, Figure 9c plots the average AI Skill Prevalence Score relative to the baseline year 2012. There was an increasing trend for high-skilled AI-intensive occupations, while this measure dropped for the other skill groups between 2012-14 and gradually went back to their baseline level around 2020. Appendix Table B.19 lists occupations with the top and bottom AI Skill Prevalence Score in 2021. "Software Developers, Applications and Systems Software" has the highest score, followed by "Management Analysts" and "Other Business Operations and Management Specialists." All occupations in Panel A with a high score are from the high-skilled AI-complement group. In contrast, most of

[20]The AI Skill Prevalence Score is standardized within a year.

Table 9: Effects of AI Skill Prevalence on Labor Market Outcomes, 2012-21

	Dep. Var.:			
	Emp. per 100,000 capita	%Emp share[1]	Log mean hourly wage	%Wage income[2]
	(1)	(2)	(3)	(4)
Panel A. Using Occupation-Year AI Skill Prevalence Score				
AI Skill Prevalence Score[3]	33.8***	0.034***	0.008**	0.070***
	(7.1)	(0.007)	(0.003)	(0.010)
Observations	186,799	186,799	183,018	186,799
R-squared	0.132	0.132	0.345	0.168
Panel B. Using State-Year AI Skill Prevalence Score				
AI Skill Prevalence Score[4]	16.0**	0.016**	0.003	0.012
	(6.5)	(0.007)	(0.006)	(0.009)
AI skill prevalence ×				
High-skilled AI-complement occ	30.4***	0.030***	0.024***	0.061***
	(11.0)	(0.011)	(0.007)	(0.023)
High-skilled not-yet-AI occ	6.6	0.007	0.002	0.012
	(7.6)	(0.008)	(0.007)	(0.011)
Middle-skilled occ	0.2	0.000	-0.013**	0.002
	(7.2)	(0.007)	(0.006)	(0.010)
Observations	192,008	192,008	187,960	192,008
R-squared	0.128	0.128	0.340	0.156
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group in Panel B is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
[1,2] The unit of the employment share and the share of wage income is a percentage point.
[3] The AI Skill Prevalence Score in Panel A is constructed at the 4-digit-occupation-by-year level and standardized within a year.
[4] The AI Skill Prevalence Score in Panel B is constructed at the state-year level and standardized within a year.

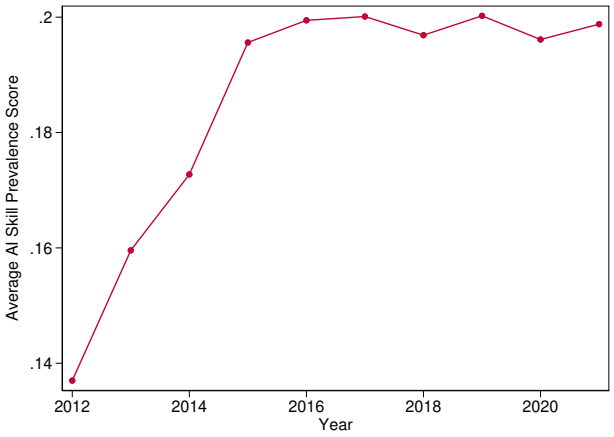
occupations with a low score are routine-intensive (i.e., from the middle-skilled group).

Table 9 tests the relationship between AI Skill Prevalence Score and labor market outcomes. Panel A presents estimates from a regression on the 4-digit-occupation-by-year AI Skill Prevalence Score, which is standardized within a year. The source of variation comes from within occupations. A one standard deviation increase in an occupation's AI Skill Prevalence Score correlates with 34 more employed people per 100,000 capita, a 0.034pp increase in the share of employment, a 0.8% increase in mean hourly wage, and a 0.070pp increase in the wage income share, all of which are statistically significant.

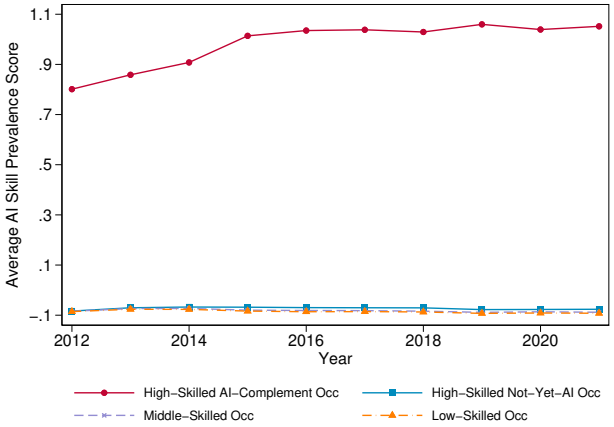
However, to make the estimates comparable to my main analysis which captures the across-group variation using the state-year AI posting shares, I construct a state-year AI Skill Prevalence Score by performing a PCA on the matrix of AI skill frequencies in job postings across all states and years. This

Figure 9: Trends in Average AI Skill Prevalence Score, 2012-21

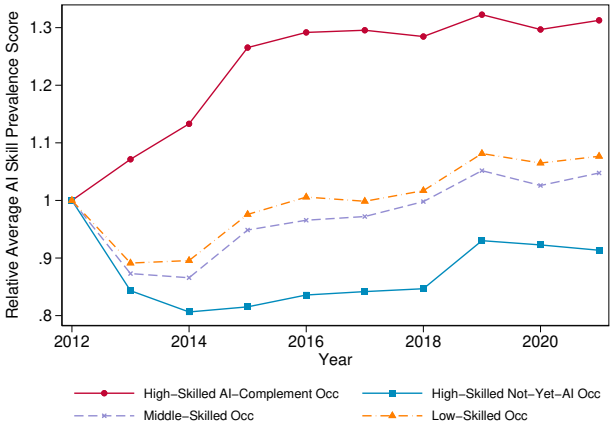
(a) Average AI Skill Prevalence Score Across All Occupations



(b) Average AI Skill Prevalence Score by Skill Group



(c) Average AI Skill Prevalence Score Relative to Baseline Year 2012



Notes: The occupation-year AI Skill Prevalence Score is standardized within a year. In Subfigure 9c, the AI Skill Prevalence Score for each skill group in year 2012 is used as the baseline. Each line represents the following ratio, $\frac{\text{AI Skill Prevalence Score}_{k,t}}{\text{AI Skill Prevalence Score}_{k,2012}}$, where k represents a skill group and t is year.

alternative measure captures the prevalence of AI skills being listed in job descriptions (i.e., the intensity of AI-developing activities) at the state-year level. Appendix Table B.20 lists states with the top and bottom AI Skill Prevalence Score in 2021. California had the highest score, followed by Texas, New York, Virginia, Massachusetts, and Illinois. Appendix Figure B.7a plots this measure by BLS regions. Both New York/New Jersey and the Southwest experienced an increase over time, while other regions had a decline. Although California had the highest score, the Western U.S. had a downward trend due to states with pretty low scores classified into this region (e.g., Alaska, Hawaii, and Nevada). Appendix Figure B.7b is the same as Appendix Figure B.7a but fixing the range of Y axis to make these curves more visually comparable. The Western U.S. had a consistently high score over time and New York/New Jersey experienced a consistent growth in this measure. The AI Skill Prevalence Score for both regions was much higher than that for other regions.

Panel B of Table 9 uses the same specification as my main results but replacing the AI posting share with the state-year AI Skill Prevalence Score. The estimates capture the across-group variation—the difference in the prevalence of AI skills across skill groups within a state. Compared with low-skilled occupations, a one standard deviation increase in this measure is associated with 30 more employed people, 0.030pp increase in the share of employment, a 2.4% mean hourly wage gain, and a 0.061pp increase in the wage income share for high-skilled AI-complement occupations. There is also a 1.3% decline in mean hourly wage for middle-skilled occupations, compared with the baseline group, the low-skilled group. These estimates indicate the existence of employment and wage gaps between abstract and AI-intensive occupations and other skill groups, consistent with my main results in Section 5.1.

Estimates in Panel B of Table 9 also sheds light on Proposition 4 in Section 2.2 which discusses the relationship between the reinstatement and displacement effect of AI. These estimates indicate a wider wage gap between high- and middle-skilled occupations but a narrower wage gap between low- and middle-skilled occupations, suggesting that the displacement effect of AI on relative wages for middle-skilled labor dominates the reinstatement effect. This can be explained by the following reasons. First, AI has become more productive since AI technologies have been dramatically improved during the late 2010s (LeCun, Bengio, and Hinton, 2015; Russell and Norvig, 2021; Zhang et al., 2022). Thus, AI may take over some tasks that were previously performed by middle-skilled workers. Second, improvements in AI may indirectly improve industrial automation, resulting in more automated tasks and a decline in the share of tasks performed by middle-skilled workers. Although this paper does not empirically explore the relationship between wages for middle-skilled workers and industrial automation, existing literature has demonstrated a negative relationship between labor market outcomes of people exposed to routine tasks and automation (Acemoglu, Lelarge, and Restrepo, 2020; Acemoglu

and Restrepo (2022a,b); Moll, Rachel, and Restrepo, 2022; Autor et al., 2024). Third, the current AI technologies are not able to substitute for tasks heavily relied on social skills, which are low-skilled occupations defined in Section 3.2. Although I do not find a significant relationship between mean hourly wages for low-skilled occupations and changes in demand for AI skills, Deming (2017) documents a strong and positive relationship between wages and social-skill-intensive occupations.

Finally, I show that my main results are not driven by one specific state or COVID. Appendix Table B.21 shows percentiles of the distribution of estimated effects using my main specification with one state left out at a time for all states in my sample. The estimates are consistent with my main specification, implying that my main results are not driven by one specific state (e.g., a state with an extremely high or low AI posting share). My main estimates are also similar with estimates from dropping COVID years presented in Appendix Tables B.22 and B.23, indicating that my results are not driven by COVID or work-from-home requirements during COVID.

5.3 Heterogeneity

Since the main results presented in Section 5.1 remain static over the whole sampling period, I examine heterogenity over time in this section. Appendix Figure B.8 plots how estimates for each skill group change over time when interacting the AI posting share in the main specification with year dummies. Effects on employment and the wage income share remain pretty constant over time, while effects on mean hourly wage show an increasing trend, especially for high-skilled AI-complement occupations before COVID. A possible explanation is that AI has been dramatically improved and received increasing attention from the public since the late 2010s (LeCun, Bengio, and Hinton, 2015; Zhang et al., 2022), but there was a stagnation in economic growth during COVID years. It is also worth noting that there were large employment and wage gaps between high-skilled AI-complement occupations and other skill groups over the whole sampling period. Specifically, the wage gap widened prior to COVID and slightly narrowed during COVID.

Appendix Figure B.9 further shows estimates by interacting state-year AI Skill Prevalence Score with year dummies. Different from Appendix Figure B.8, there is now an upward trend for high-skilled AI-complement occupations in terms of all four outcomes. The employment gap between abstract and AI-intensive group and other skill groups was the largest from 2019-20 while the gap in mean hourly wage was the largest between 2018-19. But on the whole, the time-varying effects of AI Skill Prevalence Score are consistent with those of the AI posting share. Abstract occupations that are AI-intensive experienced the largest growth in both employment and wages over time.

6 Discussion: AI as a General-Purpose Technology

This section discusses that AI is possibly one of the general-purpose technologies (GPT) which have profound impacts on the whole economy. Section 6.1 presents results from re-estimating equation (16) but using the share of AI postings at more granular level and argues that AI tends to affect the whole economy rather than specific occupation categories. Section 6.2 introduces an alternative occupation classification system based on the similarity in skill requirements of an occupation using machine learning. I then discuss which occupation clusters have a surge in AI hiring and the differential effects of the demand for AI skills on these occupation clusters.

6.1 AI Postings at More Granular Level and Labor Marker Outcomes

In my main specification, equation (16), the share of AI postings used as the proxy for AI growth is computed at the state-year level. The underlying assumption is that people respond to all kinds of contemporaneous job postings intended to hire workers specializing in AI-developing activities posted in the state where they live. This assumption could be threatened if AI only affects some occupations instead of the whole economy, i.e., only people from certain occupations are responding to AI postings from those specific occupations. Therefore, I re-estimate equation (16) but use the share of narrow AI postings at the 2-digit-occupation-by-state-by-year level. Now β_0 and β_k in equation (16) capture how changes in the AI posting share from a specific 2-digit occupation category affect labor market outcomes.

Appendix Table B.24 focuses on employment. Different from my main results, Table 4 in Section 5.1, the share of AI postings used in Appendix Table B.24 is computed at more granular level—the 2-digit-occupation-by-state-by-year level. The source of variation is now from within 2-digit occupation groups, rather than across groups. After controlling for a full set of fixed effects following my main specification, equation (16), none of the estimates on AI postings are statistically significant. This finding also holds in terms of wages, with estimates presented in Appendix Table B.25.

Similarly, when interacting the occupation-year AI Skill Prevalence Score with skill group dummies as presented in Appendix Table B.26, estimates become much noiser compared with using this measure at more aggregated level in Panel B of Table 9. This is due to the different source of variation in the prevalence of AI skills listed in job postings: the former one is within-group variation, while the latter one is across-group variation.

These findings accompanied with my main results indicate that the employment and wage gaps between high-skilled AI-complement occupations and other skill groups can be due to the variation in the demand for AI skills across groups, rather than within groups. Thus, AI may have impacts on the

whole economy by widening the employment and wage gaps between workers with a specialization in AI-developing tasks and others who do not possess such skills, instead of only impacting people within specific sectors. These results suggest that AI is a general-purpose technology, which is consistent with Cockburn, Henderson, and Stern (2019), Acemoglu (2021); Crafts, 2021, and Hötte et al. (2022).

6.2 Alternative Classification of Occupations

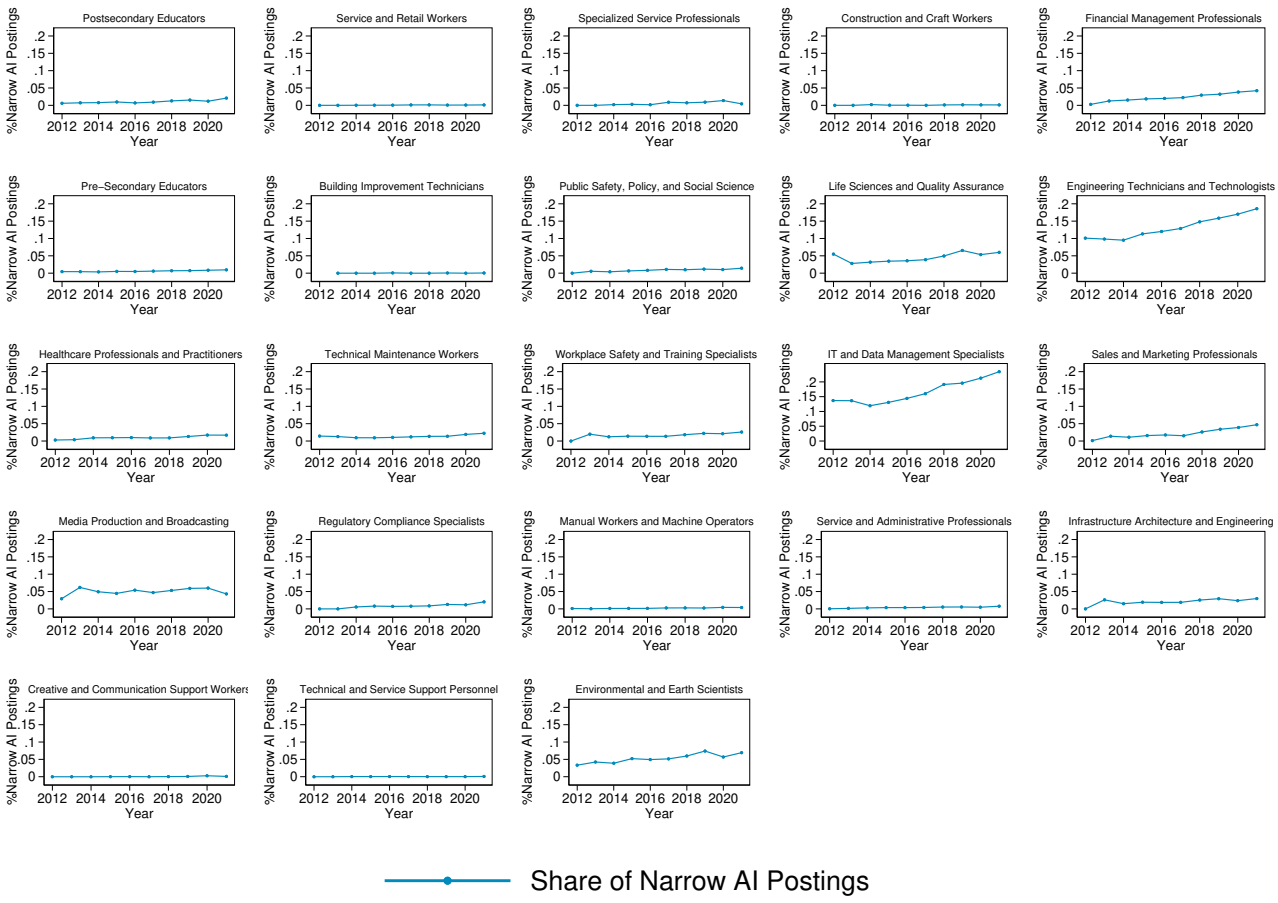
This section introduces an alternative occupation classification system to replace the 2-digit occupation group in my main specification. The broad occupation groups classified by Census or BLS are based on general work performed, but may not reflect specific skill requirements of an occupation. For example, both "Advertising and Promotions Managers" and "Architectural and Engineering Managers" are classified into "Management Occupations" (a 2-digit occupation group). The description of the former one is to "plan, direct, or coordinate advertising policies and programs," while the latter one is to "plan, direct, or coordinate activities in such fields as architecture and engineering."[21] Both occupations have the same general work performed (i.e., plan, direct, or coordinate activities), but require different specific skill sets (the former one needs knowledge of advertising and marketing while the latter one requires knowledge of architecture and engineering). However, they are classified into the same 2-digit occupation group. Using these broad occupation groups classified based on general work performed might lead to measurement errors. Thus, I propose an alternative occupation classification system (denoted as "ML occupation clusters" hereafter) based on skill similarity across occupations. I cluster occupations by skill similarity using the skill requirements reflected in job postings and a machine learning clustering algorithm.[22] Occupations with high similarity in skills are classified into the same cluster (Fogel and Modenesi, 2023). The detailed definition of this alternative occupation classification system and the procedure of developing this system are provided in Appendix D. Appendix Tables D.1-D.3 present the relationship between the ML occupation clusters and the four skill groups introduced in Section 3.2, while Appendix Table D.4 provides a list of the composition of each ML occupation cluster (i.e., the 4-digit occupations that are classified into each cluster).

Figure 10 shows that Engineering, Environment, Finance, IT, Media, and Life Sciences occupations

[21] The descriptions of these two occupations are from BLS (https://www.bls.gov/soc/2010/2010_major_groups.htm). Although the mapping between 4-digit 2010 Census Occupational Classification and the 6-digit 2010 Standard Occupational Classification (SOC) is not always one-to-one (in a few cases this mapping is one-to-many), there is a one-to-one mapping between the 2-digit Census occupation groups and the 2-digit SOC groups provided by BLS (https://www.bls.gov/cps/cenocc2010.htm). Since I do not find a detailed description of each 4-digit 2010 Census occupation, I use the 6-digit 2010 SOC code as examples. Note that the 4-digit (6-digit) code is the most detailed occupational classification in the Census (BLS) system.

[22] I use over 1,800 general and specific skills (e.g., "audit software", "clerical support", "equipment repair", "javascript") to cluster occupations. I set the total number of occupation clusters to be the same as the total number of 2-digit Census Occupational Classification, which is 23.

Figure 10: Plots of %AI Postings by ML Occupation Cluster, 2012-21



had higher and increasing demand for AI-developing skills. However, the trends in narrow AI posting shares by 2-digit Census occupation group in Appendix Figure B.10 are pretty flat, except "Computer and Mathematical Occupations" and "Architecture and Engineering Occupations." Appendix Figures B.11a and B.11b plot the mean hourly wage by ML occupation cluster and by 2-digit Census occupation group, respectively, from 2012-21. There is relatively larger variation in wages across ML occupation clusters. People who work in Engineering, Environment, Finance, IT, Public Safety, Policy, and Social Science occupations experienced higher wages with an upward trend in mean hourly wage.[23] These differences could stem from how an occupation system is developed. Since the Census classification of occupations is constructed based on general work performed rather than skill specification, it is possible that both high- and low-skilled occupations are classified into the same category which averages out the

[23]There is larger variation in the magnitude of the wage income share across ML occupation clusters (Appendix Figure B.12a) than across Census 2-digit occupational classifications (Appendix Figure B.12b). The plots of employment are noiser though (Appendix Figures B.13 and B.14).

outcomes (e.g., mean hourly wage) for this category. In addition, I plot the share of narrow AI postings by ML occupation cluster relative to the baseline year, 2012, in Appendix Figure B.15. Almost all clusters experienced an overall increasing trend, indicating that the demand for AI skills has been increased in almost every sector of the economy.

To examine the relationship between labor market outcomes for ML occupation clusters and the demand for AI skills, I re-estimate my main specification but interacting the AI posting share with ML occupation cluster dummies instead. To make the estimates comparable to my main results, I choose the "service and retail workers" cluster to be the baseline group. Estimates are presented in Table 10, which complements my main results by further showing which occupation clusters within a skill group experience growth or decline in labor market outcomes. Abstract and AI-intensive clusters experience significant growth in both employment and wages, e.g., "engineering technicians", "IT and data management", and "media production and broadcasting." In contrast, clusters with a high concentration in middle-skilled jobs, such as "technical maintenance workers" and "manual workers and machine operators," face significant declines in wages. Different from my main results that document significant correlations between labor market outcomes and the high-skilled group only, estimates from Table 10 show that almost all occupation clusters are significantly impacted by the demand for AI skills.

7 Conclusion

AI has been receiving increasing attention from academia, the industry, and the public. However, researchers have not reached a consensus on the consequences of AI to skill changes, task reallocations, inequalities, and changes in employment and wages. This paper explores how the demand for AI-developing skills influences employment and wages for heterogeneous skill groups in the U.S. I first categorize labor into four skill groups based on skill specializations: (1) a high-skilled AI-complement group that specializes in abstract tasks and possesses AI skills; (2) a high-skilled, not-yet-AI group with a concentration on abstract tasks that are not yet AI-related; (3) a middle-skilled group that is routine-intensive; and (4) a low-skilled group that is manual-intensive. I then measure changes in the demand for AI skills proxied by changes in the share of job postings that explicitly require AI skills using online job postings data. A task-based model is proposed to provide explanations for my main findings:

1. High-skilled AI-complement occupations have experienced the largest growth in employment and wages among all four skill groups associated with an increasing demand for AI skills. This growth is more than double that of high-skilled not-yet-AI occupations.
2. There is no significant relationship between changes in demand for AI skills and employment for

Table 10: Effects of Demand for AI Skills by ML Occupation Cluster, 2012-21

	Dep. Var.:			
	Emp. per 100,000 capita	%Emp share[1]	Log mean hourly wage	%Wage income[2]
	(1)	(2)	(3)	(4)
%AI postings[3]	-18.6**	-0.019**	0.005	-0.018*
	(8.9)	(0.009)	(0.004)	(0.010)
%AI postings ×				
Postsecondary educators	32.3***	0.032***	0.001	0.001
	(10.0)	(0.010)	(0.004)	(0.012)
Specialized service professionals	24.0**	0.024**	-0.012	0.022**
	(9.7)	(0.010)	(0.013)	(0.010)
Construction & craft workers	15.2	0.015	-0.003	0.017
	(12.0)	(0.012)	(0.012)	(0.011)
Finance professionals	29.2*	0.029*	0.022*	0.040*
	(15.4)	(0.015)	(0.013)	(0.024)
Pre-Secondary educators	13.7	0.014	0.009	-0.008
	(28.7)	(0.029)	(0.006)	(0.035)
Building improvement technicians	24.5***	0.024***	0.011	0.024**
	(9.4)	(0.009)	(0.011)	(0.010)
Public safety, policy, & social science	34.2**	0.034**	0.007	0.040*
	(13.5)	(0.014)	(0.010)	(0.023)
Life sciences & quality assurance	34.6***	0.035***	0.009	0.040***
	(11.2)	(0.011)	(0.011)	(0.014)
Engineering technicians	33.0***	0.033***	0.013	0.041***
	(11.2)	(0.011)	(0.008)	(0.014)
Healthcare professionals & practitioners	15.3	0.015	-0.009*	0.003
	(11.1)	(0.011)	(0.005)	(0.014)
Technical maintenance workers	13.7	0.014	-0.019***	0.007
	(9.8)	(0.010)	(0.004)	(0.010)
Workplace safety & training specialists	25.7**	0.026**	0.026***	0.024**
	(10.2)	(0.010)	(0.004)	(0.012)
IT & data management	64.9***	0.065***	0.015***	0.091***
	(19.2)	(0.019)	(0.005)	(0.034)
Sales & marketing professionals	44.3***	0.044***	0.028***	0.050**
	(15.4)	(0.015)	(0.008)	(0.021)
Media production & broadcasting	36.0***	0.036***	0.051***	0.038***
	(11.0)	(0.011)	(0.012)	(0.012)
Regulatory compliance specialists	122.9	0.123	0.002	0.178
	(76.9)	(0.077)	(0.008)	(0.122)
Manual workers & machine operators	14.3	0.014	-0.022***	0.012
	(10.3)	(0.010)	(0.005)	(0.011)
Service & administrative professionals	23.8**	0.024**	0.007	0.027**
	(10.9)	(0.011)	(0.005)	(0.013)
Infrastructure architecture & engineering	18.8	0.019	-0.002	0.009
	(14.2)	(0.014)	(0.007)	(0.021)
Creative & communication support	-75.8	-0.076	-0.016	-0.097
	(60.5)	(0.061)	(0.011)	(0.079)
Technical & service support personnel	24.7**	0.025**	0.005	0.024**
	(9.8)	(0.010)	(0.005)	(0.010)
Environmental & earth scientists	48.0***	0.048***	0.014	0.054**
	(17.2)	(0.017)	(0.021)	(0.025)
Observations	190,712	190,712	186,742	190,712
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓
ML-clustering-group FE	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓
R-squared	0.128	0.128	0.304	0.158

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group is the "service and retail workers" cluster. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1,2] The unit of the employment share and the share of wage income is a percentage point.

[3] Narrow AI definition is used when computing %AI postings at the state-year level. %AI postings is in percentage point.

middle- or low-skilled occupations. However, I document a significant and negative correlation between the intensity of AI-developing skills required in job tasks and the mean hourly wage for middle-skilled occupations.

3. The above findings suggest employment and wage gaps between abstract and AI-intensive occupations and other skill groups. These results reflect (1) a "J-shaped" curve of changes in employment associated with AI by skill group and an employment gap between high-skilled AI-complement occupations and other skill groups, and (2) wage polarization, where middle-skilled workers experience the largest decline in wages compared with other types of workers.

My main results are limited by my measures of AI and skill group classifications. Although existing literature is used as references when choosing AI phrases, there are possibly omitted phrases that can also be counted toward a "narrow AI" or "broad AI" phrase. Future research could improve the completeness of my chosen AI phrases adopted to distinguish between AI and not-yet-AI postings/occupations.

Another future research direction is to explore the impacts of Generative AI (GenAI) tools, also known as Large Language Models (LLMs). My empirical analysis mainly focuses on the complementarity of AI-developing skills, but does not discuss how GenAI tools like ChatGPT may affect the economy. This can be explained by several reasons. First, although GenAI can both complement (e.g., people may use ChatGPT to help with job tasks or problems they encounter during work such as writing emails and doing simple math) and substitute (e.g., Eloundou et al. (2023) argue that most occupations are, to some extent, exposed to LLMs) labor, employers may not list the use of these GenAI tools as one of the requirements in job postings. The access to GenAI tools like ChatGPT is simple and does not require any specialized knowledge or skill. However, people who possess AI-developing skills are essential to the improvements in GenAI. Thus, this paper focuses on workers specializing in AI-developing skills by tracking changes in the demand for these skills rather than workers using the easily accessible GenAI tools. Second, GenAI tools has become publicly known and easily accessible since 2022, which is later than the last year of job postings data that I have access to. Third, although a decline in AI postings may signal the substitution effect of AI, I do not find such a trend from the online job postings data. Thus, the postings data may not serve as a good proxy for measuring AI's substitution. However, my approach to studying AI-developing skills can be applied to explore the impacts of GenAI tools, or other technological advances, on the economy.

References

ACEMOGLU, D. (2021): "Harms of AI," Discussion paper, National Bureau of Economic Research.

ACEMOGLU, D., AND D. AUTOR (2011): "Skills, tasks and technologies: Implications for employment and earnings," in *Handbook of Labor Economics*, vol. 4, pp. 1043–1171. Elsevier.

ACEMOGLU, D., D. AUTOR, J. HAZELL, AND P. RESTREPO (2022): "Artificial intelligence and jobs: evidence from online vacancies," *Journal of Labor Economics*, 40(S1), S293–S340.

ACEMOGLU, D., C. LELARGE, AND P. RESTREPO (2020): "Competing with robots: Firm-level evidence from France," in *AEA Papers and Proceedings*, vol. 110, pp. 383–388. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

ACEMOGLU, D., AND P. RESTREPO (2018a): "Low-skill and high-skill automation," *Journal of Human Capital*, 12(2), 204–232.

——— (2018b): "The race between man and machine: Implications of technology for growth, factor shares, and employment," *American Economic Review*, 108(6), 1488–1542.

——— (2019): "Automation and new tasks: How technology displaces and reinstates labor," *Journal of Economic Perspectives*, 33(2), 3–30.

——— (2022a): "Demographics and automation," *The Review of Economic Studies*, 89(1), 1–44.

——— (2022b): "Tasks, automation, and the rise in us wage inequality," *Econometrica*, 90(5), 1973–2016.

ALEKSEEVA, L., J. AZAR, M. GINE, S. SAMILA, AND B. TASKA (2021): "The demand for AI skills in the labor market," *Labour Economics*, 71, 102002.

ANGRIST, J. D., G. W. IMBENS, AND A. B. KRUEGER (1999): "Jackknife instrumental variables estimation," *Journal of Applied Econometrics*, 14(1), 57–67.

ATALAY, E., P. PHONGTHIENGTHAM, S. SOTELO, AND D. TANNENBAUM (2020): "The evolution of work in the United States," *American Economic Journal: Applied Economics*, 12(2), 1–34.

AUTOR, D., C. CHIN, A. SALOMONS, AND B. SEEGMILLER (2024): "New frontiers: The origins and content of new work, 1940–2018," *The Quarterly Journal of Economics*, p. qjae008.

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

AUTOR, D. H., AND D. DORN (2013): "The growth of low-skill service jobs and the polarization of the US labor market," *American Economic Review*, 103(5), 1553–97.

AUTOR, D. H., F. LEVY, AND R. J. MURNANE (2003): "The skill content of recent technological change: An empirical exploration," *The Quarterly Journal of Economics*, 118(4), 1279–1333.

BLOOM, N., T. A. HASSAN, A. KALYANI, J. LERNER, AND A. TAHOUN (2020): "The geography of new technologies," *Institute for New Economic Thinking Working Paper Series*, (126).

BRYNJOLFSSON, E., D. ROCK, AND C. SYVERSON (2019): "Artificial intelligence and the modern productivity paradox," *The Economics of Artificial Intelligence: An Agenda*, 23, 23–57.

COCKBURN, I. M., R. HENDERSON, AND S. STERN (2019): "The Impact of Artificial Intelligence on Innovation," *The Economics of Artificial Intelligence: An Agenda*, pp. 115–146.

CRAFTS, N. (2021): "Artificial intelligence as a general-purpose technology: an historical perspective," *Oxford Review of Economic Policy*, 37(3).

DAFOE, A. (2018): "AI governance: a research agenda," *Governance of AI Program, Future of Humanity Institute, University of Oxford: Oxford, UK*, 1442, 1443.

DAUTH, W., S. FINDEISEN, J. SUEDEKUM, AND N. WOESSNER (2021): "The adjustment of labor markets to robots," *Journal of the European Economic Association*, 19(6), 3104–3153.

DEMING, D. J. (2017): "The growing importance of social skills in the labor market," *The Quarterly Journal of Economics*, 132(4), 1593–1640.

DEMING, D. J., AND K. NORAY (2020): "Earnings dynamics, changing job skills, and STEM careers," *The Quarterly Journal of Economics*, 135(4), 1965–2005.

DEMING, D. J., AND K. L. NORAY (2018): "STEM careers and the changing skill requirements of work," Discussion paper, National Bureau of Economic Research.

DILLENDER, M., AND E. FORSYTHE (2022): "Computerization of white collar jobs," Discussion paper, National Bureau of Economic Research.

DORN, D. (2009): "Essays on inequality, spatial interaction, and the demand for skills," Ph.D. thesis, Verlag nicht ermittelbar.

ELOUNDOU, T., S. MANNING, P. MISHKIN, AND D. ROCK (2023): "Gpts are gpts: An early look at the labor market impact potential of large language models," *arXiv preprint arXiv:2303.10130*.

FABER, M., A. SARTO, AND M. TABELLINI (2019): "The impact of technology and trade on migration: Evidence from the US," *Harvard Business School BGIE Unit Working Paper*, pp. 20–071.

FELTEN, E., M. RAJ, AND R. C. SEAMANS (2019): "The effect of artificial intelligence on human labor: An ability-based approach," in *Academy of Management Proceedings*, vol. 2019, p. 15784. Academy of Management Briarcliff Manor, NY 10510.

FOGEL, J., AND B. MODENESI (2023): "What is a Labor Market? Classifying Workers and Jobs Using Network Theory," *arXiv e-prints*, pp. arXiv–2311.

GOLDFARB, A., B. TASKA, AND F. TEODORIDIS (2023): "Could machine learning be a general purpose technology? a comparison of emerging technologies using data from online job postings," *Research Policy*, 52(1), 104653.

