ESSAYS ON IMPACTS OF ARTIFICIAL INTELLIGENCE ON LABOR MARKET OUTCOMES AND EDUCATIONAL CHOICES

By

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ABSTRACT

This dissertation examines impacts of Artificial Intelligence (AI) on labor market outcomes and educational choices. The first chapter focuses on labor supply by exploring the relationship between the growth of AI and college major choices. The second chapter turns to labor demand, studying the impacts of AI job postings on labor market outcomes of heterogeneous skill groups. The last chapter analyzes how AI adoption in firms affects gender wage gaps.

The first chapter explores how the rise in AI shapes college major choice. I propose a new method to measure how well a major prepares students to work with AI by matching phrases for AI subfields with college major descriptions. I then define AI skill-related majors as those that provide AI-related skill training. Those majors that are most complementary to AI have systematically high growth rates of bachelor's degree conferrals from 1990 to 2019. In contrast, I find evidence suggesting that majors that are most exposed to AI-driven substitution grow relatively slowly, especially at elite universities.

In the second chapter, I study effects of 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.

The last chapter analyzes the link between gender wage gaps and AI adoption. Using a real-time, high-frequency data on AI adoption in business, I construct measures for current, expected, and continuing AI adoption. AI adoption at the state-month level narrows within-occupation gender wage gaps in mean hourly wages, whereas AI adoption at the industry-month level exhibits a non-monotonic pattern in within-industry, between-occupation gender wage gaps across different percentiles of the wage distribution. The gap widens at the 10^{th} percentile and the median, but shrinks at the 90^{th} percentile. However, using data on online job postings that require AI skills, I find that a higher share of AI postings benefits women more than men across the wage distribution.

This dissertation is dedicated to my parents.
Thank you for always believing in me.

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INTRODUCTION

The past decades have witnessed rapid technological advances that have profoundly impacted the economy, driving productivity growth, the creation of new tasks, changes in skill requirements, job displacement, and wage inequality. Although the impacts of past technologies, such as computerization, automation, and industrial robots, on the labor market have been studied extensively, the influence of Artificial Intelligence (AI), which has grown rapidly over the last decade, remains less discussed but continues to expand.

The key difference between previous technologies and AI is the type of tasks they can perform. Past technologies like automation and robots are compatible with routine tasks because these tasks are decomposed into a series of explicitly programmed steps. Existing literature studying these past technologies (e.g., Krusell et al., 2000; Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018a,b, 2019, 2020, 2021, 2022; Brussevich et al., 2019; Acemoglu et al., 2020; Deming and Noray, 2020; Moll et al., 2021) finds that middle-skilled or less educated workers are negatively affected in terms of employment and earnings, while assumes high-skilled workers who specialize in abstract tasks that require decision making and problem solving are unaffected. However, AI can "mimic" human reasoning by learning from the big data to predict patterns and make rational decisions (LeCun et al., 2015; Zhang et al., 2022). Thus, AI can not only complement workers and increase their productivity, but also put some high-skilled workers at the threat of being displaced. Therefore, it is important to understand the impact of AI on the labor market, as policymakers should implement measures to reduce inequality and provide guidance to workers on enhancing their comparative advantage when selecting majors and seeking employment.

There is a growing literature studying the implications for the labor market of AI, focusing on job displacements, changes in skill requirements, and wage inequality. On the one hand, advances in AI technologies enhance AI's ability to perform tasks and increase technical capital, thus displacing workers (e.g., Acemoglu et al., 2022; Benmelech et al., 2024; Eloundou et al., 2024). On the other hand, AI can boost the productivity of workers with AI-developing skills (e.g., machine learning, deep learning, natural language processing) and those who utilize AI-powered tools such as Large Language Models (LLMs) and Generative AI, thus increasing the demand for AI skills (e.g., Hanson, 2021; Autor et al., 2024; Carvajal et al., 2024).

However, there are several gaps in existing research on AI, both theoretical and empirical. First, most studies focus on the demand side of the labor market, such as employment and wages, with less attention paid to the impact of AI on labor supply. Second, empirical work primarily examines the substitution effect of AI and its labor market consequences, with limited exploration of the mechanisms through which AI's complementarity affects workers with different skill sets. Third, while a small but growing body of literature investigates the gender gap in AI adoption (Park and Gelles-Watnick, 2023; Aldasoro et al., 2024; Carvajal et al., 2024; Stöhr et al., 2024; Humlum and Vestergaard, 2025), particularly regarding Generative AI tools like ChatGPT, there is little evidence on how AI adoption differentially impacts wages for women and men.

My dissertation attempts to address these gaps. I first explore the influences of AI on the labor supply side by focusing on college major choices under the growth of AI, which are presented in Chapter 1. By matching phrases of AI subfields or applications with college major descriptions, I define AI skill-related majors as those that provide trainings in AI-related skills and prepare students to produce AI, improve the performance of AI, or perform tasks complemented by AI after graduation. The relevance of AI to college majors is then measured by using (1) number of matched AI phrases and (2) changes in academic publications or relative search intensities on AI phrases. In contrast to this major-AI relatedness measure which captures how well a major prepares people to work with AI, I also propose a major-AI exposure measure which captures how easy it is for AI to substitute for the tasks of a major. This major-AI exposure measure is constructed by matching occupations to college majors and using occupational-level AI exposure scores from Felten et al. (2018, 2021) and Webb (2019). Majors that are most closely related to AI have experienced significantly higher growth rates of bachelor's degrees conferred over the past three decades. I also document a positive relationship between degrees conferred in AI skill-related majors and increases in search intensities or academic publications on rapid-growing AI subfields (e.g., deep learning, machine learning, data mining). In addition, students are less likely to choose majors that are more exposed to AI-driven substitution, especially at elite universities.

Chapter 2 turns to analyze how AI impacts the labor demand side. It focuses on AI-developing skills, such as deep learning and machine learning, and measures the effects of online job postings requiring AI skills on labor market outcomes of four skill groups, which are high-skilled AI-complement, high-skilled not-yet-AI, middle-skilled, and low-skilled. I first introduce and analyze a task-based framework extended from Acemoglu and Autor (2011), Acemoglu and Restrepo (2018a), and Autor et al. (2024) to study the economic impacts of AI on these four skill groups regarding job tasks and relative wages, which motivates my empirical analysis. I assume that AI has a higher productivity than automation so that AI can perform more abstract or complex tasks while automation can only perform simpler tasks. My model implies that AI can expand the set of tasks performed by high-skilled labor and widen the wage gap between high-skilled AI-complement group and other skill groups. Leveraging the data on AI job postings at the state-year level, I document a steady increase in the proportion of AI postings for the high-skilled AI-complement group throughout my sampling period, 2012–21. This group experiences significant growth in both employment and wages associated with an increase in the demand for AI-developing skills. More specifically, compared to the low-skilled group, the abstract and AI-intensive occupations have 56 more people employed per 100,000 capita and a 2.5% growth in mean hourly wages associated with a 1 percentage point increase in the AI posting share at the state-year level. The abstract but not-yet-AI occupations also have a significant growth, but much smaller in magnitude compared to high-skilled AI-complement ones. Middle-skilled occupations experience wage declines associated with increased variation in the demand for AI-developing skills across job tasks. Thess findings suggest that gaps in employment and wages between high-skilled AI-intensive occupations and other skill groups expand as the labor market increasingly prioritizes workers with AI skills, aligning with the implications of my theoretical model.

Finally, Chapter 3 investigates the link between AI adoption and gender wage gaps. If AI has differential effects on tasks requiring different skill sets, the wage impact of AI is likely to be unevenly distributed between women and men, since these two groups of workers tend to be employed in different types of jobs. By utilizing high-frequency data on businesses' AI adoption for producing goods or services, I first find that AI adoption at the state-month level reduces the gender gap in mean hourly wages within occupations, suggesting that on average women benefit more than men from AI adoption in firms. To study the distributional effect of AI adoption, I then use the industry-month level AI adoption data to capture industry-specific trends in technological changes and employ the within-industry, between-occupation variation. I document a non-monotonic pattern in the relationship between AI adoption and gender wage gaps at the 10^{th} percentile, median, mean, and 90^{th} percentile. The gap expands at the bottom and middle of the wage distribution, but shrinks at the top. Although this high-frequency AI adoption data could reflect AI's substitution, complementarity, or both, I use job postings data to more accurately capture AI's complementarity, as indicated by the anticipated demand for AI skills proxied by job vacancies. Results show that gender wage gaps narrow across the wage distribution associated with a higher share of AI postings at the state-year level, with a stronger correlation at the upper end of the distribution.

By studying the impacts of AI on educational choices and inequalities in wages and employment, this dissertation provides insights into the economic consequences of AI. It highlights the importance of upskilling and reskilling to help individuals better adapt to changes in job requirements driven by AI, as well as the need for training programs and policy interventions to support workers in remaining competitive in the labor market.

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CHAPTER 1

COLLEGE MAJOR CHOICES UNDER THE RAPID GROWTH OF GENERAL-PURPOSE TECHNOLOGY: A STUDY ON AI

1.1 Introduction

The growth of emerging technologies profoundly influences society. On the one hand, technological advances improve living standards and productivity, and even create new job opportunities. On the other hand, they potentially increase wage inequality and cause job displacement. Understanding impacts of technological progress is important to both individuals and policymakers, as technological advances change skill requirements in the labor market as well as the task content of production (Acemoglu and Restrepo, 2019). Individuals need to acquire new skills to make themselves less likely to be replaced by new technologies, while colleges need to adjust curriculum to better align students' major choices with changes in skill requirements for the workforce shaped by new technologies.

Unlike traditional technologies such as computerization and industrial automation, Artificial Intelligence (AI) is compatible with more abstract tasks since AI can analyze big data, predict patterns, and inform decision making (Russell and Norvig, 2021). In this way, AI is more likely to impose threats to the employment prospects of those working in cognitive or abstract fields, while computerization and industrial automation are likely to replace people specialized in routine tasks, especially those in the manufacturing sector (Zhang, 2019; Nedelkoska et al., 2021; Acemoglu and Restrepo, 2022a,b). As newly emerging AI technologies such as deep learning and machine learning have substantially improved AI's performance (LeCun et al., 2015; Zhang et al., 2022) and AI's compatibility with task content of production (Acemoglu et al., 2022), workers who perform tasks that can be performed by these technologies are more likely to be replaced by AI, while those who acquire AI-complementary skills may experience employment and earnings gains (Deming and Noray, 2020; Grennan and Michaely, 2020; Alekseeva et al., 2021; Acemoglu et al., 2022). Yet there is little evidence on how people adjust their skill acquisition and educational choices in response to changes in demand for AI skills.

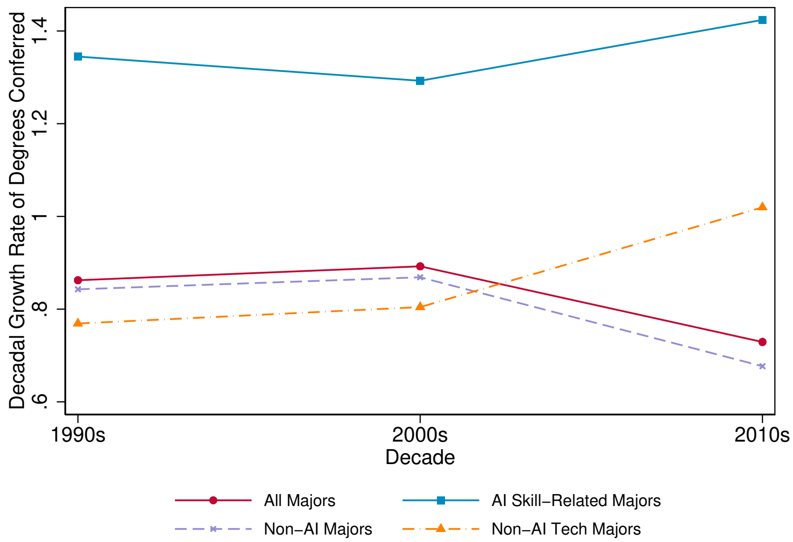
This paper investigates the relationship between the rise in AI and students' college major choices. By matching phrases for AI skills and applications with college major descriptions, I first define AI skill-related majors as those that have concentrations in AI technologies. These majors better prepare students to produce AI, improve the performance of AI, or use AI capabilities to complement their job tasks. Figure 1.1 displays decadal growth rates of bachelor's degree recipients by major from 1990-2019. Compared to the 1990s, the growth rate in completing AI majors was smaller in the 2000s but became much higher in the 2010s. This growth rate has been consistently higher than all majors, non-AI majors, and non-AI tech majors.

To distinguish general trends from responses to technological advances, I further classify AI skill-related majors into three categories, ranging from the most specific to the most general: (1) majors that are most complementary to AI; (2) majors with concentrations in AI-related computer and information processing technologies; and (3) majors associated with general computer skills which are the basic concepts and skills that students need to acquire if they plan to specialize in AI in the future. Next, I construct a measure of AI relatedness (denoted "AI Relevance Score" hereafter) to capture how well a major prepares students to work with AI using two data sources: relative Google search intensities on AI technologies and the number of academic publications in AI subfields. In addition, to capture AI exposure of a major (i.e., how likely students graduating with a major will perform tasks that are highly exposed to AI), I map occupations to college majors and separately aggregate the occupational-level AI exposure measures constructed by Felten et al. (2018, 2021) and Webb (2019) at the college major level.

I first document that, on average, majors that are most complementary to AI have experienced a decadal growth rate of 53.3% in bachelor's degrees conferred over the past three decades. Majors associated with general computer skills also grew fast in the 2010s. These findings are consistent with the trends of degree completion shown in Figure 1.1, as well as the upward trend in undergraduates completing Computer Science (CS) degrees during the 2010s documented by Zhang et al. (2022).

I then explore the relationship between AI Relevance Score (i.e., a major's complementarity

Figure 1.1 Decadal Growth Rates of Bachelor's Degree Recipients



Notes: Non-AI tech majors refer to STEM majors that are not AI skill-related.

with AI) and college major choices. Over 1990-2019, as fast-growing AI subfields (big data, data mining, deep learning, and machine learning) and AI itself are more intensively discussed by the public or studied by researchers, there is faster growth in completing majors that are most complementary to AI or general computer majors. When students witness the growing popularity of AI, they may view it as a signal for the increasing demand for AI skills. Thus, they may become more likely to choose majors that provide AI skill training to better prepare themselves to work with AI after graduation.

Unlike the positive relationship between a major's complementarity with AI and degree completion, I document a negative relationship between AI exposure and degree completion, especially when restricting to top 100 or top 50 universities in the U.S. This negative relationship indicates that students in top-end universities tend to avoid choosing majors with high AI exposure, thus being less likely to perform tasks that are more substitutable by AI.

Following the theoretical work on skill-biased technological change (e.g., Katz and Murphy, 1992; Acemoglu and Autor, 2011) and subsequent studies on how automation (e.g., Autor and Dorn, 2013; Moll et al., 2022) and industrial robots (e.g., Humlum, 2019; Acemoglu and Restrepo, 2020) affect wage inequality and job polarization, there is a growing literature exploring impacts of

AI on labor market outcomes. Acemoglu et al. (2022) use online job vacancies data and find that establishments with high AI exposure increase recruitment of workers with AI skills and reduce non-AI hiring, especially after 2014. Grennan and Michaely (2020) show that sell-side analysts with stocks that are more exposed to AI tend to leave the job, while those who stay reallocate their efforts to tasks that need more soft skills. These studies show that AI not only displaces workers with high AI exposure, but also complements those with AI skills. As a complement to these papers that focus on how AI impacts the labor market, I study how students choose their majors in response to the rapid growth of AI.

This paper also contributes to the work on college major choices by considering the role of technological change. Previous studies have investigated how college major choices respond to expected earnings (Long et al., 2015), local shocks such as local job losses (Acton, 2021), students' abilities (Arcidiacono, 2004), gender preferences (Zafar, 2013; Porter and Serra, 2020), and peer effects (De Giorgi et al., 2010; Zölitz and Feld, 2021). Dauth et al. (2021) and Di Giacomo and Lerch (2023) find that higher exposure to automation technologies increases college enrollment in Germany and the U.S., respectively. Zhang et al. (2023) explore the IT-labor relationship and find that IT complements labor with a master's degree or above. Humlum and Meyer (2022) document a wage premium in Denmark for majors concentrating in firms that produce AI. The most closely related paper to this one is Hemelt et al. (2023), who use online job vacancies data to define majors to be general (e.g., Business and Engineering) and specific (e.g., Nursing) based on how skills associated with each major differ across areas. They find a positive (negative) correlation between earnings and demand for cognitive and financial skills (social and basic computer skills). Unlike Hemelt et al. (2023), I classify majors based on whether they are related to AI to explore whether undergraduates respond to changes in a major's complementarity with or exposure to AI.

Finally, this paper introduces a novel measure of AI complementarity at the college major level. By leveraging Google search intensity and academic publications data on AI subfields, this measure – the AI Relevance Score – captures an objective view of how closely a college major provides up-to-date, popular skills that are related to AI.

The rest of the paper proceeds as follows. Section 1.2 introduces how to define AI skill-related majors and proposes measures for a major's AI exposure and complementarity with AI. Section 1.3 describes the data and presents the empirical strategy. Section 1.4 discusses the main results. Section 1.5 concludes.

1.2 Measuring AI Exposure and Relatedness

Section 1.2.1 first presents a methodology of measuring major-AI exposure by mapping occupations to college majors and using occupational-level AI exposure measures constructed by the existing literature. I then define AI skill-related majors in Section 1.2.2 by directly matching phrases for AI skills and applications to college major descriptions. Section 1.2.3 introduces AI Relevance Score which captures the complementarity of AI. Section 1.2.4 provides distributions of these AI measures.

1.2.1 AI Major Exposure

I study three different measures of AI Occupational Exposure (AIOE)[1] to construct college majors' exposure to AI by matching occupations to college majors. All of these AIOE measures capture the compatibility of AI and occupational tasks. The higher the AIOE score is, the more likely AI can perform and substitute labor in tasks of an occupation.

The first measure is from Webb (2019), who extracts verb-noun phrases from AI-related patents and matches them with verb-noun phrases in occupational descriptions from the Occupational Information Network (O*NET) database. Occupations matched with more AI patents are classified as more exposed to AI since they have more overlap-ping tasks with AI capabilities.

The second measure is from Felten et al. (2018), who use the Electronic Frontier Foundation (EFF) AI Progress Measurement dataset to track the progress on performance across AI applications (e.g., speech recognition, generating images) between 2010 and 2015. They map these AI applications to the 52 occupational abilities listed by O*NET and use the rate of improvements in AI performance to construct an ability-level AI exposure. Their AIOE is a weighted sum of 52 O*NET abilities' AI exposure, where weights are an ability's prevalence and importance within

[1] Although the Felten et al. (2018, 2021) and Webb (2019) occupational-level AI exposure measures are named differently, I use AI Occupational Exposure (AIOE) hereafter for convenience.

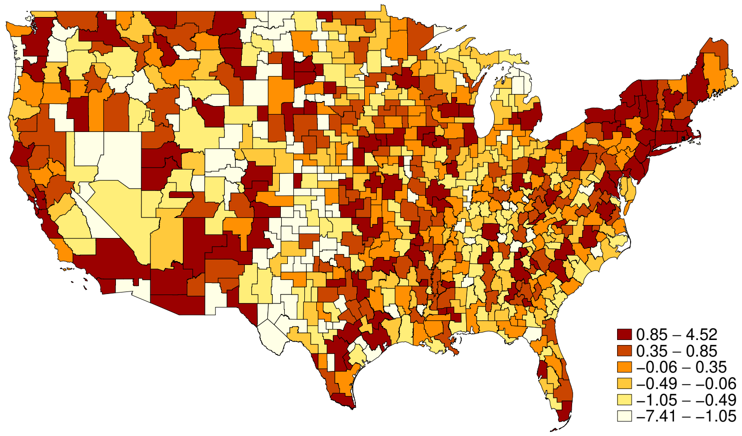
each occupation from O*NET.

The third measure is from Felten et al. (2021). Unlike Felten et al. (2018), the authors use a crowd-sourced dataset to link AI applications (e.g., image recognition, language modeling) chosen from the EFF dataset to the 52 O*NET occupational abilities. They conduct a survey on "gig workers" from Amazon's Mechanical Turk (mTurk) web service by asking these respondents whether they think each chosen AI application is related to each of the 52 O*NET occupational abilities. A matrix of relatedness between AI applications and abilities is then created based on the survey responses. Similar with Felten et al. (2018), the AIOE is calculated as a weighted sum of the ability-level AI exposure.

In Appendix Table 1A.1, occupations with the highest (lowest) scores are the most (least) exposed to AI. Tasks of the highest ranking occupations, i.e., occupations that are the most exposed to AI, are more compatible with AI while the least exposed occupations are mostly labor-intensive. Although these three AIOE measures are not highly correlated (with correlations between 0.10 and 0.30), the highest (or lowest) scoring occupations are similar regardless of which measure is used for ranking.

Figure 1.2 presents the geographic distribution of AI exposure by commuting zone (CZ) using the Felten et al. (2021) AIOE measure. CZs with a darker color have underwent higher exposure to AI. People who live in CZs with higher AI exposure are more likely to be replaced by AI in the labor market than those who live in CZs with lower AI exposure. The most exposed CZs are largely concentrated in metropolitan cities, e.g., New York City, Chicago, Miami, and Los Angeles. This finding is robust to the Felten et al. (2018) and Webb (2019) AIOE measures with the distribution shown in Appendix Figure 1A.1. It is worth noting that CZs with high AI exposure are different from those that are most exposed to routine employment, trade, or robots. Autor et al. (2013) show that CZs with the highest routine employment shares are human capital-intensive or manufacturing-intensive regions, while the latter ones are also highly exposed to trade. Acemoglu and Restrepo (2020) document that some CZs in the rust belt and Texas have been the most exposed to industrial robots.

Figure 1.2 AI Occupational Exposure (AIOE) by Commuting Zone, 2019



Notes: The Felten et al. (2021) AIOE measure is aggregated to the commuting zone level.

I then map occupations to college majors and construct AI Major Exposure (AIME) measures using each of the above three AIOE measures separately. AIME captures how likely students graduating with a major will perform tasks with high AI exposure. I use the American Community Survey (ACS) data[2] to determine the most common occupation for a major. The AIME score for major m in year t is constructed as follows:

$$\text{AIME}_{m,t} = \mathbf{1}\{o^* = \arg\max_o emp_{o,m,t}\} \times \text{AIOE}_{o^*}, \tag{1.1}$$

where $emp_{o,m,t}$ is the number of employed workers of occupation o in year t graduating with major m. $\mathbf{1}\{o^* = \arg\max_o emp_{o,m,t}\}$ denotes the most common occupation for major m in year t, which is the occupation with the largest number of employed people within the group of students graduating with the same major. AIOE_{o^*} is one of the three AIOE measures for major m's most common occupation o^*.[3] Thus, a total of three AIME measures are constructed. Students graduating with a major with a higher AIME score are more likely to work in occupations that are more exposed to AI. That is, they are more likely to perform tasks with a higher likelihood of being substituted by AI in the labor market.[4]

[2] ACS provides employment data by occupations and college majors starting from 2009. The 2018 Standard Occupational Classification (SOC) code is used to represent each occupation. The 4-digit Field of Degree (degfieldd) code classified by the Census Bureau is used to represent each major and is mapped to the 2020 6-digit Classification of Instructional Program (CIP) code in this paper for consistency using the crosswalk between the Field of Degree and CIP code provided by the Census Bureau.

[3] All of the Felten et al. (2018, 2021) and Webb (2019) AIOE measures are time-invariant.

[4] Another way to construct the AIME measure could be to weight AIOE using the proportion of people with a

Table 1.1 College Majors with the Highest/Lowest AIME Scores in 2019

Rank	Highest Scoring	Lowest Scoring
1	Actuarial Science	Sports, Kinesiology, and Physical Education/Fitness, Other
2	Accounting	Parks, Recreation, and Leisure Studies
3	Accounting and Related Services, Other	Parks, Recreation, Leisure, Fitness, and Kinesiology, Other
4	Accounting and Finance	Exercise Science and Kinesiology
5	Business/Managerial Economics	Sports, Kinesiology, and Physical Education/Fitness, General
6	Accounting and Business/Management	Parks, Recreation, and Leisure Facilities Management, General
7	Accounting Technology/Technician and Bookkeeping	Sport and Fitness Administration/Management
8	Auditing	Security System Installation, Repair, and Inspection Technology/Technician
9	Investments and Securities	Musical Instrument Fabrication and Repair
10	International Finance	Vehicle Emissions Inspection and Maintenance Technology/Technician

Notes: The AIME scores are constructed by using the Felten et al. (2021) AIOE and equation (1.1).

Table 1.1 shows college majors with the highest and lowest AIME scores in 2019 constructed by using the Felten et al. (2021) AIOE measure and equation (1.1). College majors with the highest exposure to AI, i.e., the highest AIME scores, are mostly Accounting and Finance majors. AI and IT are more compatible with accounting or finance tasks (Boukherouaa et al., 2021; Hasan, 2021; Cao, 2022). The least exposed majors align students with labor-intensive occupations that also require social skills. Appendix Table 1A.2 presents that Architecture, Chemical Engineering, and Visual and Per-forming Arts majors are also highly exposed to AI according to the other two AIME measures. Improvements in text-to-image and text-to-video AI such as DALL·E and Sora developed by OpenAI impact the creative industries (Anantrasirichai and Bull, 2022; Cetinic and She, 2022). Venkatasubramanian (2019) shows that AI is used to support chemical engineers and may transform this industry.

specific occupation within the group of people graduating with the same college major:

$$\text{AIME}_{m,t} = \sum_{o} \frac{emp_{o,m,t}}{emp_{m,t}} \times \text{AIOE}_o, \tag{1.2}$$

where $emp_{m,t}$ is the number of all employed workers in year t graduating with major m. However, this AIME measure is noiser than that constructed by the most common occupation method using equation (1.1). Since students graduating with the same major may choose different occupations, one major may have multiple weights. About 80% of majors are matched to over 100 occupations. The extreme case is that one major matches to 510 occupations. Thus, this "weighting" version of AIME might be averaged out, resulting in little variation in its distribution which will be discussed further in Section 1.2.4. This multiple weights issue may introduce noise in the AIME measure, making it less precise. By assigning a weight of one to the most common occupation as shown in equation (1.1) might address this issue.

1.2.2 Defining AI Skill-Related Majors

In contrast to the AIME score, which captures how easy it is for AI to substitute for the tasks of a major, I propose a new methodology to measure how well a major prepares students to work with AI. The biggest difference between this new measure and the AIME score discussed in Section 1.2.1 is that the former captures a major's complementarity with AI while the latter captures substitutability. Thus, these two measures are polar opposites.

To measure a major's complementarity with AI, I first define AI skill-related majors as those that provide students with AI skill training to better work with AI by mapping AI skills and applications to college major descriptions. The National Center for Education Statistics (NCES) provides a short description for each major represented by a 6-digit Classification of Instructional Program (CIP) code, which briefly describes the main concentrations of and what skills students can learn from a major/program.[5] For each 2020 CIP code, the NCES provides information on the program's title, description, and whether this CIP code, its title, or its definition underwent a notable change compared to the previous version.

Next, I extract phrases for AI skills and applications from Zhang et al. (2022) and titles and topics of top journals and conferences in the field of AI (e.g., Institute of Electrical and Electronics Engineers (IEEE) and Association for Computing Machinery (ACM)). If a major's description includes any of the chosen AI phrases, I consider it as an AI skill-related major. I classify these chosen AI phrases into three categories (from the most specific to the most general) based on Zhang et al. (2022): skills and applications that are the most closely related to AI (category 1), AI-related computer and information processing technologies (category 2), and general computer skills (category 3). Table 1.2 lists all chosen phrases in each category. If a chosen AI phrase is exactly included in a major's description, it will be considered as "matched" to this major. If the number of a major's matched AI phrases from category g ($g \in \{1, 2, 3\}$) is non-zero, then this major will be classified as an AI skill-related major in category g. Majors in category 1 have concentrations in the most specific AI skills and applications, while those in category 3 are associated with general

[5] CIP code was originally developed by NCES in 1980. Revisions occurred in 1985, 1990, 2000, 2010, and 2020.

Table 1.2 Phrases for AI Skills and Applications

Category	Phrases
Category 1: Skills and applications that are the most closely related to AI	artificial intelligence, augmented reality (AR), autonomous driving, big data, computer graphics, computer vision, data mining, deep learning, machine learning, multimedia, natural language processing (NLP), neural network, pattern recognition, robot/robotics, speech recognition, virtual reality (VR), voice recognition, 3D modeling
Category 2: AI-related computer and information processing technologies	cloud computing, computational intelligence, computational biology, computer-aided design (CAD)/ computer-aided drafting/CAD application, computer network, cybernetics, image processing, internet, internet of things (IoT), symbolic inference
Category 3: General computer skills	automatic control, automation, cognitive science/cognitive engineering, computer programming, computing theory, geographic information system (GIS), industrial internet, information system, information technology, integrated circuit, intelligent control, microchip/chip design, neuroscience, phenotype, remote sensing, software engineering, statistics, telecommunication, wireless communication

computer skills. If a major's description is matched with phrases in multiple categories, it will be classified into the category with more specific skills (i.e., the category with a smaller index). For example, if a major's description includes phrases in both categories 1 and 2, it will be considered as a category 1 major. In this way, there is no overlap between different categories.

Table 1.3 shows four examples of college major descriptions: one from each category of AI skill-related majors and a non-AI skill-related major. The phrases in red, blue, and orange are the matched AI phrases in categories 1, 2, and 3, respectively, of the corresponding major. The full lists of majors in each category of AI skill-related ones are presented in Appendix Tables 1A.3 to 1A.5. It is worth noting that a bigger number of matched AI phrases does not imply that more advanced AI skills are the concentrations of a major. A smaller number does not indicate that only preliminary AI skills can be learned from choosing this major, either. This number of matched AI phrases only objectively shows how many AI skills or applications students can acquire from the corresponding major as listed in its description provided by NCES. In other words, a greater number of matched AI phrases indicates that more versatile AI skills are the main concentrations of this major, while a smaller number implies that students learn fewer but more specific AI skills from choosing the corresponding major.

Although CIP codes have underwent revisions in 2000, 2010, and 2020, none of the college major descriptions changed in 2010 compared to the 2000 version and most of the descriptions

Table 1.3 Examples of AI Skill-Related/Non-AI Skill-Related Majors with Descriptions

2020 CIP Code	2020 CIP Title	Description	Is It an AI-Skill-Related Major?
11.0102	Artificial Intelligence	A program that focuses on the symbolic inference, representation, and simulation by computers and software of human learning and reasoning processes and capabilities, and the computer modeling of human motor control and motion. Includes instruction in computing theory, cybernetics, human factors, natural language processing, and applicable aspects of engineering, technology, and specific end-use applications.	Yes, category 1.
15.1305	Electrical/Electronics Drafting and Electrical/Electronics CAD/CADD	A program that prepares individuals to apply technical knowledge and skills to develop working schematics and representations in support of electrical/electronic engineers, computer engineers, and related professionals. Includes instruction in basic electronics, electrical systems and computer layouts; electrode-mechanical drafting; manufacturing circuitry; computer-aided drafting (cad); and electrical systems specification interpretation.	Yes, category 2.
15.1204	Computer Software Technology/Technician	A program that prepares individuals to apply basic engineering principles and technical skills to support engineers in developing, implementing, and evaluating computer software and program applications. Includes instruction in computer programming, programming languages, databases, user interfaces, networking and warehousing, encryption and security, software testing and evaluation, and customization.	Yes, category 3.
52.0301	Accounting	A program that prepares individuals to practice the profession of accounting and to perform related business functions. Includes instruction in accounting principles and theory, financial accounting, managerial accounting, cost accounting, budget control, tax accounting, legal aspects of accounting, auditing, reporting procedures, statement analysis, planning and consulting, business information systems, accounting research methods, professional standards and ethics, and applications to specific for-profit, public, and non-profit organizations.	No.

Notes: Phrases in red, blue, and orange are the matched AI skills or applications in categories 1, 2, and 3, respectively.

did not change in 2020 compared to the 2010 version.[6] 6% (4 out of 33) of college majors in category 1 and 11% (2 out of 18) in category 2 underwent slight changes in descriptions in 2020 compared to the 2010 version, but none of these changes is related to the chosen AI phrases. Of majors in category 3 that experienced changes in descriptions in 2020 (4%, or 3 out of 73), the phrase "geographic information system (GIS)" was added to one major leading to a change in its number of matched phrases. Since most college major descriptions have not changed over time, the number of matched AI phrases is assumed to be time invariant in this paper. However, due to this time invariance property, the number of matched AI phrases cannot capture the growth in AI. I then propose a new measure to link the growth in AI to college majors in the next section.

[6]NCES only provides college major descriptions for 2000, 2010, and 2020 CIP codes on its website. For older versions, only CIP codes and the corresponding titles can be found in crosswalks provided by NCES.

1.2.3 AI Relevance Score of College Majors

To capture the relatedness between the growth in AI and college majors, I construct a new measure denoted as "AI Relevance Score." This measure captures how well a major prepares students to use AI to complement their job tasks, i.e., a major's complementarity with AI.