GOLDSMITH-PINKHAM, P., I. SORKIN, AND H. SWIFT (2020): "Bartik instruments: What, when, why, and how," *American Economic Review*, 110(8), 2586–2624.

HEMELT, S. W., B. HERSHBEIN, S. MARTIN, AND K. M. STANGE (2023): "College majors and skills: Evidence from the universe of online job ads," *Labour Economics*, 85, 102429.

HÖTTE, K., T. TARANNUM, V. VERENDEL, AND L. BENNETT (2022): "Exploring Artificial Intelligence as a General Purpose Technology with Patent Data–A Systematic Comparison of Four Classification Approaches," *arXiv preprint arXiv:2204.10304*.

KATZ, L. F., AND K. M. MURPHY (1992): "Changes in relative wages, 1963–1987: supply and demand factors," *The Quarterly Journal of Economics*, 107(1), 35–78.

KOGAN, L., D. PAPANIKOLAOU, L. D. SCHMIDT, AND B. SEEGMILLER (2021): "Technology-skill complementarity and labor displacement: Evidence from linking two centuries of patents with occupations," Discussion paper, National Bureau of Economic Research.

LECUN, Y., Y. BENGIO, AND G. HINTON (2015): "Deep learning," *Nature*, 521(7553), 436–444.

MOLL, B., L. RACHEL, AND P. RESTREPO (2022): "Uneven growth: automation's impact on income and wealth inequality," *Econometrica*, 90(6), 2645–2683.

NEDELKOSKA, L., S. G. MATHA, J. MCNERNEY, A. ASSUMPCAO, D. DIODATO, AND F. NEFFKE (2021): "Eight Decades of Changes in Occupational Tasks, Computerization and the Gender Pay Gap," .

RUSSELL, S., AND P. NORVIG (2021): "Artificial Intelligence: a modern approach, 4th US ed," *University of California, Berkeley*.

WEBB, M. (2019): "The impact of artificial intelligence on the labor market," *Available at SSRN 3482150*.

ZHANG, D., N. MASLEJ, E. BRYNJOLFSSON, J. ETCHEMENDY, T. LYONS, J. MANYIKA, H. NGO, J. C. NIEBLES, M. SELLITTO, E. SAKHAEE, Y. SHOHAM, J. CLARK, AND R. PERRAULT (2022): "The AI Index 2022 Annual Report," *AI Index Steering Committee, Stanford Institute for Human-Centered AI, Stanford University*.

APPENDIX

A Propositions and Proofs

Appendix A.1 presents inequalities and propositions that are not tested in my main empirical analysis. Propositions 3′ and 4′ add additional inequalities to the ones presented in Propositions 3 and 4 in Section 2.2, while both Propositions 7 and 8 are only included in the Appendix. Proposition 7 discusses the productivity effect of AI and industrial automation on the final output. Proposition 8 sheds light on the relationship between relative wages and labor supplies. Appendix A.2 shows the proofs of all propositions.

A.1 Additional Propositions

Proposition 3′ (Displacement and reinstatement effects of AI or industrial automation).

Inequalities presented in Propsition 3 in Section 2.2:

(1) AI can displace workers in some complex tasks, $\frac{d\mathrm{A}_{H^j}}{dI_H} < 0$, $\frac{d\mathrm{A}_K}{dI_H} > 0$, $\frac{d\mathrm{A}_M}{dS} > 0$, $\frac{d\mathrm{A}_K}{dS} < 0$.

(2) AI can expand the set of tasks performed by high-skilled workers, $\frac{d\mathrm{A}_{H^j}}{dN} > 0$.

(3) Industrial automation primarily takes over simpler tasks, $\frac{d\mathrm{A}_M}{dI_M} < 0$, $\frac{d\mathrm{A}_K}{dI_M} > 0$.

Additional inequalities:

(4) While the set of tasks performed by high-skilled workers is expanded by AI, the simplest tasks that were performed by low-skilled workers may disappear, $\frac{d\mathrm{A}_L}{dN} < 0$.

(5) Labor has a learning effect, $\frac{d\mathrm{A}_L}{dI_L} > 0$, $\frac{d\mathrm{A}_K}{dI_L} < 0$.

Note that $j \in \{AI, Non\}$.

Since there is a unit measure of tasks as shown in equation 1, if new tasks favoring high-skilled labor are created (an increase in N), then the simplest tasks will disappear.

Proposition 3′ implies the learning effect of labor. An increase in I_L can represent a higher productivity of low-skilled workers in completing slightly more complex tasks. Their productivity can be increased by having more education, participating in on-the-job trainings, etc. Thus, low-skilled workers are able to perform some tasks that were previously automated due to the higher productivity of low-skilled workers and less costs of using low-skilled labor, resulting in an increase in the share of tasks performed by low-skilled workers (A_L) and a decrease in the share of automated tasks (A_K). Similar explanation can be applied to the learning effect of middle-skilled labor (represented by an increase in S).

Proposition 4′ (Relationship between relative wages and AI or industrial automation).

Inequalities presented in Propsition 4 in Section 2.2:

(1) The displacement effect of AI narrows wage gaps, $\frac{d(\frac{W_{Hj}}{W_L})}{dI_H} < 0$, $\frac{d(\frac{W_{Hj}}{W_M})}{dI_H} < 0$.

(2) The reinstatement effect of AI widens wage gaps, $\frac{d(\frac{W_{Hj}}{W_L})}{dN} > 0$, $\frac{d(\frac{W_{Hj}}{W_M})}{dN} > 0$, $\frac{d(\frac{W_M}{W_L})}{dN} > 0$.

(3) The displacement effect of industrial automation widens wage gaps, $\frac{d(\frac{W_{Hj}}{W_M})}{dI_M} > 0$, $\frac{d(\frac{W_M}{W_L})}{dI_M} > 0$.

Additional inequalities:

(4) The displacement effect of AI represented by a decrease in S widens the wage gap between the high- and middle-skilled groups, but narrows the wage gap between the middle- and low-skilled groups, $\frac{d(\frac{W_{Hj}}{W_M})}{dS} < 0$, $\frac{d(\frac{W_M}{W_L})}{dS} > 0$.

(5) The displacement effect of industrial automation represented by a decrease in I_L widens wage gaps, $\frac{d(\frac{W_{Hj}}{W_L})}{dI_L} < 0$, $\frac{d(\frac{W_M}{W_L})}{dI_L} < 0$.

Note that $j \in \{AI, Non\}$.

The displacement effect of AI on high-skilled labor (an increase in I_H) narrows wage gaps between high-skilled group and middle- or low-skilled group ($\frac{W_{Hj}}{W_M}$ and $\frac{W_{Hj}}{W_L}$), while this displacement effect on middle-skilled labor (a decrease in S) narrows wage gaps between the middle- and low-skilled groups ($\frac{W_M}{W_L}$) but widens the wage gap between the high- and middle-skilled groups ($\frac{W_{Hj}}{W_M}$). The displacement effect of industrial automation (an increase in I_M or a decrease in I_L) and the reinstatement effect of AI (an increase in N) widen these wage gaps.

Proposition 7 (Productivity effect of AI or industrial automation).

$$\begin{aligned}
\frac{dY}{dI_M} &= \frac{\sigma}{\sigma-1} Y \left[R^{1-\sigma} - (\frac{W_M}{\alpha_M(I_M)})^{1-\sigma} \right] > 0, \\
\frac{dY}{dI_H} &= \frac{\sigma}{\sigma-1} Y \left[(\frac{R}{\alpha_K})^{1-\sigma} - \mathbf{1}\{i \in \textit{AI tasks}\} (\frac{W_{H^{AI}}}{\alpha_{H^{AI}}(I_H)})^{1-\sigma} - \mathbf{1}\{i \in \textit{not-yet-AI tasks}\} (\frac{W_{H^{Non}}}{\alpha_{H^{Non}}(I_H)})^{1-\sigma} \right] \\
&> 0.
\end{aligned} \tag{A.1}$$

Improvements in AI (represented by an increase in I_H) or industrial automation (represented by an increase in I_M) both have a positive productivity effect on the final output, Y. This can be easily explained by the fact that technological improvements raise the productivity of technologies in production. The larger the gap $\frac{W_M}{\alpha_M(I_M)} - R$ or $\mathbf{1}\{i \in \text{AI tasks}\} \frac{W_{HAI}}{\alpha_{HAI}(I_H)} + \mathbf{1}\{i \in \text{not-yet-AI tasks}\} \frac{W_{HNon}}{\alpha_{HNon}(I_H)} - \frac{R}{\alpha_K}$ is, the less costly it is to replace more expensive labor with cheaper capital and the greater productivity gains are (these gaps are positive due to Assumption 3).

Proposition 8 (Relationship between relative wages and labor supplies).

$$\begin{aligned} &\frac{d\ln(\frac{W_{H^j}}{W_L})}{d\ln H^j} < 0, \quad \frac{d\ln(\frac{W_{H^j}}{W_M})}{d\ln H^j} < 0, \quad \frac{d\ln(\frac{W_{H^j}}{W_M})}{d\ln M} > 0, \\ &\frac{d\ln(\frac{W_M}{W_L})}{d\ln M} < 0, \quad \frac{d\ln(\frac{W_{H^j}}{W_L})}{d\ln L} > 0, \quad \frac{d\ln(\frac{W_M}{W_L})}{d\ln L} > 0,\ j \in \{AI, Non\}. \end{aligned} \tag{A.2}$$

When the task allocation among different skill groups remains unchanged, an increase in the labor supply of a specific skill group will put a downward pressure on wages for that group because there are more workers competing in the same set of tasks. In particular, an increase in the supply of high-skilled workers (H^j, $j \in \{AI, Non\}$) will reduce their wages and consequently have a negative impact on relative wages $\frac{W_{H^j}}{W_L}$ and $\frac{W_{H^j}}{W_M}$. An increase in the supply of middle-skilled workers (M) widens the wage gap between high- and middle-skilled workers ($\frac{W_{H^j}}{W_M}$) but reduces the wage gap between middle- and low-skilled workers ($\frac{W_M}{W_L}$) because middle-skilled workers earn less. Similarly, an increase in the supply of low-skilled workers (L) increases the wage gap between low- and middle-skilled workers ($\frac{W_M}{W_L}$) or between low- and high-skilled workers ($\frac{W_{H^j}}{W_L}$).

A.2 Proofs

A.2.1 Proof of Proposition 1

The proof of this proposition is similar to the proof of Lemma 1 in Acemoglu and Autor (2011). Intuitively, given factor prices of labor and capital, task $i = I_M$ can be performed by either industrial automation or middle-skilled labor because the cost of producing this task using either type of factors is the same. That is, $R = \frac{W_M}{\alpha_M(I_M)}$.[24] Since Assumption 3 assumes that $\exists I_M \in (N-1, S)$ such that $\frac{W_M}{\alpha_M(I_M)} > R$ and Assumption 1 assumes that $\alpha_M(i)$ is strictly increasing in i, then (1) the cost of automating any tasks $i < I_M$ is lower than using middle-skilled labor and (2) it is less costly to produce tasks $i > I_M$ using middle-skilled labor than industrial automation. The same argument applies to comparisons of other factors.

[24] The productivity of industrial automation is set to be 1 introduced in Section 2.1.

A.2.2 Proof of Proposition 2

I first show the proof of the ideal-price condition presented in equation (8). Given the CES production function expressed in equation (1), the marginal cost of producing the final good Y is:

$$P = \left[\int_{N-1}^{N} p(i)^{1-\sigma} di\right]^{\frac{1}{1-\sigma}}. \tag{A.3}$$

Equation (8) can then be derived by combining equations (3) and (A.3):

$$\begin{aligned}
1 \equiv P = \Bigg[&\int_{N-1}^{I_L} (\frac{W_L}{\alpha_L(i)})^{1-\sigma} di + \int_{I_L}^{I_M} R^{1-\sigma} di + \int_{I_M}^{S} (\frac{W_M}{\alpha_M(i)})^{1-\sigma} di + \int_{S}^{I_H} (\frac{R}{\alpha_K})^{1-\sigma} di \\
&+ \int_{I_H}^{N} (\frac{W_{H^{AI}}}{\alpha_{H^{AI}}(i)})^{1-\sigma} di + \int_{I_H}^{N} (\frac{W_{H^{Non}}}{\alpha_{H^{Non}}(i)})^{1-\sigma} di\Bigg]^{\frac{1}{1-\sigma}} \\
\Rightarrow 1 = {} & R^{1-\sigma}\left[I_M - I_L + (I_H - S)\alpha_K^{\sigma-1}\right] + W_L^{1-\sigma}\int_{N-1}^{I_L} \alpha_L(i)^{\sigma-1} di + W_M^{1-\sigma}\int_{I_M}^{S} \alpha_M(i)^{\sigma-1} di \\
&+ W_{H^{AI}}^{1-\sigma}\int_{I_H}^{N} \mathbf{1}\{i \in \text{AI tasks}\}\alpha_{H^{AI}}(i)^{\sigma-1} di + W_{H^{Non}}^{1-\sigma}\int_{I_H}^{N} \mathbf{1}\{i \in \text{not-yet-AI tasks}\}\alpha_{H^{Non}}(i)^{\sigma-1} di \\
= {} & \mathrm{A}_{H^{AI}} W_{H^{AI}}^{1-\sigma} + \mathrm{A}_{H^{Non}} W_{H^{Non}}^{1-\sigma} + \mathrm{A}_M W_M^{1-\sigma} + \mathrm{A}_L W_L^{1-\sigma} + \mathrm{A}_K R^{1-\sigma}.
\end{aligned} \tag{A.4}$$

The equilibrium factor prices expressed in equation (9) can be easily obtained by re-arranging terms of equation (6). Replacing factor prices of the ideal-price condition, equation (8), with expressions for these factor prices presented in equation (9), I can obtain the equilibrium output shown in equation (10):

$$\begin{aligned}
1 &= \mathrm{A}_{H^{AI}} W_{H^{AI}}^{1-\sigma} + \mathrm{A}_{H^{Non}} W_{H^{Non}}^{1-\sigma} + \mathrm{A}_M W_M^{1-\sigma} + \mathrm{A}_L W_L^{1-\sigma} + \mathrm{A}_K R^{1-\sigma} \\
&= \mathrm{A}_{H^{AI}}\left[Y^{\frac{1}{\sigma}} \mathrm{A}_{H^{AI}}^{\frac{1}{\sigma}} (H^{AI})^{-\frac{1}{\sigma}}\right]^{1-\sigma} + \mathrm{A}_{H^{Non}}\left[Y^{\frac{1}{\sigma}} \mathrm{A}_{H^{Non}}^{\frac{1}{\sigma}} (H^{Non})^{-\frac{1}{\sigma}}\right]^{1-\sigma} + \mathrm{A}_M\left[Y^{\frac{1}{\sigma}} \mathrm{A}_M^{\frac{1}{\sigma}} M^{-\frac{1}{\sigma}}\right]^{1-\sigma} \\
&\quad + \mathrm{A}_L W_L\left[Y^{\frac{1}{\sigma}} \mathrm{A}_L^{\frac{1}{\sigma}} L^{-\frac{1}{\sigma}}\right]^{1-\sigma} + \mathrm{A}_K\left[Y^{\frac{1}{\sigma}} \mathrm{A}_K^{\frac{1}{\sigma}} K^{-\frac{1}{\sigma}}\right]^{1-\sigma} \\
&= Y^{\frac{1-\sigma}{\sigma}}\left[\mathrm{A}_{H^{AI}}^{\frac{1}{\sigma}} (H^{AI})^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_{H^{Non}}^{\frac{1}{\sigma}} (H^{Non})^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_M^{\frac{1}{\sigma}} M^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_L^{\frac{1}{\sigma}} L^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_K^{\frac{1}{\sigma}} K^{\frac{\sigma-1}{\sigma}}\right].
\end{aligned} \tag{A.5}$$

A.2.3 Proof of Propositions 3 and 3′

I present the proof for $\frac{d\mathrm{A}_{H^{AI}}}{dI_H} > 0$ (that is, $\frac{d\mathrm{A}_{H^j}}{dI_H} > 0, j \in \{AI, Non\}$, when $j = AI$) in Proposition 3. The proof for other inequalities in Propositions 3 and 3′ is analogous. Given equation (7),

$$\begin{aligned}\frac{d\mathrm{A}_{H^{AI}}}{dI_H} &= \frac{d\int_{I_H}^{N}\mathbf{1}\{i \in \text{AI tasks}\}\alpha_{H^{AI}}(i)^{\sigma-1}di}{dI_L} \\ &= \mathbf{1}\{i \in \text{AI tasks}\}\alpha_{H^{AI}}(N)^{\sigma-1}\frac{d(N)}{di} - \mathbf{1}\{i \in \text{AI tasks}\}\alpha_{H^{AI}}(I_H)^{\sigma-1} \\ &= \mathbf{1}\{i \in \text{AI tasks}\}\alpha_{H^{AI}}(I_H)^{\sigma-1} > 0.\end{aligned} \tag{A.6}$$

A.2.4 Proof of Propositions 4 and 4′

Given the equilibrium factor prices presented in equation (9) and Proposition 3,

$$\frac{d(\frac{W_{H^j}}{W_L})}{dI_H} = \frac{d\left[\frac{\mathrm{A}_{H^j}^{1/\sigma}(H^j)^{-1/\sigma}}{\mathrm{A}_L^{1/\sigma}L^{-1/\sigma}}\right]}{dI_H} = \frac{\frac{d\mathrm{A}_{H^j}}{dI_H}\frac{1}{\sigma}\mathrm{A}_{H^j}^{\frac{1-\sigma}{\sigma}}(H^j)^{-1/\sigma}}{\mathrm{A}_L^{1/\sigma}L^{-1/\sigma}} < 0,\ j \in \{AI, Non\}. \tag{A.7}$$

Similar for the other inequalities in Propositions 4 and 4′.

A.2.5 Proof of Proposition 5

Given the equilibrium factor prices presented in equation (9) and Assumption 1,

$$\begin{aligned}\frac{d(\frac{W_{H^{AI}}}{W_L})}{d\alpha_{H^{AI}}(i)} &= \frac{d\mathrm{A}_{H^{AI}}}{d\alpha_{H^{AI}}(i)}\frac{\frac{1}{\sigma}\mathrm{A}_{H^{AI}}^{\frac{1-\sigma}{\sigma}}(H^{AI})^{-\frac{1}{\sigma}}}{\mathrm{A}_L^{\frac{1}{\sigma}}L^{-\frac{1}{\sigma}}} \\ &= \frac{d\left[\int_{I_H}^{N}\mathbf{1}\{i \in \text{AI tasks}\}\alpha_{H^{AI}}(i)^{\sigma-1}di\right]}{d\alpha_{H^{AI}}(i)}\frac{\frac{1}{\sigma}\mathrm{A}_{H^{AI}}^{\frac{1-\sigma}{\sigma}}(H^{AI})^{-\frac{1}{\sigma}}}{\mathrm{A}_L^{\frac{1}{\sigma}}L^{-\frac{1}{\sigma}}} \\ &= \frac{\mathbf{1}\{i \in \text{AI tasks}\}\alpha_{H^{AI}}(i)^{\sigma-1}}{\alpha'_{H^{AI}}(i)}\frac{\frac{1}{\sigma}\mathrm{A}_{H^{AI}}^{\frac{1-\sigma}{\sigma}}(H^{AI})^{-\frac{1}{\sigma}}}{\mathrm{A}_L^{\frac{1}{\sigma}}L^{-\frac{1}{\sigma}}} > 0.\end{aligned} \tag{A.8}$$

Similar for the other inequalities in Proposition 5.

A.2.6 Proof of Proposition 6

Given the equilibrium factor prices presented in equation (9) and Assumption 1,

$$\begin{aligned}\frac{d(\frac{H^{AI}W_{H^{AI}}}{KR})}{d\alpha_{H^{AI}}(i)} &= \frac{d(\frac{H^{AI}Y^{1/\sigma}\mathrm{A}_{H^{AI}}^{1/\sigma}(H^{AI})^{-1/\sigma}}{KY^{1/\sigma}\mathrm{A}_{K}^{1/\sigma}K^{-1/\sigma}})}{d\alpha_{H^{AI}}(i)} = \frac{d\mathrm{A}_{H^{AI}}^{1/\sigma}}{d\alpha_{H^{AI}}(i)}\frac{(H^{AI})^{\frac{\sigma-1}{\sigma}}}{\mathrm{A}_{K}^{1/\sigma}K^{\frac{\sigma-1}{\sigma}}} \\ &= \frac{1}{\sigma}\mathrm{A}_{H^{AI}}^{\frac{1-\sigma}{\sigma}}\frac{d\left[\int_{I_H}^{N}\mathbf{1}\{i\in\text{AI tasks}\}\alpha_{H^{AI}}(i)^{\sigma-1}di\right]}{d\alpha_{H^{AI}}(i)}\frac{(H^{AI})^{\frac{\sigma-1}{\sigma}}}{\mathrm{A}_{K}^{1/\sigma}K^{\frac{\sigma-1}{\sigma}}} \\ &= \frac{\mathbf{1}\{i\in\text{AI tasks}\}\alpha_{H^{AI}}(i)^{\sigma-1}}{\alpha'_{H^{AI}}(i)}\frac{\frac{1}{\sigma}\mathrm{A}_{H^{AI}}^{\frac{1-\sigma}{\sigma}}(H^{AI})^{\frac{\sigma-1}{\sigma}}}{\mathrm{A}_{K}^{\frac{1}{\sigma}}K^{\frac{\sigma-1}{\sigma}}} > 0.\end{aligned} \tag{A.9}$$

Similarly,

$$\frac{d(\frac{H^{AI}W_{H^{AI}}}{KR})}{d\alpha_{K}} = -\frac{\frac{1}{\sigma}\mathrm{A}_{H^{AI}}^{\frac{1}{\sigma}}(H^{AI})^{\frac{\sigma-1}{\sigma}}}{\mathrm{A}_{K}^{\frac{1+\sigma}{\sigma}}K^{\frac{\sigma-1}{\sigma}}}(I_H-S)(\sigma-1)\alpha_K^{\sigma-2}\begin{cases}>0 & \text{if} \quad \sigma\in(0,1),\\ =0 & \text{if} \quad \sigma=1,\\ <0 & \text{if} \quad \sigma\in(1,\infty).\end{cases} \tag{A.10}$$

Thus, when $\sigma\in(0,1]$, both $\frac{d(\frac{H^{AI}W_{H^{AI}}}{KR})}{d\alpha_{H^{AI}}(i)}>0$ and $\frac{d(\frac{H^{AI}W_{H^{AI}}}{KR})}{d\alpha_{K}}>0$. However, when $\sigma\in(1,\infty)$, if we want to show $\frac{d(\frac{H^{AI}W_{H^{AI}}}{KR})}{d\alpha_{H^{AI}}(i)} > |\frac{d(\frac{H^{AI}W_{H^{AI}}}{KR})}{d\alpha_{K}}|$, then we need to prove the following is true:

$$\begin{aligned}&\frac{d(\frac{H^{AI}W_{H^{AI}}}{KR})}{d\alpha_{H^{AI}}(i)} > |\frac{d(\frac{H^{AI}W_{H^{AI}}}{KR})}{d\alpha_{K}}| \\ &\Leftarrow \frac{\mathbf{1}\{i\in\text{AI tasks}\}\alpha_{H^{AI}}(i)^{\sigma-1}}{\alpha'_{H^{AI}}(i)}\frac{\frac{1}{\sigma}\mathrm{A}_{H^{AI}}^{\frac{1-\sigma}{\sigma}}(H^{AI})^{\frac{\sigma-1}{\sigma}}}{\mathrm{A}_{K}^{\frac{1}{\sigma}}K^{\frac{\sigma-1}{\sigma}}} > \frac{\frac{1}{\sigma}\mathrm{A}_{H^{AI}}^{\frac{1}{\sigma}}(H^{AI})^{\frac{\sigma-1}{\sigma}}}{\mathrm{A}_{K}^{\frac{1+\sigma}{\sigma}}K^{\frac{\sigma-1}{\sigma}}}(I_H-S)(\sigma-1)\alpha_K^{\sigma-2} \\ &\Leftarrow \frac{\mathbf{1}\{i\in\text{AI tasks}\}\alpha_{H^{AI}}(i)^{\sigma-1}}{\alpha'_{H^{AI}}(i)}\frac{\mathrm{A}_K}{\mathrm{A}_{H^{AI}}} > (I_H-S)(\sigma-1)\alpha_K^{\sigma-2} \\ &\Leftarrow \frac{\mathbf{1}\{i\in\text{AI tasks}\}}{\alpha'_{H^{AI}}(i)}\frac{\mathrm{A}_K}{\mathrm{A}_{H^{AI}}}\left[\frac{\alpha_{H^{AI}}(i)}{\alpha_K}\right]^{\sigma-1} > (I_H-S)(\sigma-1)\alpha_K^{-1}.\end{aligned} \tag{A.11}$$

However, we cannot determine whether the last inequality is true or not without knowing the range of parameters. Thus, $\frac{d(\frac{H^{AI}W_{H^{AI}}}{KR})}{d\alpha_{H^{AI}}(i)} \gtreqless |\frac{d(\frac{H^{AI}W_{H^{AI}}}{KR})}{d\alpha_{K}}|$.

A.2.7 Proof of Proposition 7

Rewrite equation (10), the expression for the equilibrium output, as

$$Y^{\frac{\sigma-1}{\sigma}} = \mathrm{A}_{H^{AI}}^{\frac{1}{\sigma}}(H^{AI})^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_{H^{Non}}^{\frac{1}{\sigma}}(H^{Non})^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_M^{\frac{1}{\sigma}}M^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_L^{\frac{1}{\sigma}}L^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_K^{\frac{1}{\sigma}}K^{\frac{\sigma-1}{\sigma}}, \tag{A.12}$$

and differentiate both sides with respect to I_L:

$$\begin{aligned}
\frac{\sigma-1}{\sigma}Y^{-\frac{1}{\sigma}}\frac{dY}{dI_M} &= \mathrm{A}_M^{\frac{1-\sigma}{\sigma}}M^{\frac{\sigma-1}{\sigma}}\frac{d\mathrm{A}_M}{dI_M} + \mathrm{A}_K^{\frac{1-\sigma}{\sigma}}K^{\frac{\sigma-1}{\sigma}}\frac{d\mathrm{A}_K}{dI_M} \\
\frac{dY}{dI_M} &= \frac{\sigma}{\sigma-1}Y^{\frac{1}{\sigma}}\left[\mathrm{A}_M^{\frac{1-\sigma}{\sigma}}M^{\frac{\sigma-1}{\sigma}}\frac{d\mathrm{A}_M}{dI_M} + \mathrm{A}_K^{\frac{1-\sigma}{\sigma}}K^{\frac{\sigma-1}{\sigma}}\frac{d\mathrm{A}_K}{dI_M}\right] \\
\frac{dY}{dI_M} &= \frac{\sigma}{\sigma-1}Y\left[(Y\mathrm{A}_M)^{\frac{1-\sigma}{\sigma}}M^{\frac{\sigma-1}{\sigma}}\frac{d\mathrm{A}_M}{dI_M} + (Y\mathrm{A}_K)^{\frac{1-\sigma}{\sigma}}K^{\frac{\sigma-1}{\sigma}}\frac{d\mathrm{A}_K}{dI_M}\right] \\
\frac{dY}{dI_M} &= \frac{\sigma}{\sigma-1}Y\left[R^{1-\sigma} - W_M^{1-\sigma}\alpha_M(I_M)^{\sigma-1}\right] \\
\frac{dY}{dI_M} &= \frac{\sigma}{\sigma-1}Y\left[R^{1-\sigma} - (\frac{W_M}{\alpha_M(I_M)})^{1-\sigma}\right] > 0.
\end{aligned} \tag{A.13}$$

According to Assumption 3, $\exists I_M \in (N-1, S)$ such that $\frac{W_M}{\alpha_M(I_M)} > R$. Then if $\sigma \in (0,1)$, $(\frac{W_M}{\alpha_M(I_M)})^{1-\sigma} > R^{1-\sigma}$ and $\frac{\sigma}{\sigma-1} < 0$. Otherwise if $\sigma \in (1,\infty)$, $(\frac{W_M}{\alpha_M(I_M)})^{1-\sigma} < R^{1-\sigma}$ and $\frac{\sigma}{\sigma-1} > 0$. In both cases, $\frac{dY}{dI_M} > 0$. Similar for $\frac{dY}{dI_H} > 0$.

A.2.8 Proof of Proposition 8

Given the equilibrium factor prices presented in equation (9),

$$\begin{aligned}
\frac{d\ln(\frac{W_{H^j}}{W_L})}{d\ln H^j} &= \frac{d\ln\left[\frac{\mathrm{A}_{H^j}^{1/\sigma}(H^j)^{-1/\sigma}}{\mathrm{A}_L^{1/\sigma}L^{-1/\sigma}}\right]}{d\ln H^j} \\
&= \frac{d(\frac{1}{\sigma}\ln\mathrm{A}_{H^j} - \frac{1}{\sigma}\ln H^j - \frac{1}{\sigma}\ln\mathrm{A}_L + \frac{1}{\sigma}\ln L)}{d\ln H^j} \\
&= -\frac{1}{\sigma} < 0,\ j \in \{AI, Non\}.
\end{aligned} \tag{A.14}$$

Similar for the other inequalities in Proposition 8.

B Additional Figures & Tables

Figure B.1: Number of AI/CS Postings by BLS Region in LinkUp Data, 2011-22

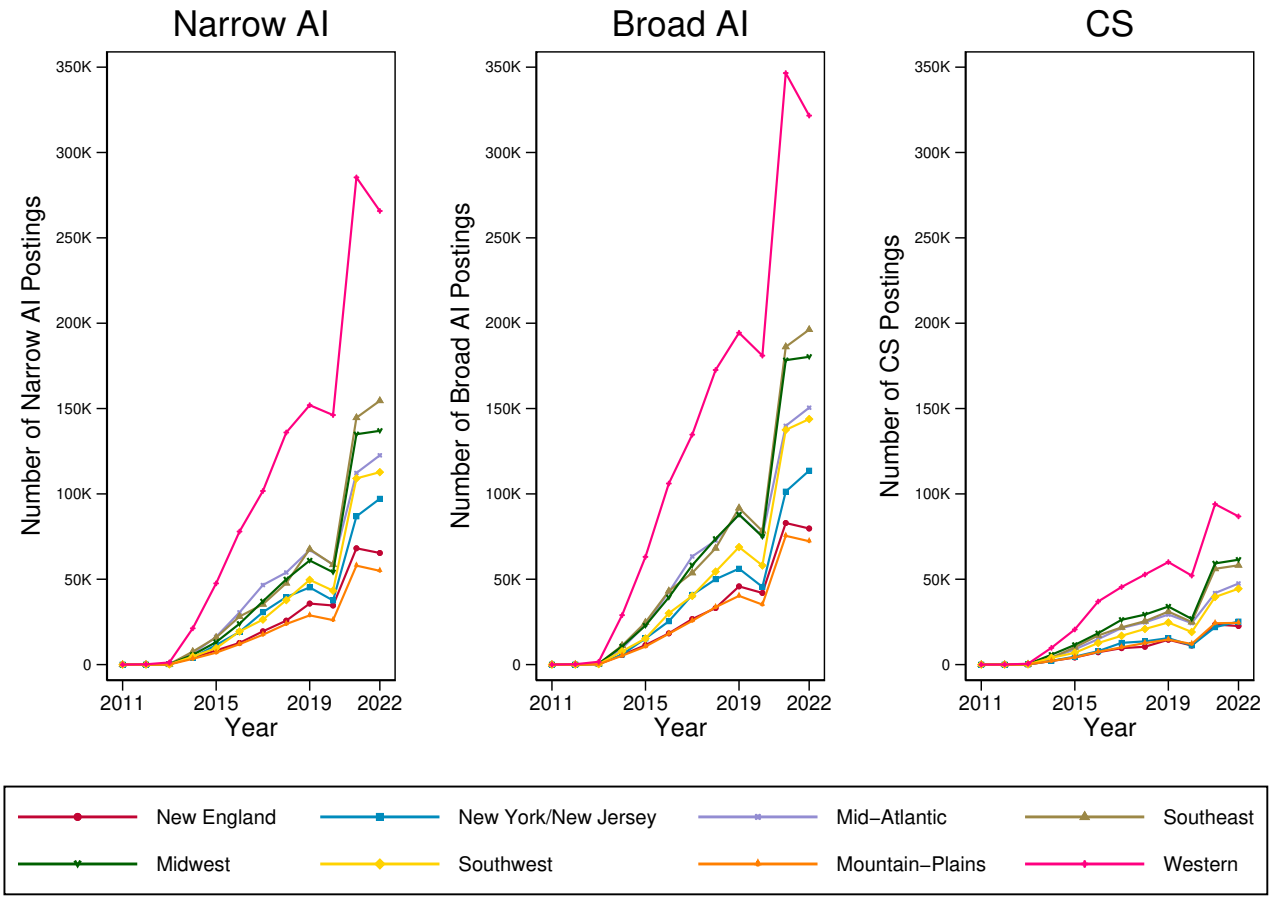


Figure B.2: Share of AI/CS Postings by BLS Region in LinkUp Data, 2011-22

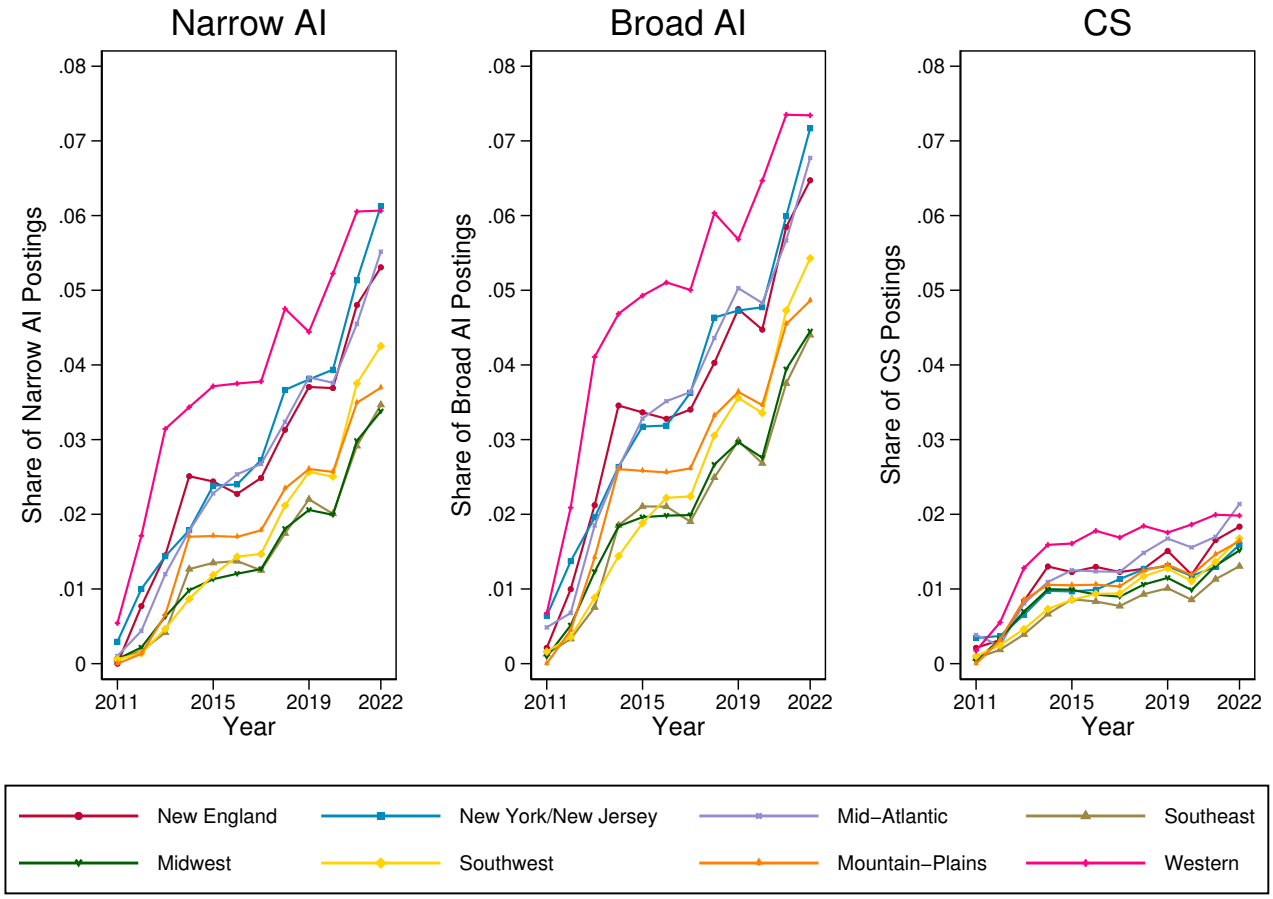
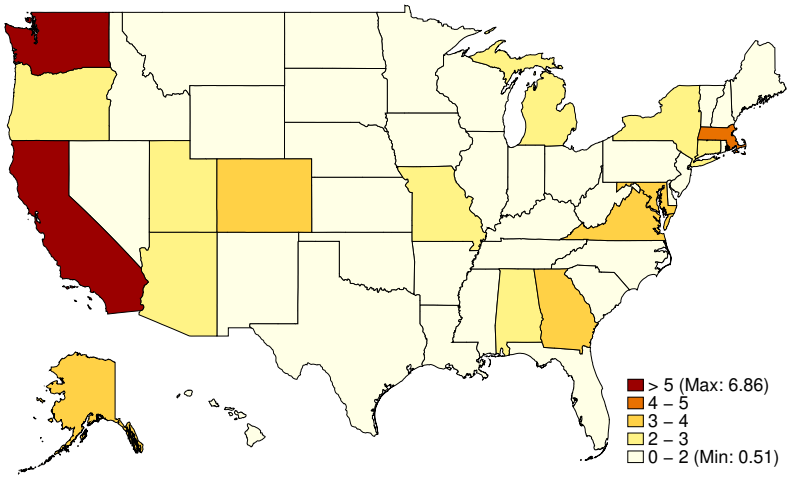
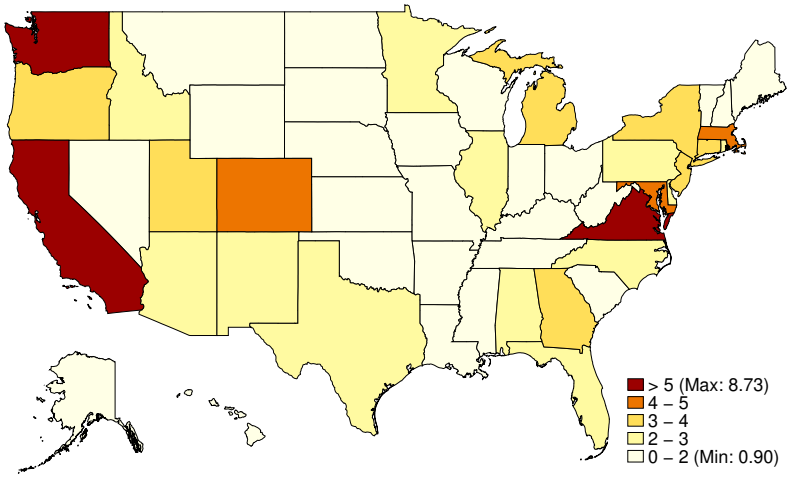


Figure B.3: Geographic Distribution of the Share of Broad AI Postings in LinkUp Data

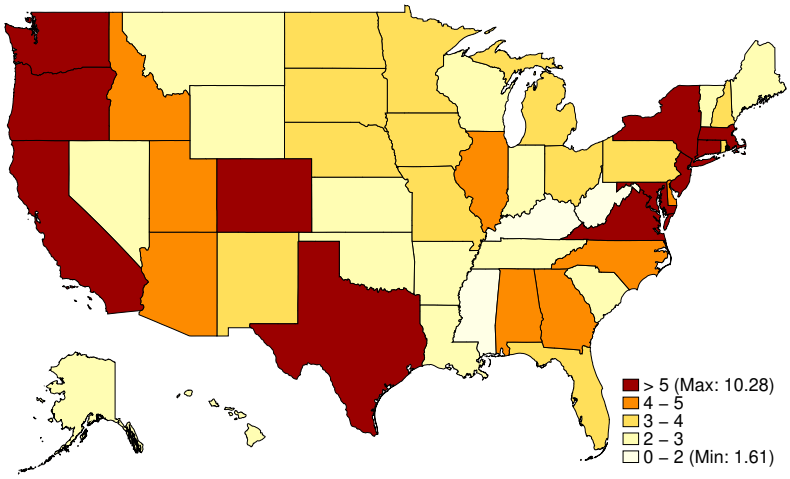
(a) 2011-14



(b) 2015-18

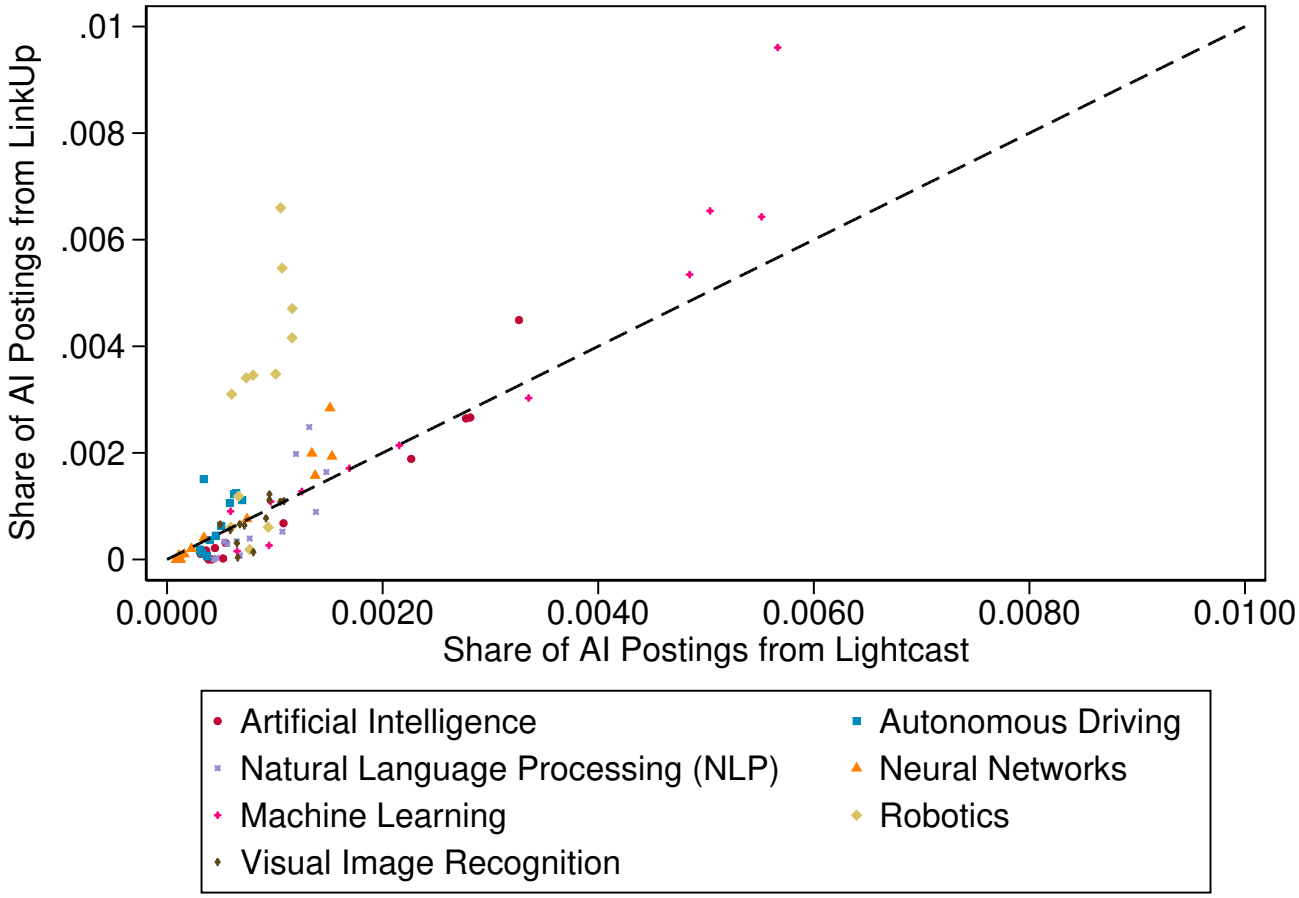


(c) 2019-22



Notes: Scales are in percentage point.

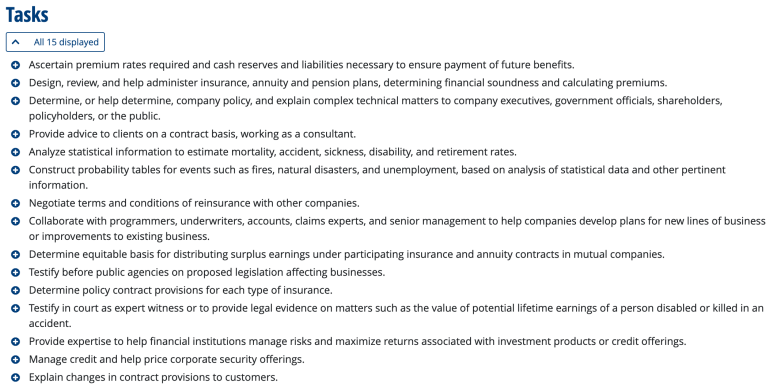
Figure B.4: Comparison between LinkUp and Lightcase Data, 2010-20



Notes: Shares of AI postings in Lightcast online job postings data is from the Stanford Institute for Human-Centered Artificial Intelligence (HAI) who purchased Lightcast data. Since Lightcast is a non-public data, HAI only shares (1) the monthly share of AI postings in each of the seven AI subcategories (artificial intelligence, autonomous driving, machine learning, natural language processing (NLP), neural networks, robotics, and visual image recognition) in the U.S. between 2010 and 2020 and (2) the state-year share of AI postings between 2019 and 2021. These data are publicly available at https://aiindex.stanford.edu/ai-index-report-2022/, provided by Zhang et al. (2022). Since the total number of AI postings in Lightcast data is not available, I compute the average monthly share of AI postings each year from (1) in Lightcast data and treat it as the annual share to compare with the annual share in LinkUp data.

Figure B.5: Occupation-Specific Information from O*NET: Using Actuaries (2019 O*NET-SOC Code: 15-2011.00) as an Example

(a) Tasks

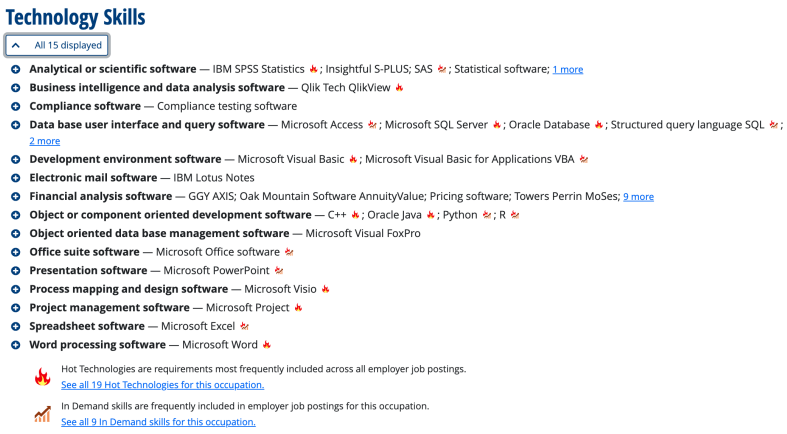


Tasks

All 15 displayed

- Ascertain premium rates required and cash reserves and liabilities necessary to ensure payment of future benefits.
- Design, review, and help administer insurance, annuity and pension plans, determining financial soundness and calculating premiums.
- Determine, or help determine, company policy, and explain complex technical matters to company executives, government officials, shareholders, policyholders, or the public.
- Provide advice to clients on a contract basis, working as a consultant.
- Analyze statistical information to estimate mortality, accident, sickness, disability, and retirement rates.
- Construct probability tables for events such as fires, natural disasters, and unemployment, based on analysis of statistical data and other pertinent information.
- Negotiate terms and conditions of reinsurance with other companies.
- Collaborate with programmers, underwriters, accounts, claims experts, and senior management to help companies develop plans for new lines of business or improvements to existing business.
- Determine equitable basis for distributing surplus earnings under participating insurance and annuity contracts in mutual companies.
- Testify before public agencies on proposed legislation affecting businesses.
- Determine policy contract provisions for each type of insurance.
- Testify in court as expert witness or to provide legal evidence on matters such as the value of potential lifetime earnings of a person disabled or killed in an accident.
- Provide expertise to help financial institutions manage risks and maximize returns associated with investment products or credit offerings.
- Manage credit and help price corporate security offerings.
- Explain changes in contract provisions to customers.

(b) Technology Skills



Technology Skills

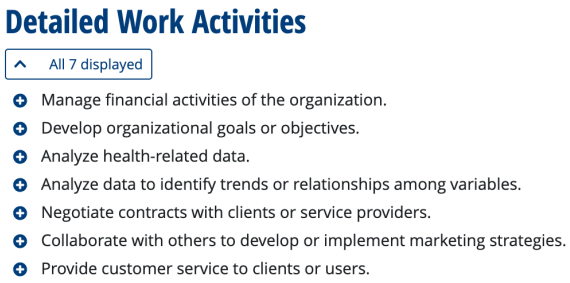
All 15 displayed

- **Analytical or scientific software** — IBM SPSS Statistics; Insightful S-PLUS; SAS; Statistical software; 1 more
- **Business intelligence and data analysis software** — Qlik Tech QlikView
- **Compliance software** — Compliance testing software
- **Data base user interface and query software** — Microsoft Access; Microsoft SQL Server; Oracle Database; Structured query language SQL; 2 more
- **Development environment software** — Microsoft Visual Basic; Microsoft Visual Basic for Applications VBA
- **Electronic mail software** — IBM Lotus Notes
- **Financial analysis software** — GGY AXIS; Oak Mountain Software AnnuityValue; Pricing software; Towers Perrin MoSes; 9 more
- **Object or component oriented development software** — C++; Oracle Java; Python; R
- **Object oriented data base management software** — Microsoft Visual FoxPro
- **Office suite software** — Microsoft Office software
- **Presentation software** — Microsoft PowerPoint
- **Process mapping and design software** — Microsoft Visio
- **Project management software** — Microsoft Project
- **Spreadsheet software** — Microsoft Excel
- **Word processing software** — Microsoft Word

Hot Technologies are requirements most frequently included across all employer job postings.
See all 19 Hot Technologies for this occupation.

In Demand skills are frequently included in employer job postings for this occupation.
See all 9 In Demand skills for this occupation.

(c) Detailed Work Activities

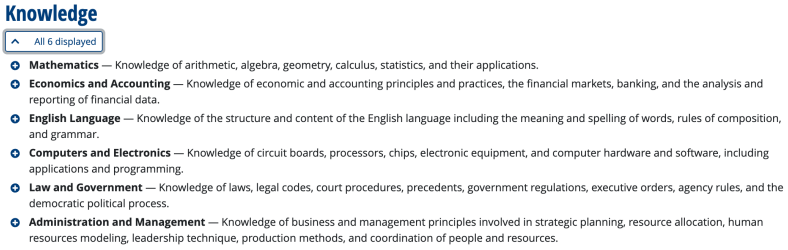


Detailed Work Activities

All 7 displayed

- Manage financial activities of the organization.
- Develop organizational goals or objectives.
- Analyze health-related data.
- Analyze data to identify trends or relationships among variables.
- Negotiate contracts with clients or service providers.
- Collaborate with others to develop or implement marketing strategies.
- Provide customer service to clients or users.

(d) Knowledge



Knowledge

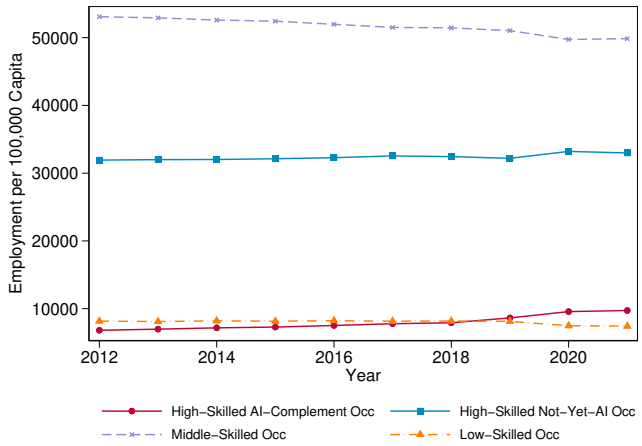
All 6 displayed

- **Mathematics** — Knowledge of arithmetic, algebra, geometry, calculus, statistics, and their applications.
- **Economics and Accounting** — Knowledge of economic and accounting principles and practices, the financial markets, banking, and the analysis and reporting of financial data.
- **English Language** — Knowledge of the structure and content of the English language including the meaning and spelling of words, rules of composition, and grammar.
- **Computers and Electronics** — Knowledge of circuit boards, processors, chips, electronic equipment, and computer hardware and software, including applications and programming.
- **Law and Government** — Knowledge of laws, legal codes, court procedures, precedents, government regulations, executive orders, agency rules, and the democratic political process.
- **Administration and Management** — Knowledge of business and management principles involved in strategic planning, resource allocation, human resources modeling, leadership technique, production methods, and coordination of people and resources.

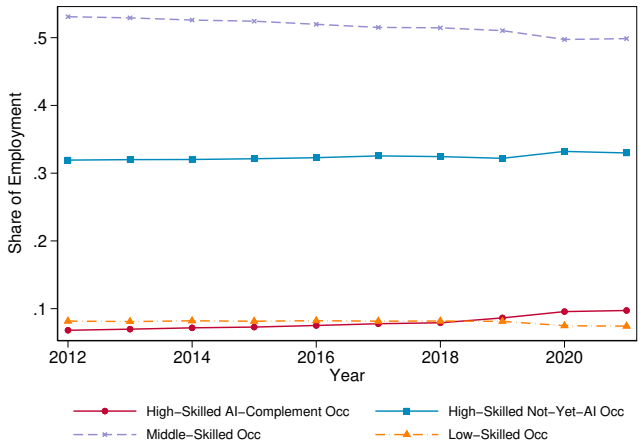
Source: https://www.onetonline.org/link/summary/15-2011.00

Figure B.6: Plots of Skill-Group-By-Year Employment, Wages, and Share of AI Postings (Using Broad AI Definition), 2012-21

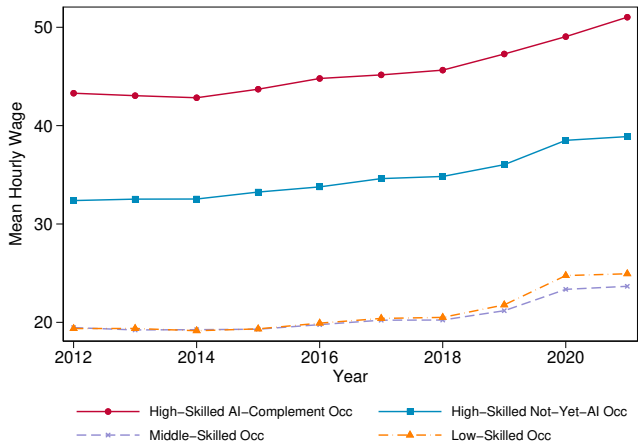
(a) Employment per 100,000 Capita



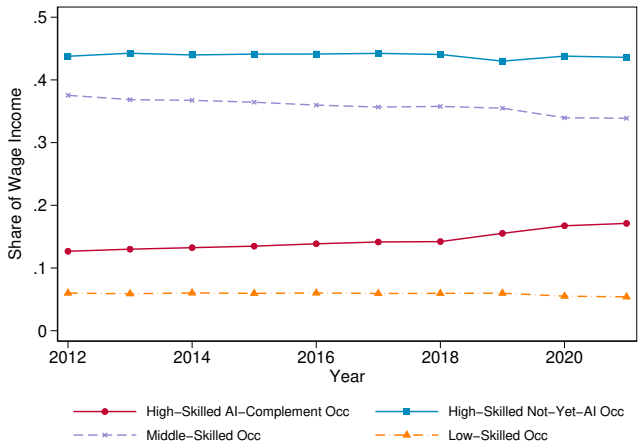
(b) Share of Employment



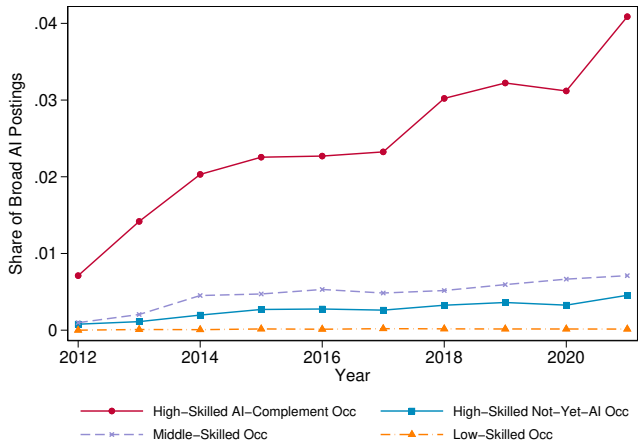
(c) Mean Hourly Wage



(d) Share of Wage Income



(e) Share of Broad AI Postings



(f) Share of CS Postings

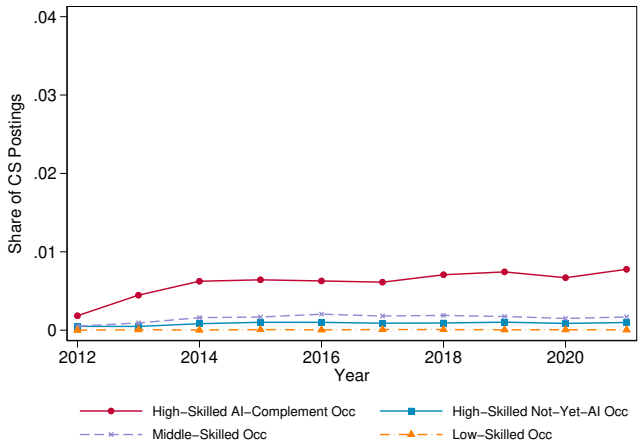
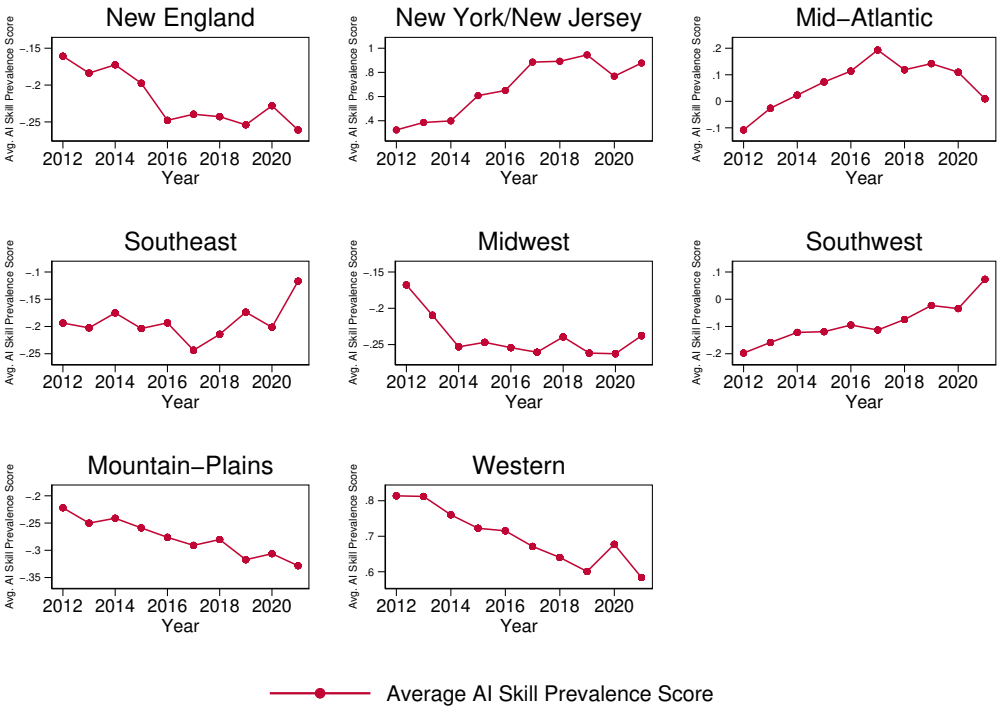
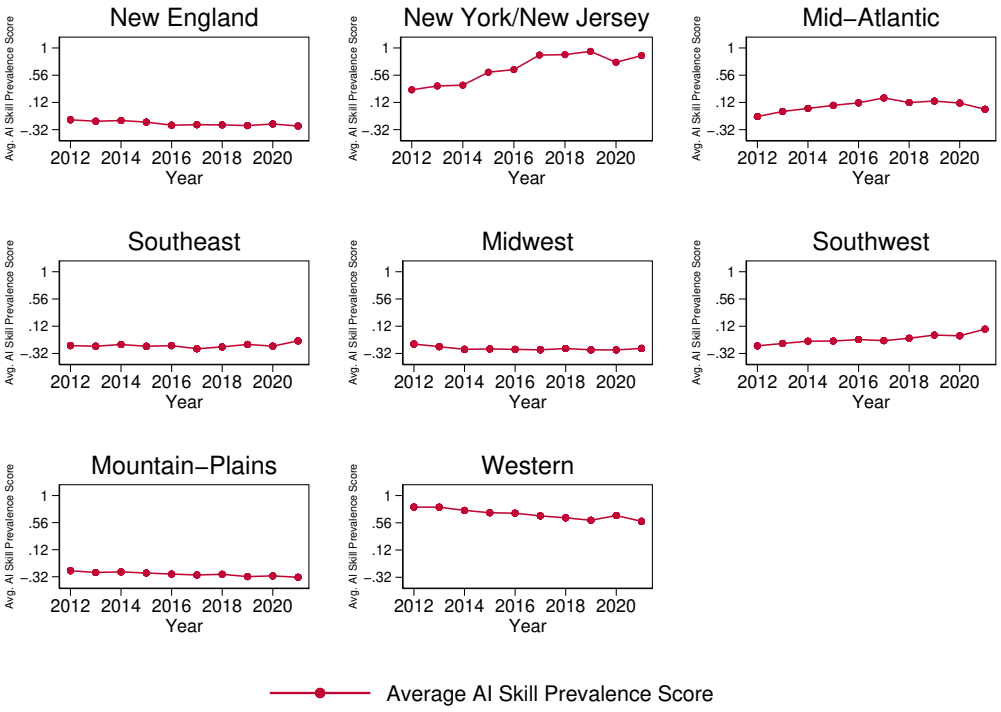


Figure B.7: Average AI Skill Prevalence Score by BLS Region, 2012-21

(a) Not Fixing the Range of Y Axis



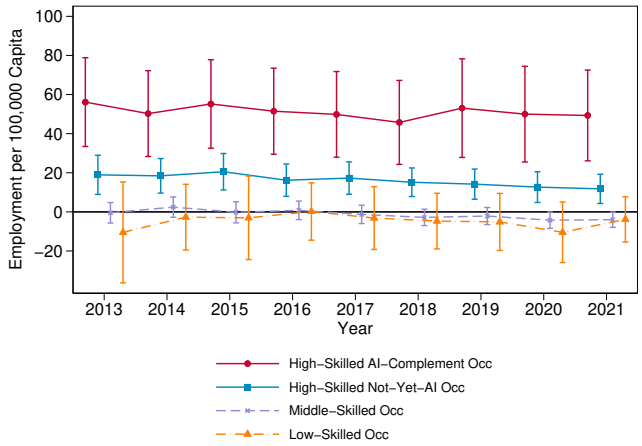
(b) Fixing the Range of Y Axis



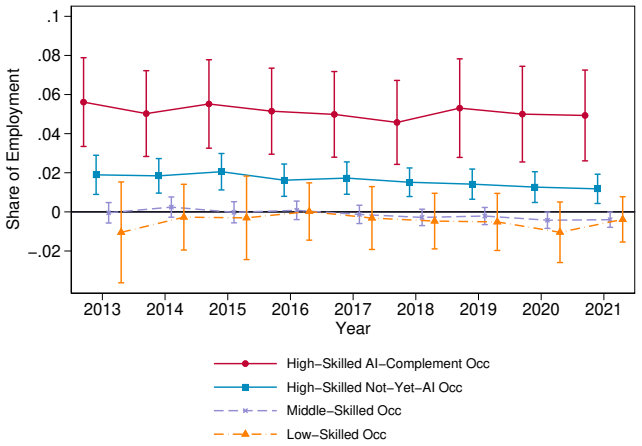
Notes: The AI Skill Prevalence Score is constructed at the state-year level and standardized within a year.

Figure B.8: Time-Varying Effects of Demand for AI Skills on Labor Market Outcomes, 2012-21

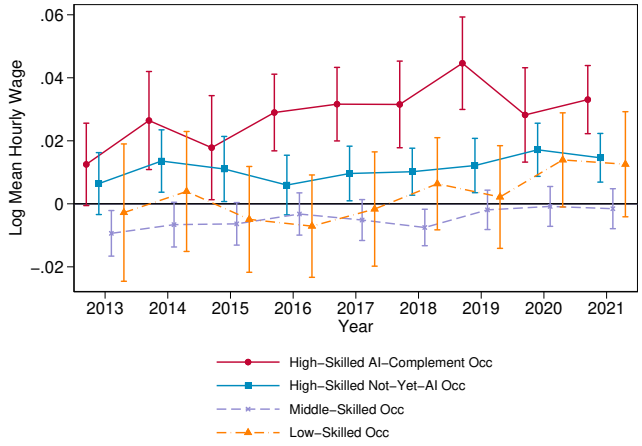
(a) Employment per 100,000 Capita



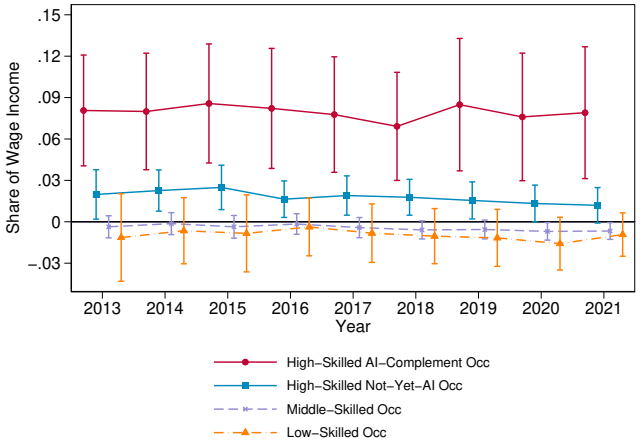
(b) Share of Employment



(c) Log Mean Hourly Wage



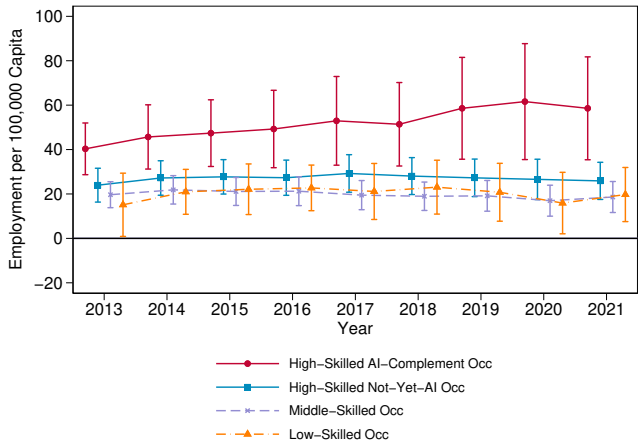
(d) Share of Wage Income



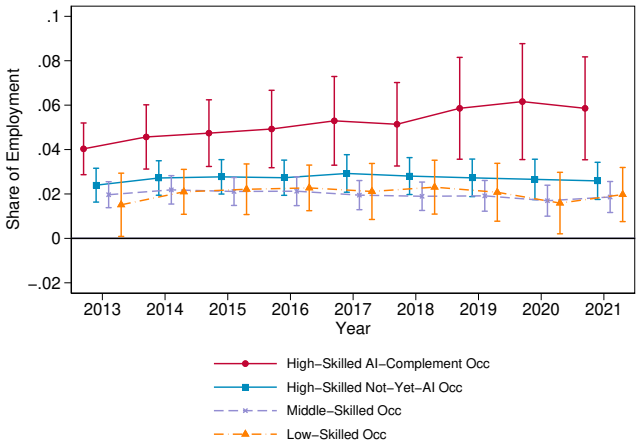
Notes: The coefficient estimates plotted in each subfigure show overall time-varying effects of changes in share of narrow AI postings on labor market outcomes. They are obtained by respectively regressing employment per 100,000 capita, share of employment (in percentage point), log mean hourly wages, and share of wage income (in percentage point) on the triple interaction term between share of narrow AI postings, skill group dummies, and year dummies, using the main specification with a full set of fixed effects (i.e., state, year, skill-group, 2-digit-occupation, and skill-group-by-year fixed effects) included. I also plot the corresponding 95% confidence intervals in each subfigure.