To measure the growing interest in AI, I use relative Google search activities for each chosen AI phrase from Google Trends data.[7] Google Trends data provides an index of relative search volumes by search terms, time ranges, and geographic areas. Although the exact number of search queries on a specific term is not available, Google Trends Index (GTI) is designed to show the relative change in search intensities over a given period and at a given location.[8] Appendix Figure 1A.2 shows GTI of search activities on some chosen AI phrases in the U.S. from 2004 to 2020.[9] Since users can compare at most five terms per request, I include "Machine Learning" and "Pattern Recognition" in both requests presented in Appendix Figure 1A.2 for comparison. Newly emerging AI technologies, such as machine learning, deep learning, and big data, have been searched more intensively than traditional AI technologies, e.g., pattern recognition and natural language processing.

Since GTI represents relative Google search intensities and Google is one of the most popular search engines worldwide, GTI can be used as a proxy for changes in people's interests in different AI subfields over time. The AI Relevance Score of major m in category g during decade τ is then constructed as follows:

$$\text{AI Relevance Score}_{m,g,\tau} = \sum_{i \in \text{AI phrases}_g} \mathbf{1}\{i \in \text{Description}_m\} \times \frac{\text{GTI}_{i,\tau_T} - \text{GTI}_{i,\tau_0}}{\text{GTI}_{i,\tau_0}}, \tag{1.3}$$

where τ, τ_0, and τ_T denote a decade, the first year in that decade, and the last year in that decade, respectively. $\mathbf{1}\{i \in \text{Description}_m\}$ indicates whether an AI phrase i in category g (where

[7] https://trends.google.com/trends/?geo=US. Stephens-Davidowitz and Varian (2014) introduce Google Trends data in details and how it can be used for social science research. Kong and Prinz (2020) use Google Trends data to study the effect of shutdown policies on unemployment during the COVID-19 pandemic.

[8] GTI ranges between 0 and 100, which is computed based on a term's proportion of search activities among all search activities on all terms per request. Suppose a user compares term A and B over period τ in location g. If term A has a GTI of 100 and term B has a GTI of 50 at time t, this implies that the number of search activities on term A at time t was twice as large as that on term B. GTI is computed separately for each request. Users can compare at most five terms per request.

[9] Google Trends data starts from Jan. 1st, 2004.

$g \in \{1, 2, 3\}$) listed in Table 1.2 is matched to major m's description. GTI_{i,τ_0} and GTI_{i,τ_T} are the start-of-decade and end-of-decade indices of Google search queries in the U.S. on an AI phrase i, respectively. Since Google Trends data starts from 2004, this AI Relevance Score is only available for the 2000s and the 2010s. Due to the same reason, τ_0 is set to be 2004 when computing the AI Relevance Score in the 2000s. The underlying assumption is that the differences in relative search intensities from 2004 to 2010 would remain unchanged if the time range is extended back to 2000.

When undergraduate students choose their fields of study, it is possible that they search for relevant information to learn more about majors they are interested in on Google. Thus, by using the decadal growth in GTI of chosen AI phrases, I assume that students respond to changes in the attention that an AI subfield has received from the public. A higher AI Relevance Score then implies that AI skills or applications associated with a major have become increasingly popular among the public in the U.S.

In addition to GTI, I use growth rates of academic publications in the field of AI to compute an alternative AI Relevance Score. Unlike GTI which captures relative search intensities on AI subfields, the growth rate of academic publications can be viewed as a proxy for course content developments. Through these developments, students can acquire more up-to-date concepts and skills and be better prepared for changes in skill requirements.

The growth rate of academic publications whose topic is one of the AI phrases listed in Table 1.2 is computed using the Web of Science (WoS) Core Collection database from Clarivate. WoS Core Collection contains more than 21,100 peer-reviewed journals, books, and proceedings in the field of Science, Social Science, and Arts and Humanities from 1900 to present. Users can search for academic publications with a specific topic published in a specific year on the WoS website.[10] Since each academic publication is counted only once by WoS, I use the total number of annual academic publications with each of the chosen AI phrases included in the topic and calculate the decadal growth rate of academic publications for each AI phrase. This alternative AI Relevance

[10]Appendix Figure 1A.3 presents examples of the search page and results.

Score of major m in category g in decade τ is constructed as follows:

$$\widehat{\text{AI Relevance Score}}_{m,g,\tau} = \sum_{i \in \text{AI phrases}_g} \mathbf{1}\{i \in \text{Description}_m\} \times \frac{\text{Publications}_{i,\tau_T} - \text{Publications}_{i,\tau_0}}{\text{Publications}_{i,\tau_0}}, \tag{1.4}$$

where $\text{Publications}_{i,\tau_0}$ and $\text{Publications}_{i,\tau_T}$ are the start-of-decade and end-of-decade numbers of academic publications with an AI phrase i in category g included in the topic, respectively. By calculating this AI Relevance Score as the sum of growth rates of publications in all AI subfields associated with a major, I equally weight each AI subfield. The underlying assumption for this equal weight is that different concentrations of a major have the same importance. Suppose a major has concentrations in pattern recognition, big data, and machine learning. Although pattern recognition is a mature AI subfield while the rest are newly emerging AI technologies, instructors who teach related courses will not solely focus on pattern recognition or quickly mention the rest, and vice versa. It is equally important for students to learn all of them. Moreover, Appendix Figure 1A.4 shows that more than 80% of AI skill-related majors are matched to only one AI phrase. One potential weight that can be applied to the construction of AI Relevance Score is the total credits of courses in each chosen AI subfield required by a major. Credits can be the proxy for the amount of contents of a specific subject or topic that students need to learn, which in turn implies how in-depth this subject is covered by a major.

By using decadal growth rates of academic publications to construct AI Relevance Score, I assume that students are responsive to the trend of AI progress. A consistently high growth rate of an AI subfield indicates that it has consistently and increasingly captured researchers' attention. In other words, this AI subfield has been a popular research topic that is worth studying. A major with concentrations in this fast-growing AI subfield is consequently assigned a relatively higher AI Relevance Score based on equation (1.4). Thus, a higher AI Relevance Score indicates a more promising future: students who choose a major with a high AI Relevance Score can learn more in-depth and up-to-date AI skills to complement their jobs after graduation. However, a potential threat to this measure is the possibility that a newly emerging technology usually has a high growth rate of academic publications due to its small baseline, while a mature technology that has a large baseline grows slowly. Since the AI Relevance Score computed by equation (1.4) cannot capture changes in the absolute number of academic publications, I then propose a complementary AI Relevance Score using decadal changes in the number of academic publications to address this threat:

$$\widetilde{\text{AI Relevance}}\ \text{Score}_{m,g,\tau} = \sum_{i \in \text{AI phrases}_g} \mathbf{1}\{i \in \text{Description}_m\} \times \Delta\text{Publications}_{i,\tau}, \tag{1.5}$$

where $\Delta\text{Publications}_{i,\tau}$ is the decadal change in the number of academic publications with an AI phrase i included in the topic. This alternative AI Relevance Score captures the relationship bewteen the intellectual capital accumulation on AI and college majors. A higher score indicates that AI skills or applications with a larger increase in the intellectual capital are concentrations of a major.

Appendix Figure 1A.5 shows decadal changes in and decadal growth rates of academic publications on a few AI phrases that have relative high growth rates over time. Deep learning and machine learning are newly emerging technologies and had a consistently rapid growth during the 2010s, while pattern recognition is a mature AI subfield that was fast-growing back in the 1990s. These trends are consistent with the upward trends in relative Google search intensities on these newly emerging technologies compared to the mature ones shown in Appendix Figure 1A.2.

1.2.4 Distribution of AI Measures across College Majors

Of the 1,355 college majors (represented by the 2020 6-digit CIP code) in my sample over the past three decades, 2.4% are defined as majors that are most complementary to AI (category 1), 1.3% are with concentrates in AI-related computer and information processing technologies (category 2), 5.4% are associated with general computer skills (category 3), 28.6% are STEM (science, technology, engineering, and mathematics) majors, and 22.9% are non-AI tech majors (i.e., non-AI STEM majors).[11]

[11] I use the 2020 STEM Designated Degree Program List provided by the U.S. Department of Homeland Security (DHS) to define STEM majors.

Figures 1.3a to 1.3c show the distribution of three AI Relevance Score measures by broad college major categories (represented by the 2020 2-digit CIP code) over 2010-2019 academic years. They highlight that these three AI Relevance Score measures capture different aspects of a major's complementarity with AI as discussed in Section 1.2.3. The AI Relevance Score constructed using relative search intensities, GTI, is of a similar magnitude for Agriculture, Engineering, Mathematics and Statistics, Physics, and Social Sciences majors. The other two AI Relevance Score measures are especially high for Mathematics and Statistics, Physics, and Social Sciences majors. It is interesting that Computer and Information Sciences majors do not have an extremely high AI Relevance Score. Since the AI Relevance Score is a weighted sum of either GTI or changes in academic publications, it is possible that this score is averaged out as CS majors focus on both traditional (e.g., pattern recognition) and newly emerging (e.g., deep learning) AI technologies. As shown in Appendix Figures 1A.2 and 1A.5, traditional AI technologies usually have lower search intensities and a stagnant growth in academic publications than newly emerging ones.

The distribution of AIME measures constructed by assigning a weight of one to the most common occupation following equation (1.1) is presented in Figures 1.3d to 1.3f.[12] All three AIME measures have high values for Communications Technology/Technician majors. Liberal Arts and Sciences and Linguistics majors are also high in AIME constructed by using the Felten et al. (2021) AIOE measure. Tasks that students graduating with these majors perform are more substitutable by AI since AI is compatible with processing languages and coverting text to images or videos.

1.3 Data and Empirical Strategy

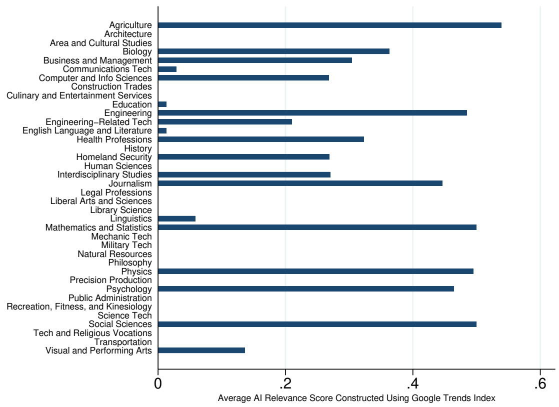
1.3.1 Data

The degree completion data between 1990-91 and 2019-20 academic years are from the Integrated Postsecondary Education Data System (IPEDS), which has surveyed all U.S. post-secondary institutions since 1993. Since the CIP codes underwent revisions, I use the crosswalk provided by

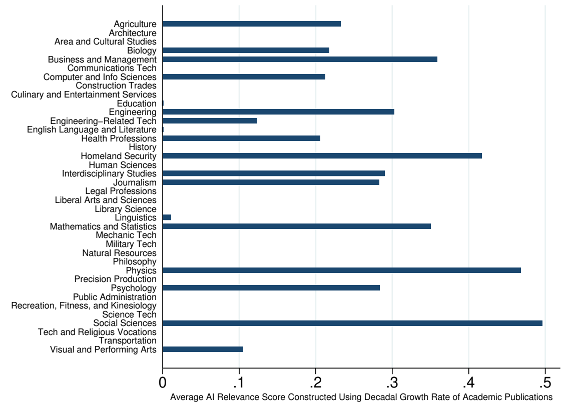
[12]Unlike AIME constructed using the most common occupations, those constructed as a weighted sum of AIOE measure using employment shares following equation (1.2) have less variation across majors as shown in Appendix Figure 1A.6. They are less precise due to the multiple weights issue explained in the footnote of Section 1.2.1.

Figure 1.3 AI Measures by Broad College Major Category, 2010-19

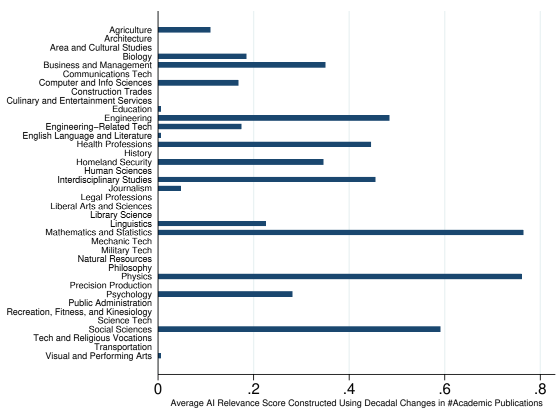
(a) AI Relevance Score—by Google Trends Index



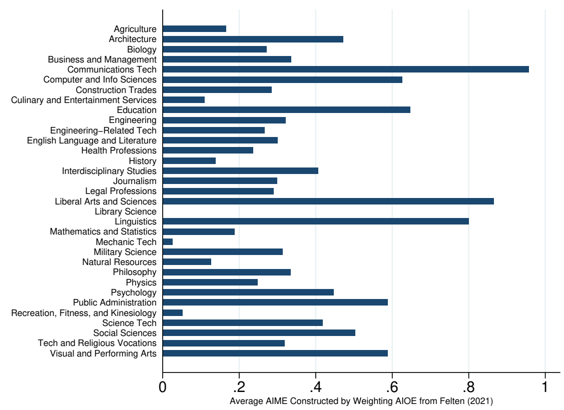
(b) AI Relevance Score—by Decadal Growth Rates of Academic Publications



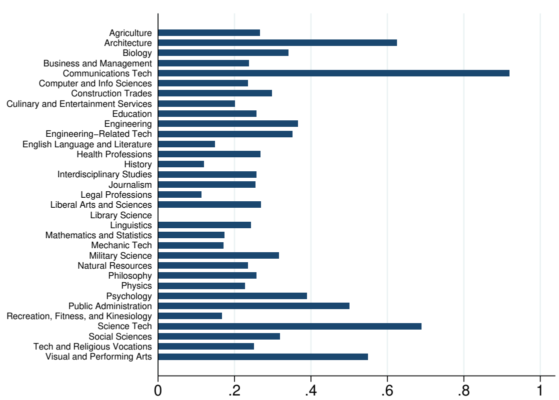
(c) AI Relevance Score—by Decadal Changes in Academic Publications



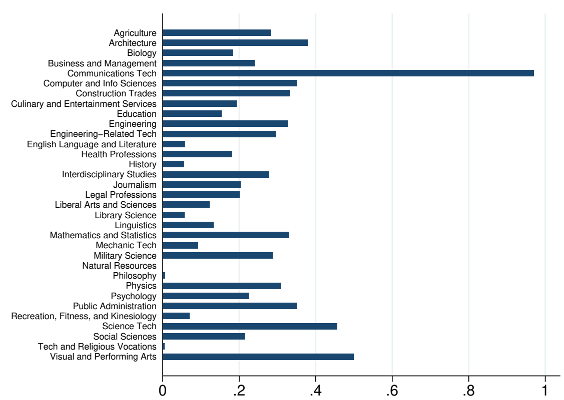
(d) AIME—by Using the Felten et al. (2021) AIOE



(e) AIME—by Using the Felten et al. (2018) AIOE



(f) AIME—by Using the Webb (2019) AIOE



Notes: Majors with a zero AI Relevance Score in subfigures (a) to (c) are those that do not match with any chosen AI phrase. The AIME measures in subfigures (d) to (f) are constructed by assigning a weight of one to the most common occupation for a major following equation (1.1). The most common occupation is the one with the largest number of employed people within the group of students graduating with the same major.

the NCES to match all CIP codes from previous versions to the most recent one (2020 CIP codes) for consistency. Due to the geographic variation in AI exposure shown in Figure 1.2 and the fact that the highest ranking or the most popular majors are different across colleges, I use the IPEDS data at the major-by-college-by-decade level. Decadal growth rates of bachelor's degree recipients for each 6-digit CIP code (i.e., the most detailed college major category) in each college are calculated to explore the relationship between the growth in AI and college major choices over the past decades. I also limit the IPEDS data to 4-year colleges because students enrolled in 4-year colleges usually have a longer period to learn about the field-specific information and their preferences than those who are enrolled in less-than-4-year colleges.

Table 1.4 provides summary statistics of average decadal completion rates between 1990-91 and 2019-20 academic years. On average, majors that are most complementary to AI (category 1) had a decadal growth rate of 136.7% for all bachelor's degree recipients, 69.9% for male, 98.4% for female, 62.9% for Whites, 14.7% for international students, and 140.0% for U.S. citizens over the past three decades. Note that this growth rate is at major-by-college-by-decade level, so they can be either positive or negative for different majors in different colleges in each decade. Thus, the average decadal growth rate for a group of recipients might be smaller if it has more negative rates that are larger in magnitude or fewer positive rates (or both) compared to other groups. Of the overall growth rates in AI majors, 46.6% are negative with an average growth rate of -63.3% while 53.4% are positive with an average of 358.6%.[13] Of the growth rates for male (female), 49.7% (47.6%) are negative with an average growth rate of -67.4% (-68.3%) while the average of positive rates is 259.9% (303.4%). Thus, the overall growth rate in AI majors is, on average, higher than that for male or female. Same explanation is applied to the comparison between the overall rate and the rate for other subgroups.

Compared with AI majors (category 1), those associated with AI-related computer and infor-

[13] The average of positive rates is much higher in magnitude than that of negative rates due to observations with a small baseline when calculating decadal growth rates. For negative rates, no matter what the baseline is, the minimum value cannot be smaller than -1. If a major, especially a newly emerging major, has a few completions in the start of a decade but experiences much more completions in the end of a decade, its growth rate will be extremely high. This then substantially increases the average of positive completion rates.

Table 1.4 Summary Statistics of Average Decadal Completion Rates, 1990-2019

	Average Decadal Growth Rate[3] of Bachelor's Degree Recipients by Major					
	All Recipients	Male	Female	Whites	International Students	U.S. Citizens
All College Majors[1]	0.829	0.479	0.643	0.493	0.181	0.828
N = 236,763	(8.017)	(3.825)	(6.595)	(4.970)	(2.955)	(8.643)
AI Skill-Related Majors[2] **in**						
Category 1	1.367	0.699	0.984	0.629	0.147	1.400
N = 3,827	(17.660)	(3.758)	(10.222)	(3.171)	(2.712)	(18.113)
Category 2	1.225	1.162	0.336	0.845	0.018	1.167
N = 755	(4.885)	(4.598)	(3.461)	(3.962)	(4.138)	(4.734)
Category 3	1.365	0.933	1.030	0.912	0.748	1.329
N = 8,668	(7.043)	(4.852)	(5.674)	(6.678)	(5.273)	(7.079)
Non-AI Majors	0.798	0.453	0.624	0.472	0.154	0.794
N = 223,513	(7.793)	(3.771)	(6.553)	(4.918)	(2.786)	(8.426)
Non-AI Tech Majors	0.867	0.585	0.704	0.546	0.518	0.893
N = 44,999	(11.096)	(4.101)	(9.737)	(4.390)	(3.773)	(12.476)

Notes: Standard deviations are shown in parentheses.
[1]Each observation is a major-college-decade cell. College majors are represented by the 2020 6-digit Classification of Instructional Programs (CIP) code. Observations with missing overall decadal completion rates are not counted.
[2]Category 1 denotes majors that are most complementary to AI; category 2 includes majors with concentrations in AI-related computer and information processing technologies; category 3 consists of majors associated with general computer skills.
[3]Growth rates are calculated at the major-college-decade level.

mation technologies (category 2) underwent larger growth in completion for male, Whites, and U.S. citizens. General computer majors (category 3) experienced similar decadal growth for all recipients and U.S. citizens with AI majors, but larger growth for other subgroups. Unlike these AI skill-related majors, non-AI tech majors had smaller growth in degrees awarded to all subgroups except international students.

Appendix Table 1A.6 further decomposes decadal growth rates presented in Table 1.4 into each decade. On average, AI majors (category 1) experienced the largest overall growth in degree completion during the 2000s, while majors in categories 2 and 3 as well as non-AI tech majors underwent the largest growth during the 2010s. The fastest growth in general computer majors (category 3) for Whites and U.S. citizens occurred in the 1990s. In addition, non-AI majors had stagnant growth over past decades for all subgroups except international students.

1.3.2 Empirical Strategy

I first document decadal changes in degree completion over the past three decades with the following specification:

$$\Delta y_{m,u,\tau} = \alpha + \sum_{k\in\{1990s,2000s,2010s\}} \sum_{g\in\{1,2,3\}} \beta_{k,g}\mathbf{1}\{m \in \text{AI Skill-Related Majors}_g\} \times \mathbf{1}\{\tau = k\} \\ + \mathbf{X}_{u,\tau_0}\mathbf{\Phi} + \delta_{m_{2digit},\tau} + \theta_{u,\tau} + \varepsilon_{m,u,\tau}, \tag{1.6}$$

where m, m_{2digit}, u, and τ denote the 2020 6-digit CIP code, the 2020 2-digit CIP code, college, and decade, respectively. g represents one of the three categories of AI skill-related majors: majors with concentrations in the most specific AI skills (category 1), majors associated with AI-related computer and information processing technologies (category 2), and majors with specilizations in general computer skills (category 3). $\Delta y_{m,u,\tau}$ is the decadal growth rate of bachelor's degree recipients in major m graduating from college u over decade τ. $\mathbf{1}\{m \in \text{AI Skill-Related Majors}_g\}$ represents the time-invariant indicator for majors in category g. $\mathbf{1}\{\tau = k\}, k \in \{1990s, 2000s, 2010s\}$ are decade dummies. The vectors $\mathbf{X}_{u,\tau_0}$ contain the start-of-decade college controls, including the share of graduates who are male and Whites. $\delta_{m_{2digit},\tau}$ and $\theta_{u,\tau}$ are the 2-digit-CIP-by-decade[14] and college-decade fixed effects, respectively. These fixed effects capture two different sources of unobserved heterogeneity: changes in preferences for broad major categories (represented by the 2-digit CIP code) across time and differences in unobserved determinants of college major choices across colleges and across time that are correlated with AI. Finally, $\varepsilon_{m,u,\tau}$ is an idiosyncratic error term.

The coefficient of interest is $\beta_{k,g}$, which captures the decadal growth in bachelor's degrees conferred in AI skill-related majors in category g. Since the binary indicator for which category a major belongs to, $\mathbf{1}\{m \in \text{AI Skill-Related Majors}_g\}$, is time invariant[15], I further interact it with decade dummies to estimate how this growth has changed over decades.

[14] Instead of the 6-digit-CIP-by-decade fixed effect, the 2-digit-CIP-by-decade fixed effect is used because the binary indicator for AI skill-related majors does not change at the 6-digit CIP level across time.

[15] As explained in Section 1.2.2, since most of the college major descriptions have not underwent a notable change over time, the binary indicator for AI skill-related majors in category g is assumed to be time invariant.

Nevertheless, the indicator for AI skill-related majors in equation (1.6) fails to capture differences in the substitutability or complementarity of AI across majors and across time. To explore the relationship between degree completion and major-level AI exposure, I re-estimate equation (1.6) by replacing the interaction term with the AIME measure constructed by equation (1.1). To study the relationship between degree completion and how well a major prepares students to use AI, I first re-estimate equation (1.6) by replacing the interaction term with AI Relevance Score measures to test students' responsiveness to a major's complementarity with AI. Second, I additionally include a few fast-growing AI subfields which have substantially improved the performance of AI over one or more decades to explore how students respond to these fast-growing AI technologies.

To analyze the relationship between fast-growing AI subfields and degree completion, I estimate the following specification:

$$\begin{aligned}\Delta y_{m,u,\tau} = \alpha + &\sum_{g\in\{1,2,3\}} \beta_g \Delta\text{GTI of AI Subfields}_\tau \times \mathbf{1}\{m \in \text{AI Skill-Related Majors}_g\} \\ &+ \sum_{g\in\{1,2,3\}} \gamma_g \text{AI Relevance Score}_{m,g,\tau} + \mathbf{X}_{u,\tau_0}\mathbf{\Phi} + \delta_{m_{2digit},\tau} + \theta_{u,\tau} + \varepsilon_{m,u,\tau},\end{aligned} \tag{1.7}$$

where AI Relevance Score$_{m,g,\tau}$ is computed for major m in category g during decade τ using relative search intensities data following equation (1.3). ΔGTI of AI Subfields$_\tau$ represents the decadal change in relative Google search intensities on any of the following phrases: "Artificial Intelligence," "Big Data," "Data Mining," "Deep Learning," and "Machine Learning." I assume that AI itself and these four fast-growing AI subfields jointly, instead of separately, affect students' college major choices because these subfields not only have largely improved the performance of AI in the 2010s but also have impacted each other over time. There are several reasons why these four newly emerging AI subfields and AI itself are included, rather than other mature AI subfields (e.g., pattern recognition). First, there has been rising interest from both the public and researchers in all of these four AI subfields and AI itself over the past two decades (Zhang et al., 2022; Google Trends data). Second, these four AI subfields are the major contributors of the rapid growth in AI during the 2010s compared to the 1990s and the 2000s (LeCun et al., 2015).

By interacting ΔGTI of AI Subfields$_\tau$ with the AI major indicators, I assume that (1) the rising interest in the aformentioned five AI technologies impact all AI skill-related majors and (2) this impact could vary by the category g a major belongs to. Although the general computer majors (category 3) are associated with general computer skills rather than specific AI skills or applications, they could also be affected by these four fast-growing AI subfields and AI itself. First, general computer skills serve as the foundation of AI. Second, students graduating with general computer majors can specialize in AI in the future (e.g., during their graduate studies). Third, students can take courses that cover specific AI skills even if they choose a more general computer major.

As explained in Section 1.2.2, changes in relative search activities may not capture the intellectual capital accumulation in AI technologies which can be the proxy for course content developments. Thus, I re-estimate equation (1.7) by (1) changing the variable of interest, ΔGTI of AI Subfields$_\tau$, to decadal growth rates of academic publications on fast-growing AI technologies and (2) replacing AI Relevance Score with the alternative one generated by the number of academic publications following equation (1.5).

1.4 Results

1.4.1 Trends in College Major Choices over the Past Decades

Table 1.5 presents estimates of equation (1.6) by including AI major indicators only (columns 1 to 3) and interacting these indicators with decade dummies (columns 4 to 6).

Column 1 shows coefficients estimated from a simple Ordinary Least Squares (OLS) regression with start-of-decade college-level controls. Compared with majors that are unrelated to AI, bachelor's recipients in majors that are most complementary to AI (category 1) increased by 55.4 percentage points (pp) over the past three decades, while degree completion in general computer majors (category 3) increased by 48.8pp. However, the OLS estimates may be overestimated due to unobserved determinants of students' preferences across majors, colleges, and time. Column 2 then adds college-decade fixed effects, while column 3 further includes 2-digit-CIP-by-decade fixed effects. After controlling for both fixed effects, the coefficient on AI majors (category 1), 53.3pp, becomes slightly smaller. At the mean decadal growth rate of 82.7%, this percentage-point effect represents an approximate 64.4% increase in decadal growth in AI majors. However, coefficients

Table 1.5 Decadal Changes in Bachelor's Degree Recipients by Major, 1990-2019

	Dep. Var.: Decadal Growth Rate of Bachelor's Degree Recipients by Major					
	All Recipients					
	(1)	(2)	(3)	(4)	(5)	(6)
Majors That Are Most Complementary to AI (Category 1) in Years:						
1990 to 2019	0.554*	0.453	0.533*			
	(0.302)	(0.298)	(0.279)			
1990 to 2000				0.454***	0.372**	0.492***
				(0.171)	(0.182)	(0.173)
2000 to 2010				0.932	0.515	0.597
				(0.601)	(0.623)	(0.615)
2010 to 2019				0.237	0.433*	0.493***
				(0.217)	(0.224)	(0.185)
Majors with Concentrations in AI-Related Computer and Information Processing Technologies (Category 2) in Years:						
1990 to 2019	0.548	-0.284	-0.511			
	(0.674)	(0.967)	(0.882)			
1990 to 2000				-0.087	-0.406	-0.474
				(0.220)	(0.293)	(0.376)
2000 to 2010				-0.074	-2.275**	-2.073*
				(0.713)	(1.079)	(1.078)
2010 to 2019				0.952*	0.969	0.505
				(0.535)	(0.791)	(0.729)
Majors Associated with General Computer Skills (Category 3) in Years:						
1990 to 2019	0.488*	0.372	0.366			
	(0.258)	(0.250)	(0.231)			
1990 to 2000				0.349	0.407	0.612
				(0.344)	(0.416)	(0.373)
2000 to 2010				0.292	-0.067	0.015
				(0.361)	(0.374)	(0.423)
2010 to 2019				0.755**	0.778**	0.579*
				(0.346)	(0.345)	(0.302)
Observations	233,519	235,838	235,838	233,519	235,838	235,838
Outcome Mean	0.807	0.827	0.827	0.807	0.827	0.827
Start-of-Decade Controls	✓			✓		
College-Decade FE		✓	✓		✓	✓
2-Digit-CIP-by-Decade FE			✓			✓

Notes: Each observation is a major-college-decade cell. The coefficients represent the estimate of β in equation (1.6). College major-clustered standard errors are shown in parentheses. The estimates in columns 1 to 3 are robust to male, female, and U.S. citizens, while those in columns 4 to 6 are robust to male, female, Whites, U.S. citizens and international students. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

on general computer majors become insignificant with any fixed effect included. I do not find any relationship between degree completion and majors associated with AI-related computer and information processing technologies (category 2), regardless of which specification is used.

Estimates shown in columns 5 and 6 indicate that majors associated with the most specific AI skills (category 1) underwent a significant growth in degree completion in both the 1990s and the

2010s, after controlling for both fixed effects. However, this growth is not significant in the 2000s. These results are robust to different specifications and different subgroups (i.e., male, female, Whites, U.S. citizens, and international students). These findings can be explained by several reasons. First, neural network and pattern recognition were two of the most popular AI subfields back in the 1990s (Jain et al., 2000) which could lead to a rise in new undergraduate students in these AI majors. During the same decade, the computing system Deep Blue defeated the chess world champion, Garry Kasparov, which caught the public's attention on AI (Audibert et al., 2022; Shao et al., 2022). Second, AI received increasing attention in the 2010s and the performance of AI was dramatically improved by newly emerging technologies (e.g., deep learning, data mining) in the same period (LeCun et al., 2015; Shao et al., 2022). This, in turn, might attract more students to choose AI-related majors in the 2010s. Third, there was a lack of important advances in AI in the 2000s compared to the 1990s and the 2010s, accompanied with a decline in the share of published books in the U.S. that mention AI (Brooks, 2021; Shao et al., 2022).

In contrast to AI majors, those associated with AI-related computer and information processing technologies (category 2) experienced a negative growth in the 2000s. This could be explained by a lack of key advances in AI during this period (Brooks, 2021; Shao et al., 2022). Since category 2 majors are associated with neither the most specific AI skills nor the most general computer skills, fewer students might choose these majors.

Bachelor's degrees awarded in general computer majors (category 3) had a significant and faster growth in the 2010s. The estimate is even larger in magnitude than that for AI majors (category 1). Since general computer majors provide students with computer skill training, advances in AI that also improve methodologies in the field of computer science will have positive impacts on these majors. During the 1990s, pattern recognition was one of the intensively studied AI subfields. Unlike pattern recognition which aims at solving problems of recognizing complex patterns, the newly emerging AI technologies (e.g., big data, deep learning, machine learning) in the 2010s are breakthroughs of fundamental techniques and methodologies in the field of AI (LeCun et al., 2015). This documented increase in completing general computer majors in the 2010s is consistent with the findings of Zhang et al. (2022). They show that the number of new CS undergraduates has largely increased from 2010 to 2020.

1.4.2 The Relationship between AI Complementarity/Exposure and College Major Choices

1.4.2.1 AI Complementarity

To further test students' responsiveness to AI subfields that have been intensively studied and are the main contributors of improvements in AI, I study the relationship between the growth in these AI subfields and college major choices. Table 1.6 presents estimates of β and γ in equation (1.7). Columns 1 to 4 only include AI Relevance Score constructed from equation (1.3), while columns 5 to 8 further add GTI of fast-growing AI subfields (big data, data mining, deep learning, and machine learning) and AI itself.

By only including contemporaneous terms, I assume that students are only responsive to the development in AI subfields occurring in the same decade. However, when only including AI Relevance Score in columns 1 and 2, there is no relationship between degree completion and how well a major trains students to learn AI skills over 2000-19.[16] Columns 3 and 4 replace the contemporaneous AI Relevance Score with the lagged one. After controlling for both fixed effects, a 1pp increase in the lagged AI Relevance Score of AI majors (category 1) significantly raised the decadal growth in completing these majors by 3.709pp. The estimate on lagged AI Relevance Score for general computer majors (category 3) implies a smaller and less significant effect of 0.691pp. These findings suggest that there is a lag in students learning how well a major prepares them to work with AI when choosing their fields of study without controlling for relative search intensities on fast-growing AI technologies.

Columns 5 and 6 further add contemporaneous interaction terms between GTI of fast-growing AI subfields and the binary indicator for majors in category g. The estimate for the interaction term between GTI and the AI major indicator in column 6 shows that a 1pp increase in GTI of fast-growing AI subfields leads to a 0.12pp increase in the decadal growth of completing these AI majors. The effect of 0.159pp on general computer majors (category 3) is also statistically

[16] I only explore the relationship between relative Google search intensities and degree completion over 2000-19 because the Google Trends data starts from 2004. More details can be found in Section 1.2.3.