Figure B.9: Time-Varying Effects of AI Skill Prevalence on Labor Market Outcomes, 2012-21

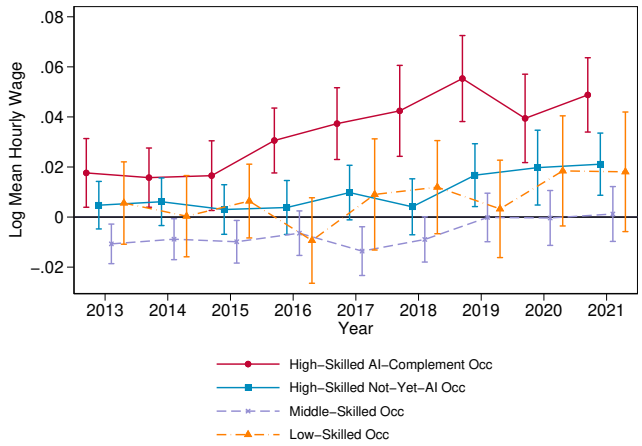
(a) Employment per 100,000 Capita



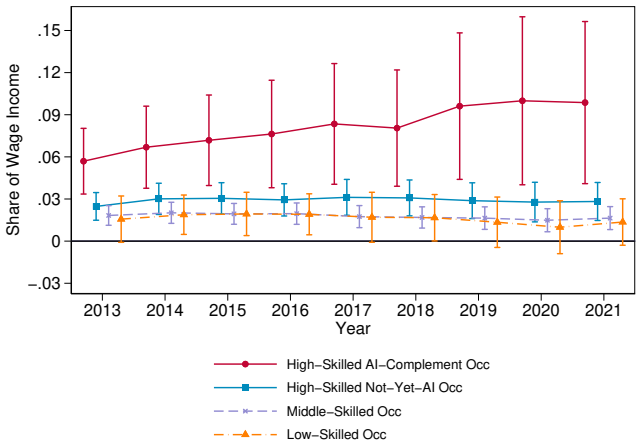
(b) Share of Employment



(c) Log Mean Hourly Wage

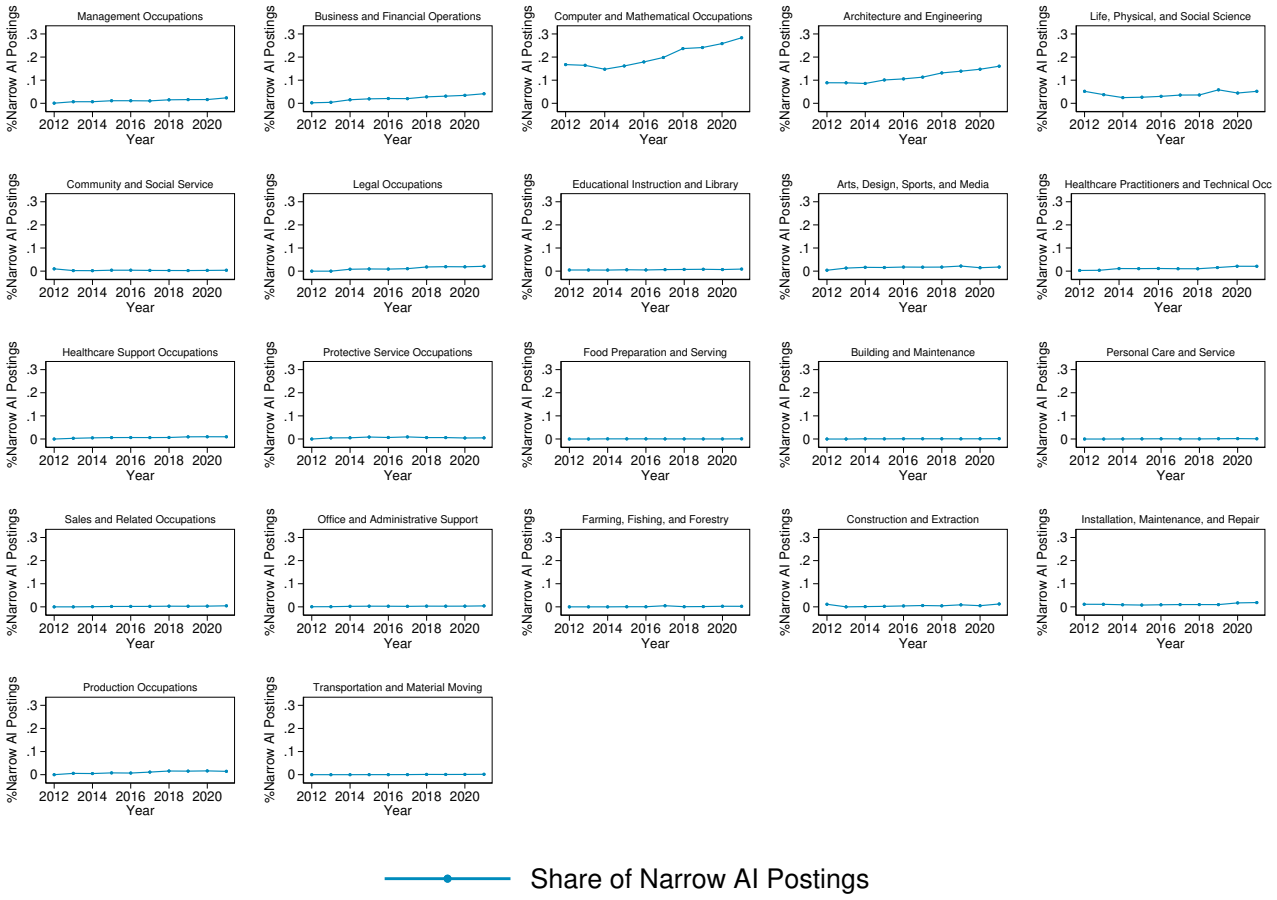


(d) Share of Wage Income



Notes: The coefficient estimates plotted in each subfigure show overall time-varying effects of AI Skill Prevalence Score on labor market outcomes. They are obtained by respectively regressing employment per 100,000 capita, share of employment (in percentage point), log mean hourly wages, and share of wage income (in percentage point) on the triple interaction term between state-year AI Skill Prevalence Score, skill group dummies, and year dummies, controlling for the full set of fixed effects (i.e., state, year, skill-group, 2-digit-occupation, and skill-group-by-year fixed effects) as my main specification. I also plot the corresponding 95% confidence intervals in each subfigure.

Figure B.10: Plots of %AI Postings by 2-digit Occupational Classification, 2012-21



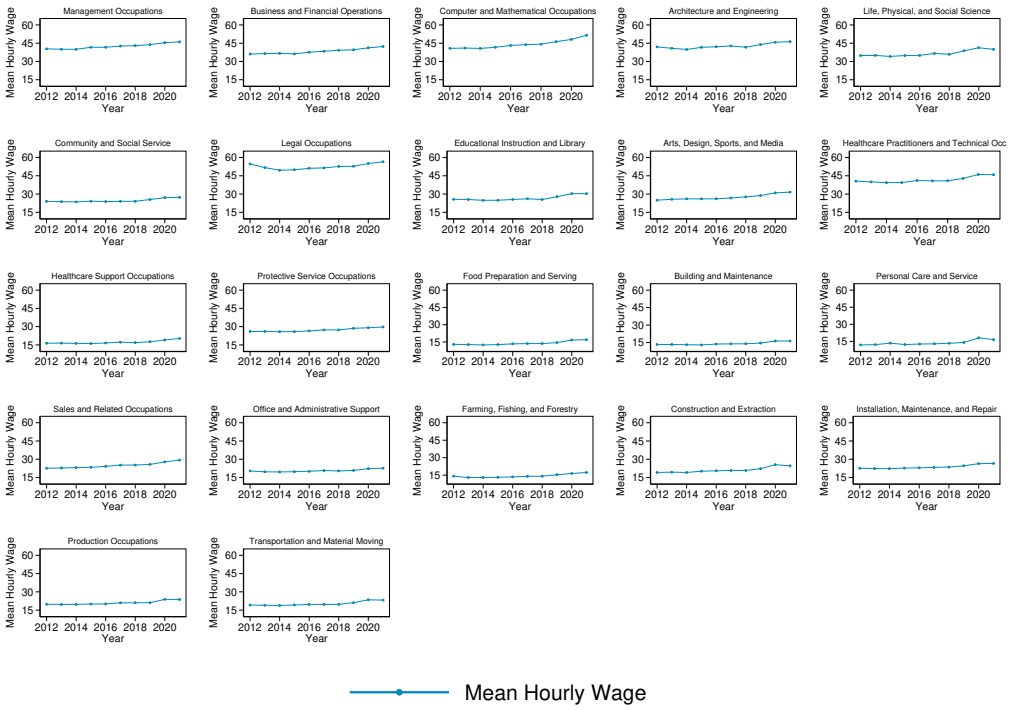
Notes: The total number of 2-digit Census Occupational Classification is 23, which is the same as the total number of my proposed ML occupation clusters. However, the "Military Specific Occupations" group is excluded from my main sample due to the absence of O*NET occupational descriptions, which are necessary for constructing the AI occupation indicators and, consequently, the skill group indicators, as explained in Section 3.2.2. Thus, only 22 Census 2-digit groups are included in my sample for plotting the share of narrow AI postings.

Figure B.11: Plots of Mean Hourly Wage by Different Occupation System, 2012-21

(a) By ML Occupation Cluster



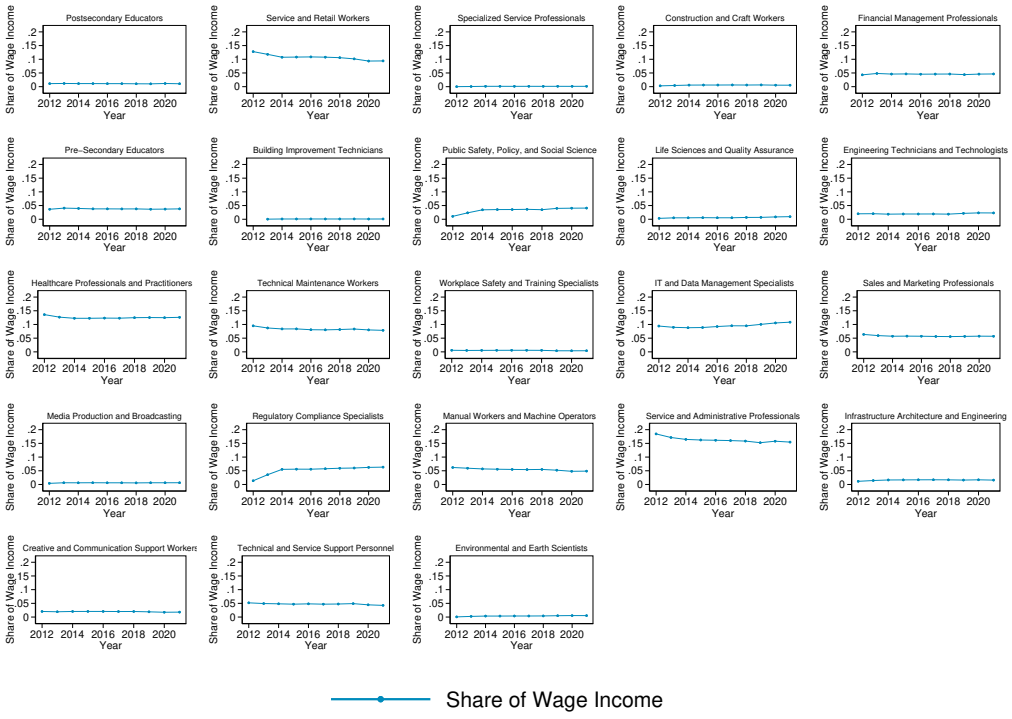
(b) By 2-digit Census Occupational Classification



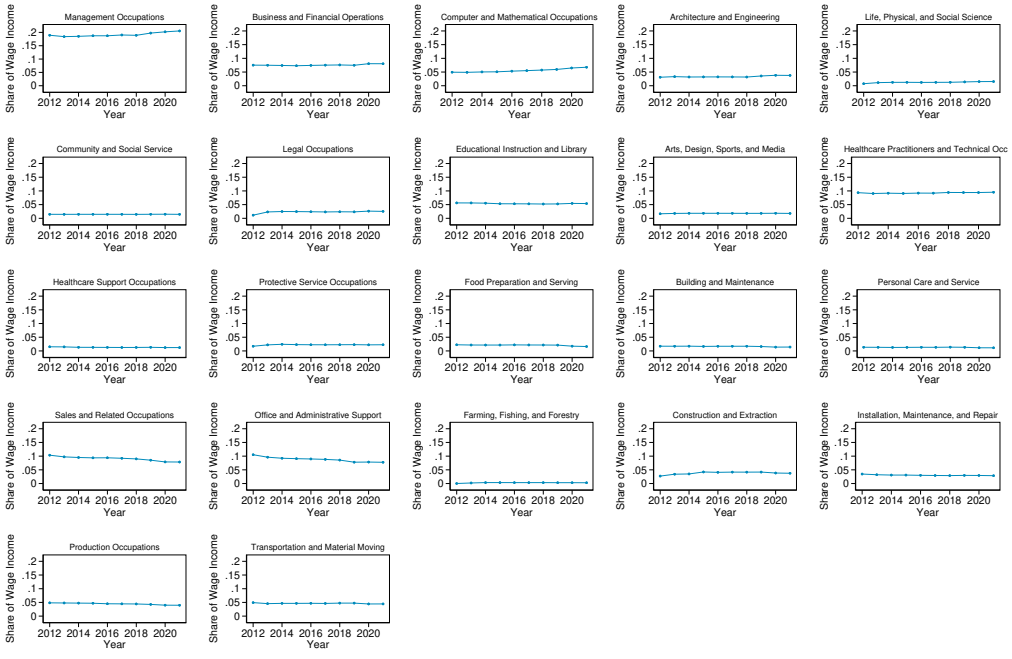
Notes: The total number of 2-digit Census Occupational Classification is 23, which is the same as the total number of my proposed ML occupation clusters. However, the "Military Specific Occupations" group is excluded from my main sample due to the absence of O*NET occupational descriptions, which are necessary for constructing the AI occupation indicators and, consequently, the skill group indicators, as explained in Section 3.2.2. Thus, only 22 Census 2-digit groups are included in my sample for plotting the mean hourly wage.

Figure B.12: Plots of %Wage Income by Different Occupation System, 2012-21

(a) By ML Occupation Cluster



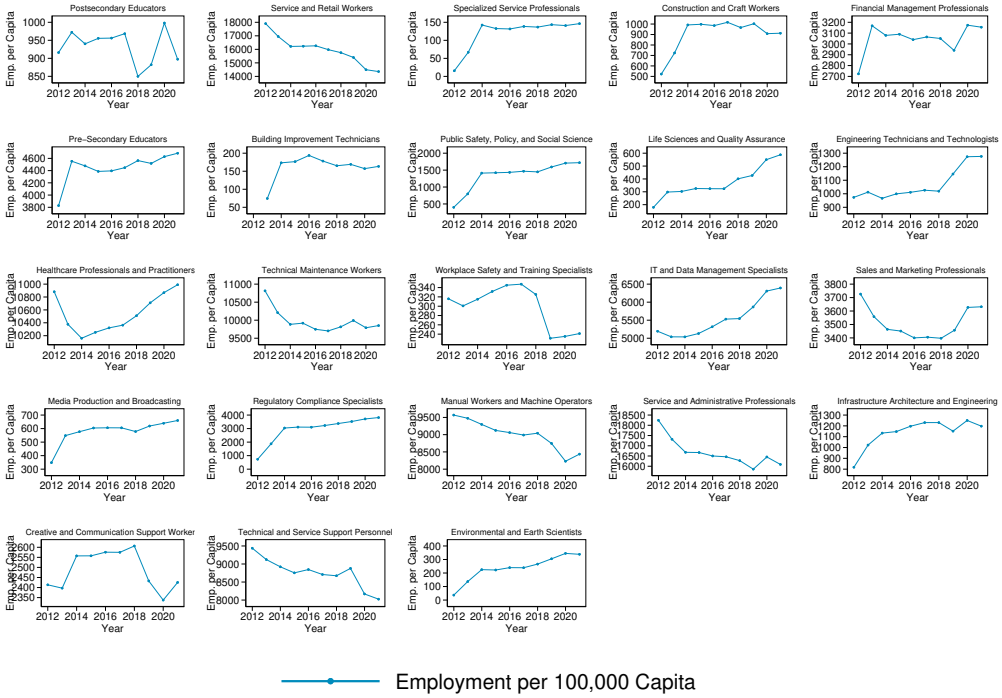
(b) By 2-digit Census Occupational Classification



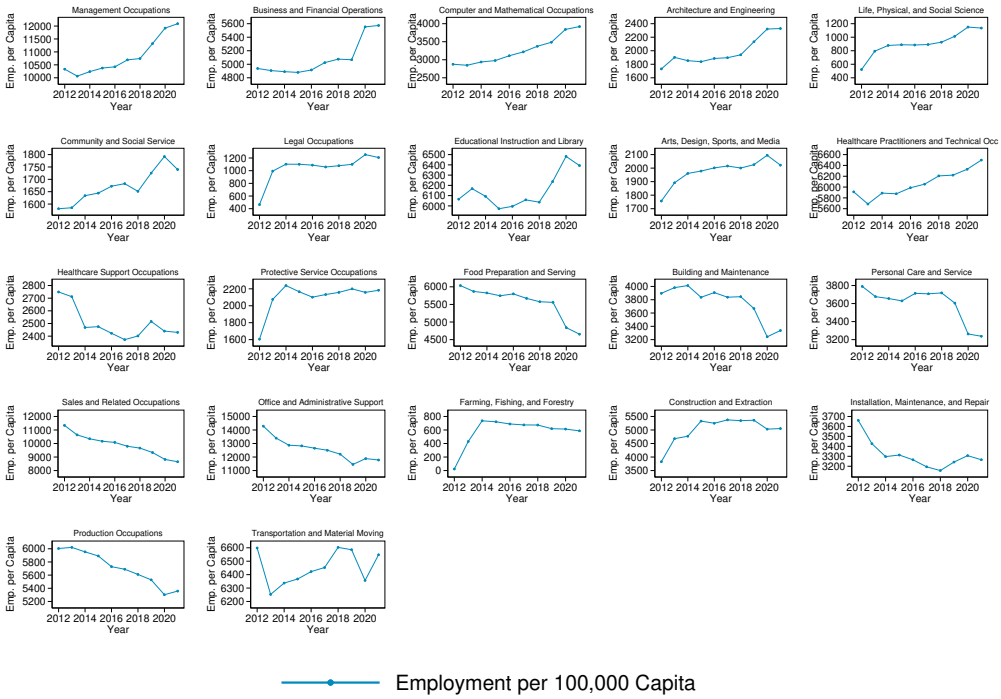
Notes: The total number of 2-digit Census Occupational Classification is 23, which is the same as the total number of my proposed ML occupation clusters. However, the "Military Specific Occupations" group is excluded from my main sample due to the absence of O*NET occupational descriptions, which are necessary for constructing the AI occupation indicators and, consequently, the skill group indicators, as explained in Section 3.2.2. Thus, only 22 Census 2-digit groups are included in my sample for plotting the share of wage income.

Figure B.13: Plots of Emp. per Capita by Different Occupation System, 2012-21

(a) By ML Occupation Cluster



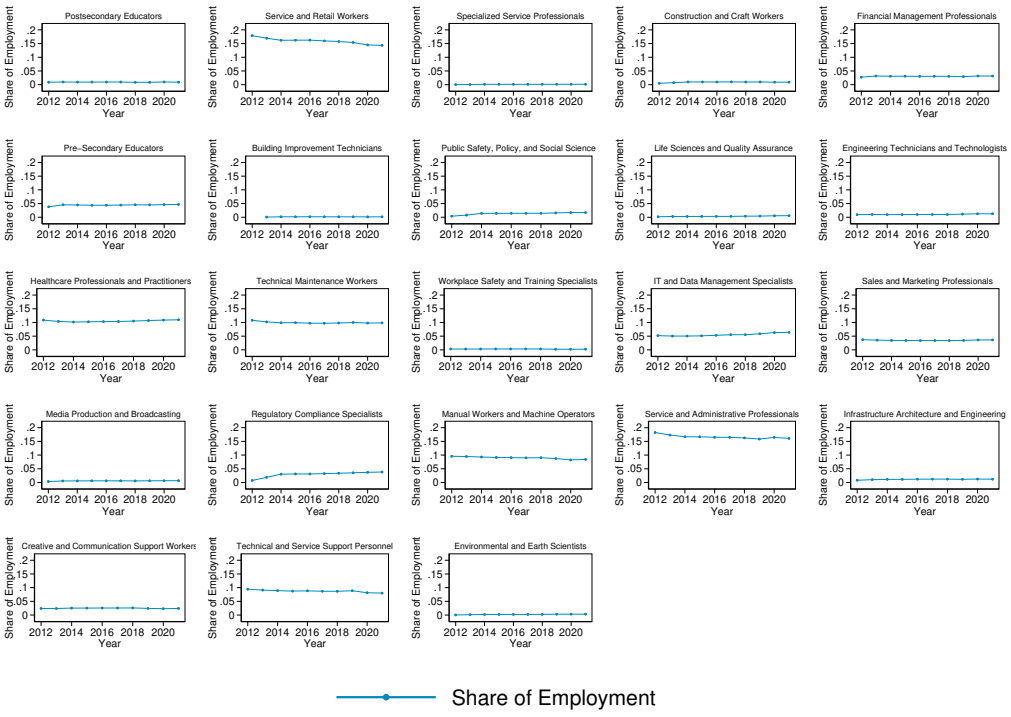
(b) By 2-digit Census Occupational Classification



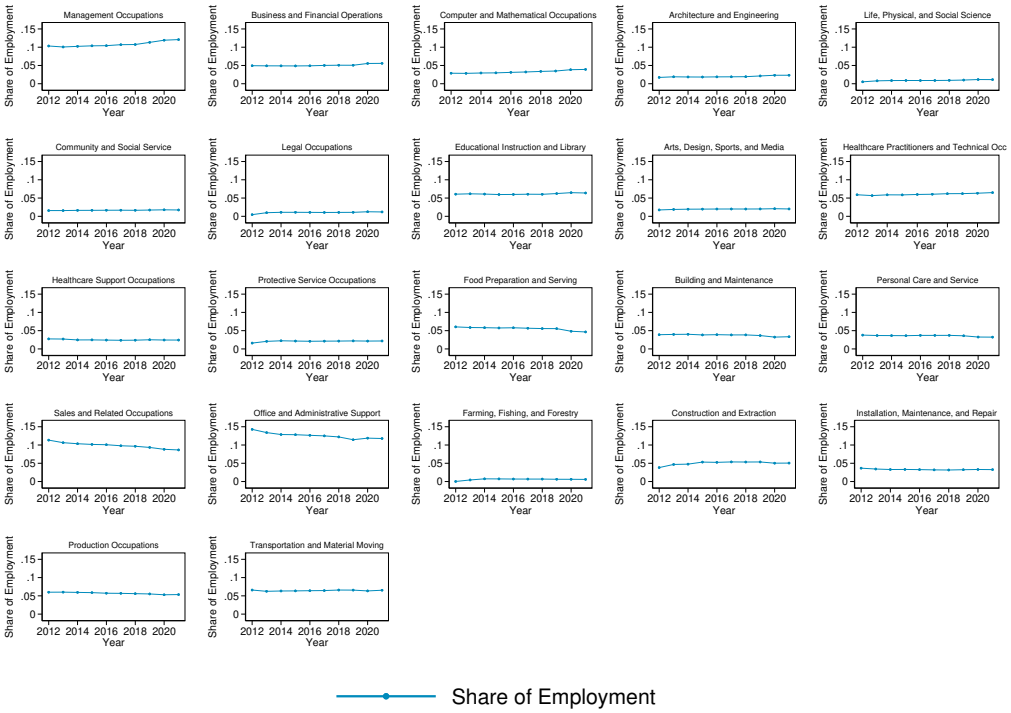
Notes: The range of Y axis is not fixed for each occupation group within an occupation system. The total number of 2-digit Census Occupational Classification is 23, which is the same as the total number of my proposed ML occupation clusters. However, the "Military Specific Occupations" group is excluded from my main sample due to the absence of O*NET occupational descriptions, which are necessary for constructing the AI occupation indicators and, consequently, the skill group indicators, as explained in Section 3.2.2. Thus, only 22 Census 2-digit groups are included in my sample for plotting the employment per capita.

Figure B.14: Plots of %Employment by Different Occupation System, 2012-21

(a) By ML Occupation Cluster

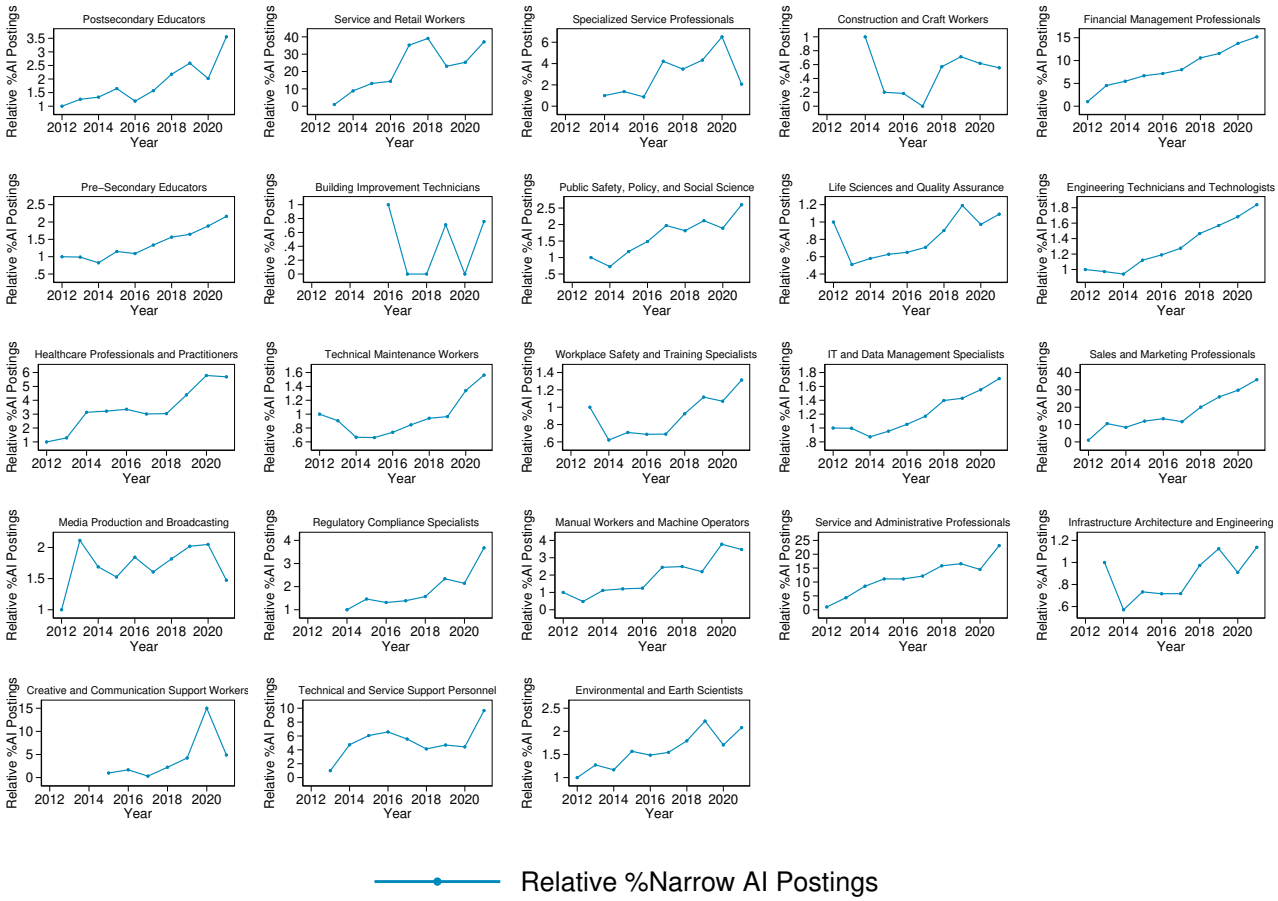


(b) By 2-digit Census Occupational Classification



Notes: The total number of 2-digit Census Occupational Classification is 23, which is the same as the total number of my proposed ML occupation clusters. However, the "Military Specific Occupations" group is excluded from my main sample due to the absence of O*NET occupational descriptions, which are necessary for constructing the AI occupation indicators and, consequently, the skill group indicators, as explained in Section 3.2.2. Thus, only 22 Census 2-digit groups are included in my sample for plotting the share of employment.

Figure B.15: %AI Postings by ML Occupation Cluster Relative to Baseline Year, 2012-21



Notes: The baseline year for each ML occupation cluster is the first year when there were narrow AI postings of this group. Each line represents the following ratio, $\frac{\%\text{Narrow AI postings}_{i,t}}{\%\text{Narrow AI postings}_{i,t_{base}}}$, where i represents a ML occupation cluster, t is year, and t_{base} is the baseline year.

Table B.1: Occupations Ranked by Share of Narrow AI Postings, 2021

OCC2010	Occupation title	Skill group	%Narrow AI Postings
	Panel A. Occupations with the Top 15 %AI Postings		
5920	Statistical Assistants	M	0.5134408
1760	Physical Scientists, All Other	H^{AI}	0.5022625
1240	Mathematicians and Statisticians	H^{AI}	0.4595848
1400	Computer Hardware Engineers	H^{AI}	0.4479544
1020	Software Developers, Applications and Systems Software	H^{AI}	0.4286178
1700	Astronomers and Physicists	M	0.2866242
8550	Woodworkers Including Model Makers and Patternmakers, All Other	M	0.25
7010	Computer, Automated Teller, and Office Machine Repairers	M	0.2305805
1800	Economists and Market Researchers	H^{AI}	0.2304875
1010	Computer Programmers	H^{AI}	0.2256069
1410	Electrical and Electronics Engineers	H^{AI}	0.2237831
1460	Mechanical Engineers	H^{AI}	0.2184486
1200	Actuaries	H^{AI}	0.2033132
1000	Computer Scientists and Systems Analysts/Network systems Analysts/Web Developers	H^{AI}	0.2027434
1560	Surveying and Mapping Technicians	H^{Non}	0.2007183
	Panel B. Occupations with the Bottom 15 %AI Postings		
8640	Chemical Processing Machine Setters, Operators, and Tenders	M	0
4500	Barbers	M	0
3700	First-Line Supervisors of Correctional Officers	L	0
3800	Bailiffs, Correctional Officers, and Jailers	L	0
6460	Plasterers and Stucco Masons	M	0
2760	Entertainers and Performers, Sports and Related Workers, All Other	H^{Non}	0
5410	Reservation and Transportation Ticket Agents and Travel Clerks	M	0
4420	Ushers, Lobby Attendants, and Ticket Takers	M	0
5630	Weighers, Measurers, Checkers, and Samplers, Recordkeeping	M	0
6130	Logging Workers	L	0
9650	Pumping Station Operators	M	0
4830	Travel Agents	M	0
5540	Postal Service Clerks	M	0
2050	Directors, Religious Activities and Education	H^{Non}	0
7160	Automotive Glass Installers and Repairers	M	0

Notes: The share of narrow AI postings in this table is calculated at the 4-digit-occupation-by-year level. There is a tie in the lowest share of narrow AI postings, with 64 occupations having no narrow AI posting. 15 out of 64 occupations are randomly chosen and listed in Panel B. H^{AI}, H^{Non}, M, and L represent high-skilled AI-complement, high-skilled not-yet-AI, middle-skilled, and low-skilled occupation group, respectively.

Table B.2: Effects of Demand for AI Skills on Employment per Capita—Adopting Different SSIVs, 2012-21

	Dep. Var.: Employment per 100,000 capita				
		"Leave-One-Out" SSIV by summing across			
	OLS	2-digit OCC	4-digit OCC	4-digit NAICS	ML occupation cluster[1]
	(1)	(2)	(3)	(4)	(5)
%AI postings[2]	-6.146	-92.339***	-23.431	-17.202	-71.854***
	(8.282)	(19.785)	(15.930)	(14.465)	(16.847)
%AI postings ×					
High-skilled AI-complement occ	55.756***	112.148***	104.546***	107.041***	115.332***
	(14.940)	(27.069)	(25.826)	(25.458)	(27.218)
High-skilled not-yet-AI occ	20.065**	46.987**	43.239**	44.447**	51.323***
	(10.099)	(19.926)	(19.693)	(18.122)	(19.648)
Middle-skilled occ	2.868	10.546	10.996	10.270	14.428
	(8.991)	(18.021)	(18.083)	(15.803)	(17.382)
Skill group =					
High-skilled AI-complement occ	-333.383*	-361.106*	-282.738	-356.421*	-204.808
	(187.602)	(190.281)	(228.930)	(189.121)	(135.222)
High-skilled not-yet-AI occ	-209.460	-220.774	-127.816	-219.972	-138.956
	(184.689)	(187.992)	(236.239)	(186.713)	(132.753)
Middle-skilled occ	-192.177	-194.626	-114.134	-195.785	-161.660
	(181.375)	(184.771)	(230.363)	(183.521)	(118.682)
Observations	192,008	192,008	202,796	192,008	190,712
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓	✓
R-squared	0.129	0.122	0.129	0.128	0.121
Cragg-Donald Wald F statistic		2594.341	7772.793	3414.392	2722.659

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The ML occupation cluster is an alternative occupation classification constructed by clustering occupations based on skill requirements using machine learning. Details are presented in Section 6.2.

[2] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

Table B.3: Effects of Demand for AI Skills on Share of Employment—Adopting Different SSIVs, 2012-21

	Dep. Var.: Share of Employment[1]				
		"Leave-One-Out" SSIV by summing across			
	OLS	2-digit OCC	4-digit OCC	4-digit NAICS	ML occupation cluster[2]
	(1)	(2)	(3)	(4)	(5)
%AI postings[3]	-0.006	-0.092***	-0.023	-0.017	-0.072***
	(0.008)	(0.020)	(0.016)	(0.014)	(0.017)
%AI postings ×					
High-skilled AI-complement occ	0.056***	0.112***	0.105***	0.107***	0.115***
	(0.015)	(0.027)	(0.026)	(0.025)	(0.027)
High-skilled not-yet-AI occ	0.020**	0.047**	0.043**	0.044**	0.051***
	(0.010)	(0.020)	(0.020)	(0.018)	(0.020)
Middle-skilled occ	0.003	0.011	0.011	0.010	0.014
	(0.009)	(0.018)	(0.018)	(0.016)	(0.017)
Skill group =					
High-skilled AI-complement occ	-0.333*	-0.361*	-0.283	-0.356*	-0.205
	(0.188)	(0.190)	(0.229)	(0.189)	(0.135)
High-skilled not-yet-AI occ	-0.209	-0.221	-0.128	-0.220	-0.139
	(0.185)	(0.188)	(0.236)	(0.187)	(0.133)
Middle-skilled occ	-0.192	-0.195	-0.114	-0.196	-0.162
	(0.181)	(0.185)	(0.230)	(0.184)	(0.119)
Observations	192,008	192,008	202,796	192,008	190,712
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓	✓
R-squared	0.129	0.122	0.129	0.128	0.121
Cragg-Donald Wald F statistic		2594.341	7772.793	3414.392	2722.659

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The unit of the share of employment is a percentage point.

[2] The ML occupation cluster is an alternative occupation classification constructed by clustering occupations based on skill requirements using machine learning. Details are presented in Section 6.2.

[3] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

Table B.4: Effects of Demand for AI Skills on Mean Hourly Wage—Adopting Different SSIVs, 2012-21

	Dep. Var.: Log mean hourly wage				
		Leave-One-Out IV by summing across			
	OLS	2-digit OCC	4-digit OCC	4-digit NAICS	ML occupation cluster[1]
	(1)	(2)	(3)	(4)	(5)
%AI postings[2]	0.005	0.010	-0.002	-0.005	0.012
	(0.005)	(0.014)	(0.010)	(0.013)	(0.013)
%AI postings ×					
High-skilled AI-complement occ	0.025***	0.050***	0.048***	0.055***	0.044***
	(0.007)	(0.010)	(0.010)	(0.011)	(0.010)
High-skilled not-yet-AI occ	0.007	0.029***	0.025***	0.029***	0.026***
	(0.006)	(0.010)	(0.009)	(0.010)	(0.009)
Middle-skilled occ	-0.009	0.005	0.003	0.002	-0.002
	(0.005)	(0.009)	(0.008)	(0.010)	(0.009)
Skill group =					
High-skilled AI-complement occ	0.441***	0.431***	0.431***	0.428***	0.381***
	(0.104)	(0.104)	(0.098)	(0.103)	(0.115)
High-skilled not-yet-AI occ	0.126	0.117	0.127	0.117	0.171
	(0.096)	(0.096)	(0.094)	(0.095)	(0.109)
Middle-skilled occ	-0.088	-0.094	-0.101	-0.092	-0.098
	(0.092)	(0.092)	(0.090)	(0.091)	(0.095)
Observations	187,960	187,960	198,588	187,960	186,742
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓	✓
R-squared	0.340	0.339	0.341	0.340	0.302
Cragg-Donald Wald F statistic		2454.979	7515.481	3252.866	2595.872

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The ML occupation cluster is an alternative occupation classification constructed by clustering occupations based on skill requirements using machine learning. Details are presented in Section 6.2.

[2] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

Table B.5: Effects of Demand for AI Skills on Wage Income Share—Adopting Different SSIVs, 2012-21

	Dep. Var.: Share of wage income[1]				
		Leave-One-Out IV by summing across			
	OLS	2-digit OCC	4-digit OCC	4-digit NAICS	ML occupation cluster[2]
	(1)	(2)	(3)	(4)	(5)
%AI postings[3]	-0.011	-0.101***	-0.026	-0.025	-0.082***
	(0.011)	(0.025)	(0.020)	(0.018)	(0.021)
%AI postings ×					
High-skilled AI-complement occ	0.089***	0.158***	0.148***	0.148***	0.159***
	(0.026)	(0.040)	(0.038)	(0.036)	(0.040)
High-skilled not-yet-AI occ	0.026*	0.056**	0.051*	0.056**	0.059**
	(0.014)	(0.027)	(0.027)	(0.025)	(0.027)
Middle-skilled occ	0.005	0.014	0.015	0.014	0.015
	(0.012)	(0.022)	(0.022)	(0.020)	(0.022)
Skill group =					
High-skilled AI-complement occ	-0.151	-0.184	-0.090	-0.177	0.037
	(0.166)	(0.168)	(0.221)	(0.167)	(0.131)
High-skilled not-yet-AI occ	-0.029	-0.042	0.072	-0.042	0.101
	(0.159)	(0.163)	(0.231)	(0.162)	(0.115)
Middle-skilled occ	-0.169	-0.172	-0.165	-0.174	-0.127*
	(0.141)	(0.145)	(0.206)	(0.144)	(0.076)
Observations	192,008	192,008	202,796	192,008	190,712
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓	✓
R-squared	0.158	0.152	0.154	0.156	0.150
Cragg-Donald Wald F statistic		2594.341	7772.793	3414.392	2722.659

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The unit of the share of wage income is a percentage point.

[2] The ML occupation cluster is an alternative occupation classification constructed by clustering occupations based on skill requirements using machine learning. Details are presented in Section 6.2.

[3] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

Table B.6: Effects of Demand for AI Skills on Employment per Capita—Controlling for CS Skills with SSIV Approach,2012-21

	Dep. Var.: Employment per 100,000 capita				
		Leave-One-Out IV by summing across			
	OLS	2-digit OCC	4-digit OCC	4-digit NAICS	ML occupation cluster[1]
	(1)	(2)	(3)	(4)	(5)
%AI postings[2]	-3.319	230.823***	-21.448*	-11.059	-81.387***
	(7.305)	(69.433)	(11.001)	(8.898)	(23.373)
%AI postings ×					
High-skilled AI-complement occ	50.117***	74.264	80.628***	76.245***	148.067***
	(13.951)	(47.849)	(27.198)	(20.555)	(38.270)
High-skilled not-yet-AI occ	17.475*	48.567	31.679**	32.214***	65.866**
	(9.068)	(33.341)	(15.230)	(10.759)	(27.776)
Middle-skilled occ	1.214	15.045	-13.824	-0.380	18.935
	(7.837)	(31.375)	(10.474)	(9.124)	(25.563)
%CS postings[3]	-20.644	10,597.27***	-258.415***	-160.357**	-287.229***
	(16.402)	(2659.423)	(84.086)	(71.667)	(93.169)
%CS postings ×					
High-skilled AI-complement occ	34.595*	440.349*	118.009	212.925***	-189.905**
	(19.244)	(230.409)	(100.192)	(75.302)	(94.463)
High-skilled not-yet-AI occ	15.984	203.431	57.044	83.368	-97.905
	(17.927)	(185.603)	(85.209)	(71.702)	(79.981)
Middle-skilled occ	10.290	203.121	135.208*	71.801	-52.257
	(17.749)	(175.500)	(80.918)	(64.526)	(75.213)
Skill group =					
High-skilled AI-complement occ	-339.642*	-522.176**	-372.870*	-396.763**	-267.485
	(189.454)	(217.974)	(200.537)	(197.764)	(166.744)
High-skilled not-yet-AI occ	-212.117	-345.447*	-226.329	-233.944	-188.700
	(186.650)	(205.772)	(197.692)	(196.731)	(162.947)
Middle-skilled occ	-193.763	-416.912**	-215.101	-206.787	-147.224
	(183.421)	(203.557)	(194.491)	(193.099)	(156.835)
Observations	192,008	192,008	192,008	192,008	190,712
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓	✓
R-squared	0.129	-18.991	0.123	0.126	0.097
Cragg-Donald Wald F statistic		1.396	234.610	83.690	292.027

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The ML occupation cluster is an alternative occupation classification constructed by clustering occupations based on skill requirements using machine learning. Details are presented in Section 6.2.

[2] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

[3] Phrases that belong to broad AI category but not narrow AI category are used to compute %CS postings at the state-year level. %CS postings is in percentage point.

Table B.7: Effects of Demand for AI Skills on Share of Employment—Controlling for CS Skills with SSIV Approach,2012-21

	Dep. Var.: Share of employment[1]				
		Leave-One-Out IV by summing across			
	OLS	2-digit OCC	4-digit OCC	4-digit NAICS	ML occupation cluster[2]
	(1)	(2)	(3)	(4)	(5)
%AI postings[3]	-0.003	0.231***	-0.021*	-0.011	-0.081***
	(0.007)	(0.069)	(0.011)	(0.009)	(0.023)
%AI postings ×					
High-skilled AI-complement occ	0.050***	0.074	0.081***	0.076***	0.148***
	(0.014)	(0.048)	(0.027)	(0.021)	(0.038)
High-skilled not-yet-AI occ	0.017*	0.049	0.032**	0.032***	0.066**
	(0.009)	(0.033)	(0.015)	(0.011)	(0.028)
Middle-skilled occ	0.001	0.015	-0.014	-0.000	0.019
	(0.008)	(0.031)	(0.010)	(0.009)	(0.026)
%CS postings[4]	-0.021	10.597***	-0.258***	-0.160**	-0.287***
	(0.016)	(2.659)	(0.084)	(0.072)	(0.093)
%CS postings ×					
High-skilled AI-complement occ	0.035*	0.440*	0.118	0.213***	-0.190**
	(0.019)	(0.230)	(0.100)	(0.075)	(0.094)
High-skilled not-yet-AI occ	0.016	0.203	0.057	0.083	-0.098
	(0.018)	(0.186)	(0.085)	(0.072)	(0.080)
Middle-skilled occ	0.010	0.203	0.135*	0.072	-0.052
	(0.018)	(0.176)	(0.081)	(0.065)	(0.075)
Skill group =					
High-skilled AI-complement occ	-0.340*	-0.522**	-0.373*	-0.397**	-0.267
	(0.189)	(0.218)	(0.201)	(0.198)	(0.167)
High-skilled not-yet-AI occ	-0.212	-0.345*	-0.226	-0.234	-0.189
	(0.187)	(0.206)	(0.198)	(0.197)	(0.163)
Middle-skilled occ	-0.194	-0.417**	-0.215	-0.207	-0.147
	(0.183)	(0.204)	(0.194)	(0.193)	(0.157)
Observations	192,008	192,008	192,008	192,008	190,712
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓	✓
R-squared	0.129	-18.991	0.123	0.126	0.097
Cragg-Donald Wald F statistic		1.396	234.610	83.690	292.027

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The unit of the share of employment is a percentage point.

[2] The ML occupation cluster is an alternative occupation classification constructed by clustering occupations based on skill requirements using machine learning. Details are presented in Section 6.2.

[3] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

[4] Phrases that belong to broad AI category but not narrow AI category are used to compute %CS postings at the state-year level. %CS postings is in percentage point.

Table B.8: Effects of Demand for AI Skills on Mean Hourly Wage—Controlling for CS Skills with SSIV Approach,2012-21

	Dep. Var.: Log mean hourly wage				
		Leave-One-Out IV by summing across			
	OLS	2-digit OCC	4-digit OCC	4-digit NAICS	ML occupation cluster[2]
	(1)	(2)	(3)	(4)	(5)
%AI postings[2]	0.004	-0.006	0.004	0.010	0.008
	(0.006)	(0.020)	(0.014)	(0.018)	(0.019)
%AI postings ×					
High-skilled AI-complement occ	0.034***	0.032	0.037**	0.060***	0.073***
	(0.008)	(0.021)	(0.015)	(0.019)	(0.024)
High-skilled not-yet-AI occ	0.013*	0.033**	0.030**	0.021	0.048***
	(0.007)	(0.016)	(0.012)	(0.016)	(0.018)
Middle-skilled occ	-0.008	-0.006	0.001	-0.011	-0.002
	(0.006)	(0.015)	(0.012)	(0.016)	(0.018)
%CS postings[3]	0.006	-0.807	0.018	0.025	0.102
	(0.017)	(0.663)	(0.065)	(0.111)	(0.080)
%CS postings ×					
High-skilled AI-complement occ	-0.057**	0.090	0.058	-0.037	-0.143
	(0.023)	(0.085)	(0.063)	(0.081)	(0.095)
High-skilled not-yet-AI occ	-0.033*	-0.034	-0.026	0.049	-0.115*
	(0.019)	(0.061)	(0.051)	(0.069)	(0.069)
Middle-skilled occ	-0.004	0.045	0.011	0.085	0.005
	(0.018)	(0.058)	(0.049)	(0.068)	(0.067)
Skill group =					
High-skilled AI-complement occ	0.452***	0.419***	0.421***	0.436***	0.555***
	(0.104)	(0.106)	(0.105)	(0.107)	(0.105)
High-skilled not-yet-AI occ	0.132	0.129	0.123	0.108	0.236**
	(0.097)	(0.098)	(0.098)	(0.099)	(0.098)
Middle-skilled occ	-0.087	-0.087	-0.095	-0.109	-0.002
	(0.093)	(0.094)	(0.094)	(0.096)	(0.095)
Observations	187,960	187,960	187,960	187,960	186,742
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓	✓
R-squared	0.340	0.275	0.340	0.338	0.341
Cragg-Donald Wald F statistic		1.819	225.433	77.326	278.088

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The ML occupation cluster is an alternative occupation classification constructed by clustering occupations based on skill requirements using machine learning. Details are presented in Section 6.2.

[2] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

[3] Phrases that belong to broad AI category but not narrow AI category are used to compute %CS postings at the state-year level. %CS postings is in percentage point.

Table B.9: Effects of Demand for AI Skills on Wage Income Share—Controlling for CS Skills with SSIV Approach,2012-021

	Dep. Var.: Share of wage income[1]				
		Leave-One-Out IV by summing across			
	OLS	2-digit OCC	4-digit OCC	4-digit NAICS	ML occupation cluster[2]
	(1)	(2)	(3)	(4)	(5)
%AI postings[3]	-0.012	0.204***	-0.041***	-0.022*	-0.111***
	(0.010)	(0.067)	(0.014)	(0.012)	(0.030)
%AI postings ×					
High-skilled AI-complement occ	0.086***	0.113*	0.124***	0.116***	0.215***
	(0.025)	(0.059)	(0.039)	(0.033)	(0.055)
High-skilled not-yet-AI occ	0.030**	0.093**	0.061**	0.048***	0.106***
	(0.014)	(0.040)	(0.024)	(0.016)	(0.040)
Middle-skilled occ	0.006	0.029	0.000	0.005	0.031
	(0.011)	(0.031)	(0.012)	(0.012)	(0.032)
%CS postings[4]	0.000	10.574***	-0.189**	-0.159*	-0.251**
	(0.016)	(2.637)	(0.076)	(0.082)	(0.101)
%CS postings ×					
High-skilled AI-complement occ	0.013	0.481*	0.115	0.224**	-0.296**
	(0.027)	(0.254)	(0.122)	(0.100)	(0.137)
High-skilled not-yet-AI occ	-0.021	0.002	-0.066	0.051	-0.271***
	(0.019)	(0.181)	(0.086)	(0.085)	(0.104)
Middle-skilled occ	-0.006	0.138	0.072	0.061	-0.109
	(0.017)	(0.162)	(0.069)	(0.070)	(0.082)
Skill group =					
High-skilled AI-complement occ	-0.153	-0.355*	-0.196	-0.220	-0.041
	(0.167)	(0.210)	(0.179)	(0.176)	(0.152)
High-skilled not-yet-AI occ	-0.026	-0.132	-0.027	-0.050	0.019
	(0.161)	(0.190)	(0.172)	(0.173)	(0.148)
Middle-skilled occ	-0.168	-0.382**	-0.183	-0.183	-0.117
	(0.143)	(0.178)	(0.153)	(0.155)	(0.116)
Observations	192,008	192,008	192,008	192,008	190,712
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓	✓
R-squared	0.158	-13.519	0.153	0.155	0.123
Cragg-Donald Wald F statistic		1.396	234.610	83.690	292.027

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group in columns is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The unit of the share of wage income is a percentage point.

[2] The ML occupation cluster is an alternative occupation classification constructed by clustering occupations based on skill requirements using machine learning. Details are presented in Section 6.2.

[3] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

[4] Phrases that belong to broad AI category but not narrow AI category are used to compute %CS postings at the state-year level. %CS postings is in percentage point.

Table B.10: Effects of Demand for AI Skills on Employment—Controlling for Software/Robot Exposure, 2012-21

	Dep. Var.:			
	Emp. per 100,000 capita		Share of Emp.[1]	
	Main spec.	Control for exposure to software/robot	Main spec.	Control for exposure to software/robot
	(1)	(2)	(3)	(4)
%AI postings[2]	-6.146	-6.068	-0.006	-0.006
	(8.282)	(8.286)	(0.008)	(0.008)
%AI postings ×				
High-skilled AI-complement occ	55.756***	55.665***	0.056***	0.056***
	(14.940)	(14.935)	(0.015)	(0.015)
High-skilled not-yet-AI occ	20.065**	20.157**	0.020**	0.020**
	(10.099)	(10.126)	(0.010)	(0.010)
Middle-skilled occ	2.868	2.754	0.003	0.003
	(8.991)	(9.011)	(0.009)	(0.009)
Software exposure[3]		-29.705		-0.030
		(84.576)		(0.085)
Robot exposure[4]		41.908		0.042
		(59.383)		(0.059)
Skill group =				
High-skilled AI-complement occ	-333.383*	-328.487*	-0.333*	-0.328*
	(187.602)	(189.279)	(0.188)	(0.189)
High-skilled not-yet-AI occ	-209.460	-202.830	-0.209	-0.203
	(184.689)	(186.656)	(0.185)	(0.187)
Middle-skilled occ	-192.177	-196.507	-0.192	-0.197
	(181.375)	(179.849)	(0.181)	(0.180)
Observations	192,008	190,859	192,008	190,859
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓
R-squared	0.129	0.129	0.129	0.129

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group in columns is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The unit of the share of employment is a percentage point.

[2] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

[3,4] The software and robot exposure scores are constructed by Webb (2019), which measure the capabilities in software and robots for performing an occupation's tasks.

Table B.11: Effects of Demand for AI Skills on Wages—Controlling for Software/Robot Exposure, 2012-21

	Dep. Var.:			
	Log mean houly wages		Share of wage income[1]	
	Main spec.	Control for exposure to software/robot	Main spec.	Control for exposure to software/robot
	(1)	(2)	(3)	(4)
%AI postings[2]	0.005	0.005	-0.011	-0.011
	(0.005)	(0.005)	(0.011)	(0.011)
%AI postings ×				
High-skilled AI-complement occ	0.025***	0.025***	0.089***	0.089***
	(0.007)	(0.007)	(0.026)	(0.026)
High-skilled not-yet-AI occ	0.007	0.008	0.026*	0.027*
	(0.006)	(0.006)	(0.014)	(0.015)
Middle-skilled occ	-0.009	-0.008	0.005	0.005
	(0.005)	(0.005)	(0.012)	(0.012)
Software exposure[3]		0.144*		0.000
		(0.081)		(0.064)
Robot exposure[4]		-0.092**		-0.010
		(0.042)		(0.041)
Skill group =				
High-skilled AI-complement occ	0.441***	0.440***	-0.151	-0.144
	(0.104)	(0.103)	(0.166)	(0.167)
High-skilled not-yet-AI occ	0.126	0.128	-0.029	-0.020
	(0.096)	(0.095)	(0.159)	(0.161)
Middle-skilled occ	-0.088	-0.089	-0.169	-0.165
	(0.092)	(0.089)	(0.141)	(0.140)
Observations	187,960	186,911	192,008	190,859
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓
R-squared	0.340	0.345	0.158	0.157

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group in columns is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The unit of the share of wage income is a percentage point.

[2] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

[3,4] The software and robot exposure scores are constructed by Webb (2019), which measure the capabilities in software and robots for performing an occupation's tasks.

Table B.12: Effects of Demand for AI Skills on Employment—Comparing Narrow vs. Broad AI Definition, 2012-21

	Dep. Var.:			
	Emp. per 100,000 capita		Share of Emp.[1]	
	Main spec.: narrow AI def.	Broad AI def.	Main spec.: narrow AI def.	Broad AI def.
	(1)	(2)	(3)	(4)
%AI postings[2]	-6.146	-6.426	-0.006	-0.006
	(8.282)	(7.180)	(0.008)	(0.007)
%AI postings ×				
High-skilled AI-complement occ	55.756***	40.379***	0.056***	0.040***
	(14.940)	(11.235)	(0.015)	(0.011)
High-skilled not-yet-AI occ	20.065**	17.276*	0.020**	0.017*
	(10.099)	(8.877)	(0.010)	(0.009)
Middle-skilled occ	2.868	2.654	0.003	0.003
	(8.991)	(7.791)	(0.009)	(0.008)
Skill group =				
High-skilled AI-complement occ	-333.383*	-359.568*	-0.333*	-0.360*
	(187.602)	(187.916)	(0.188)	(0.188)
High-skilled not-yet-AI occ	-209.460	-207.855	-0.209	-0.208
	(184.689)	(186.267)	(0.185)	(0.186)
Middle-skilled occ	-192.177	-193.676	-0.192	-0.194
	(181.375)	(182.588)	(0.181)	(0.183)
Observations	192,008	192,008	192,008	192,008
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓
R-squared	0.129	0.130	0.129	0.130

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group in columns is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The unit of the share of employment is a percentage point.

[2] In columns 1 and 3 (2 and 4), narrow (broad) AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

Table B.13: Effects of Demand for AI Skills on Wages—Comparing Narrow vs. Broad AI Definition, 2012-21

	Dep. Var.:			
	Log mean houly wages		Share of wage income[1]	
	Main spec.: narrow AI def.	Broad AI def.	Main spec.: narrow AI def.	Broad AI def.
	(1)	(2)	(3)	(4)
%AI postings[2]	0.005	0.004	-0.011	-0.010
	(0.005)	(0.004)	(0.011)	(0.009)
%AI postings ×				
High-skilled AI-complement occ	0.025***	0.017***	0.089***	0.061***
	(0.007)	(0.005)	(0.026)	(0.019)
High-skilled not-yet-AI occ	0.007	0.005	0.026*	0.022*
	(0.006)	(0.005)	(0.014)	(0.013)
Middle-skilled occ	-0.009	-0.007	0.005	0.004
	(0.005)	(0.004)	(0.012)	(0.010)
Skill group =				
High-skilled AI-complement occ	0.441***	0.353***	-0.151	-0.213
	(0.104)	(0.108)	(0.166)	(0.166)
High-skilled not-yet-AI occ	0.126	0.126	-0.029	-0.026
	(0.096)	(0.096)	(0.159)	(0.161)
Middle-skilled occ	-0.088	-0.086	-0.169	-0.172
	(0.092)	(0.092)	(0.141)	(0.143)
Observations	187,960	187,960	192,008	192,008
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓
R-squared	0.340	0.335	0.158	0.158

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group in columns is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The unit of the share of wage income is a percentage point.

[2] In columns 1 and 3 (2 and 4), narrow (broad) AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

Table B.14: Effects of Demand for AI Skills on Employment per Capita—Using AI Posting Share Quintiles, 2012-21

	Dep. Var.: Employment per 100,000 capita				
		Leave-One-Out IV by summing across			
	OLS	2-digit OCC	4-digit OCC	4-digit NAICS	ML occupation cluster[2]
	(1)	(2)	(3)	(4)	(5)
%AI postings[3]	-6.216	-85.276***	-36.123**	-13.202	-56.901***
	(8.286)	(19.489)	(15.230)	(14.441)	(15.184)
%AI postings ×					
High-skilled occ × AI occ (q5)	48.853***	99.140***	90.803***	96.294***	101.648***
	(12.974)	(24.210)	(21.893)	(22.795)	(23.490)
High-skilled occ × AI occ (q4)	38.268***	79.798***	73.485***	80.581***	83.682***
	(13.342)	(25.707)	(23.289)	(25.579)	(25.421)
High-skilled occ × AI occ (q3)	10.131	31.974	26.344	27.874	31.521*
	(10.305)	(19.617)	(18.004)	(18.882)	(18.635)
High-skilled occ × AI occ (q2)	-6.320	11.232	2.387	0.804	6.653
	(13.476)	(23.393)	(22.058)	(20.595)	(22.658)
High-skilled occ × AI occ (q1)	11.129	12.545	19.884	23.376	13.795
	(10.147)	(23.463)	(20.025)	(17.422)	(23.596)
Middle-skilled occ	2.876	10.715	10.850	10.264	10.607
	(8.991)	(18.012)	(16.224)	(15.799)	(16.758)
Skill group =					
High-skilled occ × AI occ (q5)	-349.610*	-373.521**	-368.446*	-370.143**	-324.360**
	(187.009)	(189.883)	(189.206)	(188.629)	(164.379)
High-skilled occ × AI occ (q4)	-175.111	-191.474	-189.621	-192.923	-218.962
	(191.082)	(193.761)	(193.115)	(192.522)	(168.215)
High-skilled occ × AI occ (q3)	70.477	62.172	63.610	62.475	81.577
	(256.242)	(258.880)	(258.203)	(257.453)	(233.694)
High-skilled occ × AI occ (q2)	13.270	-46.608	-16.595	-11.378	-23.859
	(212.031)	(241.724)	(238.168)	(233.475)	(239.980)
High-skilled occ × AI occ (q1)	-383.211**	-385.143**	-387.530**	-388.782**	-358.280**
	(182.666)	(186.549)	(185.660)	(184.996)	(161.318)
Middle-skilled occ	-186.631	-189.173	-190.062	-190.342	-153.562
	(181.869)	(185.228)	(184.440)	(183.981)	(157.866)
Observations	192,008	192,008	192,008	192,008	190,712
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓	✓
R-squared	0.143	0.137	0.142	0.141	0.137
Cragg-Donald Wald F statistic		1,417.981	2,625.620	1,932.669	1,495.119

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group in columns is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The ML occupation cluster is an alternative occupation classification constructed by clustering occupations based on skill requirements using machine learning. Details are presented in Section 6.2.

[2] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

Table B.15: Effects of Demand for AI Skills on Share of Employment—Using AI Posting Share Quintiles, 2012-21

	Dep. Var.: Share of employment[1]				
		Leave-One-Out IV by summing across			
	OLS	2-digit OCC	4-digit OCC	4-digit NAICS	ML occupation cluster[2]
	(1)	(2)	(3)	(4)	(5)
%AI postings[3]	-0.006	-0.085***	-0.036**	-0.013	-0.057***
	(0.008)	(0.019)	(0.015)	(0.014)	(0.015)
%AI postings ×					
High-skilled occ × AI occ (q5)	0.049***	0.099***	0.091***	0.096***	0.102***
	(0.013)	(0.024)	(0.022)	(0.023)	(0.023)
High-skilled occ × AI occ (q4)	0.038***	0.080***	0.073***	0.081***	0.084***
	(0.013)	(0.026)	(0.023)	(0.026)	(0.025)
High-skilled occ × AI occ (q3)	0.010	0.032	0.026	0.028	0.032*
	(0.010)	(0.020)	(0.018)	(0.019)	(0.019)
High-skilled occ × AI occ (q2)	-0.006	0.011	0.002	0.001	0.007
	(0.013)	(0.023)	(0.022)	(0.021)	(0.023)
High-skilled occ × AI occ (q1)	0.011	0.013	0.020	0.023	0.014
	(0.010)	(0.023)	(0.020)	(0.017)	(0.024)
Middle-skilled occ	0.003	0.011	0.011	0.010	0.011
	(0.009)	(0.018)	(0.016)	(0.016)	(0.017)
Skill group =					
High-skilled occ × AI occ (q5)	-0.350*	-0.374**	-0.368*	-0.370**	-0.324**
	(0.187)	(0.190)	(0.189)	(0.189)	(0.164)
High-skilled occ × AI occ (q4)	-0.175	-0.191	-0.190	-0.193	-0.219
	(0.191)	(0.194)	(0.193)	(0.193)	(0.168)
High-skilled occ × AI occ (q3)	0.070	0.062	0.064	0.062	0.082
	(0.256)	(0.259)	(0.258)	(0.257)	(0.234)
High-skilled occ × AI occ (q2)	0.013	-0.047	-0.017	-0.011	-0.024
	(0.212)	(0.242)	(0.238)	(0.233)	(0.240)
High-skilled occ × AI occ (q1)	-0.383**	-0.385**	-0.388**	-0.389**	-0.358**
	(0.183)	(0.187)	(0.186)	(0.185)	(0.161)
Middle-skilled occ	-0.187	-0.189	-0.190	-0.190	-0.154
	(0.182)	(0.185)	(0.184)	(0.184)	(0.158)
Observations	192,008	192,008	192,008	192,008	190,712
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓	✓
R-squared	0.143	0.137	0.142	0.141	0.137
Cragg-Donald Wald F statistic		1,417.981	2,625.620	1,932.669	1,495.119

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group in columns is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The unit of the share of employment is a percentage point.

[2] The ML occupation cluster is an alternative occupation classification constructed by clustering occupations based on skill requirements using machine learning. Details are presented in Section 6.2.

[3] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

Table B.16: Effects of Demand for AI Skills on Mean Hourly Wage—Using AI Posting Share Quintiles, 2012-21

	Dep. Var.: Log mean hourly wage				
		Leave-One-Out IV by summing across			
	OLS	2-digit OCC	4-digit OCC	4-digit NAICS	ML occupation cluster[1]
	(1)	(2)	(3)	(4)	(5)
%AI postings[2]	0.005	0.012	0.004	-0.005	0.018
	(0.005)	(0.014)	(0.011)	(0.013)	(0.013)
%AI postings ×					
High-skilled occ × AI occ (q5)	0.025***	0.051***	0.049***	0.056***	0.047***
	(0.006)	(0.010)	(0.009)	(0.011)	(0.009)
High-skilled occ × AI occ (q4)	0.013**	0.040***	0.035***	0.037***	0.036***
	(0.006)	(0.010)	(0.009)	(0.011)	(0.010)
High-skilled occ × AI occ (q3)	0.004	0.023*	0.018*	0.022*	0.018
	(0.007)	(0.012)	(0.011)	(0.012)	(0.012)
High-skilled occ × AI occ (q2)	0.006	0.022	0.021*	0.029**	0.020
	(0.008)	(0.014)	(0.013)	(0.014)	(0.013)
High-skilled occ × AI occ (q1)	-0.012	0.001	-0.001	-0.002	0.019
	(0.015)	(0.026)	(0.023)	(0.029)	(0.028)
Middle-skilled occ	-0.009	0.005	0.003	0.002	-0.001
	(0.005)	(0.009)	(0.008)	(0.010)	(0.009)
Skill group =					
High-skilled occ × AI occ (q5)	0.334***	0.324***	0.324***	0.321***	0.424***
	(0.105)	(0.105)	(0.105)	(0.105)	(0.104)
High-skilled occ × AI occ (q4)	0.189*	0.178*	0.180*	0.179*	0.258**
	(0.103)	(0.103)	(0.103)	(0.102)	(0.101)
High-skilled occ × AI occ (q3)	0.149	0.140	0.142	0.141	0.242**
	(0.121)	(0.121)	(0.121)	(0.120)	(0.119)
High-skilled occ × AI occ (q2)	0.061	0.007	0.009	-0.015	0.020
	(0.117)	(0.125)	(0.125)	(0.125)	(0.122)
High-skilled occ × AI occ (q1)	0.045	0.040	0.040	0.040	0.095
	(0.133)	(0.133)	(0.133)	(0.133)	(0.135)
Middle-skilled occ	-0.081	-0.088	-0.087	-0.086	-0.000
	(0.093)	(0.093)	(0.093)	(0.092)	(0.092)
Observations	187,960	187,960	187,960	187,960	186,742
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓	✓
R-squared	0.339	0.338	0.338	0.338	0.340
Cragg-Donald Wald F statistic		1,338.611	2,515.017	1,839.275	1,424.106

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group in columns is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The ML occupation cluster is an alternative occupation classification constructed by clustering occupations based on skill requirements using machine learning. Details are presented in Section 6.2.