Table 1.6 The Relationship between Google Trends Index (GTI) of Fast-Growing AI Subfields and College Major Choices, 2000-19

	Dep. Var.: Decadal Growth Rate of Bachelor's Degree Recipients by Major							
	All Recipients							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GTI of Fast-Growing AI Subfields ×								
1{major ∈ Category 1}					0.106	0.120*		
					(0.070)	(0.062)		
1{major ∈ Category 2}					0.376*	0.231		
					(0.202)	(0.185)		
1{major ∈ Category 3}					0.227***	0.159**		
					(0.074)	(0.069)		
Lagged GTI of Fast-Growing AI Subfields ×								
1{major ∈ Category 1}							0.179	0.920
							(0.807)	(0.669)
1{major ∈ Category 1}							-1.394	-0.493
							(1.433)	(1.315)
1{major ∈ Category 1}							-0.757	0.229
							(1.409)	(1.444)
AI Relevance Score[1] of Majors in								
Category 1	4.768	5.372			4.746	5.392		
	(4.019)	(4.004)			(4.015)	(3.983)		
Category 2	-2.004	-2.086			-2.599	-2.421		
	(2.777)	(2.718)			(3.036)	(2.840)		
Category 3	0.329	0.294			0.071	0.117		
	(0.495)	(0.498)			(0.456)	(0.492)		
Lagged AI Relevance Score of Majors in								
Category 1			2.797***	3.709***			3.408*	6.644***
			(1.052)	(0.977)			(2.036)	(1.900)
Category 2			7.726	5.082			3.209	3.441
			(6.849)	(4.764)			(2.213)	(2.383)
Category 3			0.901**	0.691*			0.412	0.841
			(0.430)	(0.369)			(1.121)	(1.075)
Observations	171,628	171,628	79,096	79,096	171,628	171,628	79,096	79,096
Outcome Mean	0.814	0.814	0.726	0.726	0.814	0.814	0.726	0.726
College-Decade FE	✓	✓	✓	✓	✓	✓	✓	✓
2-Digit-CIP-by-Decade FE		✓		✓		✓		✓

Notes: Each observation is a major-college-decade cell. The coefficients in each column are estimated by using equation (1.7). Category 1 denotes majors that are most complementary to AI; category 2 includes majors with concentrations in AI-related computer and information processing technologies; category 3 consists of majors associated with general computer skills. College major-clustered standard errors are shown in parentheses. The estimates in columns 1 to 4 are robust to all groups of recipients, while those in columns 5 to 8 are robust to male, female, Whites, and U.S. citizens. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
[1]AI Relevance Score is constructed from equation (1.3) by using Google Trends data.

significant and even larger in magnitude compared with AI majors after controlling for both fixed effects in column 6. Students respond to the contemporaneous rising interests in fast-growing AI subfields and AI itself. If fast-growing AI technologies are more intensively searched by the public, students are more likely to choose majors associated with either specific AI skills or general computer skills.

Nevertheless, I do not find such significant correlation for category 2 majors (the ones that are neither specific nor general) after including both types of fixed effects. Since only 1.3% of majors are classified into category 2, the estimates might be imprecise due to few observations. Another possible explanation is that students might major in the most specific AI or the most general computer majors with a minor in category 2. Due to the lack of data on minors[17], this paper cannot explore this mechanism empirically.

In contrast to columns 5 and 6 which include contemporaneous terms, columns 7 and 8 only consider the lagged ones. However, I find no discernible relationship between degree completion and lagged relative search intensities on fast-growing AI subfields and AI itself. Since technology is progressing rapidly, students might be more sensitive to the current technological advances.

Findings from Table 1.6 then imply that students respond to contemporaneous increasing attention fast-growing AI subfields (big data, data mining, deep learning, and machine learning) and AI itself have received from the public when choosing majors associated with either the most specific AI skills or the most general computer skills. The contemporaneous popularity of an AI skill-related major's key concentrations might not be the determinant.

I then explore if students are responsive to course content developments proxied by academic publications on fast-growing AI technologies. Similar with Table 1.6, columns 1 to 4 of Appendix Table 1A.7 only include AI Relevance Score measures constructed from equation (1.4), while columns 5 to 8 further add decadal growth rates of academic publications on fast-growing AI subfields and AI itself.

In column 6, a 1pp increase in the growth in academic publications on fast-growing AI subfields and AI itself is associated with a 0.052pp increase in the decadal growth rate of degree completion in AI majors (category 1). This finding is consistent with the positive correlation between relative Google search activities on these fast-growing AI technologies and degree completion in AI majors presented in Table 1.6. Similar with relative search intensities, a rise in academic publications on fast-growing AI technologies indicates that they have received increasing attention from researchers.

[17] IPEDS does not provide degree completion data on students' minors.

Instructors may update syllabi based on theories and methodologies introduced and discussed in academic publications to provide students with the most up-to-date course materials. These course content developments could then affect students' college major choices.

Nonetheless, there is no relationship between degrees conferred in AI skill-related majors and decadal changes in academic publications on these fast-growing AI technologies (estimates are presented in Appendix Table 1A.8). Although some estimates on these decadal changes are statistically significant, they are small in magnitude. For example, in column 8 of Appendix Table 1A.8[18], a 0.0094pp increase in the growth of AI majors (category 1) is associated with a 1pp increase in lagged decadal changes in academic publications on fast-growing AI technologies. Since undergraduate students are less likely to read journal or conference papers, it is possible that they are not sensitive to the actual changes in the number of academic publications when choosing their fields of study.

1.4.2.2 AI Exposure

This section explores the relationship between AI exposure and college major choices. Unlike Section 1.4.2.1 which uses degree completion data over the past three decades, this section specifically focuses on the 2010s. This is because ACS has started to collect information on college majors since 2009. Thus, I do not have employment data to map occupations to college majors before 2009. One may argue that the following assumption could be imposed to construct the AIME measure for years before 2009: the mapping between college majors and occupations observed for 2009 to 2019 would also hold for the 1990s and the 2000s. However, this is a strong assumption because occupational choices may have changed over time based on changes in skill requirements. Thus, estimates obtained under this assumption may be biased.

Since the top-ranking or the most popular majors vary across colleges, information students' received prior to college may affect their choices of college or major. Table 1.7 shows results from re-estimating equation (1.6) by (1) replacing the outcome variable, the decadal growth rate of bachelor's recipients, with the annual growth rate and (2) using the average AIME measure in

[18]The unit of measurement of the dependent variable in Appendix Table 1A.8 only is a percentage point. In this way, the estimates are scaled differently to avoid presenting numerous estimates of "0.000".

Table 1.7 Annual Changes in Bachelor's Degree Recipients with AI Major Exposure (AIME), 2011-19

	Dep. Var.: Annual Growth Rate of Bachelor's Degree Recipients by Major All Recipients					
	AIME Constructed Using Felten et al. (2021) AIOE Measure		AIME Constructed Using Felten et al. (2018) AIOE Measure		AIME Constructed Using Webb (2019) AIOE Measure	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Full Sample						
Avg. AIME in Years Before College[1]	-0.038*	-0.042	-0.023	-0.037	0.015	-0.010
	(0.021)	(0.028)	(0.022)	(0.027)	(0.024)	(0.021)
Observations	89,379	89,377	89,379	89,377	111,291	111,289
Outcome Mean	0.111	0.111	0.111	0.111	0.123	0.123
Panel B. Restricting to Top 50 Universities						
Avg. AIME in Years Before College	-0.032	-0.142***	-0.043	-0.149***	-0.027	-0.107**
	(0.038)	(0.047)	(0.041)	(0.048)	(0.048)	(0.042)
Observations	4,968	4,958	4,968	4,958	6,174	6,159
Outcome Mean	0.058	0.058	0.058	0.058	0.087	0.087
College-Year FE	✓	✓	✓	✓	✓	✓
2-Digit-CIP-by-Year FE		✓		✓		✓

Notes: Each observation is a major-college-year cell. The coefficients in each column are estimated by using equation (1.6) but replacing the interaction term with the AIME measure constructed using equation (1.1). The AIME score is rescaled to have a range between 0 and 1. College major-clustered standard errors are shown in parentheses. In Panel A, the estimates in (1) columns 1 and 2 are robust to female, U.S. citizens, and international students; (2) columns 3 and 4 are robust to female and U.S. citizens; and (3) columns 5 and 6 are robust to male, U.S. citizens and international students. In Panel B, the estimates are robust to U.S. citizens and Whites. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
[1]The average AIME is calculated as the average of AIME measures in students' sophomore year to senior year of high school.

years before college.[19]

Panel A of Table 1.7 presents results obtained from the full sample. In column 1, when only including college-year fixed effect, a 10pp increase in the average AIME of a major is correlated with a 0.0038pp decrease in its annual growth rate. Note that an increase in the AIME score implies that students graduating with the corresponding major are more likely to perform tasks with high AI exposure. Since IT substitutes college graduates in routine-intensive industries (Zhang et al., 2023), this negative estimate then suggests that students tend to avoid choosing majors with high

[19]This average AIME is calculated as the average of AIME measures in students' sophomore year through senior year of high school. Since the AIME measures in different years are highly correlated, including them separately may cause multicollinearity. Specifically, for the AIME measures constructed using the Felten et al. (2021) AIOE measure, the correlation between any two of the AIME measures in sophomore year to senior year of high school is about 0.96. For the AIME measures constructed using the Felten et al. (2018) and Webb (2019) measures, the correlation ranges bewteen 0.96 to 0.98 and 0.96 to 0.97, respectively.

AI exposure to be less substituted by AI after graduation. However, none of the estimates on the average AIME are statistically significant after further controlling for 2-digit-CIP-by-year fixed effect (column 2 in Panel A). By including both types of fixed effects, column 2 compares majors within the same broad category (the 2-digit CIP) and among the same college during the same year, while column 1 compares *all* majors (the 6-digit CIP) offered in the same college during the same year. Thus, the former may lose some variation in AIME as the 6-digit majors within the same 2-digit category may share a high similarity in their AI exposure. This finding suggests that the negative correlation between AI exposure and degree completion stems from the difference in AI exposure across, rather than within, broad major categories. However, there is no discernible relationship between degree completion and the average AIME constructed by using either the Felten et al. (2018) or Webb (2019) AIOE measure (columns 3 to 6).[20]

The insignificant correlation between the average AIME over years before college and degree completion might be explained by students' abilities. Students in top-end universities are more likely to have higher abilities and be more sensitive to technological changes. Thus, they may react more quickly to AI exposure by adjusting their human capital investment, e.g., choosing their college majors. Panel B of Table 1.7 presents the relationship between AIME and degree completion by restricting the sample to top 50 universities in the U.S.[21] Now estimates (columns 2, 4, and 6 in Panel B) on the average AIME become significantly negative and much larger in magnitude regardless of which AIOE is used to construct AIME. Students enrolled in top-end universities are less likely to choose majors that are highly exposed to AI, compared with students from all 4-year institutions. These results are robust to restricting the sample to top 100 universities as shown in Appendix Table 1A.10, although estimates are smaller in magnitude.

[20] Appendix Table 1A.9 presents coefficients on the "weighting" version of AIME constructed by equation (1.2) which suffers from the multiple weights issue as explained in the footnote of Section 1.2.1. I do not find any evidence in Panels A and B on the correlation between degree completion and AI exposure. However, in Panel C for which the AIME is the weighted sum of Webb (2019) AIOE measure, the point estimate on the average AIME in column 1 of Panel C is significantly positive. Two possible reasons could explain these inconsistently signed estimates. First, the Webb (2019) measure captures different aspects of AI compared to the Felten et al. (2018, 2021) measures (Acemoglu et al., 2022). Second, this "weighting" version of AIME might be noisy as explained in Section 1.2.1, possibly resulting in imprecise estimates.

[21] The top 50 universities listed in the Best National University Ranking by U.S. News are used (https://www.usnews.com/best-colleges/rankings/national-universities).

Since the above AIME measure captures an aggregate shock, Appendix Tables 1A.11 and 1A.12 present the correlation between geographical variation in a major's AI exposure across county and state, respectively, and degree completion. Consistent with equation (1.1), the AIME measure for major m, geographical location g (either county or state), and year t is constructed as follows:

$$\text{AIME}_{m,g,t} = \mathbf{1}\{o^* = \arg\max_{o} emp_{o,m,g,t}\} \times \text{AIOE}_{o^*}. \tag{1.8}$$

Estimates in Panel B of Appendix Table 1A.11 suggest that majors in counties that are most exposed to AI grow relatively slowly, especially at top-end universities. These estimates are larger in magnitude compared to Table 1.7 but also have larger standard errors. However, I do not find any significant correlation between these geographical variation across state and degree completion as presented in Appendix Table 1A.12.[22] Due to the lack of college-level employment data, the underlying assumption of using the ACS employment data to construct $AIME_{m,g,t}$ following equation (1.8) is that the distribution of employment by major for people living in a county/state is the same as the distribution for people graduating from a college located in the same county/state. This assumption might be too strong, leading to imprecise estimates in Appendix Tables 1A.11 and 1A.12.

1.5 Conclusion

As an intensively studied and growing general-purpose technology over the past decades, AI not only raises human productivity but also leads to job displacement and changes in skill requirements in the labor market. However, the relationship between human capital accumulation and AI has received relatively little attention from researchers. By constructing a new measure which captures how well a college major prepares students to use AI to complement their work after graduation and using the degree completion data, this paper shows that AI skill-related majors have experienced a dramatic growth in bachelor's degree recipients over the past three decades,

[22] Appendix Tables 1A.13 and 1A.14 display estimates on geographical variation in the "weighting" version of AIME constructed as follows:

$$\text{AIME}_{m,g,t} = \sum_{o} \frac{emp_{o,m,g,t}}{emp_{m,g,t}} \times \text{AIOE}_{o}. \tag{1.9}$$

Estimates now become much noiser: they are significantly negative using either Felten et al. (2018, 2021) AIOE when restricting to elite universities, but become positive if using Webb (2019) AIOE.

especially majors associated with either the most specific AI skills or the most general computer skills. This growth has been statistically significant and similar in magnitude during the 1990s and the 2010s, but not in the 2000s. Moreover, I document a significantly positive relationship between degrees conferred in majors associated with the most specific AI skills and rising interests from both the public and researchers in fast-growing AI subfields (big data, data mining, deep learning, and machine learning) and AI itself. In addition, there is some evidence showing that degree completion is negatively correlated with AI exposure. This negative correlation becomes stronger when restricting the sample to top-end universities. Higher-ability students tend to avoid choosing majors that are more exposed to AI to be less substituted by AI in the labor market.

These results suggest that colleges should make adjustments to the curricula of majors that are related to AI to better prepare students to acquire AI-related skills. However, due to the lack of data on college curricula, I am not able to test whether colleges respond quickly to the growth in AI. This is an important area of future research, as it helps colleges take action on advising and providing relevant training for students.

Another limitation of this paper is the lack of individual-level data on students' dynamic decisions on declaring their fields of study. With this individual-level data, researchers would be able to estimate dynamic models of college major choices to explore the role of the growth in AI. Moreover, other determinants of college major choices (e.g., ability and parental influence) can also be taken into account as complements of the impact of AI on major choices by using the individual-level data. Future research can also explore the labor market performance of students who graduate with AI skill-related majors, e.g., whether they perform tasks that are complemented by AI. Finally, such individual-level data would allow for an analysis of the effects of changes in supply of AI-skilled labor on employment and the wage distribution.

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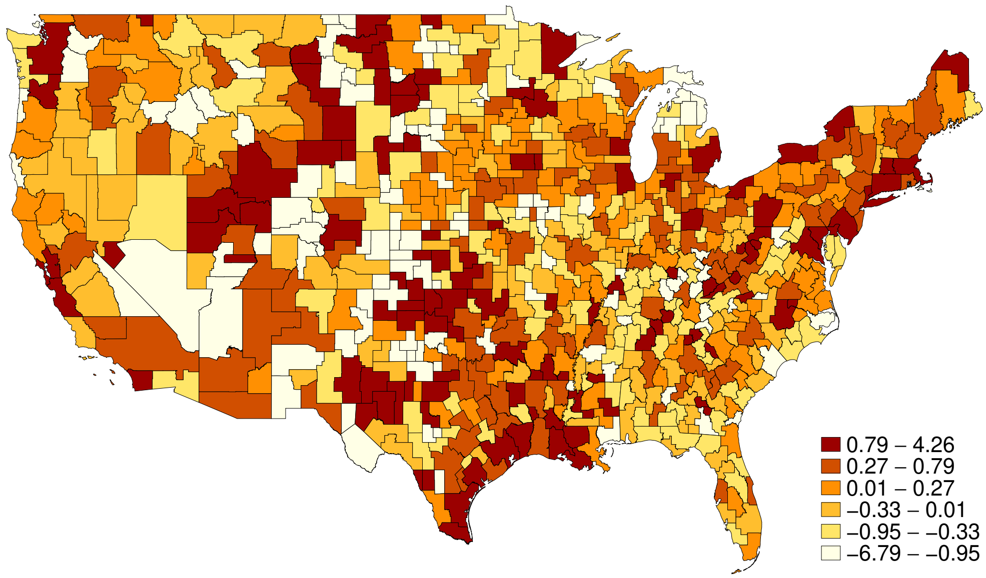
APPENDIX 1A

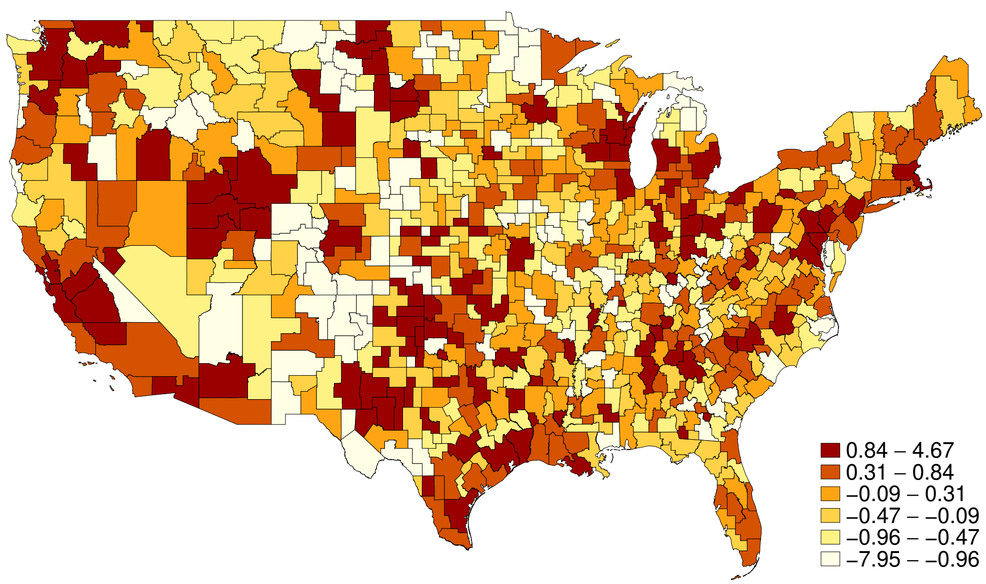
ADDITIONAL FIGURES & TABLES

Figure 1A.1 AI Occupational Exposure (AIOE) by Commuting Zone (Continued), 2019

(a) Felten et al. (2018) AIOE Measure



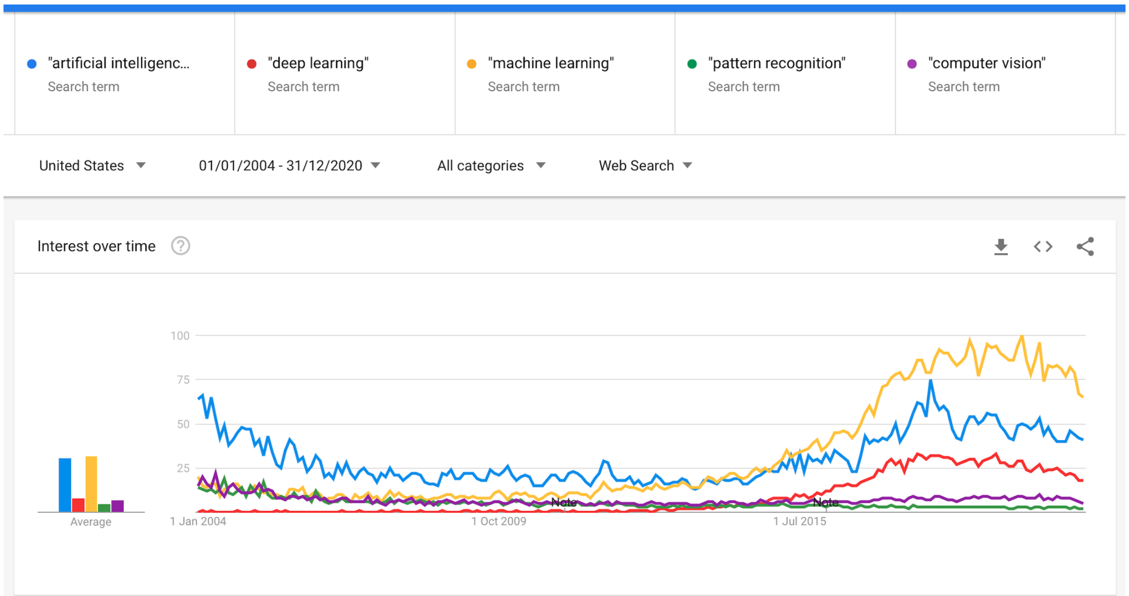
(b) Webb (2019) AIOE Measure



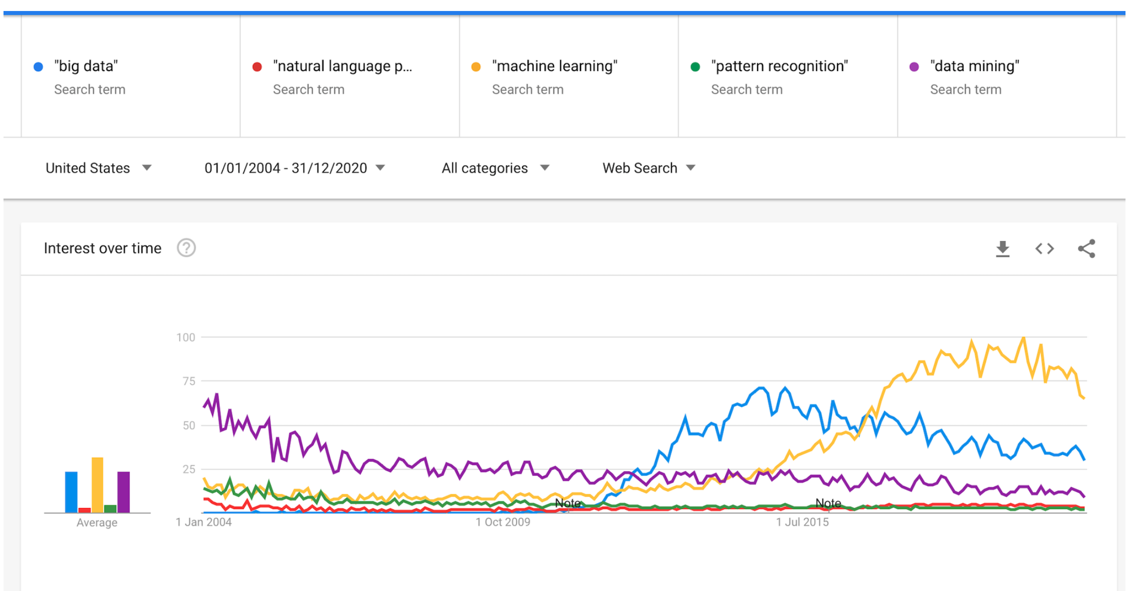
Notes: Both the Felten et al. (2018) and Webb (2019) AIOE measures are aggregated to the commuting zone level.

Figure 1A.2 Changes in Google Trends Index of Search Activities on Chosen AI Phrases

(a) Comparing "Artificial Intelligence," "Deep Learning," "Machine Learning," "Pattern Recognition," and "Computer Vision"



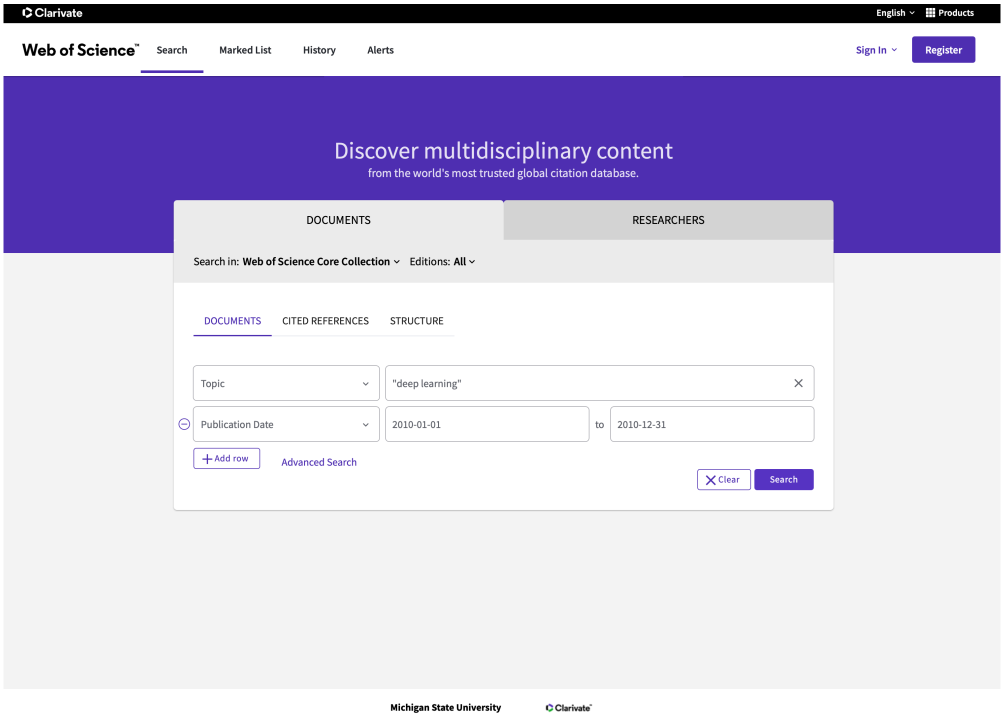
(b) Comparing "Big Data," "Natural Language Processing," "Machine Learning," "Pattern Recognition," and "Data Mining"



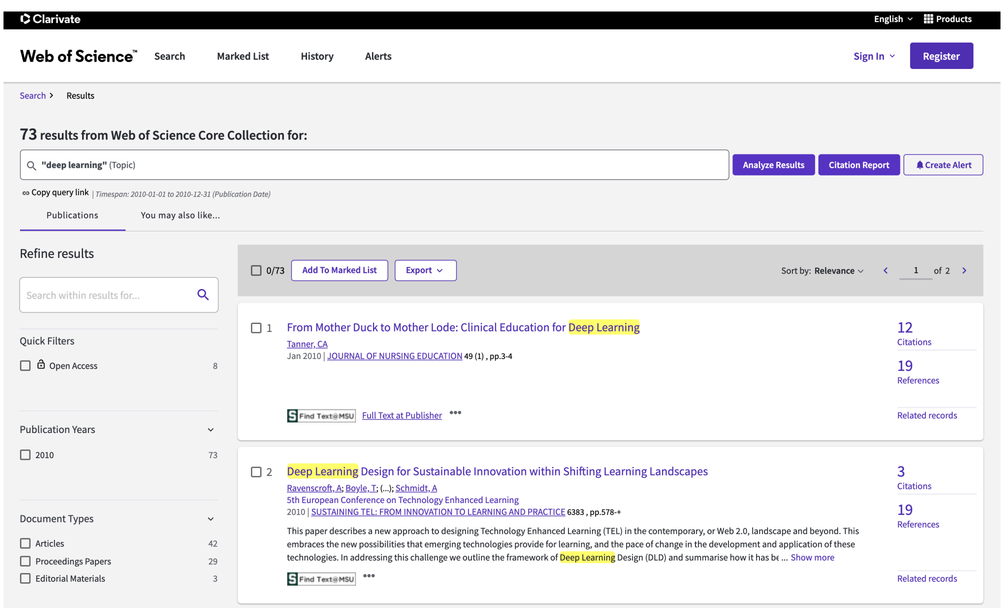
Source: https://trends.google.com/trends/?geo=US.
Notes: Google Trends website allows users to compare at most five terms per request. "Machine Learning" and "Pattern Recognition" are included in both subfigures to serve as the comparison group because "Machine Learning" is one of the AI phrases that have received increasing interests recently while "Pattern Recognition" was intensively discussed in the 1990s.

Figure 1A.3 An Example of Searching Academic Publications on the Web of Science Website

(a) An Example of the Search Page



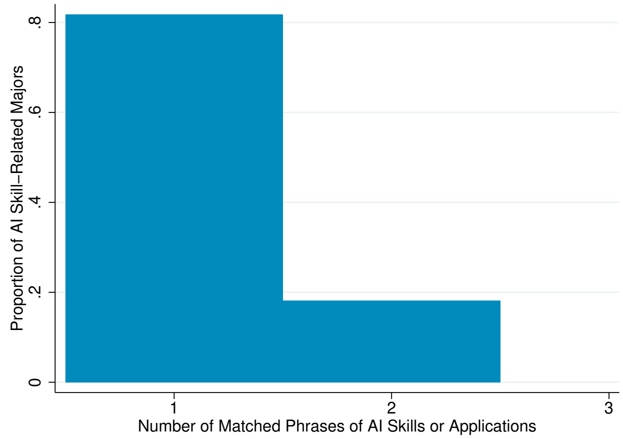
(b) An Example of the Search Result Page



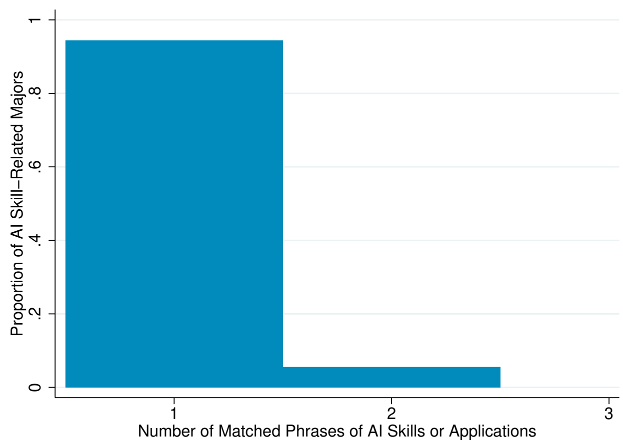
Source: Web of Science platform.