[2] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

Table B.17: Effects of Demand for AI Skills on Wage Income Share—Using AI Posting Share Quintiles, 2012-21

	Dep. Var.: Share of wage income[1]				
		Leave-One-Out IV by summing across			
	OLS	2-digit OCC	4-digit OCC	4-digit NAICS	ML occupation cluster[2]
	(1)	(2)	(3)	(4)	(5)
%AI postings[3]	-0.011	-0.088***	-0.040**	-0.019	-0.064***
	(0.011)	(0.024)	(0.019)	(0.018)	(0.019)
%AI postings ×					
High-skilled occ × AI occ (q5)	0.076***	0.139***	0.127***	0.133***	0.142***
	(0.022)	(0.034)	(0.032)	(0.032)	(0.034)
High-skilled occ × AI occ (q4)	0.055**	0.106**	0.098**	0.111**	0.112***
	(0.023)	(0.042)	(0.039)	(0.044)	(0.043)
High-skilled occ × AI occ (q3)	0.008	0.025	0.020	0.027	0.024
	(0.013)	(0.025)	(0.023)	(0.023)	(0.024)
High-skilled occ × AI occ (q2)	-0.008	0.005	-0.004	-0.004	-0.000
	(0.017)	(0.030)	(0.028)	(0.026)	(0.029)
High-skilled occ × AI occ (q1)	0.015	0.023	0.028	0.029	0.024
	(0.012)	(0.024)	(0.021)	(0.021)	(0.023)
Middle-skilled occ	0.005	0.014	0.014	0.014	0.013
	(0.012)	(0.022)	(0.020)	(0.020)	(0.021)
Skill group =					
High-skilled occ × AI occ (q5)	-0.172	-0.201	-0.194	-0.196	-0.132
	(0.164)	(0.167)	(0.167)	(0.166)	(0.146)
High-skilled occ × AI occ (q4)	0.050	0.030	0.032	0.027	-0.031
	(0.173)	(0.175)	(0.174)	(0.173)	(0.155)
High-skilled occ × AI occ (q3)	0.364	0.357	0.358	0.355	0.415
	(0.301)	(0.304)	(0.303)	(0.302)	(0.298)
High-skilled occ × AI occ (q2)	0.062	0.018	0.049	0.048	0.041
	(0.213)	(0.253)	(0.248)	(0.243)	(0.252)
High-skilled occ × AI occ (q1)	-0.319**	-0.323**	-0.324**	-0.325**	-0.311**
	(0.153)	(0.157)	(0.156)	(0.156)	(0.136)
Middle-skilled occ	-0.159	-0.162	-0.162	-0.163	-0.130
	(0.141)	(0.145)	(0.144)	(0.144)	(0.120)
Observations	192,008	192,008	192,008	192,008	190,712
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓	✓
R-squared	0.175	0.170	0.173	0.173	0.166
Cragg-Donald Wald F statistic		1,417.981	2,625.620	1,932.669	1,495.119

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group in columns is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The unit of the share of wage income is a percentage point.

[2] The ML occupation cluster is an alternative occupation classification constructed by clustering occupations based on skill requirements using machine learning. Details are presented in Section 6.2.

[3] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

Table B.18: Component Loadings for the AI Skill Prevalence Score (Ranked from the Highest to the Lowest)

AI skill	Principal component 1
Python	0.89732448
Machine learning	0.30575326
Big data	0.2575757
Artificial intelligence	0.11524112
Robotic	0.07181856
Matlab	0.06659661
Natural language processing (NLP)	0.0557427
Deep learning	0.04594767
Data mining	0.04416461
TensorFlow	0.03561318
Computer vision	0.03542881
Autonomous driving	0.02640705
PyTorch	0.02231685
Augmented reality (AR)	0.01904324
Virtual reality (VR)	0.01846953
Neural network	0.01384596
3-D modeling	0.01179794
Computer graphics	0.00799434
Voice recognition	0.0071089
Multimedia	0.00704629
Pattern recognition	0.00428575

Notes: Then component loadings are static across time, which capture the importance or weight of a narrow AI phrase in constructing the AI Skill Prevalence Score. Python allows users to choose the number of components to keep. Thus, the multi-dimensional skill set is projected to a one-dimensional space by PCA to construct this single measurement.

Table B.19: Occupations Ranked by AI Skill Prevalence Score, 2021

OCC2010	Occupation title	AI Skill Prevalence Score	Skill group
	Panel A. Occupations with the Top 15 AI Skill Prevalence Score		
1020	Software Developers, Applications and Systems Software	19.75286	H^{AI}
710	Management Analysts	2.638285	H^{AI}
730	Other Business Operations and Management Specialists	2.111124	H^{AI}
1100	Network and Computer Systems Administrators	1.96713	H^{AI}
1000	Computer Scientists and Systems Analysts/Network systems Analysts/Web Developers	1.562139	H^{AI}
840	Financial Analysts	0.5148678	H^{AI}
1240	Mathematical Science Occupations, All Other	0.4935438	H^{AI}
950	Financial Specialists, All Other	0.4659868	H^{AI}
110	Computer and Information Systems Managers	0.4455855	H^{AI}
30	Managers in Marketing, Advertising, and Public Relations	0.4433329	H^{AI}
1650	Medical Scientists, and Life Scientists, All Other	0.4405924	H^{AI}
1220	Operations Research Analysts	0.3378968	H^{AI}
1410	Electrical and Electronics Engineers	0.3365522	H^{AI}
4930	Sales Engineers	0.3293847	H^{AI}
1400	Computer Hardware Engineers	0.3147703	H^{AI}
	Panel B. Occupations with the Bottom 15 AI Skill Prevalence Score		
7160	Automotive Glass Installers and Repairers	-0.0926943	M
8420	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders	-0.0926943	M
7850	Food Cooking Machine Operators and Tenders	-0.0926943	M
940	Tax Preparers	-0.0926943	H^{Non}
8940	Tire Builders	-0.0926943	M
8920	Molders, Shapers, and Casters, Except Metal and Plastic	-0.0926943	M
8450	Upholsterers	-0.0926943	M
6700	Elevator Installers and Repairers	-0.0926943	M
6240	Carpet, Floor, and Tile Installers and Finishers	-0.0926943	M
8720	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders	-0.0926943	M
8540	Woodworking Machine Setters, Operators, and Tenders, Except Sawing	-0.0926943	M
8640	Chemical Processing Machine Setters, Operators, and Tenders	-0.0926943	M
6010	Agricultural Inspectors	-0.0926943	M
8730	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders	-0.0926943	M
3260	Health Diagnosing and Treating Practitioners, All Other	-0.0926943	H^{Non}

Notes: The occupation-year AI Skill Prevalence Score is standardized within a year. There is a tie in the lowest AI Skill Prevalence Score, with 66 occupations having the lowest score, -0.0926943. 15 out of 66 occupations are randomly chosen and listed in Panel B. H^{AI}, H^{Non}, M, and L represent high-skilled AI-complement, high-skilled not-yet-AI, middle-skilled, and low-skilled occupation group, respectively.

Table B.20: States Ranked by AI Skill Prevalence Score, 2021

Panel A. States with the Top 15 AI Skill Prevalence Score		*Panel B. States with the Bottom 15 AI Skill Prevalence Score*	
State	**AI Skill Prevalence Score**	**State**	**AI Skill Prevalence Score**
California	5.356526	Wyoming	-0.6126739
Texas	2.384235	Alaska	-0.6096864
New York	1.545264	South Dakota	-0.6029171
Washington	1.441433	Hawaii	-0.6021812
Virginia	0.9939204	Vermont	-0.5961387
Massachusetts	0.9668954	West Virginia	-0.5951093
Illinois	0.6540916	Montana	-0.5942092
Florida	0.5013081	Mississippi	-0.5881292
Georgia	0.4332158	North Dakota	-0.5876687
North Carolina	0.3860596	Maine	-0.5788439
Pennsylvania	0.2700901	Rhode Island	-0.5525354
Colorado	0.2696101	Nebraska	-0.5342934
New Jersey	0.2091825	Oklahoma	-0.5319125
Maryland	0.1105196	New Hampshire	-0.5318903
Ohio	0.0961018	Nevada	-0.5297292

Notes: The state-year AI Skill Prevalence Score is standardized within a year.

Table B.21: Distribution of Effects with One State Left Out, 2012-21

	Max	p75	p50	p25	Min
Panel A. Outcome: Employment per 100,000 Capita					
%AI postings[1]	-3.289	-5.937	-6.179	-6.433	-8.388
	(7.474)	(8.271)	(8.282)	(8.220)	(10.615)
%AI postings ×					
High-skilled AI-complement occ	68.137***	56.032***	55.775***	55.306***	46.573***
	(17.595)	(14.999)	(14.965)	(15.138)	(13.923)
High-skilled not-yet-AI occ	26.533**	20.313*	20.102**	19.879**	14.571*
	(13.017)	(10.581)	(10.117)	(10.085)	(8.759)
Middle-skilled occ	3.369	3.015	2.893	2.756	1.998
	(9.004)	(9.017)	(9.010)	(8.675)	(9.433)
Panel B. Outcome: Share of Employment[2]					
%AI postings	-0.003	-0.006	-0.008	-0.006	-0.008
	(0.007)	(0.008)	(0.008)	(0.008)	(0.011)
%AI postings ×					
High-skilled AI-complement occ	0.068***	0.056***	0.056***	0.055***	0.047***
	(0.018)	(0.015)	(0.015)	(0.015)	(0.014)
High-skilled not-yet-AI occ	0.027**	0.020*	0.020**	0.020**	0.015*
	(0.013)	(0.011)	(0.010)	(0.010)	(0.009)
Middle-skilled occ	0.003	0.003	0.003	0.003	0.002
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Panel C. Outcome: Log Mean Hourly Wage					
%AI postings	0.008	0.006	0.005	0.005	0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
%AI postings ×					
High-skilled AI-complement occ	0.034***	0.025***	0.025***	0.025***	0.023***
	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)
High-skilled not-yet-AI occ	0.015**	0.008	0.007	0.007	0.004
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Middle-skilled occ	-0.007	-0.008	-0.009	-0.009*	-0.010*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Panel D. Outcome: Share of Wage Income[3]					
%AI postings	-0.008	-0.011	-0.011	-0.0011	-0.016
	(0.010)	(0.010)	(0.011)	(0.011)	(0.014)
%AI postings ×					
High-skilled AI-complement occ	0.103***	0.089***	0.089***	0.089***	0.082***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.003)
High-skilled not-yet-AI occ	0.038**	0.027*	0.026*	0.026*	0.019
	(0.019)	(0.015)	(0.014)	(0.014)	(0.012)
Middle-skilled occ	0.007	0.005	0.005	0.005	0.004
	(0.015)	(0.012)	(0.012)	(0.012)	(0.011)

Notes: The table shows percentiles from the distribution of estimated effects using my main specification, equation (16), but leaving out one state from the analysis at a time. All columns include a set of state-year controls. The baseline group in columns is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
[1] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.
[2,3] The unit of the share of employment and the share of wage income is a percentage point.

Table B.22: Effects of Demand for AI Skills on Employment—Dropping COVID Years, 2012-19

	Dep. Var.:			
	Emp. per 100,000 capita		Share of Emp.[1]	
	Main spec.	Dropping COVID years	Main spec.	Dropping COVID years
	(1)	(2)	(3)	(4)
%AI postings[2]	-6.146	-4.594	-0.006	-0.005
	(8.282)	(9.038)	(0.008)	(0.009)
%AI postings ×				
High-skilled AI-complement occ	55.756***	55.237***	0.056***	0.055***
	(14.940)	(15.319)	(0.015)	(0.015)
High-skilled not-yet-AI occ	20.065**	20.410*	0.020**	0.020*
	(10.099)	(10.900)	(0.010)	(0.011)
Middle-skilled occ	2.868	2.822	0.003	0.003
	(8.991)	(9.797)	(0.009)	(0.010)
Skill group =				
High-skilled AI-complement occ	-333.383*	-331.370*	-0.333*	-0.331*
	(187.602)	(188.507)	(0.188)	(0.189)
High-skilled not-yet-AI occ	-209.460	-209.577	-0.209	-0.210
	(184.689)	(185.677)	(0.185)	(0.186)
Middle-skilled occ	-192.177	-197.897	-0.192	-0.198
	(181.375)	(182.244)	(0.181)	(0.182)
Observations	192,008	153,221	192,008	153,221
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓
R-squared	0.129	0.130	0.129	0.130

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group in columns is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The unit of the share of employment is a percentage point.

[2] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

Table B.23: Effects of Demand for AI Skills on Wages—Dropping COVID Years, 2012-19

	Dep. Var.:			
	Log mean houly wages		Share of wage income[1]	
	Main spec.	Dropping COVID years	Main spec.	Dropping COVID years
	(1)	(2)	(3)	(4)
%AI postings[2]	0.005	0.001	-0.011	-0.009
	(0.005)	(0.006)	(0.011)	(0.012)
%AI postings ×				
High-skilled AI-complement occ	0.025***	0.029***	0.089***	0.088***
	(0.007)	(0.007)	(0.026)	(0.026)
High-skilled not-yet-AI occ	0.007	0.009	0.026*	0.027*
	(0.006)	(0.006)	(0.014)	(0.016)
Middle-skilled occ	-0.009	-0.006	0.005	0.005
	(0.005)	(0.006)	(0.012)	(0.013)
Skill group =				
High-skilled AI-complement occ	0.441***	0.438***	-0.151	-0.145
	(0.104)	(0.106)	(0.166)	(0.166)
High-skilled not-yet-AI occ	0.126	0.126	-0.029	-0.027
	(0.096)	(0.097)	(0.159)	(0.160)
Middle-skilled occ	-0.088	-0.086	-0.169	-0.173
	(0.092)	(0.093)	(0.141)	(0.142)
Observations	187,960	150,071	192,008	153,221
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓
R-squared	0.340	0.347	0.158	0.156

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group in columns is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The unit of the share of wage income is a percentage point.

[2] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-year level. %AI postings is in percentage point.

Table B.24: Effects of Demand for AI Skills on Employment—Using AI Posting Shares at More Granular Level, 2012-21

	Dep. Var.:					
	Employment per 100,000 capita			Share of employment[1]		
	(1)	(2)	(3)	(4)	(5)	(6)
%AI postings[2]	-4.497	-64.619	-33.822	-0.004	-0.065	-0.034
	(4.136)	(40.120)	(30.439)	(0.004)	(0.040)	(0.030)
%AI postings ×						
High-skilled AI-complement occ		73.963*	44.004		0.074*	0.044
		(40.642)	(30.912)		(0.041)	(0.031)
High-skilled not-yet-AI occ		51.016	35.362		0.051	0.035
		(40.994)	(31.099)		(0.041)	(0.031)
Middle-skilled occ		49.184	33.548		0.049	0.034
		(40.533)	(30.824)		(0.041)	(0.031)
Skill group =						
High-skilled AI-complement occ	-45.713	-165.488	-321.744*	-0.046	-0.165	-0.322*
	(107.731)	(116.754)	(190.593)	(0.108)	(0.117)	(0.191)
High-skilled not-yet-AI occ	47.720	44.293	-205.102	0.048	0.044	-0.205
	(113.162)	(124.792)	(185.128)	(0.113)	(0.125)	(0.185)
Middle-skilled occ	-58.853	-68.505	-193.837	-0.059	-0.069	-0.194
	(104.351)	(114.289)	(181.114)	(0.104)	(0.114)	(0.181)
Observations	192,008	192,008	192,008	192,008	192,008	192,008
State FE		✓	✓		✓	✓
Year FE		✓	✓		✓	✓
Skill-group FE		✓	✓		✓	✓
2-digit-occ FE			✓			✓
Skill-group FE × year FE			✓			✓
R-squared	0.012	0.022	0.129	0.012	0.022	0.129

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group in columns 2, 3, 5, and 6 is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The unit of the share of employment is a percentage point.

[2] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-by-year-by-2-digit-occupation level. %AI postings is in percentage point.

Table B.25: Effects of Demand for AI Skills on Wages—Using AI Posting Shares at More Granular Level, 2012-21

	Dep. Var.:					
	Log mean hourly wage			Share of wage income[1]		
	(1)	(2)	(3)	(4)	(5)	(6)
%AI postings[2]	0.016***	0.012	0.004	0.001	-0.042	-0.020
	(0.003)	(0.033)	(0.028)	(0.006)	(0.031)	(0.023)
%AI postings ×						
High-skilled AI-complement occ		-0.011	-0.002		0.058*	0.038
		(0.033)	(0.028)		(0.033)	(0.025)
High-skilled not-yet-AI occ		0.008	-0.002		0.027	0.018
		(0.034)	(0.028)		(0.033)	(0.025)
Middle-skilled occ		0.020	0.003		0.039	0.023
		(0.033)	(0.028)		(0.032)	(0.023)
Skill group =						
High-skilled AI-complement occ	0.557***	0.669***	0.468***	0.147	0.027	-0.138
	(0.084)	(0.090)	(0.108)	(0.101)	(0.111)	(0.169)
High-skilled not-yet-AI occ	0.263***	0.258***	0.135	0.222**	0.235*	-0.018
	(0.085)	(0.092)	(0.098)	(0.112)	(0.122)	(0.158)
Middle-skilled occ	-0.085	-0.097	-0.092	-0.056	-0.066	-0.170
	(0.078)	(0.083)	(0.094)	(0.083)	(0.090)	(0.139)
Observations	187,960	187,960	187,960	192,008	192,008	192,008
State FE		✓	✓		✓	✓
Year FE		✓	✓		✓	✓
Skill-group FE		✓	✓		✓	✓
2-digit-occ FE			✓			✓
Skill-group FE × year FE			✓			✓
R-squared	0.198	0.213	0.340	0.052	0.060	0.157

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group in columns 2, 3, 5, and 6 is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The unit of the share of wage income is a percentage point.

[2] Narrow AI definition is used when defining skill groups and computing %AI postings at the state-by-year-by-2-digit-occupation level. %AI postings is in percentage point.

Table B.26: Effects of Occupation-Year AI Skill Prevalence Interacting with Skill Group Dummies, 2012-21

	Dep. Var.:			
	Emp. per 100,000 capita	%Emp share[1]	Log mean hourly wage	%Wage income[2]
	(1)	(2)	(3)	(4)
AI Skill Prevalence Score[3]	34,346.52***	34.347***	7.875	40.574***
	(8,689.240)	(8.689)	(8.106)	(4.538)
AI skill prevalence ×				
High-skilled AI-complement occ	-34,313.02***	-34.313***	-7.866	-40.504***
	(8,689.252)	(8.689)	(8.106)	(4.538)
High-skilled not-yet-AI occ	-33,103.8***	-33.104***	-7.107	-38.406***
	(8,707.614)	(8.708)	(8.113)	(4.636)
Middle-skilled occ	-28,173.44***	-28.173***	-6.950	-32.674***
	(8,916.063)	(8.916)	(8.130)	(5.242)
Observations	186,799	186,799	183,018	186,799
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Skill-group FE	✓	✓	✓	✓
2-digit-occ FE	✓	✓	✓	✓
Skill-group FE × year FE	✓	✓	✓	✓
R-squared	0.177	0.177	0.347	0.225

Notes: Each observation is an occupation-state-year cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. All columns include a set of state-year controls. The baseline group in Panel B is the low-skilled group. Occupation-clustered standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1,2] The unit of the employment share and the share of wage income is a percentage point.

[3] The AI Skill Prevalence Score is constructed at the 4-digit-occupation-by-year level and standardized within a year.

C 4-digit Occupations Within a Skill Group

Since the LinkUp job postings data used to construct the skill groups introduced in Section 3.2 is collected at the 2019 O*NET-SOC level and the labor market outcome data from IPUMS-ACS uses a harmonized occupation system, OCC2010[25], constructed by IPUMS-ACS based on the 2010 Census Occupational Classification, a crosswalk is needed to map these two occupational classification systems. Due to the lack of available crosswalk to directly map 2019 O*NET-SOC to OCC2010, I first construct skill group indicators at 6-digit 2019 O*NET-SOC level, and then map 2019 O*NET-SOC to 2010 O*NET-SOC to 2010 SOC to OCC2010 to obtain skill group indicators for each 4-digit OCC2010. For the majority of occupations, there is a one-to-one mapping between different occupational coding systems. In the case of one-to-many mapping, if an occupation is mapped to multiple occupations with different skill group indicators, I keep the skill group indicator with a higher number of total postings.

In my final sample, there are 428 OCC2010 between 2012 and 2021. Note that the IPUMS-ACS OCC2010 coding scheme has 493 occupations in total. The ones that are not included in my sample are due to two reasons. First, some of these occupations do not have a detailed description in O*NET since my AI occupation indicator is constructed as an intersection between AI occupations defined by using LinkUp data and those defined by using O*NET data (as explained in Section 3.2.2).[26] Second, some occupations did not show up in IPUMS-ACS data between 2012 and 2021, such as "Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic" (7960) and "Shoe Machine Operators and Tenders" (8340). Appendix Table C.1 lists the time-variant skill group indicator for all 4-digit occupations in my final sample. Since I also construct a static skill group indicator, each panel of Appendix Table C.1 shows occupations that are classified into the corresponding skill group using this time-invariant skill group system.[27]

[25] https://usa.ipums.org/usa-action/variables/OCC2010#description_section. The OCC2010 coding systems from Census and IPUMS-ACS are not exactly the same. According to IPUMS, "In the interest of harmonization, however, the scheme has been modified to achieve the most consistent categories across time. That is, some categories that provide more detail in the 2010 scheme were grouped together because earlier categories are inseparable when more than one occupation is coded together." These two systems can be easily mapped based on occupation titles. In my analysis, I use IPUMS-ACS OCC2010 system because my labor market outcome data is from IPUMS-ACS.

[26] My empirical results are robust to using AI occupation indicator defined by using only LinkUp data instead of taking the intersection.

[27] My empirical results are robust to using the time-invariant skill group indicators.

Table C.1: Time-Variant Skill Group Indicators for 4-digit Occupations

OCC2010	Occupation title	Skill group indicator during			Ever
		2011-14	2015-18	2019-22	changed
	Panel A. High-Skilled AI-Complement Group Using Time-Invariant Skill Group Indicator				
0030	Managers in Marketing, Advertising, and Public Relations	H^{Non}	H^{Non}	H^{AI}	✓
0110	Computer and Information Systems Managers	H^{AI}	H^{AI}	H^{AI}	
0300	Architectural and Engineering Managers	H^{AI}	H^{AI}	H^{AI}	
0710	Management Analysts	H^{AI}	H^{AI}	H^{AI}	
0730	Other Business Operations and Management Specialists	H^{AI}	H^{AI}	H^{AI}	
0840	Financial Analysts	H^{AI}	H^{AI}	H^{AI}	
0950	Financial Specialists, All Other	H^{AI}	H^{AI}	H^{AI}	
1000	Computer Scientists and Systems Analysts/Network systems Analysts/Web Developers	H^{AI}	H^{AI}	H^{AI}	
1010	Computer Programmers	H^{AI}	H^{AI}	H^{AI}	
1020	Software Developers, Applications and Systems Software	H^{AI}	H^{AI}	H^{AI}	
1060	Database Administrators	H^{AI}	H^{AI}	H^{AI}	
1100	Network and Computer Systems Administrators	H^{AI}	H^{AI}	H^{AI}	
1200	Actuaries	H^{AI}	H^{AI}	H^{AI}	
1220	Operations Research Analysts	H^{AI}	H^{AI}	H^{AI}	
1240	Mathematical Science Occupations, All Other	H^{AI}	H^{AI}	H^{AI}	
1320	Aerospace Engineers	H^{AI}	H^{AI}	H^{AI}	
1350	Chemical Engineers	H^{Non}	H^{AI}	H^{AI}	✓
1400	Computer Hardware Engineers	H^{AI}	H^{AI}	H^{AI}	
1410	Electrical and Electronics Engineers	H^{AI}	H^{AI}	H^{AI}	
1430	Industrial Engineers, including Health and Safety	H^{AI}	H^{AI}	H^{AI}	
1440	Marine Engineers and Naval Architects	H^{AI}	H^{AI}	H^{AI}	
1450	Materials Engineers	H^{AI}	H^{AI}	H^{AI}	
1460	Mechanical Engineers	H^{AI}	H^{AI}	H^{AI}	
1530	Engineers, All Other	H^{AI}	H^{AI}	H^{AI}	
1650	Medical Scientists, and Life Scientists, All Other	H^{AI}	H^{AI}	H^{AI}	
1710	Atmospheric and Space Scientists	H^{AI}	H^{AI}	H^{AI}	
1760	Physical Scientists, All Other	H^{AI}	H^{AI}	H^{AI}	
1800	Economists and Market Researchers	H^{AI}	H^{AI}	H^{AI}	
2840	Technical Writers	H^{AI}	H^{AI}	H^{AI}	
4930	Sales Engineers	H^{AI}	H^{AI}	H^{AI}	
	Panel B. High-Skilled Not-Yet-AI Group Using Time-Invariant Skill Group Indicator				
0010	Chief Executives and Legislators/Public Administration	H^{Non}	H^{Non}	H^{Non}	
0020	General and Operations Managers	H^{Non}	H^{Non}	H^{Non}	
0100	Administrative Services Managers	H^{Non}	H^{Non}	H^{Non}	
0120	Financial Managers	H^{Non}	H^{Non}	H^{Non}	
0130	Human Resources Managers	H^{Non}	H^{Non}	H^{Non}	
0140	Industrial Production Managers	H^{Non}	H^{Non}	H^{Non}	
0150	Purchasing Managers	H^{Non}	H^{Non}	H^{Non}	
0205	Farmers, Ranchers, and Other Agricultural Managers	H^{Non}	H^{Non}	H^{Non}	
0220	Constructions Managers	H^{Non}	H^{Non}	H^{Non}	
0230	Education Administrators	H^{Non}	H^{Non}	H^{Non}	
0310	Food Service and Lodging Managers	H^{Non}	H^{Non}	H^{Non}	
0330	Gaming Managers	H^{Non}	H^{Non}	/	
0350	Medical and Health Services Managers	H^{Non}	H^{Non}	H^{Non}	
0360	Natural Science Managers	H^{Non}	H^{Non}	H^{Non}	
0410	Property, Real Estate, and Community Association Managers	H^{Non}	H^{Non}	H^{Non}	
0420	Social and Community Service Managers	H^{Non}	H^{Non}	H^{Non}	
0430	Managers, All Other (Including Postmasters)	H^{Non}	H^{Non}	H^{Non}	
0500	Agents and Business Managers of Artists, Performers, and Athletes	H^{Non}	H^{Non}	H^{Non}	
0510	Buyers and Purchasing Agents, Farm Products	H^{Non}	H^{Non}	H^{Non}	
0520	Wholesale and Retail Buyers, Except Farm Products	H^{Non}	H^{Non}	H^{Non}	
0530	Purchasing Agents, Except Wholesale, Retail, and Farm Products	H^{Non}	H^{Non}	H^{Non}	

OCC2010	Occupation title	Skill group indicator during			Ever
		2011-14	2015-18	2019-22	changed
0540	Claims Adjusters, Appraisers, Examiners, and Investigators	H^{Non}	H^{Non}	H^{Non}	
0600	Cost Estimators	H^{Non}	H^{Non}	H^{Non}	
0620	Human Resources, Training, and Labor Relations Specialists	H^{Non}	H^{Non}	H^{Non}	
0700	Logisticians	H^{Non}	H^{Non}	H^{Non}	
0720	Meeting and Convention Planners	H^{Non}	H^{Non}	H^{Non}	
0800	Accountants and Auditors	H^{Non}	H^{Non}	H^{Non}	
0810	Appraisers and Assessors of Real Estate	H^{Non}	H^{Non}	H^{Non}	
0820	Budget Analysts	H^{Non}	H^{Non}	H^{Non}	
0830	Credit Analysts	H^{Non}	H^{Non}	H^{Non}	
0850	Personal Financial Advisors	H^{Non}	H^{Non}	H^{Non}	
0860	Insurance Underwriters	H^{Non}	H^{Non}	H^{Non}	
0910	Credit Counselors and Loan Officers	H^{Non}	H^{Non}	H^{Non}	
0930	Tax Examiners and Collectors, and Revenue Agents	H^{Non}	H^{Non}	H^{Non}	
0940	Tax Preparers	H^{Non}	H^{Non}	H^{Non}	
1050	Computer Support Specialists	H^{Non}	H^{Non}	H^{Non}	
1300	Architects, Except Naval	H^{Non}	H^{Non}	H^{Non}	
1310	Surveyors, Cartographers, and Photogrammetrists	H^{Non}	H^{Non}	H^{Non}	
1360	Civil Engineers	H^{AI}	H^{AI}	H^{Non}	✓
1420	Environmental Engineers	H^{AI}	H^{Non}	H^{Non}	✓
1520	Petroleum, Mining and Geological Engineers, Including Mining Safety Engineers	H^{Non}	H^{Non}	H^{AI}	✓
1560	Surveying and Mapping Technicians	H^{Non}	H^{Non}	H^{Non}	
1600	Agricultural and Food Scientists	H^{Non}	H^{Non}	H^{Non}	
1610	Biological Scientists	H^{AI}	H^{Non}	H^{Non}	✓
1640	Conservation Scientists and Foresters	H^{Non}	H^{Non}	H^{Non}	
1720	Chemists and Materials Scientists	H^{Non}	H^{Non}	H^{Non}	
1820	Psychologists	H^{Non}	H^{Non}	H^{Non}	
1840	Social Scientists, All Other	H^{Non}	H^{Non}	H^{Non}	
2000	Counselors	H^{Non}	H^{Non}	H^{Non}	
2010	Social Workers	H^{Non}	H^{Non}	H^{Non}	
2020	Community and Social Service Specialists, All Other	H^{Non}	H^{Non}	H^{Non}	
2040	Clergy	H^{Non}	H^{Non}	H^{Non}	
2050	Directors, Religious Activities and Education	H^{Non}	H^{Non}	H^{Non}	
2100	Lawyers, and Judges, Magistrates, and other Judicial Workers	H^{Non}	H^{Non}	H^{Non}	
2200	Postsecondary Teachers	H^{Non}	H^{Non}	H^{Non}	
2300	Preschool and Kindergarten Teachers	H^{Non}	H^{Non}	H^{Non}	
2310	Elementary and Middle School Teachers	H^{Non}	H^{Non}	H^{Non}	
2320	Secondary School Teachers	H^{Non}	H^{Non}	H^{Non}	
2330	Special Education Teachers	H^{Non}	H^{Non}	H^{Non}	
2340	Other Teachers and Instructors	H^{Non}	H^{Non}	H^{Non}	
2400	Archivists, Curators, and Museum Technicians	H^{Non}	H^{Non}	H^{Non}	
2430	Librarians	H^{Non}	H^{Non}	H^{Non}	
2540	Teacher Assistants	H^{Non}	H^{Non}	H^{Non}	
2550	Education, Training, and Library Workers, All Other	H^{Non}	H^{Non}	H^{Non}	
2700	Actors, Producers, and Directors	H^{Non}	H^{Non}	H^{Non}	
2760	Entertainers and Performers, Sports and Related Workers, All Other	H^{Non}	H^{Non}	H^{Non}	
2810	Editors, News Analysts, Reporters, and Correspondents	H^{Non}	H^{Non}	H^{Non}	
2825	Public Relations Specialists	H^{Non}	H^{Non}	H^{Non}	
2850	Writers and Authors	H^{Non}	H^{Non}	H^{Non}	
2860	Media and Communication Workers, All Other	H^{Non}	H^{Non}	H^{Non}	
2920	Television, Video, and Motion Picture Camera Operators and Editors	H^{Non}	H^{Non}	H^{Non}	
3000	Chiropractors	H^{Non}	H^{Non}	H^{Non}	
3010	Dentists	H^{Non}	H^{Non}	H^{Non}	
3030	Dieticians and Nutritionists	H^{Non}	H^{Non}	H^{Non}	
3040	Optometrists	H^{Non}	H^{Non}	H^{Non}	
3060	Physicians and Surgeons	H^{Non}	H^{Non}	H^{Non}	
3110	Physician Assistants	H^{Non}	H^{Non}	H^{Non}	
3120	Podiatrists	H^{Non}	H^{Non}	H^{Non}	