Figure 1A.4 Share of AI Skill-Related Majors by the Number of Matched AI Phrases

(a) Category 1: Majors that are Most Complementary to AI



(b) Category 2: Majors with Concentrations in AI-Related Computer and Information Processing Technologies



(c) Category 3: Majors Associated with General Computer Skills

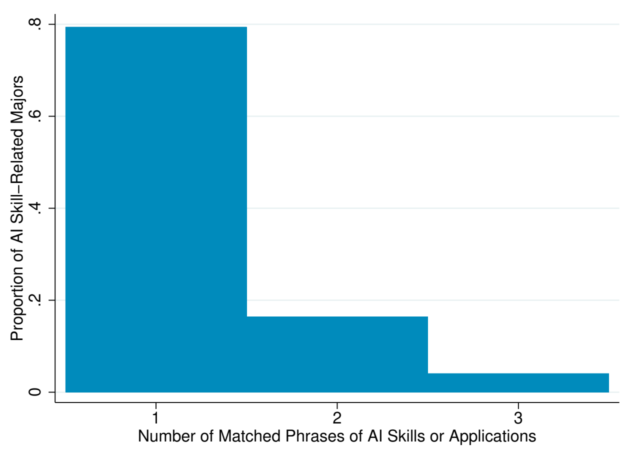
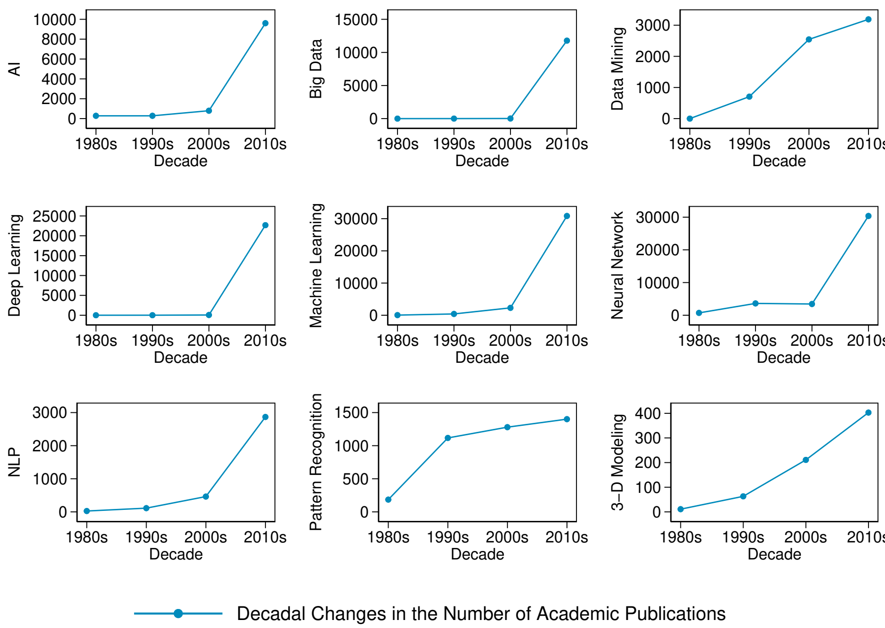
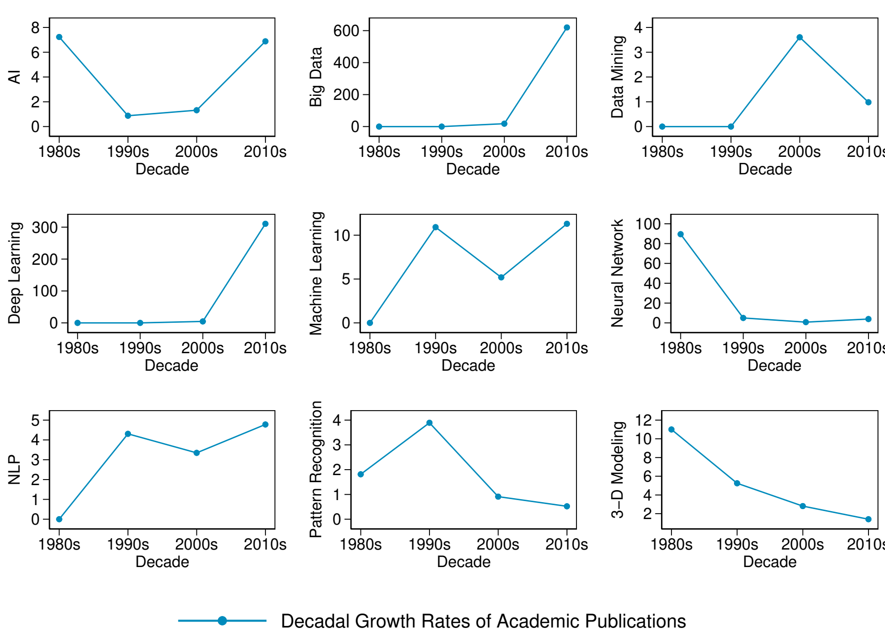


Figure 1A.5 Decadal Changes in and Growth Rates of Academic Publications on Some AI Subfields

(a) Decadal Changes



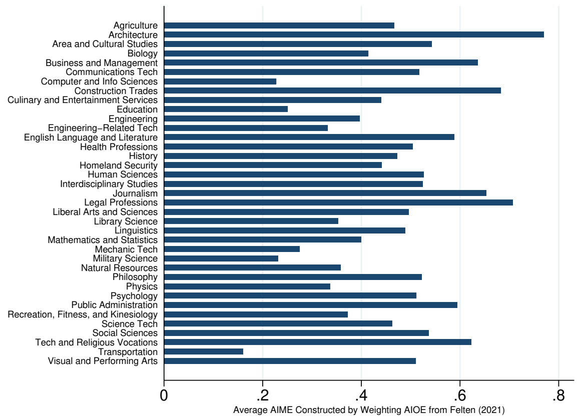
(b) Decadal Growth Rates



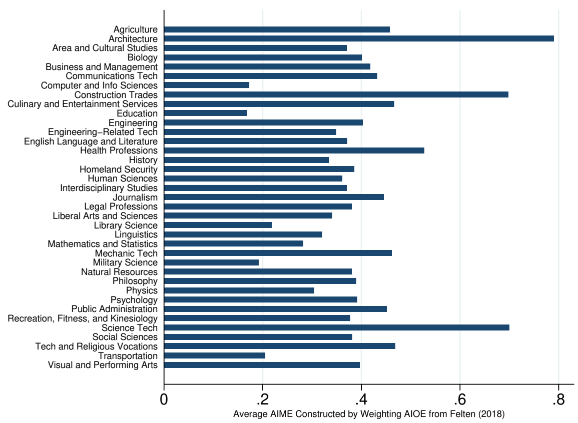
Source: Web of Science Core Collection database.

Figure 1A.6 "Weighting" Version of AIME Measure by Broad College Major Category, 2010-19

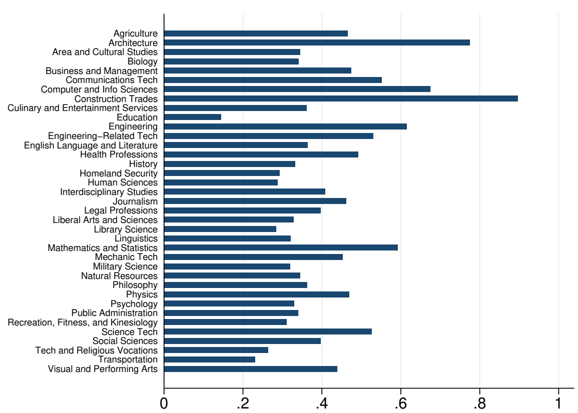
(a) AIME—by Weighting the Felten et al. (2021) AIOE



(b) AIME—by Weighting the Felten et al. (2018) AIOE



(c) AIME—by Weighting the Webb (2019) AIOE



Notes: AIME is constructed as the weighted sum of the AIOE measure following equation (1.2).

Table 1A.1 Occupations with the Highest/Lowest AIOE Scores

(a) Felten et al. (2021) AIOE Measure

Rank	Highest Scoring	Lowest Scoring
1	Genetic Counselors	Dancers
2	Financial Examiners	Exercise Trainers and Group Fitness Instructors
3	Actuaries	Helpers—Painters, Paperhangers, Plasterers, and Stucco Masons
4	Budget Analysts	Reinforcing Iron and Rebar Workers
5	Judges, Magistrate Judges, and Magistrates	Pressers, Textile, Garment, and Related Materials
6	Procurement Clerks	Helpers—Brickmasons, Blockmasons, Stonemasons, and Tile and Marble Setters
7	Accountants and Auditors	Dining Room and Cafeteria Attendants and Bartender Helpers
8	Mathematicians	Fence Erectors
9	Judicial Law Clerks	Helpers—Roofers
10	Education Administrators, Postsecondary	Slaughterers and Meat Packers

(b) Felten et al. (2018) AIOE Measure

Rank	Highest Scoring	Lowest Scoring
1	Airline Pilots, Copilots, and Flight Engineers	Models
2	Physicists	Telemarketers
3	Surgeons	Locker Room, Coatroom, and Dressing Room Attendants
4	Commercial Pilots	Graders and Sorters, Agricultural Products
5	Air Traffic Controllers	Shampooers
6	Dentists, General	Maids and Housekeeping Cleaners
7	Biochemists and Biophysicists	Cleaners of Vehicles and Equipment
8	Oral and Maxillofacial Surgeons	Slaughterers and Meat Packers
9	First-Line Supervisors of Firefighting and Prevention Workers	Dining Room and Cafeteria Attendants and Bartender Helpers
10	Microbiologists	Food Servers, Nonrestaurant

(c) Webb (2019) AIOE Measure

Rank	Highest Scoring	Lowest Scoring
1	Railroad Brake, Signal, and Switch Operators and Locomotive Firers	Cooks, Restaurant
2	Captains, Mates, and Pilots of Water Vessels	Agricultural Sciences Teachers, Postsecondary
3	Water and Wastewater Treatment Plant and System Operators	Healthcare Support Workers, All Other
4	Political Scientists	Social Work Teachers, Postsecondary
5	Civil Engineering Technologists and Technicians	English Language and Literature Teachers, Postsecondary
6	Chemical Engineers	Criminal Justice and Law Enforcement Teachers, Postsecondary
7	Aerospace Engineering and Operations Technologists and Technicians	Credit Authorizers, Checkers, and Clerks
8	Gas Plant Operators	Recreation and Fitness Studies Teachers, Postsecondary
9	Administrative Law Judges, Adjudicators, and Hearing Officers	Political Science Teachers, Postsecondary
10	Marine Engineers and Naval Architects	Morticians, Undertakers, and Funeral Arrangers

Table 1A.2 College Majors with the Highest/Lowest AIME Scores in 2019 (Continued)

(a) AIME—by Using the Felten et al. (2018) AIOE

Rank	Highest Scoring	Lowest Scoring
1	Landscape Architecture	Entomology
2	Architecture and Related Services, Other	Zoology/Animal Biology
3	Interior Architecture	Zoology/Animal Biology, Other
4	Architectural Technology/Technician	Electrical/Electronics Maintenance and Repair Technologies/ Technicians, Other
5	Architectural History and Criticism, General	Parts and Warehousing Operations and Maintenance Technology/ Technician
6	Architecture	Alternative Fuel Vehicle Technology/Technician
7	Environmental Design/Architecture	Industrial Electronics Technology/Technician
8	City/Urban, Community, and Regional Planning	Aircraft Powerplant Technology/Technician
9	Naval Architecture and Marine Engineering	Appliance Installation and Repair Technology/Technician
10	Chemical Engineering	Communications Systems Installation and Repair Technology/ Technician

(b) AIME—by Using the Webb (2019) AIOE

Rank	Highest Scoring	Lowest Scoring
1	Chemical Engineering	Entomology
2	Graphic Design	Zoology/Animal Biology, Other
3	Commercial Photography	Zoology/Animal Biology
4	Illustration	Christian Studies
5	Interior Design	Philosophy, Other
6	Industrial and Product Design	Buddhist Studies
7	Design and Visual Communications, General	Religious/Sacred Music
8	Fashion/Apparel Design	Pastoral Studies/Counseling
9	Design and Applied Arts, Other	Hindu Studies
10	Commercial and Advertising Art	Bible/Biblical Studies

Table 1A.3 List of AI Skill-Related Majors in Category 1 (Associated with the Most Specific AI Skills)

2020 CIP Code	**2020 CIP Title**
10.0304	Animation, Interactive Technology, Video Graphics, and Special Effects
10.0308	Computer Typography and Composition Equipment Operator
11.0102	Artificial Intelligence
11.0204	Computer Game Programming
11.0801	Web Page, Digital/Multimedia and Information Resources Design
11.0803	Computer Graphics
11.0804	Modeling, Virtual Environments and Simulation
13.0501	Educational/Instructional Technology
14.4201	Mechatronics, Robotics, and Automation Engineering
15.0101	Architectural Engineering Technologies/Technicians
15.0405	Robotics Technology/Technician
15.0406	Automation Engineer Technology/Technician
15.0407	Mechatronics, Robotics, and Automation Engineering Technology/Technician
15.1102	Surveying Technology/Surveying
16.0102	Linguistics
23.1303	Professional, Technical, Business, and Scientific Writing
26.1103	Bioinformatics
30.2501	Cognitive Science, General
30.3101	Human Computer Interaction
30.3901	Economics and Computer Science
30.5202	Digital Humanities
30.7001	Data Science, General
30.7101	Data Analytics, General
30.7102	Business Analytics
30.7104	Financial Analytics
42.2701	Cognitive Psychology and Psycholinguistics
50.0402	Commercial and Advertising Art
50.0409	Graphic Design
50.0411	Game and Interactive Media Design
50.0913	Music Technology
51.0909	Surgical Technology/Technologist
51.2703	Medical Illustration/Medical Illustrator
52.1301	Management Science

Table 1A.4 List of AI Skill-Related Majors in Category 2 (Associated with AI-Related Computer and Infomation Processing Technologies)

2020 CIP Code	**2020 CIP Title**
11.0902	Cloud Computing
11.1003	Computer and Information Systems Security/Auditing/Information Assurance
11.1004	Web/Multimedia Management and Webmaster
11.1006	Computer Support Specialist
14.0999	Computer Engineering, Other
14.1004	Telecommunications Engineering
14.4701	Electrical and Computer Engineering
15.0305	Telecommunications Technology/Technician
15.1302	CAD/CADD Drafting and/or Design Technology/Technician
15.1304	Civil Drafting and Civil Engineering CAD/CADD
15.1305	Electrical/Electronics Drafting and Electrical/Electronics CAD/CADD
26.1101	Biometry/Biometrics
26.1199	Biomathematics, Bioinformatics, and Computational Biology, Other
27.0303	Computational Mathematics
43.0403	Cyber/Computer Forensics and Counterterrorism
51.2706	Medical Informatics
52.0208	E-Commerce/Electronic Commerce
52.0407	Business/Office Automation/Technology/Data Entry

Table 1A.5 List of AI Skill-Related Majors in Category 3 (Associated with General Computer Skills)

2020 CIP Code	2020 CIP Title
01.0106	Agricultural Business Technology/Technician
01.8105	Veterinary Anatomy
01.8110	Veterinary Preventive Medicine, Epidemiology, and Public Health
09.0702	Digital Communication and Media/Multimedia
11.0103	Information Technology
11.0104	Informatics
11.0105	Human-Centered Technology Design
11.0202	Computer Programming, Specific Applications
11.0205	Computer Programming, Specific Platforms
11.0299	Computer Programming, Other
11.0901	Computer Systems Networking and Telecommunications
11.1001	Network and System Administration/Administrator
11.1005	Information Technology Project Management
11.1099	Computer/Information Technology Services Administration and Management, Other
13.0603	Educational Statistics and Research Methods
14.0103	Applied Engineering
14.0501	Bioengineering and Biomedical Engineering
14.0902	Computer Hardware Engineering
14.0903	Computer Software Engineering
14.1301	Engineering Science
14.3701	Operations Research
14.3801	Surveying Engineering
15.0613	Manufacturing Engineering Technology/Technician
15.1204	Computer Software Technology/Technician
15.1501	Engineering/Industrial Management
26.0708	Animal Behavior and Ethology
26.1102	Biostatistics
26.1501	Neuroscience
26.1599	Neurobiology and Neurosciences, Other
27.0304	Computational and Applied Mathematics
27.0305	Financial Mathematics
27.0501	Statistics, General
27.0502	Mathematical Statistics and Probability
27.0503	Mathematics and Statistics
27.0599	Statistics, Other
27.0601	Applied Statistics, General
27.9999	Mathematics and Statistics, Other
30.2502	Contemplative Studies/Inquiry
30.3801	Earth Systems Science
30.4101	Environmental Geosciences
30.4401	Geography and Environmental Studies
40.0403	Atmospheric Physics and Dynamics
40.0404	Meteorology
40.0512	Cheminformatics/Chemistry Informatics
40.0601	Geology/Earth Science, General
40.0603	Geophysics and Seismology
42.2706	Behavioral Neuroscience
42.2813	Applied Psychology
42.2815	Performance and Sport Psychology
43.0301	Homeland Security
43.0407	Geospatial Intelligence
43.0408	Law Enforcement Intelligence Analysis
45.0102	Research Methodology and Quantitative Methods
45.0202	Physical and Biological Anthropology
45.0501	Demography and Population Studies
45.0603	Econometrics and Quantitative Economics
45.0701	Geography
45.0702	Geographic Information Science and Cartography
50.0917	Sound Arts
51.0706	Health Information/Medical Records Administration/Administrator
51.0905	Nuclear Medical Technology/Technologist
51.2003	Pharmaceutics and Drug Design
51.2007	Pharmacoeconomics/Pharmaceutical Economics
51.3303	Naturopathic Medicine/Naturopathy
52.0207	Customer Service Management
52.0209	Transportation/Mobility Management
52.0216	Science/Technology Management
52.1201	Management Information Systems, General
52.1206	Information Resources Management
52.1207	Knowledge Management
52.1302	Business Statistics
52.1304	Actuarial Science
52.2101	Telecommunications Management

Table 1A.6 Summary Statistics of Average Decadal Completion Rates Decomposed into Each Decade, 1990-2019

	Average Decadal Growth Rate[3] of Bachelor's Degree Recipients by Major					
	All Recipients	Male	Female	Whites	International Students	U.S. Citizens
			Panel A. 1990-2000			
All College Majors[1]	0.862	0.476	0.691	1.162	-0.184	1.461
N = 64,503	(4.910)	(3.234)	(4.159)	(5.451)	(1.869)	(6.717)
AI Skill-Related Majors[2] **in**						
Category 1	1.228	0.878	0.707	1.680	0.083	1.828
N = 651	(4.216)	(2.779)	(2.437)	(4.285)	(1.553)	(3.940)
Category 2	0.717	0.960	0.560	1.179	0.000	1.001
N = 20	(2.031)	(2.321)	(1.992)	(1.932)	(0.000)	(2.578)
Category 3	1.393	1.042	0.964	2.671	0.123	3.397
N = 1,844	(9.249)	(6.722)	(3.357)	(15.792)	(2.069)	(20.432)
Non-AI Majors	0.843	0.453	0.683	1.099	-0.205	1.388
N = 61,988	(4.727)	(3.054)	(4.193)	(4.689)	(1.865)	(5.722)
Non-AI Tech Majors	0.769	0.493	0.636	1.136	-0.133	1.557
N = 12,398	(3.414)	(2.667)	(2.605)	(3.872)	(1.627)	(5.837)
			Panel B. 2000-2010			
All College Majors	0.892	0.571	0.646	0.520	-0.100	0.884
N = 92,818	(10.279)	(4.120)	(8.266)	(4.924)	(2.083)	(10.145)
AI Skill-Related Majors in						
Category 1	1.784	0.684	1.204	0.651	-0.330	1.817
N = 1,547	(26.963)	(3.376)	(15.042)	(3.086)	(1.111)	(25.914)
Category 2	0.672	0.719	-0.057	0.008	-0.625	0.645
N = 281	(3.633)	(3.941)	(3.556)	(2.083)	(0.633)	(3.534)
Category 3	1.117	0.795	0.537	0.667	-0.064	1.023
N = 3,343	(4.766)	(3.218)	(3.308)	(3.966)	(3.455)	(4.313)
Non-AI Majors	0.869	0.559	0.642	0.514	-0.095	0.863
N = 87,647	(9.906)	(4.168)	(8.227)	(4.986)	(2.019)	(9.816)
Non-AI Tech Majors	0.804	0.543	0.484	0.411	-0.062	0.784
N = 17,498	(17.036)	(5.444)	(14.634)	(5.319)	(1.724)	(16.856)
			Panel C. 2010-2019			
All College Majors	0.729	0.377	0.600	0.381	0.538	0.681
N = 79,442	(6.967)	(3.888)	(5.899)	(4.952)	(3.747)	(6.742)
AI Skill-Related Majors in						
Category 1	1.027	0.649	0.875	0.508	0.770	0.960
N = 1,629	(5.927)	(4.356)	(4.747)	(3.102)	(3.872)	(5.716)
Category 2	1.589	1.430	0.607	1.232	0.622	1.492
N = 454	(5.572)	(4.962)	(3.449)	(4.557)	(5.707)	(5.359)
Category 3	1.588	1.010	1.558	0.967	1.541	1.424
N = 3,481	(7.503)	(5.031)	(8.004)	(7.145)	(6.542)	(6.680)
Non-AI Majors	0.677	0.331	0.555	0.346	0.476	0.635
N = 73,878	(6.966)	(3.795)	(5.823)	(4.861)	(3.502)	(6.771)
Non-AI Tech Majors	1.020	0.706	1.018	0.641	1.208	0.951
N = 15,103	(4.582)	(3.156)	(4.719)	(3.076)	(5.168)	(4.382)

Notes: Standard deviations are shown in parentheses.

[1]Each observation is a major-college-decade cell. College majors are represented by the 2020 6-digit Classification of Instructional Programs (CIP) code. Observations with missing overall decadal growth rates are not counted.

[2]Category 1 denotes majors that are most complementary to AI; category 2 includes majors with concentrations in AI-related computer and information processing technologies; category 3 consists of majors associated with general computer skills.

[3]Growth rates are calculated at the major-college-decade level.

Table 1A.7 The Relationship between Decadal Growth Rates of Academic Publications on Fast-Growing AI Subfields on College Major Choices, 1990-2019

	Dep. Var.: Decadal Growth Rate of Bachelor's Degree Recipients by Major							
	All Recipients							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔPublications[1] on Fast-Growing AI Subfields ×								
1{major ∈ Category 1}					0.044*	0.052***		
					(0.023)	(0.018)		
1{major ∈ Category 2}					0.079	0.036		
					(0.087)	(0.079)		
1{major ∈ Category 3}					0.070*	0.050		
					(0.040)	(0.039)		
Lagged ΔPublications on Fast-Growing AI Subfields ×								
1{major ∈ Category 1}							0.119*	0.132**
							(0.068)	(0.064)
1{major ∈ Category 2}							0.289	0.176
							(0.231)	(0.176)
1{major ∈ Category 3}							0.028	0.055*
							(0.033)	(0.031)
AI Relevance Score[2] of Majors in								
Category 1	3.316	3.659			2.843	3.087		
	(2.509)	(2.445)			(2.338)	(2.278)		
Category 2	-4.208	-4.042			-5.202	-4.481		
	(3.362)	(3.232)			(3.417)	(3.115)		
Category 3	1.320	1.155			-0.039	0.215		
	(0.829)	(0.763)			(1.126)	(1.157)		
Lagged AI Relevance Score of Majors in								
Category 1			-0.425*	-0.204			-1.117**	-0.967**
			(0.254)	(0.236)			(0.477)	(0.435)
Category 2			-2.263	-2.255			-3.638***	-3.063**
			(1.498)	(1.448)			(1.391)	(1.308)
Category 3			2.028*	1.488			1.723*	0.853
			(1.037)	(0.905)			(0.978)	(0.870)
Observations	235,838	235,838	235,838	235,838	235,838	235,838	235,838	235,838
Outcome Mean	0.827	0.827	0.827	0.827	0.827	0.827	0.827	0.827
College-Decade FE	✓	✓	✓	✓	✓	✓	✓	✓
2-Digit-CIP-by-Decade FE		✓		✓		✓		✓

Notes: Each observation is a major-college-decade cell. The coefficients in each column are estimated by using equation (1.7) and replacing terms associated with GTI to decadal growth rates of academic publications. Category 1 denotes majors that are most complementary to AI; category 2 includes majors with concentrations in AI-related computer and information processing technologies; category 3 consists of majors associated with general computer skills. College major-clustered standard errors are shown in parentheses. The estimates in columns 1 to 4 are robust to male, female, and U.S. citizens, while estimates in columns 5 to 8 are robust to all groups except international students. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] ΔPublications denotes decadal growth rates of academic publications.

[2] AI Relevance Score is constructed from equation (1.4) by using decadal growth rates of academic publications.

Table 1A.8 The Relationship between Decadal Changes in Academic Publications in Fast-Growing AI Subfields on College Major Choices, 1990-2019

	Dep. Var.: Decadal Growth Rate of Bachelor's Degree Recipients by Major in Percentage Points[1]							
	All Recipients							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔPublications[2] on Fast-Growing AI Subfields ×								
1{major ∈ Category 1}					0.0002	0.0003		
					(0.0003)	(0.0003)		
1{major ∈ Category 2}					0.0029***	0.0021**		
					(0.0011)	(0.0010)		
1{major ∈ Category 3}					0.0011**	0.0006		
					(0.0005)	(0.0005)		
Lagged ΔPublications on Fast-Growing AI Subfields ×								
1{major ∈ Category 1}							0.0079**	0.0094***
							(0.0039)	(0.0036)
1{major ∈ Category 2}							0.0458**	0.0333
							(0.0223)	(0.0206)
1{major ∈ Category 3}							0.0143	0.0080
							(0.0087)	(0.0082)
AI Relevance Score[3] of Majors in								
Category 1	384.4*	376.0**			369.8*	356.3*		
	(197.7)	(191.2)			(206.6)	(203.5)		
Category 2	-93.9	-117.4			-254.2*	-226.4		
	(161.2)	(147.4)			(141.1)	(142.8)		
Category 3	38.5	56.1**			-14.2	25.8		
	(30.0)	(23.2)			(23.6)	(22.1)		
Lagged AI Relevance Score of Majors in								
Category 1			76.9	78.4			36.9	30.6
			(64.7)	(58.2)			(59.5)	(56.4)
Category 2			-34.5	-61.7			-224.3	-194.4
			(126.3)	(115.5)			(146.5)	(146.6)
Category 3			48.3	62.7**			-19.4	24.8
			(34.6)	(25.9)			(40.4)	(37.3)
Observations	235,838	235,838	235,838	235,838	235,838	235,838	235,838	235,838
Outcome Mean	82.7	82.7	82.7	82.7	82.7	82.7	82.7	82.7
College-Decade FE	✓	✓	✓	✓	✓	✓	✓	✓
2-Digit-CIP-by-Decade FE		✓		✓		✓		✓

Notes: Each observation is a major-college-decade cell. The coefficients in each column are estimated by using equation (1.7) and replacing terms associated with GTI to decadal changes in academic publications. Category 1 denotes majors that are most complementary to AI; category 2 includes majors with concentrations in AI-related computer and information processing technologies; category 3 consists of majors associated with general computer skills. College major-clustered standard errors are shown in parentheses. The estimates in columns 1 to 4 are robust to female and U.S. citizens, while estimates in columns 5 to 8 are robust to all groups. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The dependent variable is shown in percentage points to scale the estimates differently in this table only due to small estimates in columns 5 to 8. Estimates and standard errors are rounded to four decimal places in this table only.

[2] ΔPublications denotes decadal changes in academic publications.

[3] AI Relevance Score is constructed from equation (1.5) by using decadal changes in academic publications.

Table 1A.9 Annual Changes in Bachelor's Degree Recipients with "Weighting" Ver. AI Major Exposure (AIME), 2011-19

	Dep. Var.: Annual Growth Rate of Bachelor's Degree Recipients by Major All Recipients					
	Panel A. AIME Constructed by Weighting Felten, Raj and Seamans (2021) Measure		Panel B. AIME Constructed by Weighting Felten, Raj and Seamans (2018) Measure		Panel C. AIME Constructed by Weighting Webb (2019) Measure	
	(1)	(2)	(1)	(2)	(1)	(2)
Avg. AIME in Years Before College[1]	-0.037	-0.057	0.007	-0.057	0.150^{***}	0.055
	(0.031)	(0.041)	(0.037)	(0.052)	(0.027)	(0.037)
Observations	355,715	355,715	355,715	355,715	355,715	355,715
Outcome Mean	0.112	0.112	0.112	0.112	0.112	0.112
College-Year FE	✓	✓	✓	✓	✓	✓
2-Digit-CIP-by-Year FE		✓		✓		✓

Notes: Each observation is a major-college-year cell. The coefficients in each column are estimated by using equation (1.6) but replacing the interaction term with the "weighting" version of AIME measure constructed by (1.2). The AIME score is rescaled to have a range between 0 and 1. College major-clustered standard errors are shown in parentheses. The estimates in (1) both Panels A and B are robust to U.S. citizens and Whites; and (3) Panel C are robust to female, U.S. citizens, and Whites. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1]The average AIME is calculated as the average of AIME measures in students' sophomore year to senior year of high school.

Table 1A.10 Annual Changes in Bachelor's Degree Recipients with AI Major Exposure (AIME), Top 100 Universities over 2011-19

	Dep. Var.: Annual Growth Rate of Bachelor's Degree Recipients by Major All Recipients					
	Panel A. AIME Constructed by Using Felten, Raj and Seamans (2021) Measure		Panel B. AIME Constructed by Using Felten, Raj and Seamans (2018) Measure		Panel C. AIME Constructed by Using Webb (2019) Measure	
	(1)	(2)	(1)	(2)	(1)	(2)
Avg. AIME in Years Before College[1]	-0.055**	-0.094**	-0.055*	-0.094**	-0.027	-0.077**
	(0.027)	(0.045)	(0.029)	(0.042)	(0.041)	(0.034)
Observations	9,674	9,673	9,674	9,673	12,011	12,005
Outcome Mean	0.065	0.065	0.065	0.065	0.101	0.101
College-Year FE	✓	✓	✓	✓	✓	✓
2-Digit-CIP-by-Year FE		✓		✓		✓

Notes: Each observation is a major-college-year cell. The coefficients in each column are estimated by using equation (1.6) but replacing the interaction term with the AIME measure constructed by equation (1.1). The AIME score is rescaled to have a range between 0 and 1. College major-clustered standard errors are shown in parentheses. The estimates in (1) Panel A are robust to female, U.S. citizens, and international students; (2) Panel B are robust to all groups except Whites; and (3) Panel C are robust to all groups except international students. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1]The average AIME is calculated as the average of AIME measures in students' sophomore year to senior year of high school.

Table 1A.11 Annual Changes in Bachelor's Degree Recipients with Geographical Variation in AI Major Exposure (AIME) across County, 2011-19

	Dep. Var.: Annual Growth Rate of Bachelor's Degree Recipients by Major All Recipients					
	AIME Constructed Using Felten et al. (2021) AIOE Measure		AIME Constructed Using Felten et al. (2018) AIOE Measure		AIME Constructed Using Webb (2019) AIOE Measure	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Full Sample						
Avg. AIME in Years Before College[1]	-0.098	-0.156	0.020	-0.060	0.087*	0.037
	(0.103)	(0.109)	(0.047)	(0.057)	(0.045)	(0.045)
Observations	27,974	27,968	29,381	29,375	40,739	40,737
Outcome Mean	0.114	0.114	0.112	0.112	0.120	0.120
Panel B. Restricting to Top 100 Universities						
Avg. AIME in Years Before College	-0.076	-0.238**	-0.052	-0.186**	-0.043	-0.170*
	(0.090)	(0.102)	(0.074)	(0.082)	(0.063)	(0.099)
Observations	4,382	4,374	4,648	4,640	6,742	6,736
Outcome Mean	0.070	0.070	0.067	0.067	0.108	0.108
Panel C. Restricting to Top 50 Universities						
Avg. AIME in Years Before College	0.150*	0.043	0.062	0.027	0.040	-0.054
	(0.077)	(0.095)	(0.062)	(0.078)	(0.061)	(0.071)
Observations	2,416	2,399	2,582	2,565	3,818	3,809
Outcome Mean	0.044	0.046	0.039	0.040	0.066	0.067
College-Year FE	✓	✓	✓	✓	✓	✓
2-Digit-CIP-by-Year FE		✓		✓		✓

Notes: Each observation is a major-college-year cell. The coefficients in each column are estimated by using equation (1.6) but replacing the interaction term with the AIME measure constructed using equation (1.8). The AIME score is rescaled to have a range between 0 and 1. College major-clustered standard errors are shown in parentheses. In Panel A, the estimates are robust to all groups except international students. In Panel B, the estimates are robust to U.S. citizens. In Panel C, (1) the estimates in columns 2, 3, 4, and 6 are robust to all groups; (2) the estimate in column 1 is robust to female, Whites, and international students; (3) the estimate in column 4 is robust to male, U.S. citizens, and Whites.

[1]The average AIME is calculated as the average of AIME measures in students' sophomore year to senior year of high school.

Table 1A.12 Annual Changes in Bachelor's Degree Recipients with Geographical Variation in AI Major Exposure (AIME) across State, 2011-19

	Dep. Var.: Annual Growth Rate of Bachelor's Degree Recipients by Major All Recipients					
	AIME Constructed Using Felten et al. (2021) AIOE Measure		AIME Constructed Using Felten et al. (2018) AIOE Measure		AIME Constructed Using Webb (2019) AIOE Measure	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Full Sample						
Avg. AIME in Years Before College[1]	-0.015	-0.028	-0.006	-0.044	0.035	0.013
	(0.031)	(0.030)	(0.031)	(0.030)	(0.032)	(0.028)
Observations	61,543	61,540	63,066	63,061	86,400	86,398
Outcome Mean	0.108	0.108	0.109	0.109	0.119	0.119
Panel B. Restricting to Top 100 Universities						
Avg. AIME in Years Before College	0.001	-0.052	-0.020	-0.078	0.033	-0.002
	(0.047)	(0.067)	(0.051)	(0.073)	(0.059)	(0.055)
Observations	6,790	6,782	6,995	6,986	9,837	9,826
Outcome Mean	0.082	0.082	0.080	0.080	0.099	0.099
Panel C. Restricting to Top 50 Universities						
Avg. AIME in Years Before College	0.028	-0.026	0.010	-0.046	0.012	-0.036
	(0.049)	(0.070)	(0.056)	(0.078)	(0.046)	(0.055)
Observations	3,489	3,475	3,594	3,580	5,140	5,126
Outcome Mean	0.063	0.063	0.061	0.060	0.073	0.074
College-Year FE	✓	✓	✓	✓	✓	✓
2-Digit-CIP-by-Year FE		✓		✓		✓

Notes: Each observation is a major-college-year cell. The coefficients in each column are estimated by using equation (1.6) but replacing the interaction term with the AIME measure constructed using equation (1.8). The AIME score is rescaled to have a range between 0 and 1. College major-clustered standard errors are shown in parentheses. In Panel A, the estimates are robust to male, U.S. citizens, and Whites. In Panels B and C, the estimates are robust to all groups except international students.

[1]The average AIME is calculated as the average of AIME measures in students' sophomore year to senior year of high school.

Table 1A.13 Annual Changes in Bachelor's Degree Recipients with Geographical Variation in "Weighting" Ver. AI Major Exposure (AIME) across County, 2011-19

	Dep. Var.: Annual Growth Rate of Bachelor's Degree Recipients by Major All Recipients					
	AIME Constructed Using Felten et al. (2021) AIOE Measure		AIME Constructed Using Felten et al. (2018) AIOE Measure		AIME Constructed Using Webb (2019) AIOE Measure	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Full Sample						
Avg. AIME in Years Before College[1]	-0.071	-0.019	0.059	0.064	0.381***	0.280***
	(0.046)	(0.040)	(0.101)	(0.079)	(0.097)	(0.105)
Observations	115,992	115,991	116,826	116,825	123,325	123,322
Outcome Mean	0.115	0.115	0.115	0.115	0.116	0.116
Panel B. Restricting to Top 100 Universities						
Avg. AIME in Years Before College	-0.015	0.100	-0.049	0.098	0.260*	0.270
	(0.115)	(0.118)	(0.127)	(0.173)	(0.134)	(0.214)
Observations	19,428	19,423	19,542	19,538	20,747	20,744
Outcome Mean	0.104	0.104	0.105	0.105	0.110	0.110
Panel C. Restricting to Top 50 Universities						
Avg. AIME in Years Before College	-0.134**	-0.068	-0.197***	-0.101	0.023	0.052
	(0.060)	(0.062)	(0.076)	(0.078)	(0.119)	(0.125)
Observations	11,163	11,157	11,226	11,223	11,848	11,844
Outcome Mean	0.070	0.070	0.070	0.070	0.074	0.074
College-Year FE	✓	✓	✓	✓	✓	✓
2-Digit-CIP-by-Year FE		✓		✓		✓

Notes: Each observation is a major-college-year cell. The coefficients in each column are estimated by using equation (1.6) but replacing the interaction term with the "weighting" version of AIME measure constructed using equation (1.9). The AIME score is rescaled to have a range between 0 and 1. College major-clustered standard errors are shown in parentheses. In Panel A, the estimates are robust to all groups. In Panel B, the estimates are robust to all groups except international students. In Panel C, the estimates are robust to male, U.S. citizens, and Whites.

[1]The average AIME is calculated as the average of AIME measures in students' sophomore year to senior year of high school.

Table 1A.14 Annual Changes in Bachelor's Degree Recipients with Geographical Variation in "Weighting" Ver. AI Major Exposure (AIME) across State, 2011-19

	Dep. Var.: Annual Growth Rate of Bachelor's Degree Recipients by Major All Recipients					
	AIME Constructed Using Felten et al. (2021) AIOE Measure		AIME Constructed Using Felten et al. (2018) AIOE Measure		AIME Constructed Using Webb (2019) AIOE Measure	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Full Sample					
Avg. AIME in Years Before College[1]	-0.010	0.010	0.054	-0.001	0.412***	0.143
	(0.047)	(0.040)	(0.065)	(0.063)	(0.076)	(0.090)
Observations	297,729	297,729	298,083	298,083	301,197	301,197
Outcome Mean	0.110	0.110	0.110	0.110	0.110	0.110
	Panel B. Restricting to Top 100 Universities					
Avg. AIME in Years Before College	-0.149*	-0.199**	-0.223**	-0.231**	0.300**	0.141
	(0.085)	(0.083)	(0.095)	(0.096)	(0.146)	(0.147)
Observations	32,372	32,369	32,392	32,389	32,765	32,761
Outcome Mean	0.105	0.105	0.105	0.105	0.106	0.106
	Panel C. Restricting to Top 50 Universities					
Avg. AIME in Years Before College	-0.233***	-0.210*	-0.291***	-0.219*	0.092	0.019
	(0.067)	(0.123)	(0.085)	(0.132)	(0.117)	(0.138)
Observations	17,400	17,389	17,408	17,397	17,618	17,606
Outcome Mean	0.082	0.082	0.082	0.082	0.082	0.082
College-Year FE	✓	✓	✓	✓	✓	✓
2-Digit-CIP-by-Year FE		✓		✓		✓

Notes: Each observation is a major-college-year cell. The coefficients in each column are estimated by using equation (1.6) but replacing the interaction term with the "weighting" version of AIME measure constructed using equation (1.9). The AIME score is rescaled to have a range between 0 and 1. College major-clustered standard errors are shown in parentheses. In Panel A, the estimates are robust to all groups except male. In Panel B, the estimates are robust to all groups. In Panel C, the estimates are robust to Whites and U.S. citizens.

[1]The average AIME is calculated as the average of AIME measures in students' sophomore year to senior year of high school.

CHAPTER 2

MACHINE VERSUS MUSCLE, BOT VERSUS BRAIN: EFFECTS OF ARTIFICIAL INTELLIGENCE ON HETEROGENEOUS SKILL GROUPS

2.1 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); 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 et al., 2019; Cockburn et al., 2019; Crafts, 2021; Hötte et al., 2022; Goldfarb et al., 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.

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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 between-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 levels of productivity 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 et al., 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

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

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-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 2.2 which motivates my empirical analysis. Section 2.3 describes the data used in my empirical analysis and defines skill groups. My empirical strategy and main results are presented in Sections 2.4 and 2.5, respectively. Section 2.6 discusses why AI can be considered as a general-purpose technology. Section 2.7 concludes.

2.2 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.

2.2.1 Environment

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

$$Y = \left[\int_{N-1}^{N} y(i)^{\frac{\sigma-1}{\sigma}} di \right]^{\frac{\sigma}{\sigma-1}}, \tag{2.1}$$

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:

$$y(i) = \alpha_{H^{AI}}(i) h^{AI}(i) + \alpha_{H^{Non}}(i) h^{Non}(i) + \alpha_M(i) m(i) + \alpha_L(i) l(i) + \alpha_K k(i), \tag{2.2}$$

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 2.1 *$\alpha_{H^j}(i)$, $\alpha_M(i)$, $\alpha_L(i)$, $\frac{\alpha_{H^j}(i)}{\alpha_M(i)}$, 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.

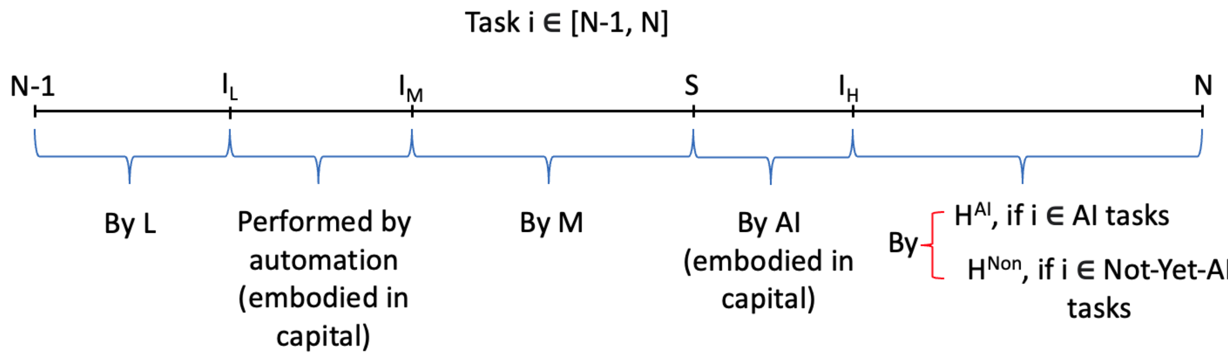
Assumption 2.2 *$\exists I_H \in [N-1, N]$ such that $\frac{\alpha_{H^{AI}}(i)}{\alpha_{H^{Non}}(i)}$ is continuously differentiable and strictly increasing (decreasing) if $i > I_H$ and requires AI skills (is not yet related to AI).*

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 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 2.2 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 2.3 *$\exists I_L, I_M \in (N-1, S)$, 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 $\frac{W_M}{\alpha_M(I_M)} > R > \frac{W_L}{\alpha_L(I_L)}$, $j \in \{AI, Non\}$.*

Figure 2.1 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.

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 2.1 and 2.2 and the effective cost assumption stated in Assumption 2.3. 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 2.1 and is formally presented as follows:

Proposition 2.1 *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 2.1 and 2.2. $I_{H^{AI}}$ ($I_{H^{Non}}$) 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 2.1(d) and 2.1(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 2.1, the equilibrium price of task i is shown below:

$$p(i) = \begin{cases} \frac{W_L}{\alpha_L(i)} & \text{if} \quad i \in [N-1, I_L], \\ R & \text{if} \quad i \in (I_L, I_M], \\ \frac{W_M}{\alpha_M(i)} & \text{if} \quad i \in (I_M, S], \\ \frac{R}{\alpha_K} & \text{if} \quad i \in (S, I_H], \\ \frac{W_H^j}{\alpha_{H^j}(i)} & \text{if} \quad i \in (I_H, N] \text{ and } j \in \{AI, Non\}, \end{cases} \tag{2.3}$$

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 (2.1), the quantity of task i can be derived as

$$y(i) = Yp(i)^{-\sigma}. \tag{2.4}$$

Combining Proposition 2.1 with equations (2.3) and (2.4), I can obtain the demand for each factor in task i as

$$\begin{aligned}
k(i) &= Y\alpha_K^{-1}p(i)^{-\sigma}, \text{ if } i \in (I_L, I_M] \cup (S, I_H] \\
l(i) &= Y\alpha_L(i)^{-1}p(i)^{-\sigma}, \text{ if } i \in [N-1, I_L] \\
m(i) &= Y\alpha_M(i)^{-1}p(i)^{-\sigma}, \text{ if } i \in (I_M, S] \\
h^j(i) &= Y\alpha_{H^j}(i)^{-1}p(i)^{-\sigma}, \text{ if } i \in (I_H, N] \text{ and } j \in \{AI, Non\}.
\end{aligned} \tag{2.5}$$

Then the factor markets clear in the equilibrium:

$$K = Y\mathrm{A}_K R^{-\sigma}, \quad L = Y\mathrm{A}_L W_L^{-\sigma}, \quad M = Y\mathrm{A}_M W_M^{-\sigma}, \quad H^j = Y\mathrm{A}_{H^j} W_{H^j}^{-\sigma}, \quad j \in \{AI, Non\}, \tag{2.6}$$

where

$$\mathrm{A}_K = (I_M - I_L) + (I_H - S)\alpha_K^{\sigma-1}, \quad \mathrm{A}_L = \int_{N-1}^{I_L} \alpha_L(i)^{\sigma-1}di, \quad \mathrm{A}_M = \int_{I_M}^{S} \alpha_M(i)^{\sigma-1}di,$$
$$\mathrm{A}_{H^{AI}} = \int_{I_H}^{N} \mathbf{1}\{i \in \text{AI tasks}\}\alpha_{H^{AI}}(i)^{\sigma-1}di, \quad \mathrm{A}_{H^{Non}} = \int_{I_H}^{N} \mathbf{1}\{i \in \text{not-yet-AI tasks}\}\alpha_{H^{Non}}(i)^{\sigma-1}di, \tag{2.7}$$

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

$$\mathrm{A}_{H^{AI}} W_{H^{AI}}^{1-\sigma} + \mathrm{A}_{H^{Non}} W_{H^{Non}}^{1-\sigma} + \mathrm{A}_M W_M^{1-\sigma} + \mathrm{A}_L W_L^{1-\sigma} + \mathrm{A}_K R^{1-\sigma} = 1. \tag{2.8}$$

Proposition 2.2 *The equilibrium factor prices and output can be expressed as:*

$$\begin{aligned}
&R = Y^{\frac{1}{\sigma}}\mathrm{A}_K^{\frac{1}{\sigma}}K^{-\frac{1}{\sigma}}, \quad W_L = Y^{\frac{1}{\sigma}}\mathrm{A}_L^{\frac{1}{\sigma}}L^{-\frac{1}{\sigma}}, \quad W_M = Y^{\frac{1}{\sigma}}\mathrm{A}_M^{\frac{1}{\sigma}}M^{-\frac{1}{\sigma}}, \quad W_{H^j} = Y^{\frac{1}{\sigma}}\mathrm{A}_{H^j}^{\frac{1}{\sigma}}(H^j)^{-\frac{1}{\sigma}}, \\
&\qquad j \in \{AI, Non\},
\end{aligned} \tag{2.9}$$

and

$$Y = \left[\mathrm{A}_{H^{AI}}^{\frac{1}{\sigma}}(H^{AI})^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_{H^{Non}}^{\frac{1}{\sigma}}(H^{Non})^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_M^{\frac{1}{\sigma}}M^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_L^{\frac{1}{\sigma}}L^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_K^{\frac{1}{\sigma}}K^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}. \tag{2.10}$$

This proposition provides intuitions for the "allocation share" of each factor defined in equation (2.7). These "allocation shares" can be viewed as the distribution parameters in the equilibrium output in equation (2.10). They indicate how different factors are allocated in producing the final good, Y.

2.2.2 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 2.3 explores the displacement effect and the reinstatement effect of AI or industrial automation. Propositions 2.4 and 2.5 study effects on relative wages. Proposition 2.6 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 2A.

Proposition 2.3 (Displacement and reinstatement effects of AI or industrial automation)

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

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

(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 ($\mathrm{A}_{Hj},\ j \in \{AI, Non\}$) 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 2.4 (Relationship between relative wages and AI or industrial automation)

(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, $\frac{d(\frac{W_{Hj}}{W_M})}{dI_M} > 0$, $\frac{d(\frac{W_M}{W_L})}{dI_M} > 0$.

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 ($\frac{W_{Hj}}{W_M}$ and $\frac{W_{Hj}}{W_L}$), 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 ($\frac{W_{Hj}}{W_M}$) or between high- and low-skilled labor ($\frac{W_{Hj}}{W_L}$) 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 2.5 (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.*

$$\frac{d(\frac{W_{H^{AI}}}{W_L})}{d\alpha_{H^{AI}}(i)} > 0, \quad \frac{d(\frac{W_{H^{AI}}}{W_M})}{d\alpha_{H^{AI}}(i)} > 0, \quad \frac{d(\frac{W_{H^{AI}}}{W_{H^{Non}}})}{d\alpha_{H^{AI}}(i)} > 0. \tag{2.11}$$

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 2.6 (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.

2.3 Data and Construction of Skill Groups

Section 2.3.1 describes the datasets I use. Section 2.3.2 introduces how I define skill groups. Section 2.3.3 presents summary statistics of job postings and labor market outcomes by skill group.

2.3.1 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, software, 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 five 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 2.3.2, 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]

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

[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 2.1 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.

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 2.3.2.1) and AI occupations (Section 2.3.2.2) which are those with a specialization 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 2.3.2.3). Occupations are classified into one of these skill groups in Section 2.3.2.4.

2.3.2.1 Defining AI Postings

The phrases for AI-developing skills I used to define AI postings are from LeCun et al. (2015), Zhang et al. (2022), and topics of top journals and conferences in the field of AI (e.g., Institute of Electrical and Electronics Engineers (IEEE) and Association for Computing Machinery (ACM)), which are listed in Table 2.1. 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 2.2 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 2B.1 and 2B.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 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.

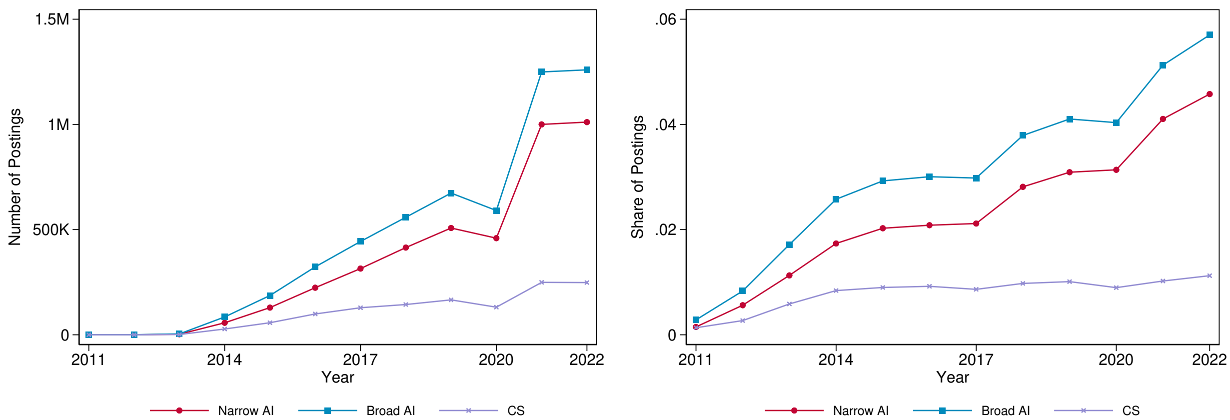
The geographic distribution of the narrow AI posting share from 2011-14, 2015-18, and 2019-22 is presented in Figure 2.3. The darker a state's color is, the more narrow AI vacancies were posted in that state. During 2011-14, only Washington was in the darkest color with the highest share of narrow AI 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

[3]CS phrases refer to those that belong to the broad AI category but not the narrow AI category as listed in Table 2.1.

[4]Guam, Puerto Rico, and Virgin Islands are dropped from my sample.

Figure 2.2 AI/CS Postings in the U.S. in LinkUp Data, 2011-22

(a) Number of AI/CS Postings (b) Share of AI/CS Postings



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 2B.3.

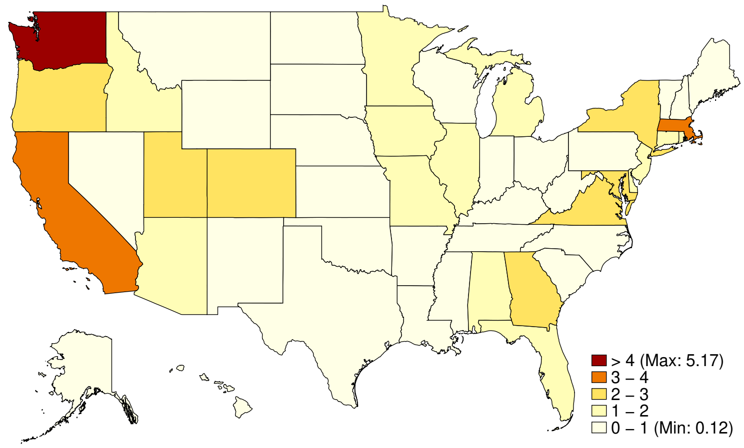
Compared to the online job postings data from Lightcast, formerly known as Burning Glass Technologies, which has been widely used in economic research (e.g., Deming and Noray, 2018, 2020; Bloom et al., 2020; Alekseeva et al., 2021; Acemoglu et al., 2022; Dillender and Forsythe, 2022; Hemelt et al., 2023), 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 2B.4. The share from Lightcast data is presented on the x-axis and that from LinkUp data is on the 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

[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) from the Stanford Institute for Human-Centered Artificial Intelligence (HAI) via https://aiindex.stanford.edu/ai-index-report-2022/, to compute the annual share of AI postings in Lightcast data.

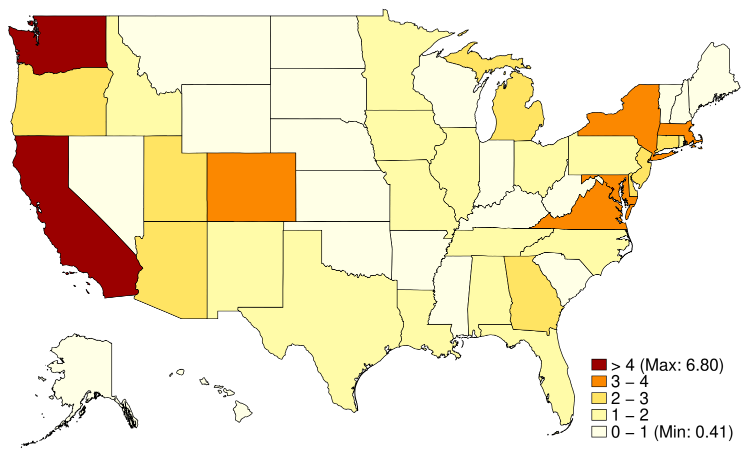
[6]The share of postings in robotics differs from that of the other subcategories, possibly because the phrases used

Figure 2.3 Geographic Distribution of the Narrow AI Posting Share in LinkUp Data

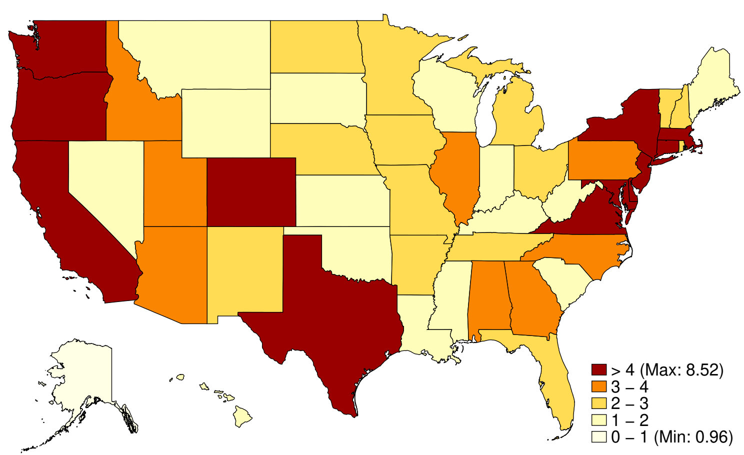
(a) 2011-14



(b) 2015-18



(c) 2019-22



Notes: Scales are in percentage point.

between the overall share of AI postings in LinkUp and Lightcast data is 0.9490.[7]

2.3.2.2 Defining AI Occupations

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

$$AIocc_{j,c,\tau} = \begin{cases} 1 \quad , \quad \text{if } \%AIpost_{j,c,\tau} > \frac{1}{N}\sum_{j\in\mathcal{J}} \%AIpost_{j,c,\tau} \\ 0 \quad , \quad \text{if } \%AIpost_{j,c,\tau} \leq \frac{1}{N}\sum_{j\in\mathcal{J}} \%AIpost_{j,c,\tau}, \end{cases} \tag{2.12}$$

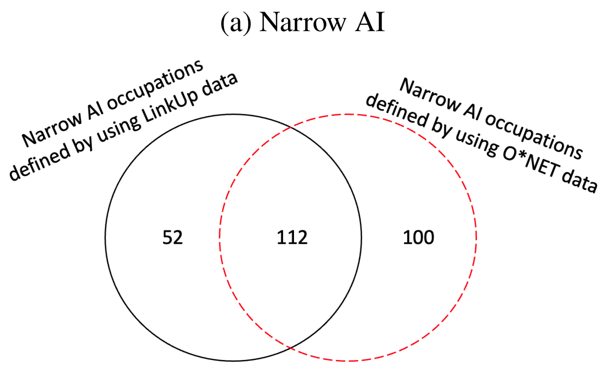
where j, $\mathcal{J}$, and N denote an occupation, the set of all occupations, and the number of all occupations. $\%AIpost_{j,c,\tau}$ is the share of AI postings in category $c \in$ {Narrow AI, Broad AI} of occupation j in the U.S. during the time period $\tau \in \{2011-14, 2015-18, 2019-22\}$. If 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.

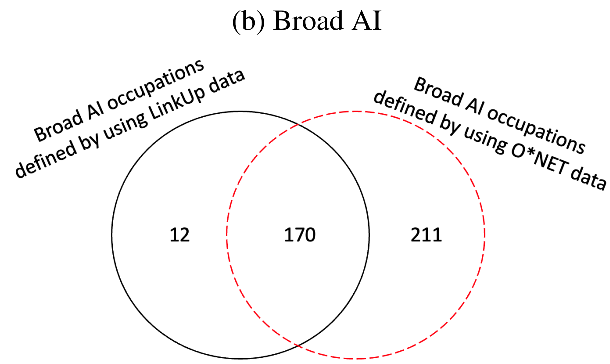
To test the validity of my choice of threshold in defining AI occupations, I cross-check AI occupations defined by using LinkUp data with those constructed by using O*NET data. To make the results comparable across datasets, I match the same set of AI phrases listed in Table 2.1 to tasks, technology skills, detailed work activities, and knowledge information of each occupation provided by O*NET (Appendix Figure 2B.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

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 2.4 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 2.4a) or broad AI (Subfigure 2.4b) definition discussed in Section 2.3.2.1, 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.

defined by using O*NET data with an overlap 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 2.4). Due to the advantages and disadvantages of both LinkUp and O*NET data discussed in Section 2.3.1, I treat the overlapping occupations as the narrow/broad AI occupations in my main analysis.

2.3.2.3 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):

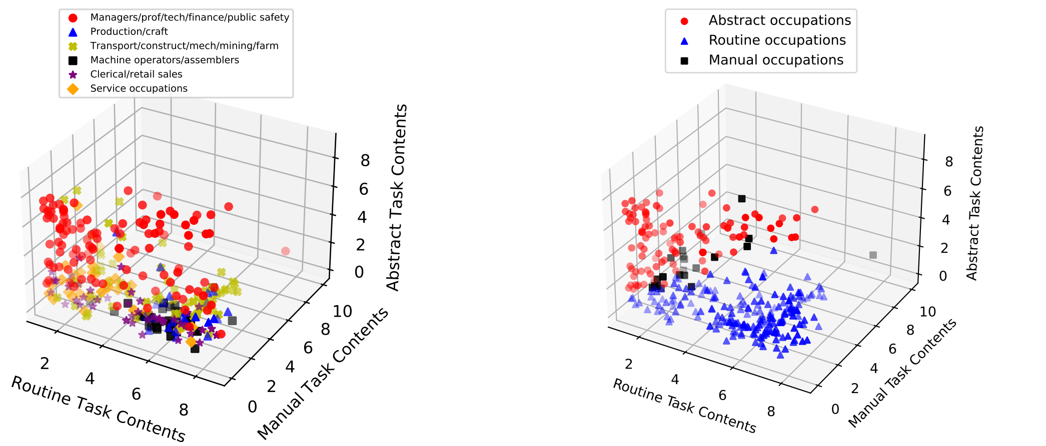
$$OccType_j = x \text{ if } T^x_{j,1980} = max\, \mathbf{T}_{j,1980}, \text{ for } x \in \{Abstract, Routine, Manual\}, \tag{2.13}$$

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

[8] An occupation in equation (2.13) 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.

Figure 2.5 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.

in 1980 by Autor and Dorn (2013) with a range between 0 and 10. Based on equation (2.13), each occupation falls into only one category.[9] Note that since Autor and Dorn (2013) use task inputs in 1980, which is the starting year of their sample, my indicators for abstract, routine, and manual occupations are static over time.

Figure 2.5 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 2.5a displays occupational task contents by Autor and Dorn (2013)'s occupation group, while Figure 2.5b divides occupations into abstract, routine, and manual ones constructed using equation (2.13). 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

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

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 2.5b, 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 labeled by black squares specialize in manual tasks.

2.3.2.4 Categorizing Occupations into Skill Groups

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

$$SkillGroup_{j,c,\tau} = \begin{cases} \text{High-skilled AI-complement} & , \text{ if } OccType_j = Abstract \ \& \ AIocc_{j,c,\tau} = 1 \\ \text{High-skilled not-yet-AI} & , \text{ if } OccType_j = Abstract \ \& \ AIocc_{j,c,\tau} = 0 \\ \text{Middle-skilled} & , \text{ if } OccType_j = Routine \\ \text{Low-skilled} & , \text{ if } OccType_j = Manual, \end{cases} \tag{2.14}$$

where j, $c \in$ {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 2.2 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 2B.1 shows a similar pattern by ranking occupations using the narrow AI posting share. Appendix Table 2C.1 provides a full list of all 4-digit occupations by skill group.

Table 2.2 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.

2.3.3 Facts about Skill Groups

Table 2.3 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 2.3 are static to better compare statistics over time.[11] Panel B of Table

[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 2C 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 2C.1, the statistics are robust to using the time-variant skill group indicators.

2.3 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 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 2.6 displays plots of employment per 100,000 capita (Figure 2.6a), the employment share (Figure 2.6b), mean hourly wage (Figure 2.6c), the wage income share (Figure 2.6d), the narrow AI posting share (Figure 2.6e) and CS posting share (Figure 2.6f), where the skill groups are defined using the narrow AI definition. The plots generated using the broad AI definition are presented in Appendix Figure 2B.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

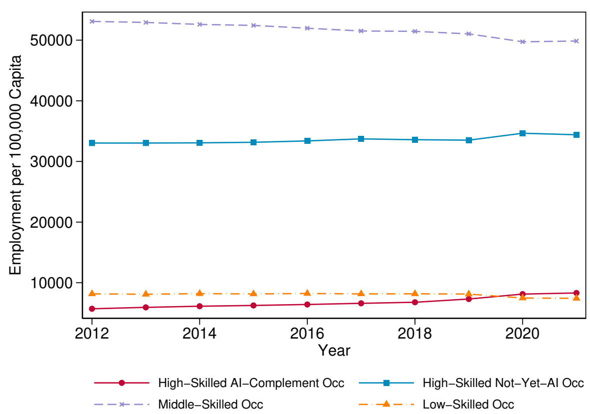
Table 2.3 Summary Statistics, 2012-21

	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

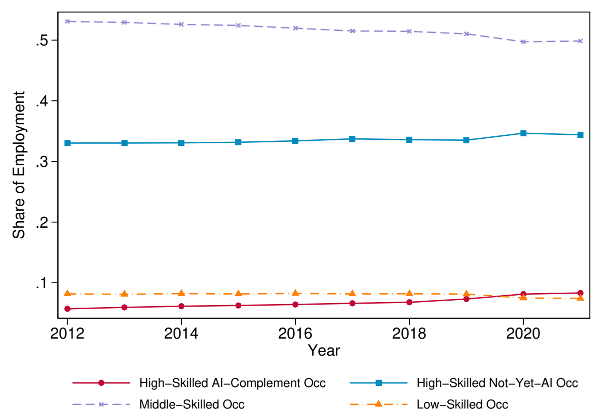
Notes: Standard deviations are shown in parentheses. Occupation is represented by OCC2010, a harmonized occupation system constructed by IPUMS-ACS based on the 2010 Census Occupational Classification. Each observation in Panel B is a 2-digit-occupation-by-state-by-year cell, while each observation in 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 2C.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.

Figure 2.6 Plots of Skill-Group-By-Year Employment, Wages, and Postings, 2012-21

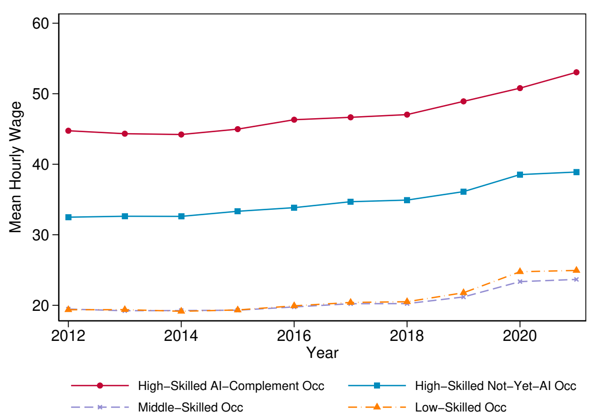
(a) Employment per 100,000 Capita



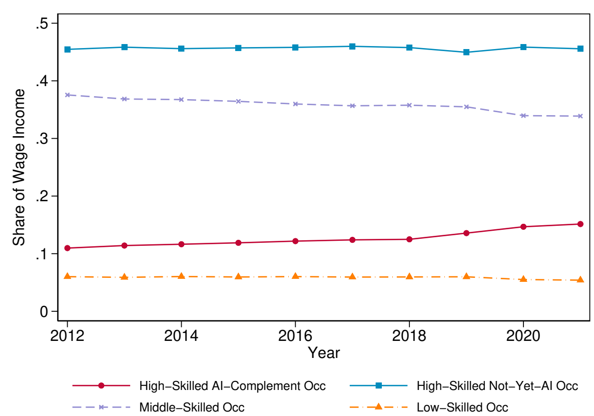
(b) Share of Employment



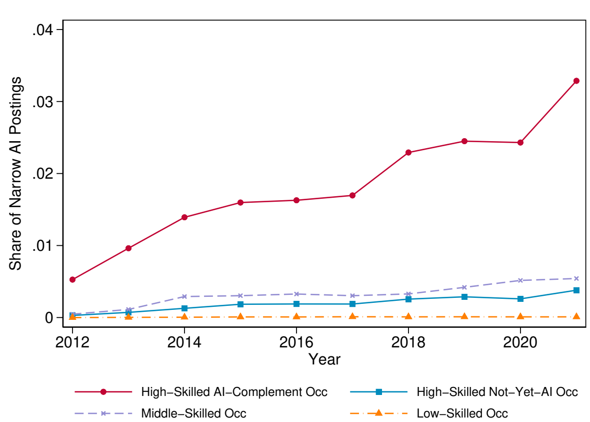
(c) Mean Hourly Wage



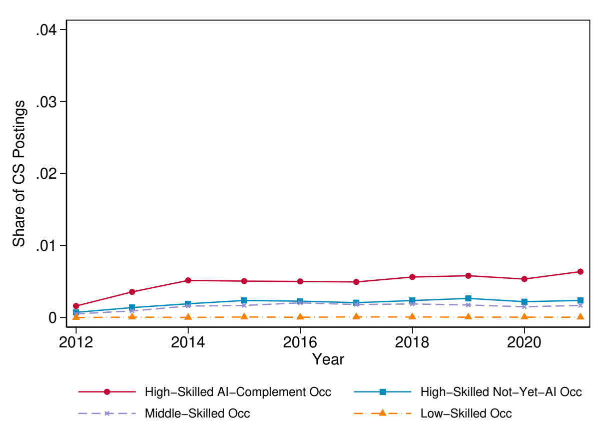
(d) Share of Wage Income



(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 2C.1.

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 2.6e, 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 2.3. Nonetheless, the share of CS postings remained consistently small for all skill groups.