OCC2010	Occupation title	Skill group indicator during			Ever
		2011-14	2015-18	2019-22	changed
3140	Audiologists	H^{Non}	H^{Non}	H^{Non}	
3150	Occupational Therapists	H^{Non}	H^{Non}	H^{Non}	
3160	Physical Therapists	H^{Non}	H^{Non}	H^{Non}	
3200	Radiation Therapists	H^{Non}	H^{Non}	H^{Non}	
3210	Recreational Therapists	H^{Non}	H^{Non}	H^{Non}	
3220	Respiratory Therapists	H^{Non}	H^{Non}	H^{Non}	
3230	Speech Language Pathologists	H^{Non}	H^{Non}	H^{Non}	
3260	Health Diagnosing and Treating Practitioners, All Other	H^{Non}	H^{Non}	H^{Non}	
3730	Supervisors, Protective Service Workers, All Other	H^{Non}	H^{Non}	H^{Non}	
4210	First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers	H^{Non}	H^{Non}	H^{Non}	
4320	First-Line Supervisors of Personal Service Workers	H^{Non}	H^{Non}	H^{Non}	
4460	Funeral Service Workers and Embalmers	H^{Non}	H^{Non}	H^{Non}	
4600	Childcare Workers	H^{Non}	H^{Non}	H^{Non}	
4620	Recreation and Fitness Workers	H^{Non}	H^{Non}	H^{Non}	
4640	Residential Advisors	H^{Non}	H^{Non}	H^{Non}	
4650	Personal Care and Service Workers, All Other	H^{Non}	H^{Non}	H^{Non}	
4700	First-Line Supervisors of Sales Workers	H^{Non}	H^{Non}	H^{Non}	
4800	Advertising Sales Agents	H^{Non}	H^{Non}	H^{Non}	
4820	Securities, Commodities, and Financial Services Sales Agents	H^{Non}	H^{Non}	H^{Non}	
4850	Sales Representatives, Wholesale and Manufacturing	H^{Non}	H^{Non}	H^{Non}	
4920	Real Estate Brokers and Sales Agents	H^{Non}	H^{Non}	H^{Non}	
4940	Telemarketers	H^{Non}	H^{Non}	H^{Non}	
4950	Door-to-Door Sales Workers, News and Street Vendors, and Related Workers	H^{Non}	H^{Non}	H^{Non}	
5000	First-Line Supervisors of Office and Administrative Support Workers	H^{Non}	H^{Non}	H^{Non}	
5100	Bill and Account Collectors	H^{Non}	H^{Non}	H^{Non}	
5520	Dispatchers	H^{Non}	H^{Non}	H^{Non}	
5840	Insurance Claims and Policy Processing Clerks	H^{Non}	H^{Non}	H^{Non}	
6200	First-Line Supervisors of Construction Trades and Extraction Workers	/	H^{Non}	H^{Non}	
7700	First-Line Supervisors of Production and Operating Workers	H^{Non}	H^{Non}	H^{Non}	
9000	Supervisors of Transportation and Material Moving Workers	H^{Non}	H^{Non}	H^{Non}	
9240	Railroad Conductors and Yardmasters	H^{Non}	H^{Non}	H^{Non}	
9260	Subway, Streetcar, and Other Rail Transportation Workers	H^{Non}	H^{Non}	H^{Non}	
	Panel C. Middle-Skilled Group Using Time-Invariant Skill Group Indicator				
0160	Transportation, Storage, and Distribution Managers	M	M	M	
0560	Compliance Officers, Except Agriculture	M	M	M	
0900	Financial Examiners	M	M	M	
1540	Drafters	M	M	M	
1550	Engineering Technicians, Except Drafters	M	M	M	
1700	Astronomers and Physicists	M	M	M	
1740	Environmental Scientists and Geoscientists	M	M	M	
1830	Urban and Regional Planners	M	M	M	
1900	Agricultural and Food Science Technicians	M	M	M	
1910	Biological Technicians	M	M	M	
1920	Chemical Technicians	M	M	M	
1930	Geological and Petroleum Technicians, and Nuclear Technicians	M	M	/	
1960	Life, Physical, and Social Science Technicians, All Other	M	M	M	
2140	Paralegals and Legal Assistants	M	M	M	
2150	Legal Support Workers, All Other	M	M	M	
2440	Library Technicians	M	M	M	
2600	Artists and Related Workers	M	M	M	
2630	Designers	M	M	M	
2800	Announcers	M	M	M	
2900	Broadcast and Sound Engineering Technicians and Radio Operators, and Media and Communication Equipment Workers, All Other	M	M	M	
2910	Photographers	M	M	M	
3050	Pharmacists	M	M	M	

OCC2010	Occupation title	Skill group indicator during			Ever
		2011-14	2015-18	2019-22	changed
3130	Registered Nurses	*M*	*M*	*M*	
3250	Veterinarians	*M*	*M*	*M*	
3300	Clinical Laboratory Technologists and Technicians	*M*	*M*	*M*	
3310	Dental Hygienists	*M*	*M*	*M*	
3320	Diagnostic Related Technologists and Technicians	*M*	*M*	*M*	
3400	Emergency Medical Technicians and Paramedics	*M*	*M*	*M*	
3410	Health Diagnosing and Treating Practitioner Support Technicians	*M*	*M*	*M*	
3500	Licensed Practical and Licensed Vocational Nurses	*M*	*M*	*M*	
3510	Medical Records and Health Information Technicians	*M*	*M*	*M*	
3520	Opticians, Dispensing	*M*	*M*	*M*	
3530	Health Technologists and Technicians, All Other	*M*	*M*	*M*	
3540	Healthcare Practitioners and Technical Occupations, All Other	*M*	*M*	*M*	
3600	Nursing, Psychiatric, and Home Health Aides	*M*	*M*	*M*	
3610	Occupational Therapy Assistants and Aides	*M*	*M*	*M*	
3620	Physical Therapist Assistants and Aides	*M*	*M*	*M*	
3630	Massage Therapists	*M*	*M*	*M*	
3640	Dental Assistants	*M*	*M*	*M*	
3650	Medical Assistants and Other Healthcare Support Occupations, All Other	*M*	*M*	*M*	
3900	Animal Control	*M*	*M*	*M*	
3910	Private Detectives and Investigators	*M*	*M*	*M*	
3930	Security Guards and Gaming Surveillance Officers	*M*	*M*	*M*	
3950	Law Enforcement Workers, All Other	*M*	*M*	*M*	
4000	Chefs and Cooks	*M*	*M*	*M*	
4010	First-Line Supervisors of Food Preparation and Serving Workers	*M*	*M*	*M*	
4030	Food Preparation Workers	*M*	*M*	*M*	
4040	Bartenders	*M*	*M*	*M*	
4050	Combined Food Preparation and Serving Workers, Including Fast Food	*M*	*M*	*M*	
4060	Counter Attendant, Cafeteria, Food Concession, and Coffee Shop	*M*	*M*	/	
4120	Food Servers, Nonrestaurant	*M*	*M*	*M*	
4130	Food Preparation and Serving Related Workers, All Other	*M*	*M*	*M*	
4140	Dishwashers	*M*	*M*	*M*	
4150	Host and Hostesses, Restaurant, Lounge, and Coffee Shop	*M*	*M*	*M*	
4200	First-Line Supervisors of Housekeeping and Janitorial Workers	*M*	*M*	*M*	
4220	Janitors and Building Cleaners	*M*	*M*	*M*	
4240	Pest Control Workers	*M*	*M*	*M*	
4250	Grounds Maintenance Workers	*M*	*M*	*M*	
4300	First-Line Supervisors of Gaming Workers	*M*	*M*	/	
4340	Animal Trainers	*M*	*M*	*M*	
4350	Nonfarm Animal Caretakers	*M*	*M*	*M*	
4400	Gaming Services Workers	*M*	*M*	*M*	
4420	Ushers, Lobby Attendants, and Ticket Takers	*M*	*M*	*M*	
4430	Entertainment Attendants and Related Workers, All Other	*M*	*M*	*M*	
4500	Barbers	*M*	*M*	*M*	
4510	Hairdressers, Hairstylists, and Cosmetologists	*M*	*M*	*M*	
4520	Personal Appearance Workers, All Other	*M*	*M*	*M*	
4540	Tour and Travel Guides	*M*	*M*	*M*	
4610	Personal Care Aides	*M*	*M*	*M*	
4720	Cashiers	*M*	*M*	*M*	
4740	Counter and Rental Clerks	*M*	*M*	*M*	
4750	Parts Salespersons	*M*	*M*	*M*	
4760	Retail Salespersons	*M*	*M*	*M*	
4810	Insurance Sales Agents	*M*	*M*	*M*	
4830	Travel Agents	*M*	*M*	*M*	
4840	Sales Representatives, Services, All Other	*M*	*M*	*M*	
4900	Models, Demonstrators, and Product Promoters	*M*	*M*	*M*	
5010	Switchboard Operators, Including Answering Service	*M*	*M*	*M*	
5020	Telephone Operators	*M*	*M*	*M*	
5110	Billing and Posting Clerks	*M*	*M*	*M*	
5120	Bookkeeping, Accounting, and Auditing Clerks	*M*	*M*	*M*	
5130	Gaming Cage Workers	*M*	*M*	/	

OCC2010	Occupation title	Skill group indicator during			Ever
		2011-14	2015-18	2019-22	changed
5140	Payroll and Timekeeping Clerks	*M*	*M*	*M*	
5150	Procurement Clerks	*M*	*M*	*M*	
5160	Bank Tellers	*M*	*M*	*M*	
5200	Brokerage Clerks	*M*	*M*	/	
5220	Court, Municipal, and License Clerks	*M*	*M*	*M*	
5230	Credit Authorizers, Checkers, and Clerks	*M*	*M*	*M*	
5240	Customer Service Representatives	*M*	*M*	*M*	
5250	Eligibility Interviewers, Government Programs	*M*	*M*	*M*	
5260	File Clerks	*M*	*M*	*M*	
5300	Hotel, Motel, and Resort Desk Clerks	*M*	*M*	*M*	
5310	Interviewers, Except Eligibility and Loan	*M*	*M*	*M*	
5320	Library Assistants, Clerical	*M*	*M*	*M*	
5330	Loan Interviewers and Clerks	*M*	*M*	*M*	
5340	New Account Clerks	*M*	*M*	*M*	
5350	Correspondent Clerks and Order CLerks	*M*	*M*	*M*	
5360	Human Resources Assistants, Except Payroll and Timekeeping	*M*	*M*	*M*	
5400	Receptionists and Information Clerks	*M*	*M*	*M*	
5410	Reservation and Transportation Ticket Agents and Travel Clerks	*M*	*M*	*M*	
5500	Cargo and Freight Agents	*M*	*M*	*M*	
5510	Couriers and Messengers	*M*	*M*	*M*	
5530	Meter Readers, Utilities	*M*	*M*	*M*	
5540	Postal Service Clerks	*M*	*M*	*M*	
5550	Postal Service Mail Carriers	*M*	*M*	*M*	
5560	Postal Service Mail Sorters, Processors, and Processing Machine Operators	*M*	*M*	*M*	
5600	Production, Planning, and Expediting Clerks	*M*	*M*	*M*	
5610	Shipping, Receiving, and Traffic Clerks	*M*	*M*	*M*	
5620	Stock Clerks and Order Fillers	*M*	*M*	*M*	
5630	Weighers, Measurers, Checkers, and Samplers, Recordkeeping	*M*	*M*	*M*	
5700	Secretaries and Administrative Assistants	*M*	*M*	*M*	
5810	Data Entry Keyers	*M*	*M*	*M*	
5820	Word Processors and Typists	*M*	*M*	*M*	
5850	Mail Clerks and Mail Machine Operators, Except Postal Service	*M*	*M*	*M*	
5860	Office Clerks, General	*M*	*M*	*M*	
5900	Office Machine Operators, Except Computer	*M*	*M*	*M*	
5910	Proofreaders and Copy Markers	*M*	*M*	*M*	
5920	Statistical Assistants	*M*	*M*	*M*	
5940	Office and Administrative Support Workers, All Other	*M*	*M*	*M*	
6010	Agricultural Inspectors	*M*	*M*	*M*	
6040	Graders and Sorters, Agricultural Products	*M*	*M*	*M*	
6050	Agricultural Sorkers, All Other	*M*	*M*	*M*	
6210	Boilermakers	*M*	*M*	*M*	
6220	Brickmasons, Blockmasons, and Stonemasons	*M*	*M*	*M*	
6230	Carpenters	*M*	*M*	*M*	
6240	Carpet, Floor, and Tile Installers and Finishers	*M*	*M*	*M*	
6250	Cement Masons, Concrete Finishers, and Terrazzo Workers	*M*	*M*	*M*	
6260	Construction Laborers	*M*	*M*	*M*	
6300	Paving, Surfacing, and Tamping Equipment Operators	*M*	*M*	/	
6320	Construction Equipment Operators Except Paving, Surfacing, and Tamping Equipment Operators	*M*	*M*	*M*	
6330	Drywall Installers, Ceiling Tile Installers, and Tapers	*M*	*M*	*M*	
6355	Electricians	*M*	*M*	*M*	
6360	Glaziers	*M*	*M*	*M*	
6400	Insulation Workers	*M*	*M*	*M*	
6420	Painters, Construction and Maintenance	*M*	*M*	*M*	
6440	Pipelayers, Plumbers, Pipefitters, and Steamfitters	*M*	*M*	*M*	
6460	Plasterers and Stucco Masons	*M*	*M*	*M*	
6515	Roofers	*M*	*M*	*M*	

OCC2010	Occupation title	Skill group indicator during			Ever
		2011-14	2015-18	2019-22	changed
6520	Sheet Metal Workers, Metal-Working	*M*	*M*	*M*	
6530	Structural Iron and Steel Workers	*M*	*M*	*M*	
6600	Helpers, Construction Trades	*M*	*M*	*M*	
6660	Construction and Building Inspectors	*M*	*M*	*M*	
6700	Elevator Installers and Repairers	*M*	*M*	*M*	
6710	Fence Erectors	*M*	*M*	*M*	
6720	Hazardous Materials Removal Workers	*M*	*M*	*M*	
6730	Highway Maintenance Workers	*M*	*M*	*M*	
6740	Rail-Track Laying and Maintenance Equipment Operators	*M*	*M*	*M*	
6765	Construction workers, All Other	*M*	*M*	*M*	
6800	Derrick, Rotary Drill, and Service Unit Operators, and Roustabouts, Oil, Gas, and Mining	*M*	*M*	*M*	
6820	Earth Drillers, Except Oil and Gas	*M*	*M*	*M*	
6830	Explosives Workers, Ordnance Handling Experts, and Blasters	*M*	*M*	*M*	
6840	Mining Machine Operators	*M*	*M*	*M*	
6940	Extraction workers, All Other	*M*	*M*	*M*	
7000	First-Line Supervisors of Mechanics, Installers, and Repairers	*M*	*M*	*M*	
7010	Computer, Automated Teller, and Office Machine Repairers	*M*	*M*	*M*	
7020	Radio and Telecommunications Equipment Installers and Repairers	*M*	*M*	*M*	
7030	Avionics Technicians	*M*	*M*	*M*	
7040	Electric Motor, Power Tool, and Related Repairers	*M*	*M*	*M*	
7100	Electrical and Electronics Repairers, Transportation Equipment, and Industrial and Utility	*M*	*M*	*M*	
7110	Electronic Equipment Installers and Repairers, Motor Vehicles	*M*	*M*	/	
7120	Electronic Home Entertainment Equipment Installers and Repairers	*M*	*M*	*M*	
7130	Security and Fire Alarm Systems Installers	*M*	*M*	*M*	
7140	Aircraft Mechanics and Service Technicians	*M*	*M*	*M*	
7150	Automotive Body and Related Repairers	*M*	*M*	*M*	
7160	Automotive Glass Installers and Repairers	*M*	*M*	*M*	
7200	Automotive Service Technicians and Mechanics	*M*	*M*	*M*	
7210	Bus and Truck Mechanics and Diesel Engine Specialists	*M*	*M*	*M*	
7220	Heavy Vehicle and Mobile Equipment Service Technicians and Mechanics	*M*	*M*	*M*	
7240	Small Engine Mechanics	*M*	*M*	*M*	
7260	Vehicle and Mobile Equipment Mechanics, Installers, and Repairers, All Other	*M*	*M*	*M*	
7300	Control and Valve Installers and Repairers	*M*	*M*	*M*	
7315	Heating, Air Conditioning, and Refrigeration Mechanics and Installers	*M*	*M*	*M*	
7320	Home Appliance Repairers	*M*	*M*	*M*	
7330	Industrial and Refractory Machinery Mechanics	*M*	*M*	*M*	
7340	Maintenance and Repair Workers, General	*M*	*M*	*M*	
7350	Maintenance Workers, Machinery	*M*	*M*	*M*	
7360	Millwrights	*M*	*M*	*M*	
7410	Electrical Power-Line Installers and Repairers	*M*	*M*	*M*	
7420	Telecommunications Line Installers and Repairers	*M*	*M*	*M*	
7430	Precision Instrument and Equipment Repairers	*M*	*M*	*M*	
7510	Coin, Vending, and Amusement Machine Servicers and Repairers	*M*	*M*	*M*	
7540	Locksmiths and Safe Repairers	*M*	*M*	*M*	
7560	Riggers	*M*	*M*	*M*	
7610	Helpers–Installation, Maintenance, and Repair Workers	*M*	*M*	*M*	
7630	Other Installation, Maintenance, and Repair Workers Including Wind Turbine Service Technicians, and Commercial Divers, and Signal and Track Switch Repairers	*M*	*M*	*M*	
7710	Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	*M*	*M*	/	
7720	Electrical, Electronics, and Electromechanical Assemblers	*M*	*M*	*M*	
7730	Engine and Other Machine Assemblers	*M*	*M*	*M*	
7740	Structural Metal Fabricators and Fitters	*M*	*M*	*M*	

OCC2010	Occupation title	Skill group indicator during			Ever
		2011-14	2015-18	2019-22	changed
7750	Assemblers and Fabricators, All Other	*M*	*M*	*M*	
7800	Bakers	*M*	*M*	*M*	
7810	Butchers and Other Meat, Poultry, and Fish Processing Workers	*M*	*M*	*M*	
7830	Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders	*M*	*M*	*M*	
7840	Food Batchmakers	*M*	*M*	*M*	
7850	Food Cooking Machine Operators and Tenders	*M*	*M*	*M*	
7900	Computer Control Programmers and Operators	*M*	*M*	*M*	
7920	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	*M*	*M*	*M*	
7930	Forging Machine Setters, Operators, and Tenders, Metal and Plastic	*M*	*M*	/	
7940	Rolling Machine Setters, Operators, and Tenders, metal and Plastic	*M*	*M*	/	
7950	Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	*M*	*M*	*M*	
8000	Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic	/	*M*	*M*	
8010	Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic	/	*M*	*M*	
8030	Machinists	*M*	*M*	*M*	
8040	Metal Furnace Operators, Tenders, Pourers, and Casters	*M*	*M*	*M*	
8100	Molders and Molding Machine Setters, Operators, and Tenders, Metal and Plastic	*M*	*M*	*M*	
8130	Tool and Die Makers	*M*	*M*	*M*	
8140	Welding, Soldering, and Brazing Workers	*M*	*M*	*M*	
8220	Metal workers and plastic workers, All Other	*M*	*M*	*M*	
8250	Prepress Technicians and Workers	*M*	*M*	*M*	
8300	Laundry and Dry-Cleaning Workers	*M*	*M*	*M*	
8310	Pressers, Textile, Garment, and Related Materials	*M*	*M*	*M*	
8320	Sewing Machine Operators	*M*	*M*	*M*	
8330	Shoe and Leather Workers and Repairers	*M*	*M*	*M*	
8350	Tailors, Dressmakers, and Sewers	*M*	*M*	*M*	
8400	Textile Bleaching and Dyeing, and Cutting Machine Setters, Operators, and Tenders	*M*	*M*	/	
8410	Textile Knitting and Weaving Machine Setters, Operators, and Tenders	*M*	*M*	/	
8420	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders	*M*	*M*	*M*	
8450	Upholsterers	*M*	*M*	*M*	
8460	Textile, Apparel, and Furnishings workers, All Other	*M*	*M*	*M*	
8500	Cabinetmakers and Bench Carpenters	*M*	*M*	*M*	
8510	Furniture Finishers	*M*	*M*	*M*	
8530	Sawing Machine Setters, Operators, and Tenders, Wood	*M*	*M*	*M*	
8540	Woodworking Machine Setters, Operators, and Tenders, Except Sawing	*M*	*M*	*M*	
8550	Woodworkers Including Model Makers and Patternmakers, All Other	*M*	*M*	*M*	
8600	Power Plant Operators, Distributors, and Dispatchers	*M*	*M*	*M*	
8610	Stationary Engineers and Boiler Operators	*M*	*M*	*M*	
8620	Water Wastewater Treatment Plant and System Operators	*M*	*M*	*M*	
8630	Plant and System Operators, All Other	*M*	*M*	*M*	
8640	Chemical Processing Machine Setters, Operators, and Tenders	*M*	*M*	*M*	
8650	Crushing, Grinding, Polishing, Mixing, and Blending Workers	*M*	*M*	*M*	
8710	Cutting Workers	*M*	*M*	*M*	
8720	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders	*M*	*M*	*M*	
8730	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders	*M*	*M*	*M*	
8740	Inspectors, Testers, Sorters, Samplers, and Weighers	*M*	*M*	*M*	
8750	Jewelers and Precious Stone and Metal Workers	*M*	*M*	*M*	
8760	Medical, Dental, and Ophthalmic Laboratory Technicians	*M*	*M*	*M*	

OCC2010	Occupation title	Skill group indicator during			Ever
		2011-14	2015-18	2019-22	changed
8800	Packaging and Filling Machine Operators and Tenders	M	M	M	
8810	Painting Workers and Dyers	M	M	M	
8830	Photographic Process Workers and Processing Machine Operators	M	M	M	
8850	Adhesive Bonding Machine Operators and Tenders	M	M	M	
8910	Etchers, Engravers, and Lithographers	M	M	M	
8920	Molders, Shapers, and Casters, Except Metal and Plastic	M	M	M	
8930	Paper Goods Machine Setters, Operators, and Tenders	M	M	M	
8940	Tire Builders	M	M	M	
8950	Helpers–Production Workers	M	M	M	
8965	Other Production Workers Including Semiconductor Processors and Cooling and Freezing Equipment Operators	M	M	M	
9040	Air Traffic Controllers and Airfield Operations Specialists	M	M	M	
9360	Automotive and Watercraft Service Attendants	M	M	M	
9510	Crane and Tower Operators	M	M	M	
9520	Dredge, Excavating, and Loading Machine Operators	M	M	/	
9560	Conveyor Operators and Tenders, and Hoist and Winch Operators	M	M	M	
9610	Cleaners of Vehicles and Equipment	M	M	M	
9620	Laborers and Freight, Stock, and Material Movers, Hand	M	M	M	
9630	Machine Feeders and Offbearers	M	M	M	
9640	Packers and Packagers, Hand	M	M	M	
9650	Pumping Station Operators	M	M	M	
9750	Material Moving Workers, All Other	M	M	M	
	Panel D. Low-Skilled Group Using Time-Invariant Skill Group Indicator				
2720	Athletes, Coaches, Umpires, and Related Workers	L	L	L	
2740	Dancers and Choreographers	L	L	L	
2750	Musicians, Singers, and Related Workers	L	L	L	
3700	First-Line Supervisors of Correctional Officers	L	L	L	
3710	First-Line Supervisors of Police and Detectives	L	L	L	
3720	First-Line Supervisors of Fire Fighting and Prevention Workers	L	L	L	
3740	Firefighters	L	L	L	
3750	Fire Inspectors	L	L	L	
3800	Sheriffs, Bailiffs, Correctional Officers, and Jailers	L	L	L	
3820	Police Officers and Detectives	L	L	L	
3940	Crossing Guards	L	L	L	
4110	Waiters and Waitresses	L	L	L	
4230	Maids and Housekeeping Cleaners	L	L	L	
4530	Baggage Porters, Bellhops, and Concierges	L	L	L	
6005	First-Line Supervisors of Farming, Fishing, and Forestry Workers	L	L	L	
6100	Fishing and Hunting Workers	L	L	L	
6120	Forest and Conservation Workers	L	L	L	
6130	Logging Workers	L	L	L	
9030	Aircraft Pilots and Flight Engineers	L	L	L	
9050	Flight Attendants and Transportation Workers and Attendants	L	L	L	
9100	Bus and Ambulance Drivers and Attendants	L	L	L	
9130	Driver/Sales Workers and Truck Drivers	L	L	L	
9140	Taxi Drivers and Chauffeurs	L	L	L	
9200	Locomotive Engineers and Operators	H^{Non}	H^{Non}	L	✓
9300	Sailors and marine oilers, and ship engineers	L	L	L	
9310	Ship and Boat Captains and Operators	L	L	L	
9350	Parking Lot Attendants	L	L	L	
9410	Transportation Inspectors	L	L	L	
9420	Transportation Workers, All Other	L	L	L	
9600	Industrial Truck and Tractor Operators	L	L	L	
9720	Refuse and Recyclable Material Collectors	L	L	L	

Table C.2: The Overlap Between 2-digit OCC2010 and Time-Variant Skill Groups, 2012-14

		Number of 4-digit occupations in skill group:				
2-digit occ. title	**4-digit OCC2010**	**High-skilled AI-complement group**	**High-skilled not-yet-AI group**	**Middle-skilled group**	**Low-skilled group**	**Total #occ.**
Management Occ.	0010-0430	2	18	1	0	21
Business and Financial Operations Occ.	0500-0950	4	18	2	0	24
Computer and Mathematical Occ.	1000-1240	8	1	0	0	9
Architecture and Engineering Occ.	1300-1560	10	5	2	0	17
Life, Physical, and Social Science Occ.	1600-1980	5	5	8	0	18
Community and Social Service Occ.	2000-2060	0	5	0	0	5
Legal Occ.	2100-2150	0	1	2	0	3
Education, Training, and Library Occ.	2200-2550	0	10	1	0	11
Arts, Design, Entertainment, Sports, and Media Occ.	2600-2920	1	7	5	3	16
Healthcare Practitioners and Technical Occ.	3000-3540	0	15	13	0	28
Healthcare Support Occ.	3600-3650	0	0	6	0	6
Protective Service Occ.	3700-3950	0	1	4	8	13
Food Preparation and Serving Related Occ.	4000-4150	0	0	10	1	11
Building and Grounds Cleaning and Maintenance Occ.	4200-4250	0	1	4	1	6
Personal Care and Service Occ.	4300-4650	0	6	11	1	18
Sales and Related Occ.	4700-4965	1	7	8	0	16
Office and Administrative Support Occ.	5000-5940	0	4	42	0	46
Farming, Fishing, and Forestry Occ.	6005-6130	0	0	3	4	7
Construction and Extraction Occ.	6200-6940	0	0	31	0	31
Installation, Maintenance, and Repair Occ.	7000-7630	0	0	32	0	32
Production Occ.	7700-8965	0	1	59	0	60
Transportation and Material Moving Occ.	9000-9750	0	4	11	12	27
Total		31	109	255	30	425

Notes: The counted occupations are from my final sample used for my main analysis. The 2-digit occupation classification used is from 2010 Census Occupational Classification. The 2-digit IPUMS-ACS OCC2010 code is mostly the same with 2010 Census Occupational Classification but further divides the following three 2-digit groups into more detailed ones: (1) "Business Operations Specialists" and "Financial Specialists" instead of "Business and Financial Operations Occ.;" (2) "Architecture and Engineering" and "Technicians" instead of "Architecture and Engineering Occ.;" (3) "Construction" and "Extraction" instead of "Construction and Extraction Occ." Since there is a one-to-one mapping between the 2-digit 2010 Census Occupational Classification and 2-digit O*NET-SOC code, I use the 2-digit 2010 Census Occupational Classification rather than the 2-digit IPUMS-ACS OCC2010 to better merge the job postings data to labor market outcome data. The coloumn of 4-digit OCC2010 shows the range of 4-digit OCC2010 code classified into each 2-digit group. The skill group indicator in this table is time-variant, which is consistent within years between 2011-14, 2015-18, and 2019-22.

Table C.3: The Overlap Between 2-digit OCC2010 and Time-Variant Skill Groups, 2015-18

2-digit occ. title	4-digit OCC2010	Number of 4-digit occupations in skill group: High-skilled AI-complement group	High-skilled not-yet-AI group	Middle-skilled group	Low-skilled group	Total #occ.
Management Occ.	0010-0430	2	18	1	0	21
Business and Financial Operations Occ.	0500-0950	4	18	2	0	24
Computer and Mathematical Occ.	1000-1240	8	1	0	0	9
Architecture and Engineering Occ.	1300-1560	10	5	2	0	17
Life, Physical, and Social Science Occ.	1600-1980	4	6	8	0	18
Community and Social Service Occ.	2000-2060	0	5	0	0	5
Legal Occ.	2100-2150	0	1	2	0	3
Education, Training, and Library Occ.	2200-2550	0	10	1	0	11
Arts, Design, Entertainment, Sports, and Media Occ.	2600-2920	1	7	5	3	16
Healthcare Practitioners and Technical Occ.	3000-3540	0	15	13	0	28
Healthcare Support Occ.	3600-3650	0	0	6	0	6
Protective Service Occ.	3700-3950	0	1	4	8	13
Food Preparation and Serving Related Occ.	4000-4150	0	0	10	1	11
Building and Grounds Cleaning and Maintenance Occ.	4200-4250	0	1	4	1	6
Personal Care and Service Occ.	4300-4650	0	6	11	1	18
Sales and Related Occ.	4700-4965	1	7	8	0	16
Office and Administrative Support Occ.	5000-5940	0	4	42	0	46
Farming, Fishing, and Forestry Occ.	6005-6130	0	0	3	4	7
Construction and Extraction Occ.	6200-6940	0	1	31	0	32
Installation, Maintenance, and Repair Occ.	7000-7630	0	0	32	0	32
Production Occ.	7700-8965	0	1	61	0	62
Transportation and Material Moving Occ.	9000-9750	0	4	11	12	27
Total		30	111	257	30	428

Notes: The counted occupations are from my final sample used for my main analysis. The 2-digit occupation classification used is from 2010 Census Occupational Classification. The 2-digit IPUMS-ACS OCC2010 code is mostly the same with 2010 Census Occupational Classification but further divides the following three 2-digit groups into more detailed ones: (1) "Business Operations Specialists" and "Financial Specialists" instead of "Business and Financial Operations Occ.;" (2) "Architecture and Engineering" and "Technicians" instead of "Architecture and Engineering Occ.;" (3) "Construction" and "Extraction" instead of "Construction and Extraction Occ." Since there is a one-to-one mapping between the 2-digit 2010 Census Occupational Classification and 2-digit O*NET-SOC code, I use the 2-digit 2010 Census Occupational Classification rather than the 2-digit IPUMS-ACS OCC2010 to better merge the job postings data to labor market outcome data. The coloumn of 4-digit OCC2010 shows the range of 4-digit OCC2010 code classified into each 2-digit group. The skill group indicator in this table is time-variant, which is consistent within years between 2011-14, 2015-18, and 2019-22.

Table C.4: The Overlap Between 2-digit OCC2010 and Time-Variant Skill Groups, 2019-21

		Number of 4-digit occupations in skill group:				
2-digit occ. title	**4-digit OCC2010**	**High-skilled AI-complement group**	**High-skilled not-yet-AI group**	**Middle-skilled group**	**Low-skilled group**	**Total #occ.**
Management Occ.	0010-0430	3	16	1	0	20
Business and Financial Operations Occ.	0500-0950	4	18	2	0	24
Computer and Mathematical Occ.	1000-1240	8	1	0	0	9
Architecture and Engineering Occ.	1300-1560	10	5	2	0	17
Life, Physical, and Social Science Occ.	1600-1980	4	6	7	0	17
Community and Social Service Occ.	2000-2060	0	5	0	0	5
Legal Occ.	2100-2150	0	1	2	0	3
Education, Training, and Library Occ.	2200-2550	0	10	1	0	11
Arts, Design, Entertainment, Sports, and Media Occ.	2600-2920	1	7	5	3	16
Healthcare Practitioners and Technical Occ.	3000-3540	0	15	13	0	28
Healthcare Support Occ.	3600-3650	0	0	6	0	6
Protective Service Occ.	3700-3950	0	1	4	8	13
Food Preparation and Serving Related Occ.	4000-4150	0	0	9	1	10
Building and Grounds Cleaning and Maintenance Occ.	4200-4250	0	1	4	1	6
Personal Care and Service Occ.	4300-4650	0	6	10	1	17
Sales and Related Occ.	4700-4965	1	7	8	0	16
Office and Administrative Support Occ.	5000-5940	0	4	40	0	44
Farming, Fishing, and Forestry Occ.	6005-6130	0	0	3	4	7
Construction and Extraction Occ.	6200-6940	0	1	30	0	31
Installation, Maintenance, and Repair Occ.	7000-7630	0	0	31	0	31
Production Occ.	7700-8965	0	1	56	0	57
Transportation and Material Moving Occ.	9000-9750	0	3	10	13	26
Total		31	108	244	31	414

Notes: The counted occupations are from my final sample used for my main analysis. The 2-digit occupation classification used is from 2010 Census Occupational Classification. The 2-digit IPUMS-ACS OCC2010 code is mostly the same with 2010 Census Occupational Classification but further divides the following three 2-digit groups into more detailed ones: (1) "Business Operations Specialists" and "Financial Specialists" instead of "Business and Financial Operations Occ.;" (2) "Architecture and Engineering" and "Technicians" instead of "Architecture and Engineering Occ.;" (3) "Construction" and "Extraction" instead of "Construction and Extraction Occ." Since there is a one-to-one mapping between the 2-digit 2010 Census Occupational Classification and 2-digit O*NET-SOC code, I use the 2-digit 2010 Census Occupational Classification rather than the 2-digit IPUMS-ACS OCC2010 to better merge the job postings data to labor market outcome data. The coloumn of 4-digit OCC2010 shows the range of 4-digit OCC2010 code classified into each 2-digit group. The skill group indicator in this table is time-variant, which is consistent within years between 2011-14, 2015-18, and 2019-22.