2.4 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:

$$\begin{aligned} y_{o4,s,t} =& \alpha + \beta_0 \% AIpost_{s,t} + \sum_{k \in \{H^{AI}, H^{Non}, M\}} \tau_k \mathbf{1}\{SkillGroup_{o4} = k\} \\ &+ \sum_{k \in \{H^{AI}, H^{Non}, M\}} \beta_k \% AIpost_{s,t} \times \mathbf{1}\{SkillGroup_{o4} = k\} \\ &+ \mathbf{X}_{s,t}\mathbf{\Phi} + \delta_s + \theta_t + \varepsilon_{o4,s,t}, \end{aligned} \tag{2.15}$$

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

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

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 (2.15) 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 (2.15) 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 2C.2-2C.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

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

for differences in unobserved determinants of labor market performances across broad occupation categories.[14]

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

$$\begin{aligned} y_{o4,s,t} =& \alpha + \beta_0 \% AIpost_{s,t} + \sum_{k \in \{H^{AI}, H^{Non}, M\}} \tau_k \mathbf{1}\{SkillGroup_{o4} = k\} \\ &+ \sum_{k \in \{H^{AI}, H^{Non}, M\}} \beta_k \% AIpost_{s,t} \times \mathbf{1}\{SkillGroup_{o4} = k\} \\ &+ \mathbf{X}_{s,t}\mathbf{\Phi} + \delta_s + \theta_t + \gamma_{o2} + \mu_{k,t} + \varepsilon_{o4,s,t}, \end{aligned} \tag{2.16}$$

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.

2.5 Results

2.5.1 Main Results

2.5.1.1 AI and Employment

Table 2.4 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

[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.

Table 2.4 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^2	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.

number of employed people associated with a 1pp increase in the AI posting share, regardless of which skill group this occupation belongs to.

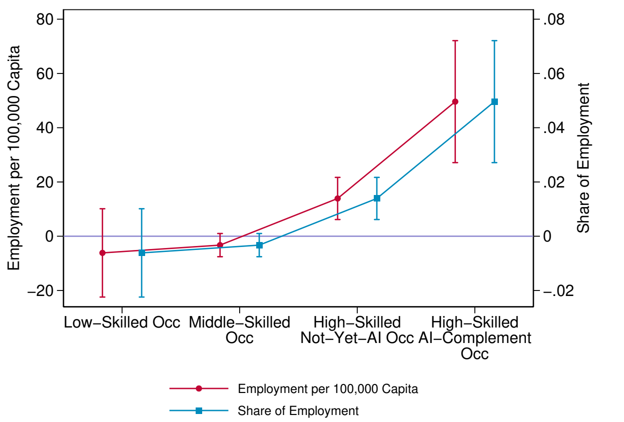
Column 2 interacts the AI posting share with skill group indicators and includes state, year, and skill-group fixed effects to explore effects of the demand for AI skills on heterogeneous skill groups. The coefficient on the interaction term between the AI posting share and the high-skilled AI-complement 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 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 (2.16). 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 2.3 in Section 2.2.2, which implies that the reinstatement effect of AI brings a significant employment growth for high-skilled AI-complement occupations.

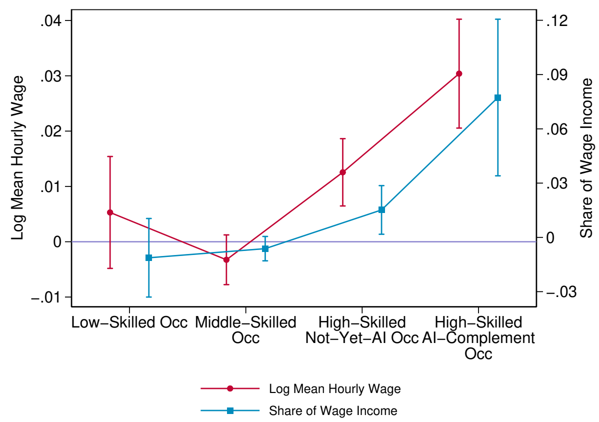
I also plot estimated coefficients from my main specification for all four skill groups in Figure 2.7a. The red line represents estimates from the regression of employment per capita, while the blue line presents estimates from the regression of the employment share. The right tail of both curves is 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 et al. (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

Figure 2.7 Overall Effects of Demand for AI Skills on Labor Market Outcomes, 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. 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.

highest mean hourly wage as shown in Figure 2.6c. In addition, Felten et al. (2019) do not find a significant relationship between AI and employment growth for low-wage occupations, which is also consistent with my results.

2.5.1.2 AI and Wages

Table 2.5 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. Coefficients on skill group indicators show an interesting finding:

Table 2.5 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^2	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.

mean hourly 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 2.4 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 2.5, 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 2.5 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 light on Proposition 2.6, 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 and other skill groups. Figure 2.7b 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 et al. (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,

[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.

I find that the wage gap between high-skilled AI-complement and low-skilled occupations widens as demand for AI skills increases.

2.5.2 Robustness

The main results in Section 2.5.1 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 2B.

First, I test the potential endogeneity issue by adopting a shift-share instrumental variable (SSIV) (Goldsmith-Pinkham et al., 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 et al., 1999; Goldsmith-Pinkham et al., 2020). This "leave-one-out" SSIV for state

s and year t is:

$$AIpost\ share\ IV_{s,t} = \sum_{o2} E_{o2,s,2011} \frac{\sum_{s' \neq s} \sum_{o4} \#AIpost_{o4,o2,s',t}}{\sum_{s' \neq s} \sum_{o4} \#post_{o4,o2,s',t}}, \tag{2.17}$$

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 2.6 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 (2.17) 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 2B.2 and 2B.3, which reassure a consistent pattern in employment gaps between skill groups.

Columns 3 and 4 of Table 2.6 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

[16]Details on how I propose this alternative occupational classification will be explained in Section 2.6.2.

Table 2.6 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^2	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.

using SSIVs summing over different occupation groups are presented in Appendix Tables 2B.4 and 2B.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 the share of CS postings using the same specification as in my baseline model. Table 2.7 shows estimates from regressions of employment per capita and wages. Columns 1, 3, and 5 show

Table 2.7 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^2	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.

estimates from my main specification, while columns 2, 4, and 6 show estimates obtained from additionally controlling for the CS posting share. Coefficients 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]

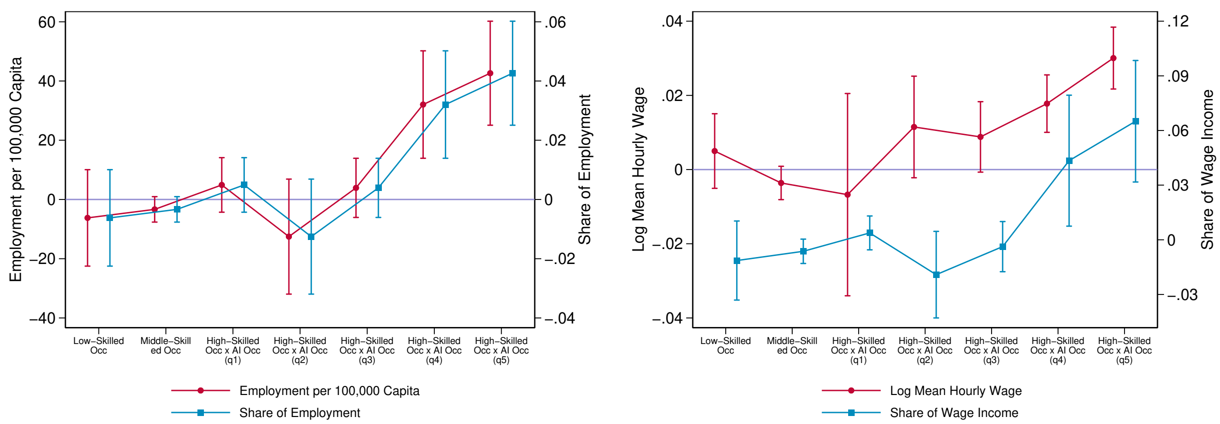
Appendix Tables 2B.10 and 2B.11 reassure that my main results are not driven by CS skills through controlling for exposure to software and robots using the measures constructed by Webb (2019). These measures capture the capabilities in software and robots for performing an occupation's tasks. After controlling for software and robot exposure, estimates are almost the same with those from my main specification. Appendix Tables 2B.12 and 2B.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, coefficients on broad AI posting shares become smaller compared with coefficients 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 (2.12) 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 2.8 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

[17] I also construct SSIVs for the CS posting share using equation (2.17) by replacing AI postings with CS postings. Appendix Tables 2B.6-2B.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 2B.6-2B.9 reassuare that my main results are not driven by CS skills. Regardless of the magnitude and significance level of coefficients on CS posting shares, coefficients 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.

Figure 2.8 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.

Figure 2.8. 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 2.8) 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 Score indicates the intensity that AI-developing skills are

[18]These results are robust to using the SSIV approach, with estimates presented in Appendix Tables 2B.14-2B.17.

[19]Each element in this matrix represents how many times a narrow AI phrase listed in Table 2.1 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 component loading is calculated for each narrow AI skill using PCA, which captures the importance

Table 2.8 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^2	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.

required for performing tasks of an occupation. The higher this score is, the more AI-intensive activities an occupation involves. Appendix Table 2B.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 2.9 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 2.9a). 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 2.9b). To make trends in this measure by skill group comparable, Figure 2.9c 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 2B.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 occupations with a low score are routine-intensive (i.e., from the middle-skilled group).

Table 2.9 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.

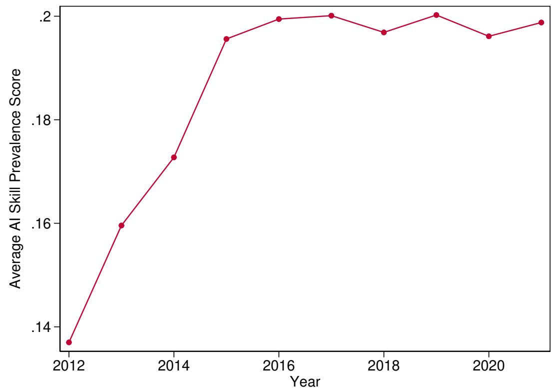
However, to make the estimates comparable to my main analysis which captures the between-

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.

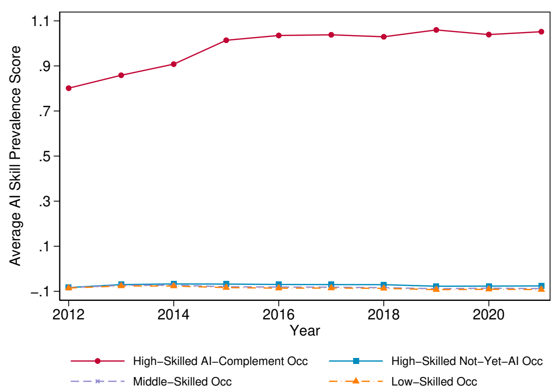
[20] The AI Skill Prevalence Score is standardized within a year.

Figure 2.9 Trends in Average AI Skill Prevalence Score, 2012-21

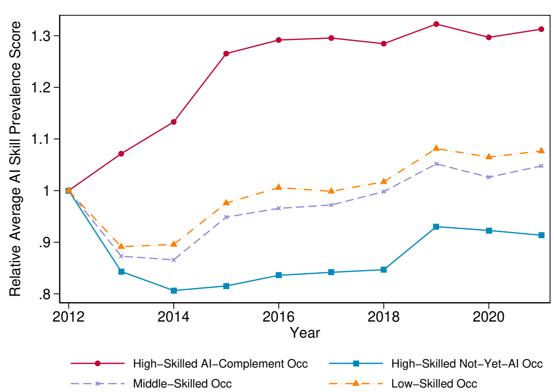
(a) Average AI Skill Prevalence Score across All Occupations



(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 2.9c, 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.

Table 2.9 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^2	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^2	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.

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 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 2B.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 2B.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 2B.7b is the same as Appendix Figure 2B.7a but fixing the range of the 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 2.9 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 between-group variation—the difference in the prevalence of AI skills between 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 2.5.1.

Estimates in Panel B of Table 2.9 also sheds light on Proposition 2.4 in Section 2.2.2 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 et al., 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 et al., 2020; Acemoglu and Restrepo, 2022a,b; Moll et al., 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 2.3.2. 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 2B.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 2B.22 and 2B.23, indicating that my results are not driven by COVID or work-from-home requirements during COVID.

2.5.3 Heterogeneity

Since the main results presented in Section 2.5.1 remain static over the whole sampling period, I examine heterogeneity over time in this section. Appendix Figure 2B.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 et al., 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 2B.9 further shows estimates by interacting state-year AI Skill Prevalence

Score with year dummies. Different from Appendix Figure 2B.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.

2.6 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 2.6.1 presents results from re-estimating equation (2.16) 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 2.6.2 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.

2.6.1 AI Postings at More Granular Level and Labor Marker Outcomes

In my main specification, equation (2.16), 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 (2.16) 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 (2.16) capture how changes in the AI posting share from a specific 2-digit occupation category affect labor market outcomes.

Appendix Table 2B.24 focuses on employment. Different from my main results, Table 2.4 in Section 2.5.1, the share of AI postings used in Appendix Table 2B.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 between groups. After controlling for a full set of fixed effects following my main specification, equation (2.16), none of the coefficients on AI postings are statistically significant. This finding also holds in terms of wages, with estimates presented in Appendix Table 2B.25.

Similarly, when interacting the occupation-year AI Skill Prevalence Score with skill group dummies as presented in Appendix Table 2B.26, estimates become much noisier compared with using this measure at more aggregated level in Panel B of Table 2.9. 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 between-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 between 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 et al. (2019), Acemoglu (2021), Crafts (2021), and Hötte et al. (2022).

2.6.2 Alternative Classification of Occupations

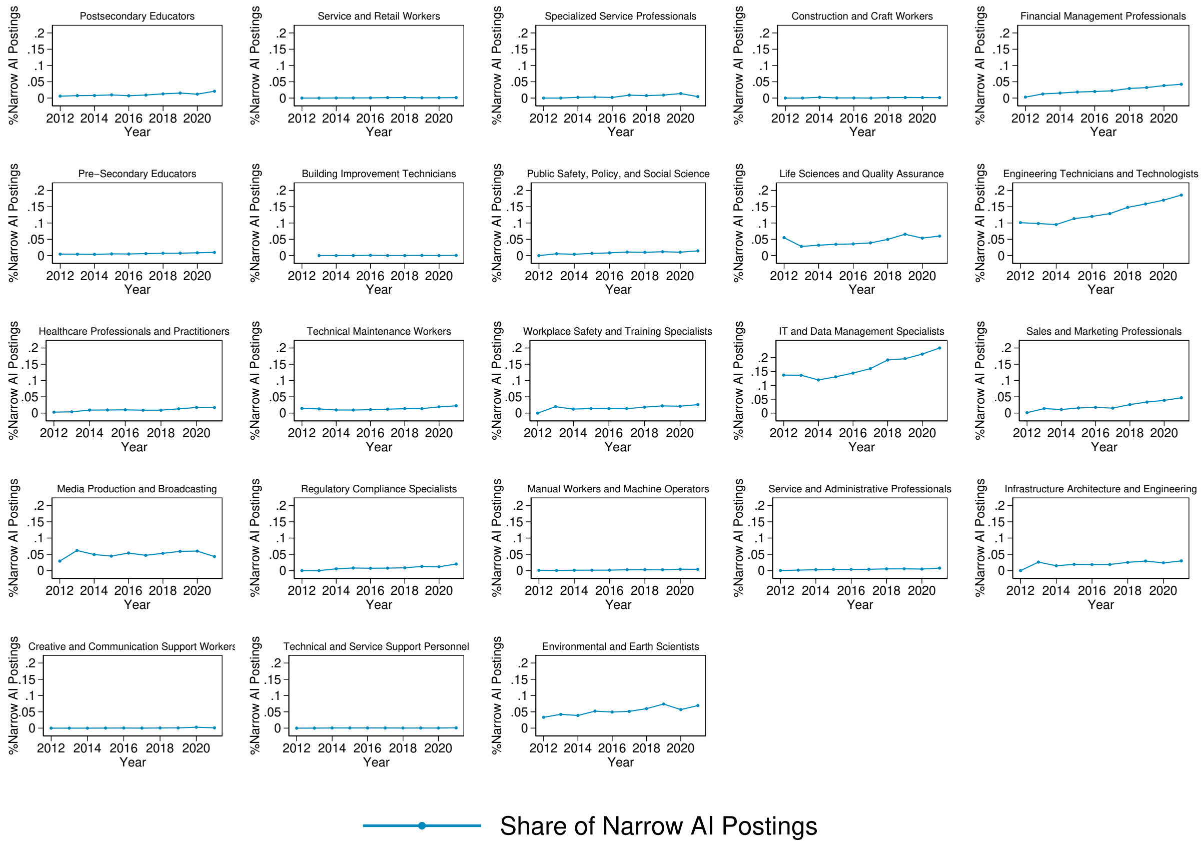
This section introduces an alternative occupation classification system to replace the 2-digit occupation group in my main specification. The broad occupation groups classified by Census or BLS are based on general work performed, but may not reflect specific skill requirements of an occupation. For 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 2D. Appendix Tables 2D.1-2D.3 present the relationship between the ML occupation clusters and the four skill groups introduced in Section 2.3.2, while Appendix Table 2D.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 2.10 shows that Engineering, Environment, Finance, IT, Media, and Life Sciences occupations 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 2B.10 are pretty flat, except "Computer and Mathematical Occupations" and "Architecture and Engineering Occupations." Appendix Figures 2B.11a and 2B.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

[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 2.10 Plots of %AI Postings by ML Occupation Cluster, 2012-21



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 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 2B.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

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

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 2.10, 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, coefficients from Table 2.10 show that almost all occupation clusters are significantly impacted by the demand for AI skills.

2.7 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 reallocation, 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.

Table 2.10 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^2	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.

2. There is no significant relationship between changes in demand for AI skills and employment for 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.

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APPENDIX 2A

PROPOSITIONS AND PROOFS

Appendix 2A.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 2.3 and 2.4 in Section 2.2.2, while both Propositions 2A.7 and 2A.8 are only included in the Appendix. Proposition 2A.7 discusses the productivity effect of AI and industrial automation on the final output. Proposition 2A.8 sheds light on the relationship between relative wages and labor supplies. Appendix 2A.2 shows the proofs of all propositions.

2A.1 Additional Propositions

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

Inequalities presented in Proposition 2.3 in Section 2.2.2:

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

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

(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 (2.1), 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 Proposition 2.4 in Section 2.2.2:

(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 2A.7 (Productivity effect of AI or industrial automation)

$$\frac{dY}{dI_M} = \frac{\sigma}{\sigma-1}Y\left[R^{1-\sigma} - (\frac{W_M}{\alpha_M(I_M)})^{1-\sigma}\right] > 0,$$
$$\frac{dY}{dI_H} = \frac{\sigma}{\sigma-1}Y\left[(\frac{R}{\alpha_K})^{1-\sigma} - \mathbf{1}\{i \in AI\ tasks\}(\frac{W_{H^{AI}}}{\alpha_{H^{AI}}(I_H)})^{1-\sigma} - \mathbf{1}\{i \in not\text{-}yet\text{-}AI\ tasks\}(\frac{W_{H^{Non}}}{\alpha_{H^{Non}}(I_H)})^{1-\sigma}\right]$$
$$> 0. \tag{2A.1}$$

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 $\mathbf{1}\{i \in \text{AI tasks}\}\frac{W_{H^{AI}}}{\alpha_{H^{AI}}(I_H)} + \mathbf{1}\{i \in \text{not-yet-AI tasks}\}\frac{W_{H^{Non}}}{\alpha_{H^{Non}}(I_H)} - \frac{R}{\alpha_K}$ 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 2.3).

Proposition 2A.8 (Relationship between relative wages and labor supplies)

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

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 ($\frac{W_{H^j}}{W_L}$).

2A.2 Proofs

2A.2.1 Proof of Proposition 2.1

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, $R = \frac{W_M}{\alpha_M(I_M)}$.[1] Since Assumption 2.3 assumes that $\exists I_M \in (N-1, S)$ such that $\frac{W_M}{\alpha_M(I_M)} > R$ and Assumption 2.1 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.

2A.2.2 Proof of Proposition 2.2

I first show the proof of the ideal-price condition presented in equation (2.8). Given the CES production function expressed in equation (2.1), the marginal cost of producing the final good Y is:

$$P = \left[\int_{N-1}^{N} p(i)^{1-\sigma} di\right]^{\frac{1}{1-\sigma}}. \tag{2A.3}$$

Equation (2.8) can then be derived by combining equations (2.3) and (2A.3):

$$\begin{aligned}
1 \equiv P = &\left[\int_{N-1}^{I_L} (\frac{W_L}{\alpha_L(i)})^{1-\sigma} di + \int_{I_L}^{I_M} R^{1-\sigma} di + \int_{I_M}^{S} (\frac{W_M}{\alpha_M(i)})^{1-\sigma} di + \int_{S}^{I_H} (\frac{R}{\alpha_K})^{1-\sigma} di\right.\\
&\left. + \int_{I_H}^{N} (\frac{W_{H^{AI}}}{\alpha_{H^{AI}}(i)})^{1-\sigma} di + \int_{I_H}^{N} (\frac{W_{H^{Non}}}{\alpha_{H^{Non}}(i)})^{1-\sigma} di\right]^{\frac{1}{1-\sigma}}\\
\Rightarrow 1 = &R^{1-\sigma}\left[I_M - I_L + (I_H - S)\alpha_K^{\sigma-1}\right] + W_L^{1-\sigma}\int_{N-1}^{I_L} \alpha_L(i)^{\sigma-1} di + W_M^{1-\sigma}\int_{I_M}^{S} \alpha_M(i)^{\sigma-1} di\\
&+ W_{H^{AI}}^{1-\sigma}\int_{I_H}^{N} \mathbf{1}\{i \in \text{AI tasks}\}\alpha_{H^{AI}}(i)^{\sigma-1} di + W_{H^{Non}}^{1-\sigma}\int_{I_H}^{N} \mathbf{1}\{i \in \text{not-yet-AI tasks}\}\alpha_{H^{Non}}(i)^{\sigma-1} di\\
= &\mathrm{A}_{H^{AI}} W_{H^{AI}}^{1-\sigma} + \mathrm{A}_{H^{Non}} W_{H^{Non}}^{1-\sigma} + \mathrm{A}_M W_M^{1-\sigma} + \mathrm{A}_L W_L^{1-\sigma} + \mathrm{A}_K R^{1-\sigma}.
\end{aligned} \tag{2A.4}$$

The equilibrium factor prices expressed in equation (2.9) can be easily obtained by re-arranging terms of equation (2.6). Replacing factor prices of the ideal-price condition, equation (2.8), with

[1] The productivity of industrial automation is set to be 1 introduced in Section 2.2.1.

expressions for these factor prices presented in equation (2.9), I can obtain the equilibrium output shown in equation (2.10):

$$
\begin{aligned}
1 &= \mathrm{A}_{H^{AI}} W_{H^{AI}}^{1-\sigma} + \mathrm{A}_{H^{Non}} W_{H^{Non}}^{1-\sigma} + \mathrm{A}_M W_M^{1-\sigma} + \mathrm{A}_L W_L^{1-\sigma} + \mathrm{A}_K R^{1-\sigma} \\
&= \mathrm{A}_{H^{AI}} \left[Y^{\frac{1}{\sigma}} \mathrm{A}_{H^{AI}}^{\frac{1}{\sigma}} (H^{AI})^{-\frac{1}{\sigma}} \right]^{1-\sigma} + \mathrm{A}_{H^{Non}} \left[Y^{\frac{1}{\sigma}} \mathrm{A}_{H^{Non}}^{\frac{1}{\sigma}} (H^{Non})^{-\frac{1}{\sigma}} \right]^{1-\sigma} + \mathrm{A}_M \left[Y^{\frac{1}{\sigma}} \mathrm{A}_M^{\frac{1}{\sigma}} M^{-\frac{1}{\sigma}} \right]^{1-\sigma} \\
&\quad + \mathrm{A}_L W_L \left[Y^{\frac{1}{\sigma}} \mathrm{A}_L^{\frac{1}{\sigma}} L^{-\frac{1}{\sigma}} \right]^{1-\sigma} + \mathrm{A}_K \left[Y^{\frac{1}{\sigma}} \mathrm{A}_K^{\frac{1}{\sigma}} K^{-\frac{1}{\sigma}} \right]^{1-\sigma} \\
&= Y^{\frac{1-\sigma}{\sigma}} \left[\mathrm{A}_{H^{AI}}^{\frac{1}{\sigma}} (H^{AI})^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_{H^{Non}}^{\frac{1}{\sigma}} (H^{Non})^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_M^{\frac{1}{\sigma}} M^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_L^{\frac{1}{\sigma}} L^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_K^{\frac{1}{\sigma}} K^{\frac{\sigma-1}{\sigma}} \right].
\end{aligned}
\tag{2A.5}
$$

2A.2.3 Proof of Propositions 2.3 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 2.3. The proof for other inequalities in Propositions 2.3 and 3′ is analogous. Given equation (2.7),

$$
\begin{aligned}
\frac{d\mathrm{A}_{H^{AI}}}{dI_H} &= \frac{d\int_{I_H}^{N} \mathbf{1}\{i \in \text{AI tasks}\} \alpha_{H^{AI}}(i)^{\sigma-1} di}{dI_L} \\
&= \mathbf{1}\{i \in \text{AI tasks}\} \alpha_{H^{AI}}(N)^{\sigma-1} \frac{d(N)}{di} - \mathbf{1}\{i \in \text{AI tasks}\} \alpha_{H^{AI}}(I_H)^{\sigma-1} \\
&= \mathbf{1}\{i \in \text{AI tasks}\} \alpha_{H^{AI}}(I_H)^{\sigma-1} > 0.
\end{aligned}
\tag{2A.6}
$$

2A.2.4 Proof of Propositions 2.4 and 4′

Given the equilibrium factor prices presented in equation (2.9) and Proposition 2.3,

$$
\frac{d(\frac{W_{H^j}}{W_L})}{dI_H} = \frac{d\left[\frac{\mathrm{A}_{H^j}^{1/\sigma} (H^j)^{-1/\sigma}}{\mathrm{A}_L^{1/\sigma} L^{-1/\sigma}} \right]}{dI_H} = \frac{\frac{d\mathrm{A}_{H^j}}{dI_H} \frac{1}{\sigma} \mathrm{A}_{H^j}^{\frac{1-\sigma}{\sigma}} (H^j)^{-1/\sigma}}{\mathrm{A}_L^{1/\sigma} L^{-1/\sigma}} < 0, \ j \in \{AI, Non\}. \tag{2A.7}
$$

Similar for the other inequalities in Propositions 2.4 and 4′.

2A.2.5 Proof of Proposition 2.5

Given the equilibrium factor prices presented in equation (2.9) and Assumption 2.1,

$$
\begin{aligned}
\frac{d(\frac{W_{H^{AI}}}{W_L})}{d\alpha_{H^{AI}}(i)} &= \frac{d\mathrm{A}_{H^{AI}}}{d\alpha_{H^{AI}}(i)} \frac{\frac{1}{\sigma}\mathrm{A}_{H^{AI}}^{\frac{1-\sigma}{\sigma}}(H^{AI})^{-\frac{1}{\sigma}}}{\mathrm{A}_L^{\frac{1}{\sigma}} L^{-\frac{1}{\sigma}}} \\
&= \frac{d\left[\int_{I_H}^{N} \mathbf{1}\{i \in \text{AI tasks}\}\alpha_{H^{AI}}(i)^{\sigma-1} di\right]}{d\alpha_{H^{AI}}(i)} \frac{\frac{1}{\sigma}\mathrm{A}_{H^{AI}}^{\frac{1-\sigma}{\sigma}}(H^{AI})^{-\frac{1}{\sigma}}}{\mathrm{A}_L^{\frac{1}{\sigma}} L^{-\frac{1}{\sigma}}} \\
&= \frac{\mathbf{1}\{i \in \text{AI tasks}\}\alpha_{H^{AI}}(i)^{\sigma-1}}{\alpha'_{H^{AI}}(i)} \frac{\frac{1}{\sigma}\mathrm{A}_{H^{AI}}^{\frac{1-\sigma}{\sigma}}(H^{AI})^{-\frac{1}{\sigma}}}{\mathrm{A}_L^{\frac{1}{\sigma}} L^{-\frac{1}{\sigma}}} > 0.
\end{aligned}
\tag{2A.8}
$$

Similar for the other inequalities in Proposition 2.5.

2A.2.6 Proof of Proposition 2.6

Given the equilibrium factor prices presented in equation (2.9) and Assumption 2.1,

$$
\begin{aligned}
\frac{d(\frac{H^{AI}W_{H^{AI}}}{KR})}{d\alpha_{H^{AI}}(i)} &= \frac{d(\frac{H^{AI}Y^{1/\sigma}\mathrm{A}_{H^{AI}}^{1/\sigma}(H^{AI})^{-1/\sigma}}{KY^{1/\sigma}\mathrm{A}_K^{1/\sigma}K^{-1/\sigma}})}{d\alpha_{H^{AI}}(i)} = \frac{d\mathrm{A}_{H^{AI}}^{1/\sigma}}{d\alpha_{H^{AI}}(i)} \frac{(H^{AI})^{\frac{\sigma-1}{\sigma}}}{\mathrm{A}_K^{1/\sigma} K^{\frac{\sigma-1}{\sigma}}} \\
&= \frac{1}{\sigma}\mathrm{A}_{H^{AI}}^{\frac{1-\sigma}{\sigma}} \frac{d\left[\int_{I_H}^{N} \mathbf{1}\{i \in \text{AI tasks}\}\alpha_{H^{AI}}(i)^{\sigma-1} di\right]}{d\alpha_{H^{AI}}(i)} \frac{(H^{AI})^{\frac{\sigma-1}{\sigma}}}{\mathrm{A}_K^{1/\sigma} K^{\frac{\sigma-1}{\sigma}}} \\
&= \frac{\mathbf{1}\{i \in \text{AI tasks}\}\alpha_{H^{AI}}(i)^{\sigma-1}}{\alpha'_{H^{AI}}(i)} \frac{\frac{1}{\sigma}\mathrm{A}_{H^{AI}}^{\frac{1-\sigma}{\sigma}}(H^{AI})^{\frac{\sigma-1}{\sigma}}}{\mathrm{A}_K^{\frac{1}{\sigma}} K^{\frac{\sigma-1}{\sigma}}} > 0.
\end{aligned}
\tag{2A.9}
$$

Similarly,

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

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:

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

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

2A.2.7 Proof of Proposition 2A.7

Rewrite equation (2.10), the expression for the equilibrium output, as

$$Y^{\frac{\sigma-1}{\sigma}} = \mathrm{A}_{H^{AI}}^{\frac{1}{\sigma}}(H^{AI})^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_{H^{Non}}^{\frac{1}{\sigma}}(H^{Non})^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_M^{\frac{1}{\sigma}}M^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_L^{\frac{1}{\sigma}}L^{\frac{\sigma-1}{\sigma}} + \mathrm{A}_K^{\frac{1}{\sigma}}K^{\frac{\sigma-1}{\sigma}}, \tag{2A.12}$$

and differentiate both sides with respect to I_L:

$$\begin{aligned}
\frac{\sigma-1}{\sigma}Y^{-\frac{1}{\sigma}}\frac{dY}{dI_M} &= \mathrm{A}_M^{\frac{1-\sigma}{\sigma}}M^{\frac{\sigma-1}{\sigma}}\frac{d\mathrm{A}_M}{dI_M} + \mathrm{A}_K^{\frac{1-\sigma}{\sigma}}K^{\frac{\sigma-1}{\sigma}}\frac{d\mathrm{A}_K}{dI_M} \\
\frac{dY}{dI_M} &= \frac{\sigma}{\sigma-1}Y^{\frac{1}{\sigma}}\left[\mathrm{A}_M^{\frac{1-\sigma}{\sigma}}M^{\frac{\sigma-1}{\sigma}}\frac{d\mathrm{A}_M}{dI_M} + \mathrm{A}_K^{\frac{1-\sigma}{\sigma}}K^{\frac{\sigma-1}{\sigma}}\frac{d\mathrm{A}_K}{dI_M}\right] \\
\frac{dY}{dI_M} &= \frac{\sigma}{\sigma-1}Y\left[(Y\mathrm{A}_M)^{\frac{1-\sigma}{\sigma}}M^{\frac{\sigma-1}{\sigma}}\frac{d\mathrm{A}_M}{dI_M} + (Y\mathrm{A}_K)^{\frac{1-\sigma}{\sigma}}K^{\frac{\sigma-1}{\sigma}}\frac{d\mathrm{A}_K}{dI_M}\right] \\
\frac{dY}{dI_M} &= \frac{\sigma}{\sigma-1}Y\left[R^{1-\sigma} - W_M^{1-\sigma}\alpha_M(I_M)^{\sigma-1}\right] \\
\frac{dY}{dI_M} &= \frac{\sigma}{\sigma-1}Y\left[R^{1-\sigma} - (\frac{W_M}{\alpha_M(I_M)})^{1-\sigma}\right] > 0.
\end{aligned} \tag{2A.13}$$

According to Assumption 2.3, $\exists I_M \in (N-1, S)$ 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 $\frac{dY}{dI_H} > 0$.

2A.2.8 Proof of Proposition 2A.8

Given the equilibrium factor prices presented in equation (2.9),

$$\begin{aligned}\frac{d\ln(\frac{W_{H^j}}{W_L})}{d\ln H^j} &= \frac{d\ln\left[\frac{A_{H^j}^{1/\sigma}(H^j)^{-1/\sigma}}{A_L^{1/\sigma}L^{-1/\sigma}}\right]}{d\ln H^j} \\ &= \frac{d(\frac{1}{\sigma}\ln A_{H^j} - \frac{1}{\sigma}\ln H^j - \frac{1}{\sigma}\ln A_L + \frac{1}{\sigma}\ln L)}{d\ln H^j} \\ &= -\frac{1}{\sigma} < 0,\ j \in \{AI, Non\}.\end{aligned} \tag{2A.14}$$

Similar for the other inequalities in Proposition 2A.8.

APPENDIX 2B

ADDITIONAL FIGURES & TABLES

Figure 2B.1 Number of AI/CS Postings by BLS Region in LinkUp Data, 2011-22

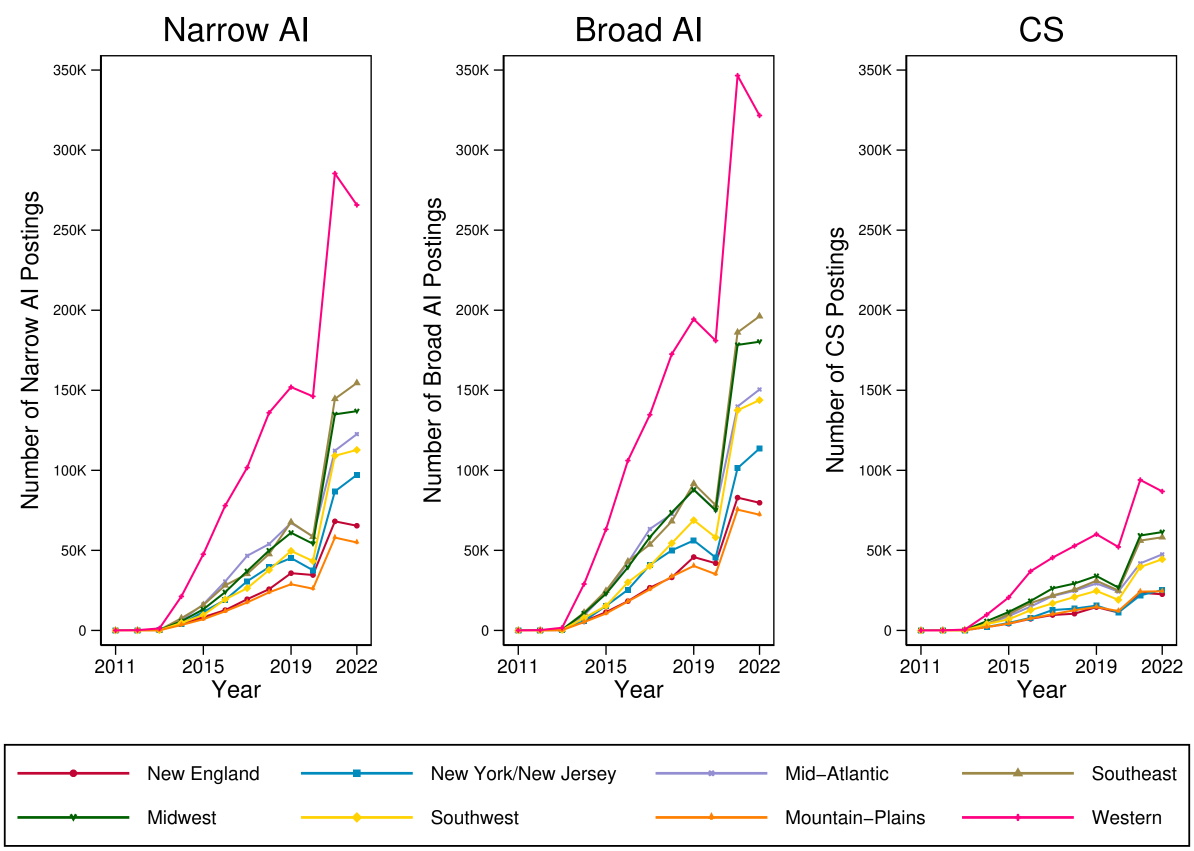


Figure 2B.2 Share of AI/CS Postings by BLS Region in LinkUp Data, 2011-22

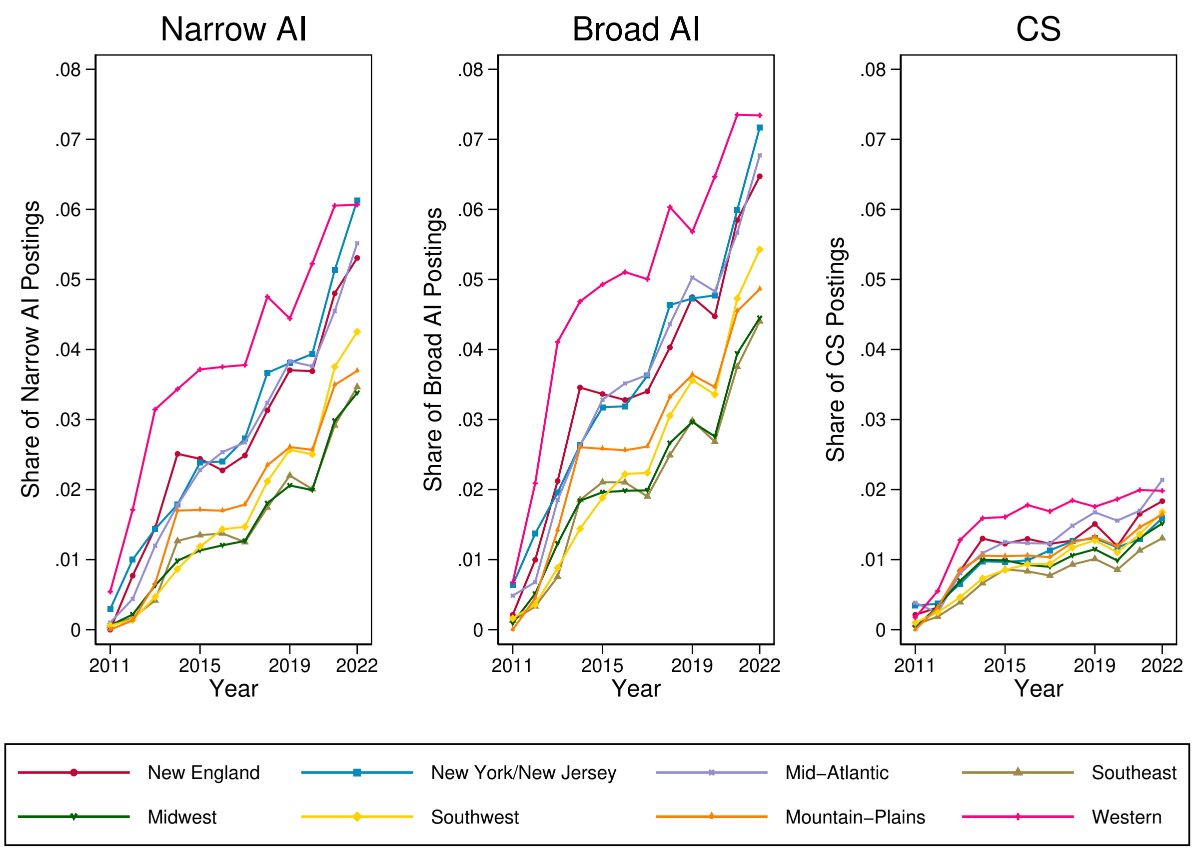
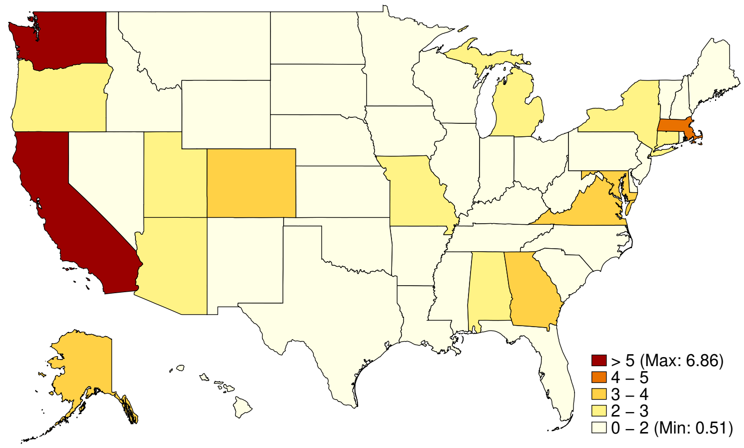
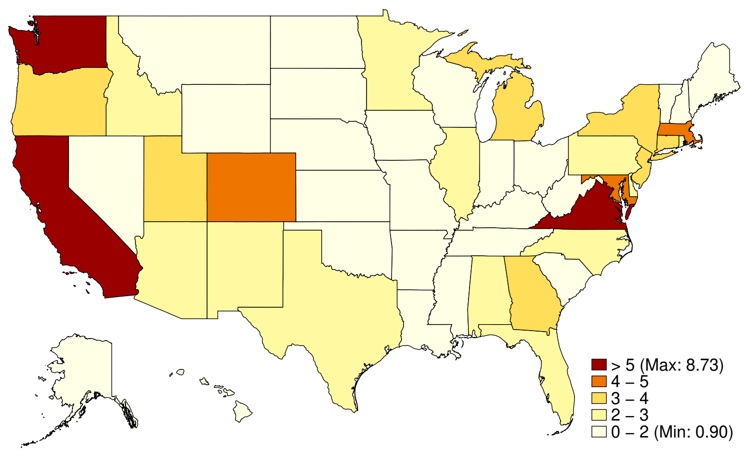


Figure 2B.3 Geographic Distribution of the Share of Broad AI Postings in LinkUp Data

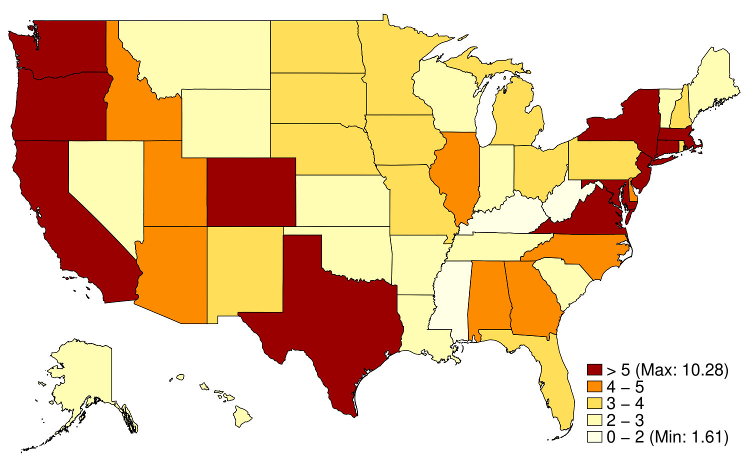
(a) 2011-14



(b) 2015-18

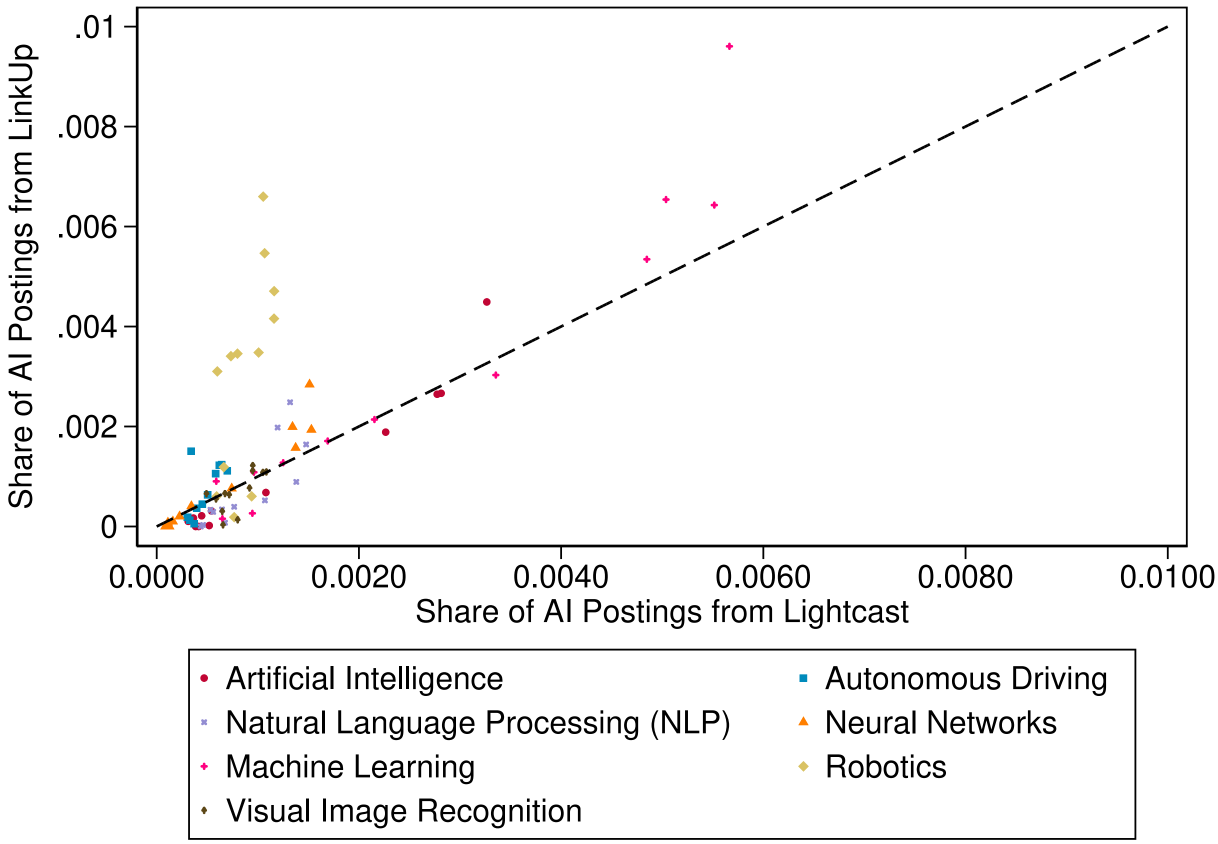


(c) 2019-22



Notes: Scales are in percentage point.

Figure 2B.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 2B.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 2B.6 Plots of Skill-Group-By-Year Employment, Wages, and Share of AI Postings (Using Broad AI Definition), 2012-21

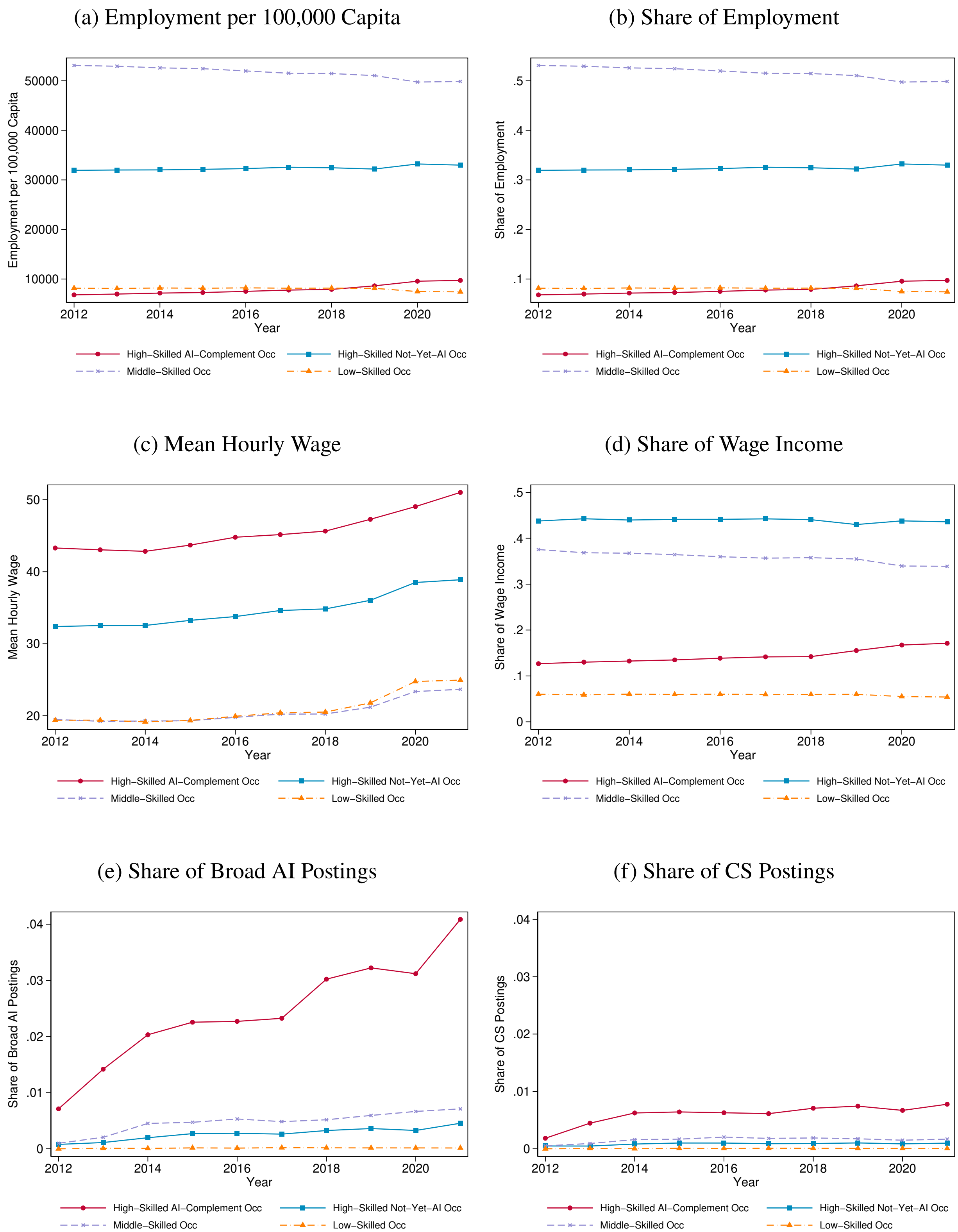
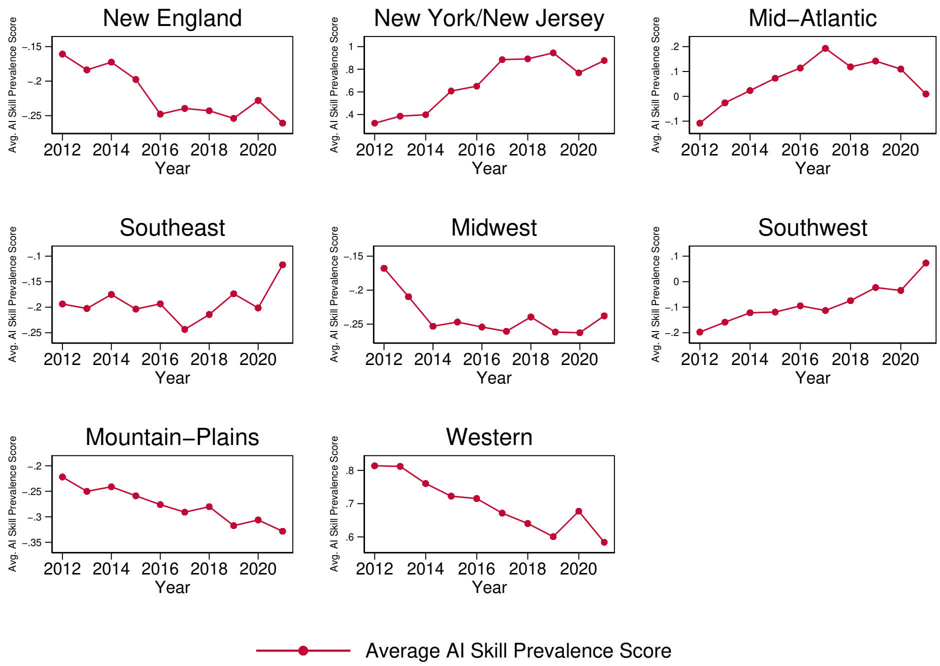
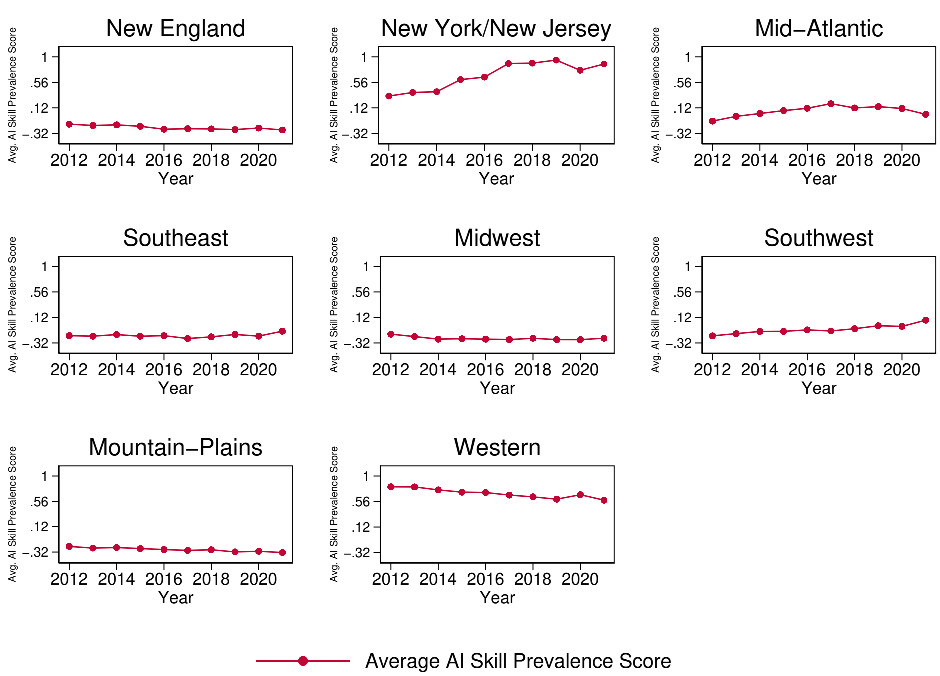


Figure 2B.7 Average AI Skill Prevalence Score by BLS Region, 2012-21

(a) Not Fixing the Range of the Y-Axis



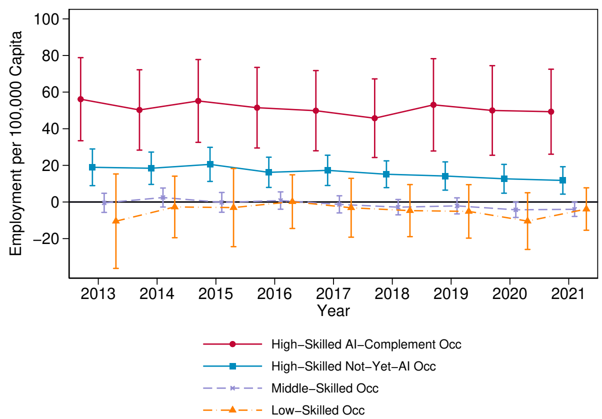
(b) Fixing the Range of the Y-Axis



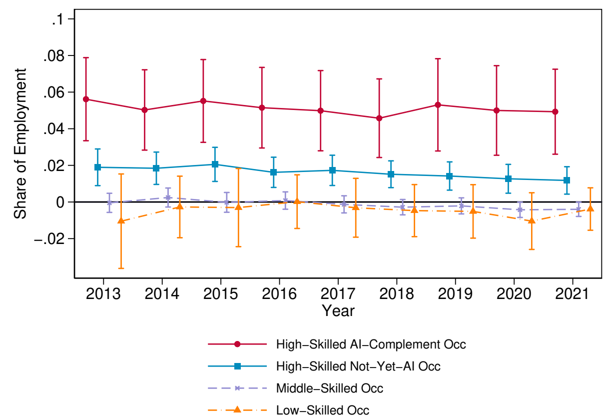
Notes: The AI Skill Prevalence Score is constructed at the state-year level and standardized within a year.

Figure 2B.8 Time-Varying Effects of Demand for AI Skills on Labor Market Outcomes, 2012-21

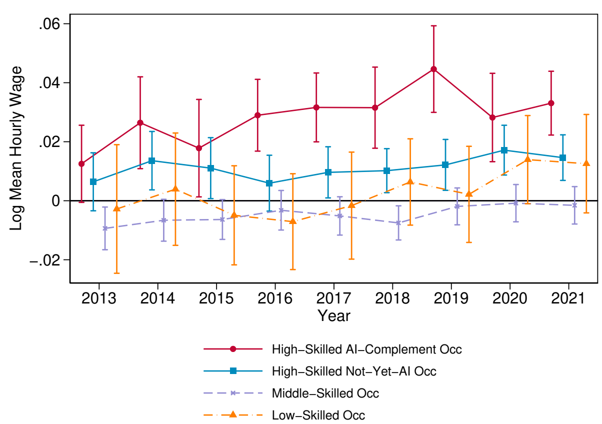
(a) Employment per 100,000 Capita



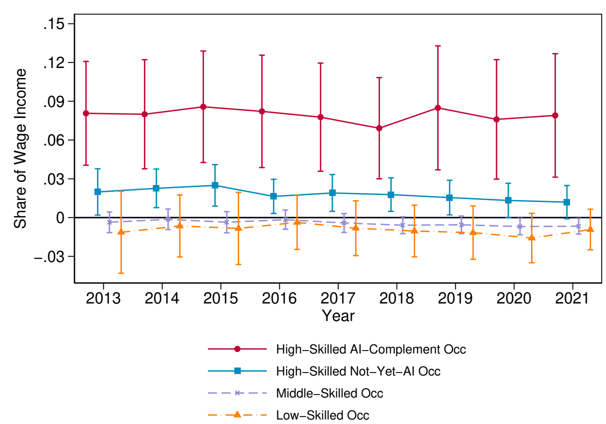
(b) Share of Employment



(c) Log Mean Hourly Wage



(d) Share of Wage Income

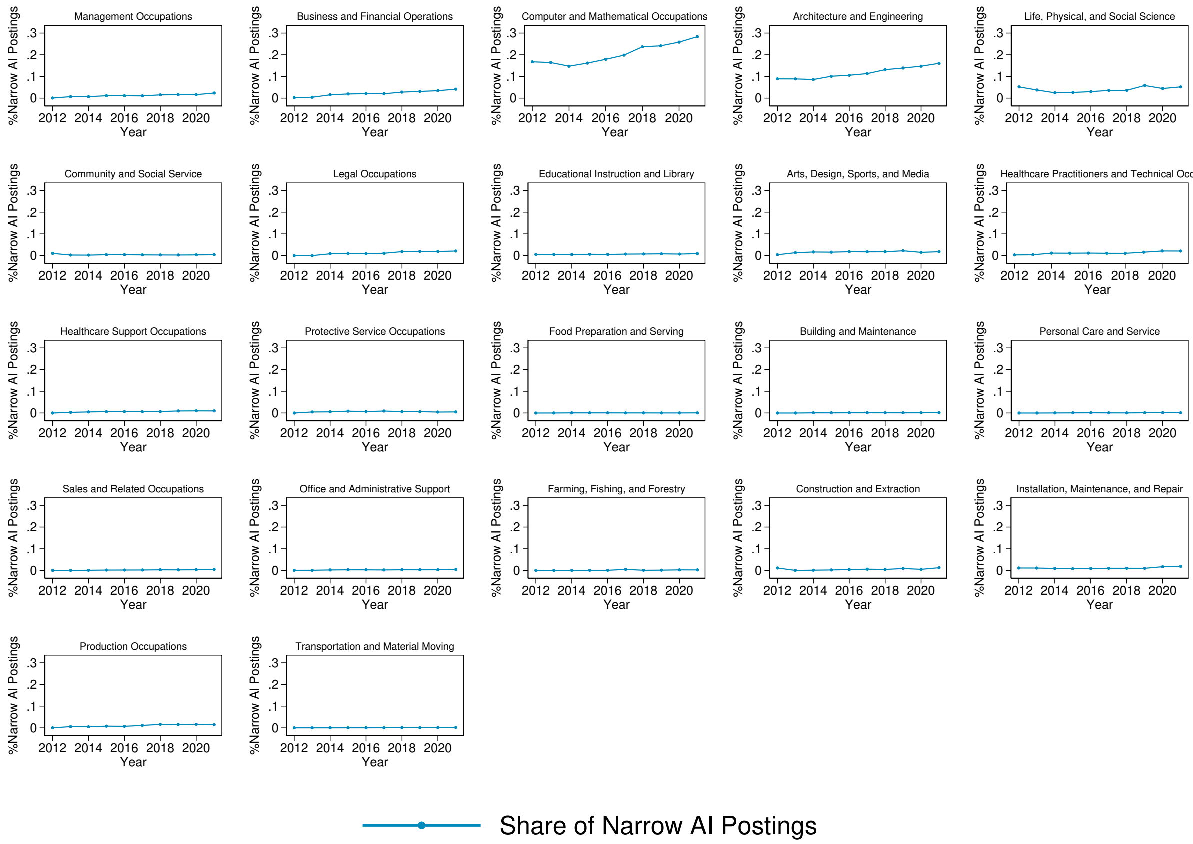


Notes: The coefficient estimates plotted in each subfigure show overall time-varying effects of changes in share of narrow AI postings on labor market outcomes. They are obtained by respectively regressing employment per 100,000 capita, share of employment (in percentage point), log mean hourly wages, 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 2B.9 Time-Varying Effects of AI Skill Prevalence on Labor Market Outcomes, 2012-21

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 2B.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 2.3.2.2. Thus, only 22 Census 2-digit groups are included in my sample for plotting the share of narrow AI postings.

Figure 2B.11 Plots of Mean Hourly Wage by Different Occupation System, 2012-21

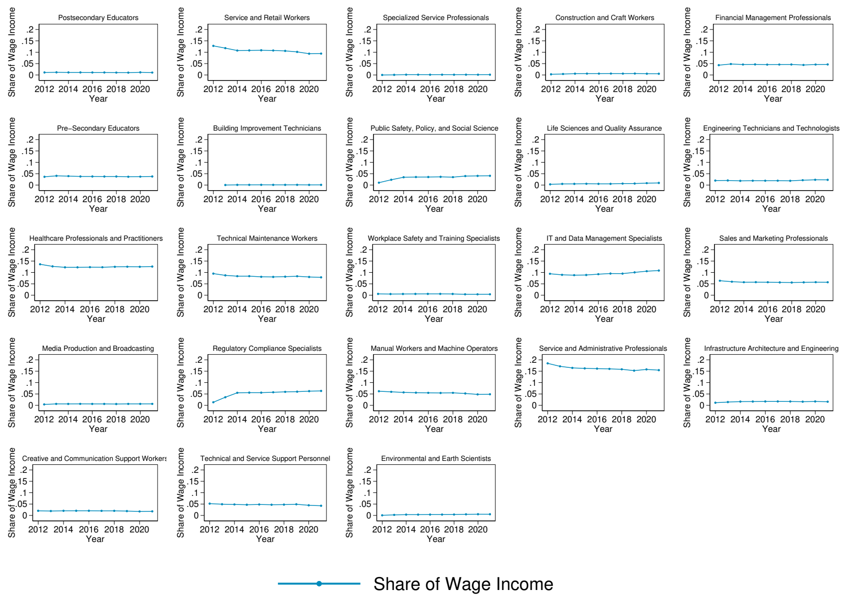
(a) By ML Occupation Cluster

(b) By 2-Digit Census Occupational Classification

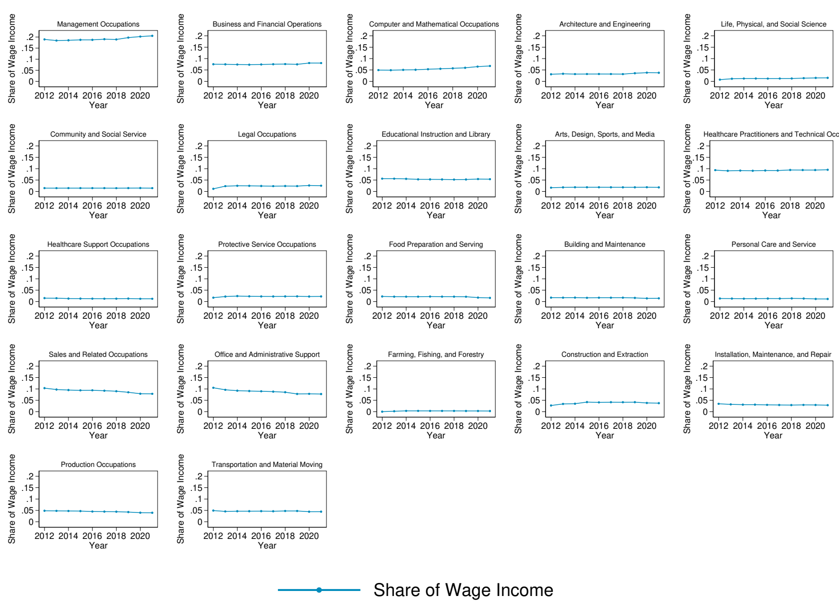
Notes: The total number of 2-digit Census Occupational Classification is 23, which is the same as the total number of my proposed ML occupation clusters. However, the "Military Specific Occupations" group is excluded from my main sample due to the absence of O*NET occupational descriptions, which are necessary for constructing the AI occupation indicators and, consequently, the skill group indicators, as explained in Section 2.3.2.2. Thus, only 22 Census 2-digit groups are included in my sample for plotting the mean hourly wage.