D ML Occupation Clusters

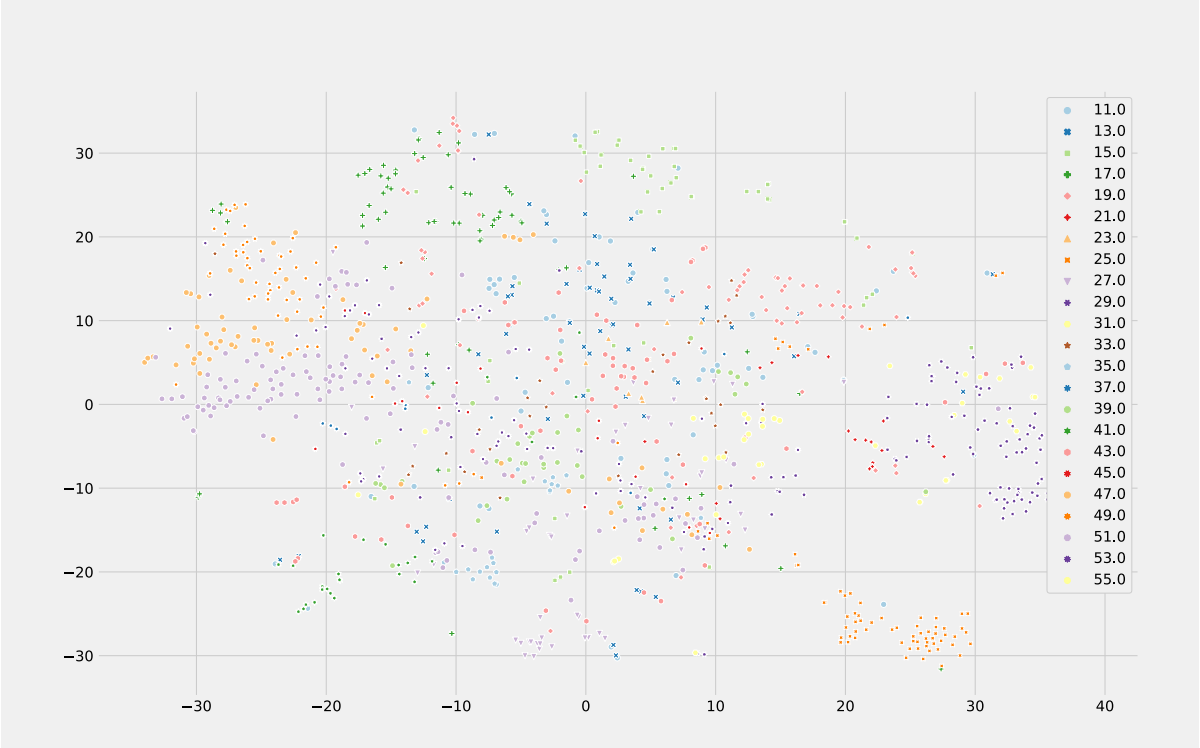
This section introduces how I construct the ML occupation clusters using job postings data and machine learning algorithms. I first extract over 1,800 skills from (1) the skill dictionary provided by Lightcast, formerly known as Burning Glass Technologies; (2) basic skills, technology skills, knowledge, and hot technologies from O*NET; and (3) my chosen AI phrases listed in Table 1. Some examples of these skills are "algorithm development", "audit software", "bioinformatics", "clerical support", "direct marketing", "equipment repair", and "javascript". Next, I match skills to the raw text of over 200 million job postings collected by LinkUp and calculate the frequency of each skill appeared in a posting. I then collapse the posting-skill matrix to an occupation-skill matrix as an occupation consists of numerous postings. Finally, I use machine learning clustering algorithms to cluster occupations based on the similarity in skills. Occupations with higher similarity in skills are supposed to fall into the same cluster.

To compare my proposed ML occupation clusters and Census/BLS 2-digit groups, I create a visualization of multi-dimensional skills by different occupation system in Appendix Figure D.1. Each marker in the figure represents an occupation. Different colors and symbols are used to distinguish clusters. Since there are over 1,800 skills (i.e., over 1,800 dimensions), I use a dimensionality reduction algorithm to reduce the high dimensions to only two dimensions. Thus, the x and y axis in Appendix Figure D.1 have no empirical meaning. They represent the projection of a high-dimensional data. The most important takeaway of this figure is the relative distance between occupations within the same cluster. The closer two markers are, the higher similarity in over 1,800 skills they share. Occupations within the same Census/BLS 2-digit group scatter everywhere (Appendix Figure D.1a),[28] while most occupations within the same ML group proposed by me cluster together (Appendix Figure D.1b). This finding further supports that the Census/BLS occupation system does not capture specific skill requirements of an occupation or skill similarity between occupations. Appendix Tables D.1-D.3 show the overlap between ML occupation clusters and the time-variant skill groups during different time periods, while Appendix Table D.4 lists the ML occupation cluster for all 4-digit occupations. The titles of each cluster are named based on 4-digit occupation titles within the cluster.

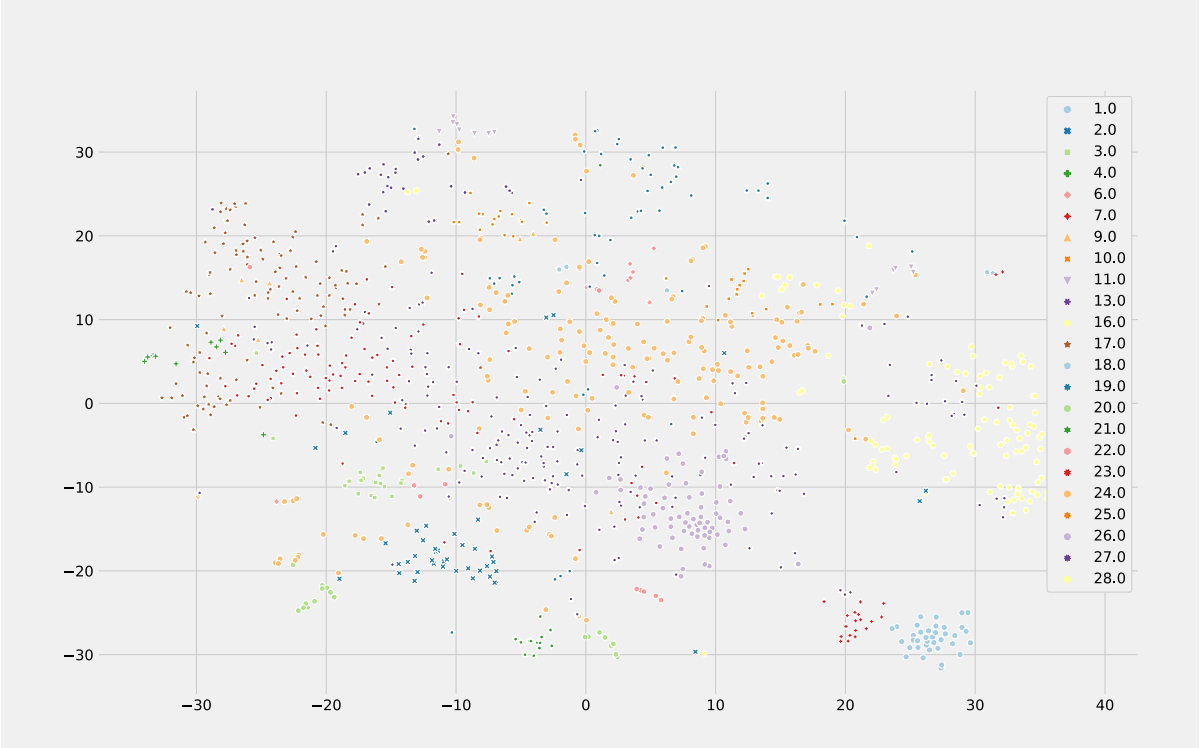
[28] There is a one-to-one mapping between the 2-digit Census Occupational Classification and the 2-digit BLS SOC groups. Thus, in Appendix Figure D.1a, the 2-digit SOC code is used to represent the broad occupation group.

Figure D.1: 2-D Visualization of Multi-Dimensional Skills

(a) By 2-digit Census Occupational Classification



(b) By ML Occupation Cluster



Notes: The AI Skill Prevalence Score is constructed at the state-year level and standardized within a year.

Table D.1: The Overlap Between ML Occupation Clusters and Time-Variant Skill Groups, 2012-14

	Number of 4-digit occupations in skill group:				
ML occupation cluster:	**High-skilled AI-complement group**	**High-skilled not-yet-AI group**	**Middle-skilled group**	**Low-skilled group**	**Total #occ.**
#1 Postsecondary educators	0	1	0	0	1
#2 Service & retail workers	0	6	23	1	30
#3 Specialized service professionals	0	1	3	0	4
#4 Construction & craft workers	0	0	5	0	5
#6 Finance professionals	2	3	1	0	6
#7 Pre-Secondary educators	0	5	0	0	5
#9 Building improvement technicians	0	0	3	0	3
#10 Public safety, policy, & social science	1	2	1	2	6
#11 Life sciences & quality assurance	3	3	1	0	7
#13 Engineering technicians	7	1	1	0	9
#16 Healthcare professionals & practitioners	0	18	17	0	35
#17 Technical maintenance workers	0	1	58	2	61
#18 Workplace safety & training specialists	0	1	0	0	1
#19 IT & data management	11	7	1	0	19
#20 Sales & marketing professionals	2	7	2	0	112
#21 Media production & broadcasting	1	3	3	0	7
#22 Regulatory compliance specialists	0	1	4	0	5
#23 Manual workers & machine operators	0	3	47	4	54
#24 Service & administrative professionals	0	32	36	6	74
#25 Infrastructure architecture & engineering	3	4	2	0	9
#26 Creative & communication support workers	0	0	2	2	4
#27 Technical & service support personnel	0	8	44	13	65
#28 Environmental & earth scientists	1	1	1	0	3
Total	31	108	255	30	424

Notes: The counted occupations are from my final sample used for my main analysis. The index for ML occupation clusters is a randomly chosen number. There is no meaning for this index. The skill group indicator in this table is time-variant, which is consistent within years between 2011-14, 2015-18, and 2019-22.

Table D.2: The Overlap Between ML Occupation Clusters and Time-Variant Skill Groups, 2015-18

	Number of 4-digit occupations in skill group:				
ML occupation cluster:	**High-skilled AI-complement group**	**High-skilled not-yet-AI group**	**Middle-skilled group**	**Low-skilled group**	**Total #occ.**
#1 Postsecondary educators	0	1	0	0	1
#2 Service & retail workers	0	6	23	1	30
#3 Specialized service professionals	0	1	3	0	4
#4 Construction & craft workers	0	0	5	0	5
#6 Finance professionals	2	3	1	0	6
#7 Pre-Secondary educators	0	5	0	0	5
#9 Building improvement technicians	0	0	3	0	3
#10 Public safety, policy, & social science	1	2	1	2	6
#11 Life sciences & quality assurance	3	3	1	0	7
#13 Engineering technicians	7	1	1	0	9
#16 Healthcare professionals & practitioners	0	18	17	0	35
#17 Technical maintenance workers	0	1	60	2	63
#18 Workplace safety & training specialists	0	1	0	0	1
#19 IT & data management	11	7	1	0	19
#20 Sales & marketing professionals	2	7	2	0	11
#21 Media production & broadcasting	1	3	3	0	7
#22 Regulatory compliance specialists	0	1	4	0	5
#23 Manual workers & machine operators	0	3	47	4	54
#24 Service & administrative professionals	0	32	36	6	74
#25 Infrastructure architecture & engineering	2	5	2	0	9
#26 Creative & communication support workers	0	0	2	2	4
#27 Technical & service support personnel	0	8	44	13	65
#28 Environmental & earth scientists	1	1	1	0	3
Total	30	109	257	30	426

Notes: The counted occupations are from my final sample used for my main analysis. The index for ML occupation clusters is a randomly chosen number. There is no meaning for this index. The skill group indicator in this table is time-variant, which is consistent within years between 2011-14, 2015-18, and 2019-22.

Table D.3: The Overlap Between ML Occupation Clusters and Time-Variant Skill Groups, 2019-22

	Number of 4-digit occupations in skill group:				
ML occupation cluster:	**High-skilled AI-complement group**	**High-skilled not-yet-AI group**	**Middle-skilled group**	**Low-skilled group**	**Total #occ.**
#1 Postsecondary educators	0	1	0	0	1
#2 Service & retail workers	0	6	23	1	30
#3 Specialized service professionals	0	1	3	0	4
#4 Construction & craft workers	0	0	5	0	5
#6 Finance professionals	2	3	1	0	6
#7 Pre-Secondary educators	0	5	0	0	5
#9 Building improvement technicians	0	0	3	0	3
#10 Public safety, policy, & social science	1	2	1	2	6
#11 Life sciences & quality assurance	3	3	1	0	7
#13 Engineering technicians	7	1	1	0	9
#16 Healthcare professionals & practitioners	0	18	17	0	35
#17 Technical maintenance workers	0	1	56	2	59
#18 Workplace safety & training specialists	0	1	0	0	1
#19 IT & data management	11	7	1	0	19
#20 Sales & marketing professionals	3	6	2	0	11
#21 Media production & broadcasting	1	3	3	0	7
#22 Regulatory compliance specialists	0	1	4	0	5
#23 Manual workers & machine operators	0	3	44	4	1
#24 Service & administrative professionals	0	31	33	6	70
#25 Infrastructure architecture & engineering	2	5	2	0	9
#26 Creative & communication support workers	0	0	2	2	4
#27 Technical & service support personnel	0	7	41	14	62
#28 Environmental & earth scientists	1	1	1	0	3
Total	31	106	244	31	412

Notes: The counted occupations are from my final sample used for my main analysis. The index for ML occupation clusters is a randomly chosen number. There is no meaning for this index. The skill group indicator in this table is time-variant, which is consistent within years between 2011-14, 2015-18, and 2019-22.

Table D.4: 4-digit Occupations by ML Occupation Cluster

OCC2010	Occupation title	OCC2010	Occupation title
	ML Occupation Cluster #1: Postsecondary Educators		
2200	Postsecondary Teachers		
	ML Occupation Cluster #2: Service and Retail Workers		
20	General and Operations Managers	4750	Parts Salespersons
310	Food Service and Lodging Managers	4760	Retail Salespersons
510	Buyers and Purchasing Agents, Farm Products	4900	Models, Demonstrators, and Product Promoters
520	Wholesale and Retail Buyers, Except Farm Products	4950	Door-to-Door Sales Workers, News and Street Vendors, and
2630	Designers		Related Workers
3520	Opticians, Dispensing	5300	Hotel, Motel, and Resort Desk Clerks
4000	Chefs and Cooks	5620	Stock Clerks and Order Fillers
4010	First-Line Supervisors of Food Preparation and Serving Workers	6010	Agricultural Inspectors
4030	Food Preparation Workers	7800	Bakers
4120	Food Servers, Nonrestaurant	7810	Butchers and Other Meat, Poultry, and Fish Processing Workers
4140	Dishwashers	7840	Food Batchmakers
4200	First-Line Supervisors of Housekeeping and Janitorial Workers	8300	Laundry and Dry-Cleaning Workers
4610	Personal Care Aides	8810	Painting Workers and Dyers
4700	First-Line Supervisors of Sales Workers	9050	Flight Attendants and Transportation Workers and Attendants
4720	Cashiers	9640	Packers and Packagers, Hand
4740	Counter and Rental Clerks		
	ML Occupation Cluster #3: Specialized Service Professionals		
3910	Private Detectives and Investigators	6360	Glaziers
4460	Funeral Service Workers and Embalmers	8450	Upholsterers
	ML Occupation Cluster #4: Construction and Craft Workers		
6210	Boilermakers	8500	Cabinetmakers and Bench Carpenters
6230	Carpenters	8540	Woodworking Machine Setters, Operators, and Tenders
6330	Drywall Installers, Ceiling Tile Installers, and Tapers		Except Sawing
	ML Occupation Cluster #6: Financial Management Professionals		
120	Financial Managers	840	Financial Analysts
800	Accountants and Auditors	950	Financial Specialists, All Other
820	Budget Analysts	5120	Bookkeeping, Accounting, and Auditing Clerks
	ML Occupation Cluster #7: Pre-Secondary Educators		
2310	Elementary and Middle School Teachers	2340	Other Teachers and Instructors
2320	Secondary School Teachers	2540	Teacher Assistants
2330	Special Education Teachers		
	ML Occupation Cluster #9: Building Improvement Technicians		
6240	Carpet, Floor, and Tile Installers and Finishers	6765	Construction Workers, All Other
6400	Insulation Workers		
	ML Occupation Cluster #10: Public Safety, Policy, and Social Science		
10	Chief Executives and Legislators/Public Administration	1830	Urban and Regional Planners
1640	Conservation Scientists and Foresters	3720	First-Line Supervisors of Fire Fighting and Prevention Workers
1800	Economists and Market Researchers	3820	Police Officers and Detectives
	ML Occupation Cluster #11: Life Sciences and Quality Assurance		
360	Natural Science Managers	1650	Medical Scientists, and Life Scientists, All Other
1240	Mathematical Science Occupations, All Other	1720	Chemists and Materials Scientists
1350	Chemical Engineers	1910	Biological Technicians
1610	Biological Scientists		
	ML Occupation Cluster #13: Engineering Technicians and Technologists		
1320	Aerospace Engineers	1460	Mechanical Engineers
1400	Computer Hardware Engineers	1530	Engineers, All Other
1410	Electrical and Electronics Engineers	1600	Agricultural and Food Scientists
1430	Industrial Engineers, including Health and Safety	1700	Astronomers and Physicists
1450	Materials Engineers		
	ML Occupation Cluster #16: Healthcare Professionals and Practitioners		
350	Medical and Health Services Managers	3230	Speech Language Pathologists
1820	Psychologists	3260	Health Diagnosing and Treating Practitioners, All Other
2000	Counselors	3300	Clinical Laboratory Technologists and Technicians
2010	Social Workers	3310	Dental Hygienists
2020	Community and Social Service Specialists, All Other	3320	Diagnostic Related Technologists and Technicians
2040	Clergy	3400	Emergency Medical Technicians and Paramedics
3030	Dieticians and Nutritionists	3410	Health Diagnosing and Treating Practitioner Support Technicians
3050	Pharmacists	3500	Licensed Practical and Licensed Vocational Nurses
3060	Physicians and Surgeons	3510	Medical Records and Health Information Technicians
3110	Physician Assistants	3530	Health Technologists and Technicians, All Other
3120	Podiatrists	3540	Healthcare Practitioners and Technical Occupations, All Other
3130	Registered Nurses	3600	Nursing, Psychiatric, and Home Health Aides
3140	Audiologists	3610	Occupational Therapy Assistants and Aides
3150	Occupational Therapists	3620	Physical Therapist Assistants and Aides
3160	Physical Therapists	3640	Dental Assistants
3200	Radiation Therapists	3650	Medical Assistants and Other Healthcare Support Occupations,
3210	Recreational Therapists		All Other
3220	Respiratory Therapists	5310	Interviewers, Except Eligibility and Loan

OCC2010	Occupation title	OCC2010	Occupation title
	ML Occupation Cluster #17: Technical Maintenance Workers		
1550	Engineering Technicians, Except Drafters	7420	Telecommunications Line Installers and Repairers
4250	Grounds Maintenance Workers	7430	Precision Instrument and Equipment Repairers
6260	Construction Laborers	7510	Coin, Vending, and Amusement Machine Servicers and Repairers
6300	Paving, Surfacing, and Tamping Equipment Operators		
6320	Construction Equipment Operators Except Paving, Surfacing, and Tamping Equipment Operators	7540	Locksmiths and Safe Repairers
		7710	Aircraft Structure, Surfaces, Rigging, and Systems Assemblers
6355	Electricians	7720	Electrical, Electronics, and Electromechanical Assemblers
6440	Pipelayers, Plumbers, Pipefitters, and Steamfitters	7900	Computer Control Programmers and Operators
6500	Reinforcing Iron and Rebar Workers	7930	Forging Machine Setters, Operators, and Tenders, Metal and Plastic
6520	Sheet Metal Workers, Metal-Working		
6530	Structural Iron and Steel Workers	7950	Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic
6600	Helpers, Construction Trades		
6700	Elevator Installers and Repairers	7960	Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic
6730	Highway Maintenance Workers		
6740	Rail-Track Laying and Maintenance Equipment Operators	8000	Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic
6800	Derrick, Rotary Drill, and Service Unit Operators, and Roustabouts, Oil, Gas, and Mining		
		8010	Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic
6820	Earth Drillers, Except Oil and Gas		
7000	First-Line Supervisors of Mechanics, Installers, and Repairers	8030	Machinists
7010	Computer, Automated Teller, and Office Machine Repairers	8130	Tool and Die Makers
7020	Radio and Telecommunications Equipment Installers and Repairers	8140	Welding, Soldering, and Brazing Workers
7030	Avionics Technicians	8150	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic
7040	Electric Motor, Power Tool, and Related Repairers		
7100	Electrical and Electronics Repairers, Transportation Equipment, and Industrial and Utility	8210	Tool Grinders, Filers, and Sharpeners
		8220	Metal Workers and Plastic Workers, All Other
7130	Security and Fire Alarm Systems Installers	8600	Power Plant Operators, Distributors, and Dispatchers
7140	Aircraft Mechanics and Service Technicians	8610	Stationary Engineers and Boiler Operators
7150	Automotive Body and Related Repairers	8620	Water Wastewater Treatment Plant and System Operators
7200	Automotive Service Technicians and Mechanics	8630	Plant and System Operators, All Other
7210	Bus and Truck Mechanics and Diesel Engine Specialists	8740	Inspectors, Testers, Sorters, Samplers, and Weighers
7220	Heavy Vehicle and Mobile Equipment Service Technicians and Mechanics	8965	Other Production Workers Including Semiconductor Processors and Cooling and Freezing Equipment Operators
7240	Small Engine Mechanics	9240	Railroad Conductors and Yardmasters
7300	Control and Valve Installers and Repairers	9410	Transportation Inspectors
7315	Heating, Air Conditioning, and Refrigeration Mechanics and Installers	9420	Transportation Workers, All Other
		9510	Crane and Tower Operators
7330	Industrial and Refractory Machinery Mechanics	9520	Dredge, Excavating, and Loading Machine Operators
7340	Maintenance and Repair Workers, General	9650	Pumping Station Operators
7350	Maintenance Workers, Machinery	9750	Material moving workers, All Other
7360	Millwrights		
7410	Electrical Power-Line Installers and Repairers		
	ML Occupation Cluster #18: Workplace Safety and Training Specialists		
130	Human Resources Managers		
	ML Occupation Cluster #19: IT and Data Management Specialists		
100	Administrative Services Managers		Analysts/Web Developers
110	Computer and Information Systems Managers	1010	Computer Programmers
140	Industrial Production Managers	1020	Software Developers, Applications and Systems Software
150	Purchasing Managers	1050	Computer Support Specialists
220	Constructions Managers	1060	Database Administrators
300	Architectural and Engineering Managers	1100	Network and Computer Systems Administrators
530	Purchasing Agents, Except Wholesale, Retail, and Farm Products	1200	Actuaries
700	Logisticians	1220	Operations Research Analysts
710	Management Analysts	2840	Technical Writers
1000	Computer Scientists and Systems Analysts/Network Systems	5920	Statistical Assistants
	ML Occupation Cluster #20: Sales and Marketing Professionals		
30	Managers in Marketing, Advertising, and Public Relations	4820	Securities, Commodities, and Financial Services Sales Agents
730	Other Business Operations and Management Specialists	4840	Sales Representatives, Services, All Other
2825	Public Relations Specialists	4850	Sales Representatives, Wholesale and Manufacturing
2850	Writers and Authors	4930	Sales Engineers
4800	Advertising Sales Agents	4940	Telemarketers
4810	Insurance Sales Agents		
	ML Occupation Cluster #21: Media Production and Broadcasting		
1710	Atmospheric and Space Scientists	2900	Broadcast and Sound Engineering Technicians and Radio Operators, and Media and Communication Equipment Workers, All Other
2600	Artists and Related Workers		
2700	Actors, Producers, and Directors		
2800	Announcers	2920	Television, Video, and Motion Picture Camera Operators and Editors
2810	Editors, News Analysts, Reporters, and Correspondents		
	ML Occupation Cluster #22: Regulatory Compliance Specialists		
430	Managers, All Other (Including Postmasters)	7120	Electronic Home Entertainment Equipment Installers and Repairers
560	Compliance Officers, Except Agriculture		
900	Financial Examiners	7320	Home Appliance Repairers

OCC2010	Occupation title
	ML Occupation Cluster #23: Manual Workers and Machine Operators
4220	Janitors and Building Cleaners
4230	Maids and Housekeeping Cleaners
5540	Postal Service Clerks
5550	Postal Service Mail Carriers
5560	Postal Service Mail Sorters, Processors, and Processing Machine Operators
5610	Shipping, Receiving, and Traffic Clerks
5850	Mail Clerks and Mail Machine Operators, Except Postal Service
5900	Office Machine Operators, Except Computer
6050	Agricultural Workers, All Other
6220	Brickmasons, Blockmasons, and Stonemasons
6250	Cement Masons, Concrete Finishers, and Terrazzo Workers
6420	Painters, Construction and Maintenance
6940	Extraction Workers, All Other
7160	Automotive Glass Installers and Repairers
7260	Vehicle and Mobile Equipment Mechanics, Installers, and Repairers, All Other
7560	Riggers
7610	Helpers–Installation, Maintenance, and Repair Workers
7700	First-Line Supervisors of Production and Operating Workers
7730	Engine and Other Machine Assemblers
7740	Structural Metal Fabricators and Fitters
7750	Assemblers and Fabricators, All Other
7830	Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders
7850	Food Cooking Machine Operators and Tenders
7920	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic
7940	Rolling Machine Setters, Operators, and Tenders, Metal and Plastic
8040	Metal Furnace Operators, Tenders, Pourers, and Casters
8100	Molders and Molding Machine Setters, Operators, and Tenders, Metal and Plastic
8200	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic
8310	Pressers, Textile, Garment, and Related Materials
8320	Sewing Machine Operators
8340	Shoe Machine Operators and Tenders
8400	Textile Bleaching and Dyeing, and Cutting Machine Setters, Operators, and Tenders
8410	Textile Knitting and Weaving Machine Setters, Operators, and Tenders
8420	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders
8510	Furniture Finishers
8530	Sawing Machine Setters, Operators, and Tenders, Wood
8640	Chemical Processing Machine Setters, Operators, and Tenders
8650	Crushing, Grinding, Polishing, Mixing, and Blending Workers
8710	Cutting Workers
8720	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders
8730	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders
8760	Medical, Dental, and Ophthalmic Laboratory Technicians
8800	Packaging and Filling Machine Operators and Tenders
8850	Adhesive Bonding Machine Operators and Tenders
8860	Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders
8920	Molders, Shapers, and Casters, Except Metal and Plastic
8930	Paper Goods Machine Setters, Operators, and Tenders
8940	Tire Builders
8950	Helpers–Production Workers
9000	Supervisors of Transportation and Material Moving Workers
9260	Subway, Streetcar, and Other Rail Transportation Workers
9300	Sailors and Marine Oilers, and Ship Engineers
9560	Conveyor Operators and Tenders, and Hoist and Winch Operators
9600	Industrial Truck and Tractor Operators
9620	Laborers and Freight, Stock, and Material Movers, Hand
9630	Machine Feeders and Offbearers
9720	Refuse and Recyclable Material Collectors
	ML Occupation Cluster #24: Service and Administrative Professionals
160	Transportation, Storage, and Distribution Managers
205	Farmers, Ranchers, and Other Agricultural Managers
230	Education Administrators
330	Gaming Managers
410	Property, Real Estate, and Community Association Managers
420	Social and Community Service Managers
500	Agents and Business Managers of Artists, Performers, and Athletes
540	Claims Adjusters, Appraisers, Examiners, and Investigators
620	Human Resources, Training, and Labor Relations Specialists
720	Meeting and Convention Planners
810	Appraisers and Assessors of Real Estate
830	Credit Analysts
850	Personal Financial Advisors
860	Insurance Underwriters
910	Credit Counselors and Loan Officers
930	Tax Examiners and Collectors, and Revenue Agents
1310	Surveyors, Cartographers, and Photogrammetrists
1560	Surveying and Mapping Technicians
1900	Agricultural and Food Science Technicians
1920	Chemical Technicians
1930	Geological and Petroleum Technicians, and Nuclear Technicians
1960	Life, Physical, and Social Science Technicians, All Other
2050	Directors, Religious Activities and Education
2100	Lawyers, and Judges, Magistrates, and Other Judicial Workers
2140	Paralegals and Legal Assistants
2150	Legal Support Workers, All Other
2400	Archivists, Curators, and Museum Technicians
2430	Librarians
2440	Library Technicians
2550	Education, Training, and Library Workers, All Other
2860	Media and Communication Workers, All Other
3700	First-Line Supervisors of Correctional Officers
3710	First-Line Supervisors of Police and Detectives
3730	Supervisors, Protective Service Workers, All Other
3750	Fire Inspectors
3800	Sheriffs, Bailiffs, Correctional Officers, and Jailers
3900	Animal Control
3930	Security Guards and Gaming Surveillance Officers
4300	First-Line Supervisors of Gaming Workers
4320	First-Line Supervisors of Personal Service Workers
4530	Baggage Porters, Bellhops, and Concierges
4540	Tour and Travel Guides
4620	Recreation and Fitness Workers
4640	Residential Advisors
4830	Travel Agents
4920	Real Estate Brokers and Sales Agents
5000	First-Line Supervisors of Office and Administrative Support Workers
5100	Bill and Account Collectors
5110	Billing and Posting Clerks
5140	Payroll and Timekeeping Clerks
5150	Procurement Clerks
5160	Bank Tellers
5200	Brokerage Clerks
5220	Court, Municipal, and License Clerks
5240	Customer Service Representatives
5250	Eligibility Interviewers, Government Programs
5320	Library Assistants, Clerical
5330	Loan Interviewers and Clerks
5340	New Account Clerks
5350	Correspondent clerks and order clerks
5360	Human Resources Assistants, Except Payroll and Timekeeping
5400	Receptionists and Information Clerks
5500	Cargo and Freight Agents
5520	Dispatchers
5600	Production, Planning, and Expediting Clerks
5700	Secretaries and Administrative Assistants
5810	Data Entry Keyers
5840	Insurance Claims and Policy Processing Clerks
5860	Office Clerks, General
5910	Proofreaders and Copy Markers
5940	Office and Administrative Support Workers, All Other
6005	First-Line Supervisors of Farming, Fishing, and Forestry Workers
6840	Mining Machine Operators
9040	Air Traffic Controllers and Airfield Operations Specialists
	ML Occupation Cluster #25: Infrastructure Architecture and Engineering
600	Cost Estimators
1300	Architects, Except Naval
1360	Civil Engineers
1420	Environmental Engineers
1440	Marine Engineers and Naval Architects
1520	Petroleum, Mining and Geological Engineers, Including Mining Safety Engineers
1540	Drafters
6200	First-Line Supervisors of Construction Trades and Extraction Workers
6660	Construction and Building Inspectors

OCC2010	Occupation title	OCC2010	Occupation title
	ML Occupation Cluster #26: Creative and Communication Support Workers		
2740	Dancers and Choreographers	5820	Word Processors and Typists
5020	Telephone Operators	9130	Driver/Sales Workers and Truck Drivers
	ML Occupation Cluster #27: Technical and Service Support Personnel		
940	Tax Preparers	5510	Couriers and Messengers
2300	Preschool and Kindergarten Teachers	5530	Meter Readers, Utilities
2720	Athletes, Coaches, Umpires, and Related Workers	5630	Weighers, Measurers, Checkers, and Samplers, Recordkeeping
2750	Musicians, Singers, and Related Workers	6040	Graders and Sorters, Agricultural Products
2910	Photographers	6100	Fishing and Hunting Workers
3000	Chiropractors	6120	Forest and Conservation Workers
3010	Dentists	6130	Logging Workers
3040	Optometrists	6460	Plasterers and Stucco Masons
3250	Veterinarians	6515	Roofers
3630	Massage Therapists	6710	Fence Erectors
3740	Firefighters	6720	Hazardous Materials Removal Workers
3940	Crossing Guards	6830	Explosives Workers, Ordnance Handling Experts, and Blasters
3950	Law Enforcement Workers, All Other	7110	Electronic Equipment Installers and Repairers, Motor Vehicles
4040	Bartenders	7550	Manufactured Building and Mobile Home Installers
4050	Combined Food Preparation and Serving Workers, Including Fast Food	7630	Other Installation, Maintenance, and Repair Workers Including Wind Turbine Service Technicians, and Commercial Divers, and Signal and Track Switch Repairers
4060	Counter Attendant, Cafeteria, Food Concession, and Coffee Shop		
4110	Waiters and Waitresses	8060	Model Makers and Patternmakers, Metal and Plastic
4130	Food Preparation and Serving Related Workers, All Other	8250	Prepress Technicians and Workers
4150	Host and Hostesses, Restaurant, Lounge, and Coffee Shop	8330	Shoe and Leather Workers and Repairers
4210	First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers	8350	Tailors, Dressmakers, and Sewers
		8460	Textile, Apparel, and Furnishings Workers, All Other
4240	Pest Control Workers	8550	Woodworkers Including Model Makers and Patternmakers, All Other
4340	Animal Trainers		
4350	Nonfarm Animal Caretakers	8750	Jewelers and Precious Stone and Metal Workers
4400	Gaming Services Workers	8830	Photographic Process Workers and Processing Machine Operators
4420	Ushers, Lobby Attendants, and Ticket Takers	8910	Etchers, Engravers, and Lithographers
4430	Entertainment Attendants and Related Workers, All Other	9030	Aircraft Pilots and Flight Engineers
4500	Barbers	9100	Bus and Ambulance Drivers and Attendants
4510	Hairdressers, Hairstylists, and Cosmetologists	9140	Taxi Drivers and Chauffeurs
4520	Personal Appearance Workers, All Other	9200	Locomotive Engineers and Operators
4600	Childcare Workers	9230	Railroad Brake, Signal, and Switch Operators
5010	Switchboard Operators, Including Answering Service	9310	Ship and Boat Captains and Operators
5130	Gaming Cage Workers	9350	Parking Lot Attendants
5230	Credit Authorizers, Checkers, and Clerks	9360	Automotive and Watercraft Service Attendants
5260	File Clerks	9610	Cleaners of Vehicles and Equipment
5410	Reservation and Transportation Ticket Agents and Travel Clerks		
	ML Occupation Cluster #28: Environmental and Earth Scientists		
360	Natural Science Managers	1760	Physical Scientists, All Other
1740	Environmental Scientists and Geoscientists	1840	Social Scientists, All Other

Notes: There are 10 occupations that do not have any observations in 2012-2021 IPUMS-ACS data. These occupations are: Reinforcing Iron and Rebar Workers (6500), Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic (7960), Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic (8150), Tool Grinders, Filers, and Sharpeners (8210) from ML Occupation Cluster #17 Technical Maintenance Workers; Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic (8200), Shoe Machine Operators and Tenders (8340), Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders (8860) from ML Occupation Cluster #23 Manual Workers and Machine Operators; Manufactured Building and Mobile Home Installers (7550), Model Makers and Patternmakers, Metal and Plastic (8060), Railroad Brake, Signal, and Switch Operators (9230) from ML Occupation Cluster #27 Technical and Service Support Personnel. They are not included in my main analysis as my sampling period is between 2012 and 2021.