Figure 2B.12 Plots of %Wage Income by Different Occupation System, 2012-21

(a) By ML Occupation Cluster



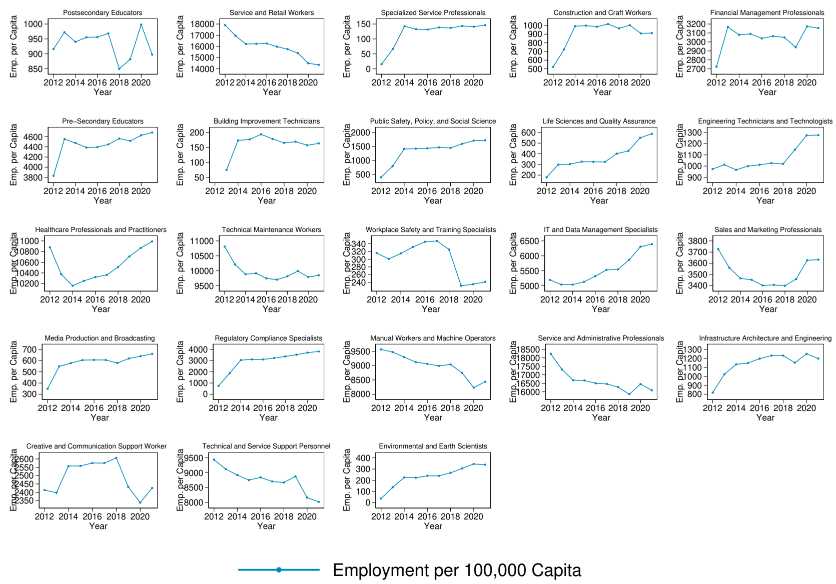
(b) By 2-Digit Census Occupational Classification



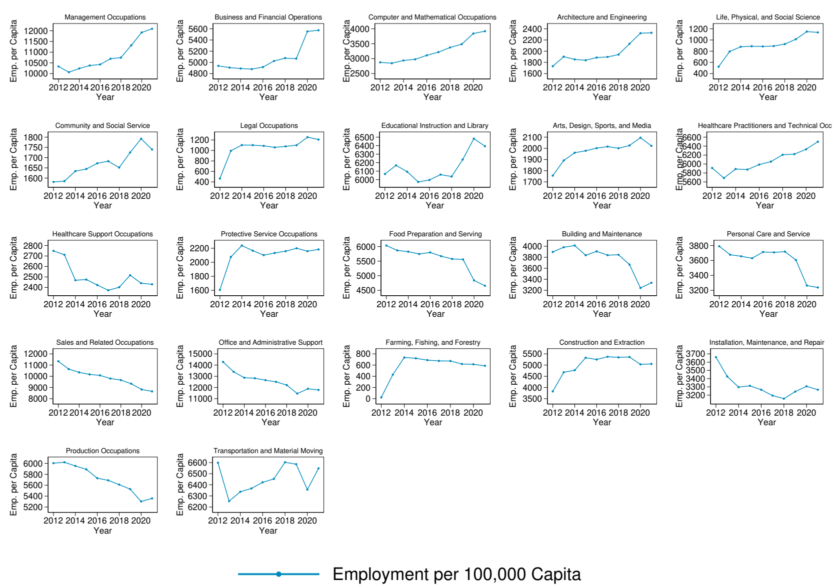
Notes: The total number of 2-digit Census Occupational Classification is 23, which is the same as the total number of my proposed ML occupation clusters. However, the "Military Specific Occupations" group is excluded from my main sample due to the absence of O*NET occupational descriptions, which are necessary for constructing the AI occupation indicators and, consequently, the skill group indicators, as explained in Section 2.3.2.2. Thus, only 22 Census 2-digit groups are included in my sample for plotting the share of wage income.

Figure 2B.13 Plots of Emp. per Capita by Different Occupation System, 2012-21

(a) By ML Occupation Cluster



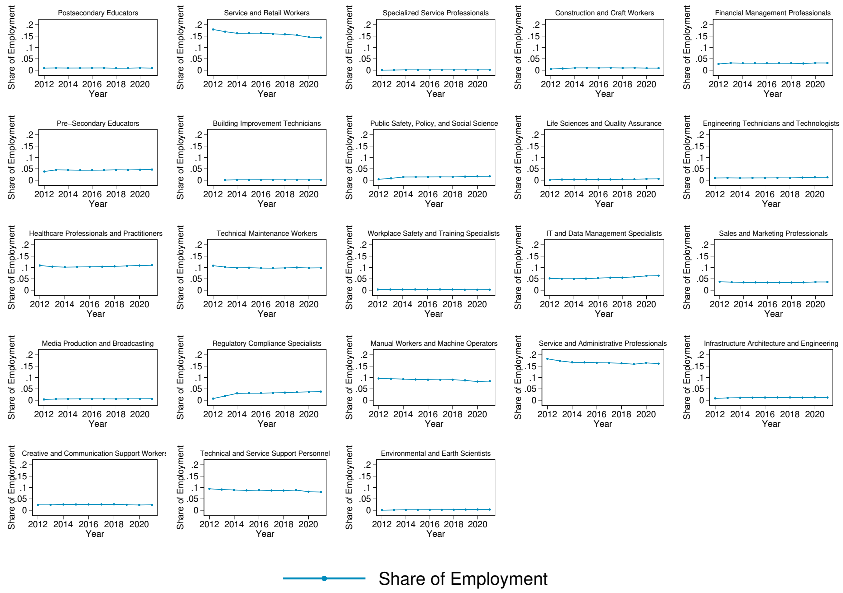
(b) By 2-Digit Census Occupational Classification



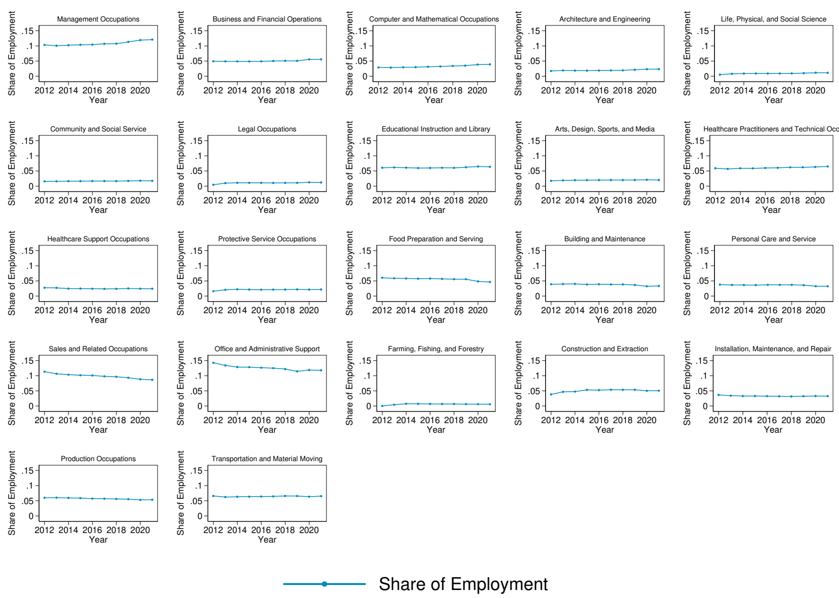
Notes: The range of the y-axis is not fixed for each occupation group within an occupation system. The total number of 2-digit Census Occupational Classification is 23, which is the same as the total number of my proposed ML occupation clusters. However, the "Military Specific Occupations" group is excluded 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 2.3.2.2. Thus, only 22 Census 2-digit groups are included in my sample for plotting the employment per capita.

Figure 2B.14 Plots of %Employment by Different Occupation System, 2012-21

(a) By ML Occupation Cluster

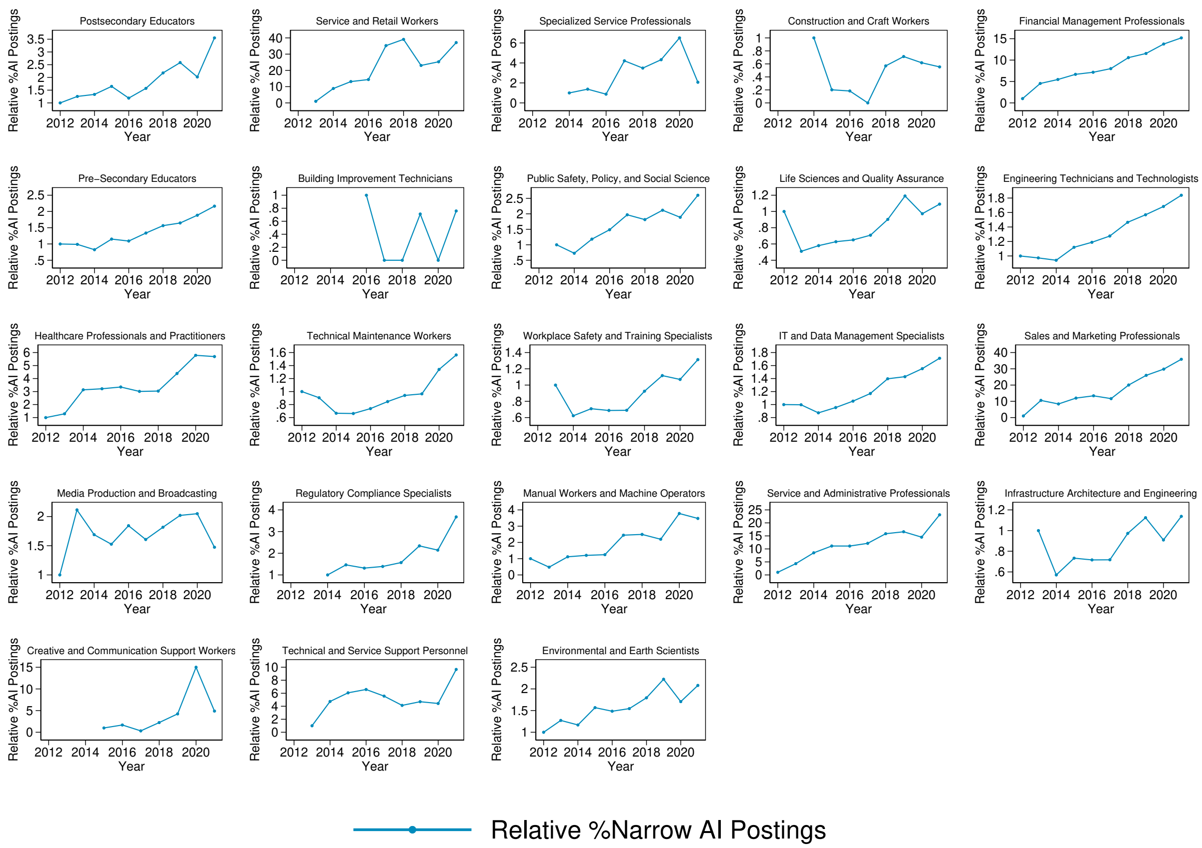


(b) By 2-Digit Census Occupational Classification



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 2.3.2.2. Thus, only 22 Census 2-digit groups are included in my sample for plotting the share of employment.

Figure 2B.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 2B.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 2B.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^2	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 2.6.2.

[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 2B.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^2	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 2.6.2.

[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 2B.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^2	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 2.6.2.

[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 2B.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^2	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 2.6.2.

[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 2B.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^2	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 2.6.2.

[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 2B.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^2	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 2.6.2.

[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 2B.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^2	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 2.6.2.

[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 2B.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^2	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 2.6.2.

[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 2B.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.	Controlling for Exposure to Software/Robot	Main Spec.	Controlling 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^2	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 2B.11 Effects of Demand for AI Skills on Wages—Controlling for Software/Robot Exposure, 2012-21

	Dep. Var.:			
	Log Mean Hourly Wages		Share of Wage Income[1]	
	Main Spec.	Controlling for Exposure to Software/Robot	Main Spec.	Controlling 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^2	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 2B.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^2	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 2B.13 Effects of Demand for AI Skills on Wages—Comparing Narrow vs. Broad AI Definition, 2012-21

	Dep. Var.:			
	Log Mean Hourly 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^2	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 2B.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^2	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 2.6.2.

[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 2B.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^2	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 2.6.2.

[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 2B.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^2	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 2.6.2.

[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 2B.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^2	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 2.6.2.

[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 2B.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 principal component analysis (PCA) to construct this single measurement.

Table 2B.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 2B.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 2B.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 (2.16), 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 2B.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^2	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 2B.23 Effects of Demand for AI Skills on Wages—Dropping COVID Years, 2012-19

	Dep. Var.:			
	Log Mean Hourly 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^2	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 2B.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^2	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 2B.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^2	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 2B.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^2	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.

APPENDIX 2C

4-DIGIT OCCUPATIONS WITHIN A SKILL GROUP

Since the LinkUp job postings data used to construct the skill groups introduced in Section 2.3.2 is collected at the 2019 O*NET-SOC level and the labor market outcome data from IPUMS-ACS uses a harmonized occupation system, OCC2010[1], 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 2.3.2.2).[2] 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 2C.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 2C.1 shows occupations that are classified into the

[1] 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.

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

corresponding skill group using this time-invariant skill group system.[3]

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

Table 2C.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}	

Table 2C.1 (cont'd)

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}	

Table 2C.1 (cont'd)

OCC2010	Occupation Title	Skill Group Indicator During			Ever
		2011-14	2015-18	2019-22	Changed
3110	Physician Assistants	H^{Non}	H^{Non}	H^{Non}	
3120	Podiatrists	H^{Non}	H^{Non}	H^{Non}	
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*	

Table 2C.1 (cont'd)

OCC2010	**Occupation Title**	**Skill Group Indicator During**			**Ever**
		2011-14	**2015-18**	**2019-22**	**Changed**
2910	Photographers	*M*	*M*	*M*	
3050	Pharmacists	*M*	*M*	*M*	
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*	

Table 2C.1 (cont'd)

OCC2010	Occupation Title	Skill Group Indicator During			Ever
		2011-14	2015-18	2019-22	Changed
5130	Gaming Cage Workers	*M*	*M*	/	
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*	

Table 2C.1 (cont'd)

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*	

Table 2C.1 (cont'd)

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*	

Table 2C.1 (cont'd)

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 2C.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 column 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 2C.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 column 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 2C.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 column 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.

APPENDIX 2D

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 2.1. 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.

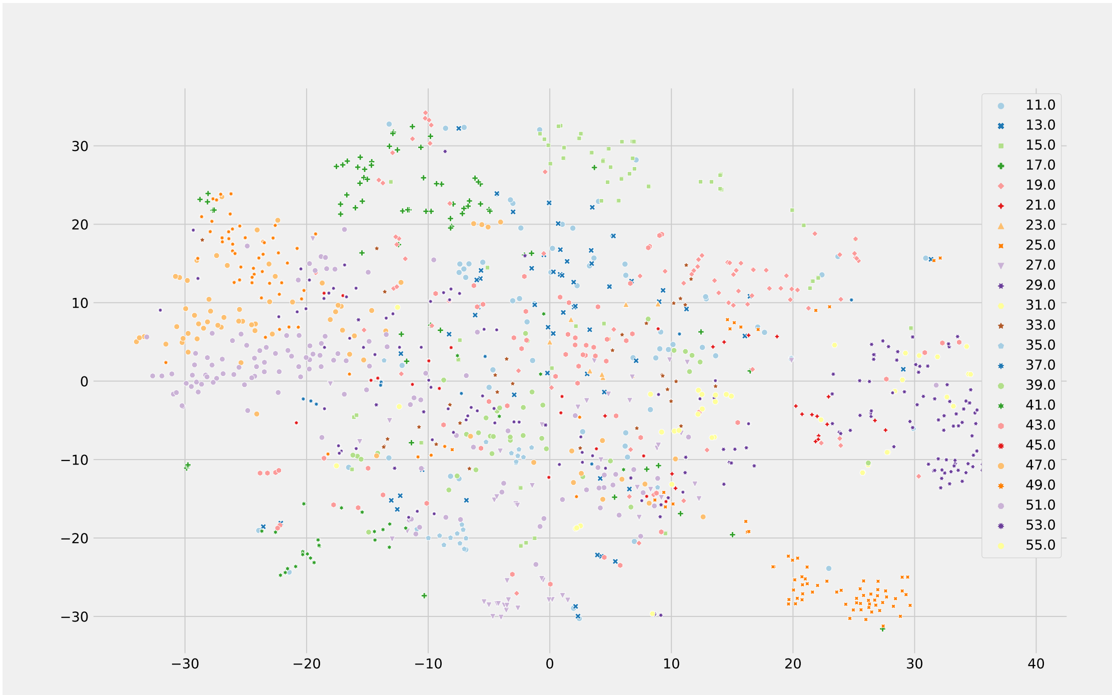
To compare my proposed ML occupation clusters and Census/BLS 2-digit groups, I create a visualization of multi-dimensional skills by different occupation system in Appendix Figure 2D.1. Each marker in the figure represents an occupation. Different colors and symbols are used to distinguish clusters. 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-axes in Appendix Figure 2D.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 2D.1a),[1] while most occupations within the same ML group proposed by me cluster together (Appendix Figure 2D.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 2D.1-2D.3 show the overlap between ML

[1]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 2D.1a, the 2-digit SOC code is used to represent the broad occupation group.

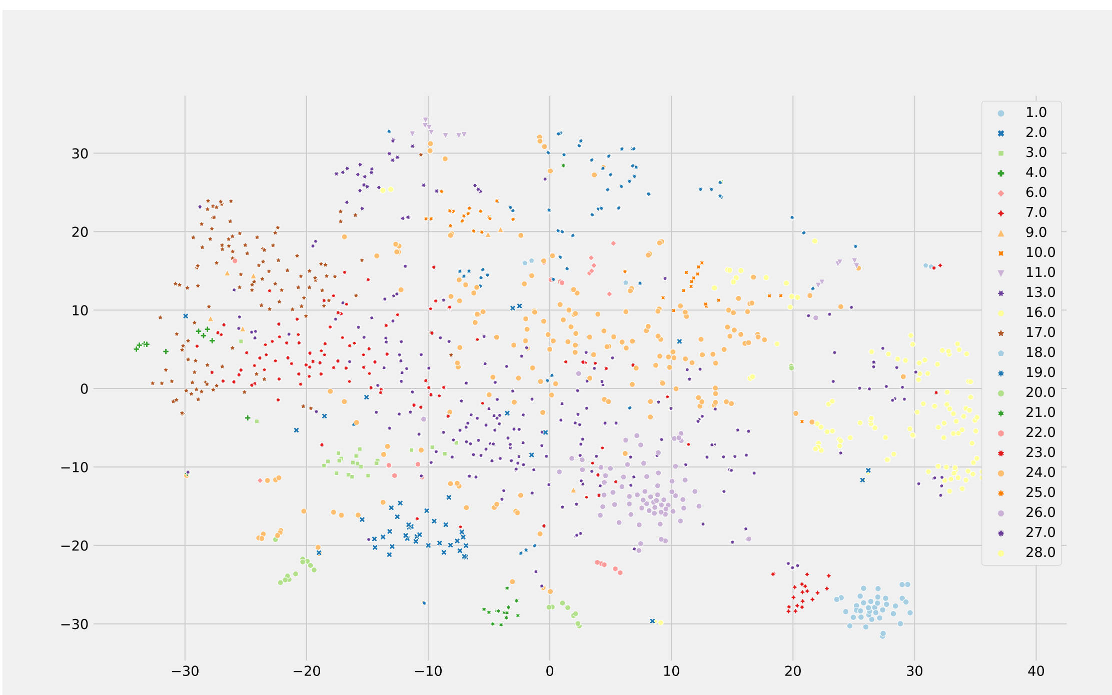
occupation clusters and the time-variant skill groups during different time periods, while Appendix Table 2D.4 lists the ML occupation cluster for all 4-digit occupations. The titles of each cluster are named based on 4-digit occupation titles within the cluster.

Figure 2D.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 2D.1 The Overlap between ML Occupation Clusters and Time-Variant Skill Groups, 2012-14

ML Occupation Cluster:	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.
#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 2D.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 2D.3 The Overlap between ML Occupation Clusters and Time-Variant Skill Groups, 2019-22

ML Occupation Cluster:	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.
#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 2D.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 Related Workers
2630	Designers	5300	Hotel, Motel, and Resort Desk Clerks
3520	Opticians, Dispensing	5620	Stock Clerks and Order Fillers
4000	Chefs and Cooks	6010	Agricultural Inspectors
4010	First-Line Supervisors of Food Preparation and Serving Workers	7800	Bakers
4030	Food Preparation Workers	7810	Butchers and Other Meat, Poultry, and Fish Processing Workers
4120	Food Servers, Nonrestaurant	7840	Food Batchmakers
4140	Dishwashers	8300	Laundry and Dry-Cleaning Workers
4200	First-Line Supervisors of Housekeeping and Janitorial Workers	8810	Painting Workers and Dyers
4610	Personal Care Aides	9050	Flight Attendants and Transportation Workers and Attendants
4700	First-Line Supervisors of Sales Workers	9640	Packers and Packagers, Hand
4720	Cashiers		
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 Except Sawing
6330	Drywall Installers, Ceiling Tile Installers, and Tapers		
	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, All Other
3210	Recreational Therapists	5310	Interviewers, Except Eligibility and Loan
3220	Respiratory Therapists		

Table 2D.4 (cont'd)

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		
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 Analysts/Web Developers	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

Table 2D.4 (cont'd)

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

Table 2D.4 (cont'd)

OCC2010	Occupation Title	OCC2010	Occupation Title
	ML Occupation Cluster #25: Infrastructure Architecture and Engineering		
600	Cost Estimators		Safety Engineers
1300	Architects, Except Naval	1540	Drafters
1360	Civil Engineers	6200	First-Line Supervisors of Construction Trades and Extraction Workers
1420	Environmental Engineers		
1440	Marine Engineers and Naval Architects	6660	Construction and Building Inspectors
1520	Petroleum, Mining and Geological Engineers, Including Mining		
	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.

CHAPTER 3

AI ADOPTION AND GENDER WAGE GAPS

3.1 Introduction

Throughout the past decade, there have been substantial advancements in Artificial Intelligence (AI) capabilities. Progress in AI subfields, such as machine learning, deep learning, computer vision, robotics, and natural language processing, has not only enhanced AI's ability to automate both routine-cognitive and routine-manual tasks (e.g., Webb, 2019; Hatzius et al., 2023; Kogan et al., 2023; Pizzinelli et al., 2023) but also improved worker productivity in cognitive, non-routine, and AI-complementary tasks (e.g., Acemoglu and Restrepo, 2018; Acemoglu and Restrepo, 2020; Brynjolfsson et al., 2023; Pizzinelli et al., 2023; Georgieff, 2024). AI's displacement effect leads to job losses and wage declines, while its augmentation effect increases labor demand and drives wage growth (Acemoglu and Restrepo, 2018). However, these effects may vary by gender. Given differences in task composition across female- and male-dominated roles, AI could widen or narrow existing gender wage gaps.

This paper examines the impact of AI adoption on gender wage gaps in the U.S. labor market. Leveraging real-time, high-frequency data from the Census Business Trends and Outlook Survey (BTOS), which has been collecting data since September 2023, I measure firms' actual AI implementation using the proportion of businesses who current use or expect to use AI in producing goods or services. To quantify the persistence of AI adoption among firms, I measure continuing AI adoption as the unconditional proportion of businesses reporting both current and expected AI use.[1] The proportion of businesses reporting AI adoption has grown rapidly since September 2023, particularly among those with continuing AI adoption.

I provide three key findings. First, I document that AI adoption at the state-year-month level is associated with a narrowing of within-occupation gender wage gaps, as it increases the mean hourly wage for women more than for men. More specifically, a 1 percentage point (pp) increase in

[1] Since the BTOS data is publicly available only at aggregated levels, such as state, sector, or firm size, but not at more granular levels like the firm level, I am unable to compute the conditional proportion of continuing AI adoption.

the state-year-month share of businesses reporting current, expected, or continuing AI usage leads to a 0.5%, 0.4%, and 3.2% increase, respectively, in women's mean hourly wage relative to men. I additionally include lagged and lead AI adoption variables to distinguish between short-term and long-term effects. The results show a significant relationship between the lagged AI adoption and the mean hourly wage but a insignificant relationship for the current AI adoption, suggesting the long-term effect narrows the gender wage gap at the mean. This finding may be due to the high correlation between the current and lagged AI adoption variables, resulting in multicollinearity issue, or the stronger power of the lagged effect in explaining the variation.

To gain a deeper understanding on the distributional effect of AI adoption on gender wage gaps, I use the within-industry, between-occupation variation along with the industry-month AI adoption to better capture industry-specific patterns. I find a non-monotonic pattern in the relationship between AI adoption and gender wage gaps across the wage distribution, where AI adoption widens gender wage gaps at the bottom and middle of the wage distribution (e.g., the 10$^{\text{th}}$ percentile and median) but narrows gaps at the top (e.g., the 90$^{\text{th}}$ percentile). Low- and middle-wage women primarily specialize in routine-intensive tasks, such as clerical and administrative jobs, making them more vulnerable to AI-driven substitution. In contrast, their male counterparts are more concentrated in manual, non-routine occupations which are less susceptible to either substitution or complementarity by current AI technologies. Thus, women at the bottom and middle of the wage distribution are disadvantaged by AI relative to men. At the top of the distribution, women can be complemented by AI, rather than being displaced, to boost their productivity, leading to greater wage gains compared to men.

Finally, I employ the state-year level data on job postings demanding AI skills to provide a clearer depiction of AI's complementarity because it is not easy to distinguish between the substitution and complementarity effect of AI using the data on AI adoption in firms. Different from results on the relationship between AI adoption and gender wage gaps, I document a monotonic trend for the impact of the AI job posting share. An increase in this share, reflecting a higher demand for AI skills, narrows gender wage gaps at the 10$^{\text{th}}$ percentile, median, mean, and 90$^{\text{th}}$ percentile, with stronger effects at the top of the distribution. This could be explained by the fact that the AI job posting share and AI adoption capture different aspects of AI, where the former one measures the expected demand for AI vacancies while the latter one captures the actual implementation of AI in producing goods or services in business.

The existence of gender wage gaps in the U.S. labor market has been extensively studied and well documented. Previous literature discusses how changes in gender wage gaps can be explained by human capital differences (Mincer and Polachek, 1974; Altonji and Blank, 1999; Blau and Kahn, 2017), occupational segregation (Goldin, 1990; Cortes and Pan, 2018), discrimination (Neumark et al., 1996; Bertrand and Mullainathan, 2004), workplace flexibility and work preferences (Bertrand et al., 2010; Goldin, 2014), bargaining and negotiation (Babcock and Laschever, 2003; Card et al., 2016), heterogeneous unobserved skills (Bacolod and Blum, 2010), and technology like computer, robots, and automation (Ge and Zhou, 2020; Domini et al., 2020). My paper contributes to this large body of work by examining how AI, a rapidly evolving technology with profound impacts, affects gender wage gaps through the mechanisms of complementarity and substitutability.

Research focusing on the link between AI and gender wage gaps is less common, with more studying its impact on the wage inequality in general. Skare et al. (2024) leverage a dataset on AI capital stock in the U.S., the EU, and Japan from 1995 to 2020 and show that AI capital stock accumulation is positively correlated with wealth disparity. Similarly, Felten et al. (2019) document a positive correlation between the exposure to AI and income inequality. Chapter 2 of my dissertation finds that workers specializing in abstract-intensive, AI-complement tasks experience the largest wage gains due to the complementarity of AI, widening wage gaps between this skill group and the rest. However, Acemoglu et al. (2022) find no significant wage effects for occupations or industries that are most exposed to AI substitution. A few studies futher examines AI's impacts on gender wage gaps. Georgieff (2024) studies the relationship between AI exposure and wage inequality in 19 OECD countries from 2014 to 2018 and finds AI does not affect gender wage gaps within occupations. Domini et al. (2020) reach to a similar conclusion by employing an event study methodology to examine changes in gender wage gaps within French firms from 2002 to 2017 in response to a surge in firm investments in automation or AI. However, the time periods studied in these two papers are prior to the period when AI gained significant public attention. The study most closely related to this paper is Huang (2025), which uses AI adoption data from 2021 and employs a long-differencing approach to investigate the impacts of AI adoption on employment, under the assumption that AI adoption was absent in 2010. My paper differs from these studies by examining the distributional effects of AI adoption in the U.S. during the 2020s on gender wage gaps.

The rest of this paper is organized as follows. Section 3.2 describes the data on AI adoption and wages. My empirical strategy is presented in Section 3.3. My main results are discussed in Section 3.4. Section 3.5 concludes.

3.2 Data and Descriptive Statistics

In this section, I will first introduce the data sources to measure AI adoption and construct gender wage gaps, and then describe patterns of current AI adoption, expected future AI use, continuing AI usage, and gender wage gaps in the U.S.

3.2.1 AI Adoption

The AI adoption data is from the Census Business Trends and Outlook Survey (BTOS), which is a high-frequency survey collecting data from representative U.S. employer businesses since September 2023. The survey asks respondents whether their business used AI technologies currently (Question 7)[2] and whether they expect their business to use AI during the next six months (Question 26)[3]. For each of these two questions, respondents can select one from three options: "Yes," "No," or "Do not know."

The BTOS data consists of approximately 1.2 million businesses, divided into six representative panels. Each panel participates in the survey once every 12 weeks for a year. Data are released every two weeks and are available at the national, 2017 North American Industry Classification

[2] According to the BTOS questionnaire, Question 7 is framed as follows: "Between MMM DD – MMM DD, did this business use Artificial Intelligence (AI) in producing goods or services? (Examples of AI: machine learning, natural language processing, virtual agents, voice recognition, etc.)." A definition of AI was added on October 23, 2023, stating: "AI Definition: Computer systems and software that are able to perform tasks normally requiring human intelligence, such as decision-making, visual perception, speech recognition, and language processing."

[3] Question 26 is framed as follows: "During the next six months, do you think this business will be using Artificial Intelligence (AI) in producing goods or services? (Examples of AI: machine learning, natural language processing, virtual agents, voice recognition, etc.)."

System (NAICS) sector (2-digit NAICS), subsector (3-digit NAICS), employment size, sector by employment size, state, and the 25 most populous Metropolitan Statistical Areas (MSAs) level.

To measure the current (expected) AI adoption in firms, I use the proportion of businesses that answered "Yes" to Question 7 (26) in the BTOS. I aggregate the bi-weekly BTOS data at the monthly level by averaging the shares to integrate it with the monthly wage data. Figure 3.1 presents the trends in AI adoption in the U.S. from September 2023 to February 2025. Although the proportion of businesses currently using or expecting to use AI in producing goods or services in the U.S. remained low (Figures 3.1a and 3.1c), it grew rapidly compared to the baseline period, September 2023, as shown in Figures 3.1b and 3.1d. Meanwhile, the proportion of businesses that neither currently use nor expect to use AI slightly declined. Figure 3.1e plots the trend in continuing AI adoption in firms, which is an unconditional share of businesses currently using and expecting to use AI computed by multiplying the proportions of businesses that answered "Yes" to both Questions 7 and 26.[4] This unconditional share of continuing AI adoption has been rising sharply over time, especially since May 2024, indicating an accelerating trend of businesses consistently adopting AI in producing goods or services.

Figure 3.2 presents the geographic distribution of the proportion of businesses currently adopting AI by state. The darker a state's color is, the more businesses adopted AI in producing goods or services in that state.[5] The current AI adoption greatly increased over time for almost all states in the U.S., especially for the West Coast and the East Coast. Almost all states were in yellow during September 2023 to February 2024, but turned into orange and red during September 2024 to February 2025. The minimum and maximum proportion increased from 3.22% to 4.36% and from 11.50% to 16.64%, respectively. Appendix Figures 3A.1 and 3A.2 display similar trends in expected and continuing AI adoption: AI adoption varied by state but consistently increased over time.

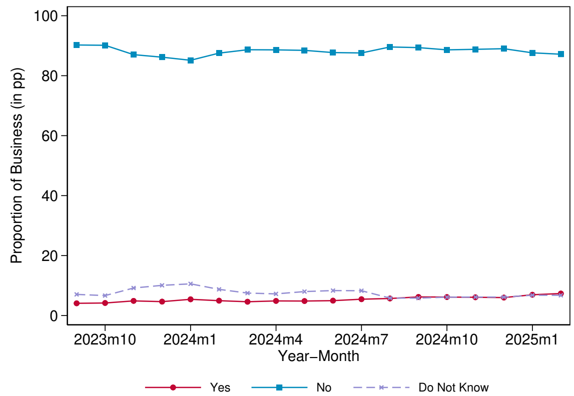
I additionally plot the current, expected, and continuing AI adoption by 2-digit NAICS code

[4]Since more granular BTOS data, such as firm-level data, is not publicly available, I am unable to compute the conditional share of businesses currently using or expecting to use AI.

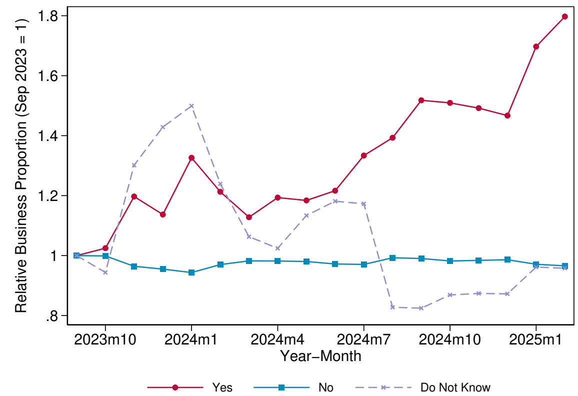
[5]States with no data means that, according to BTOS, their estimate "does not meet publication standards because of high sampling variability, poor response quality, or other concerns about the estimate quality."

Figure 3.1 Trends in AI Adoption, Sep. 2023 - Feb. 2025

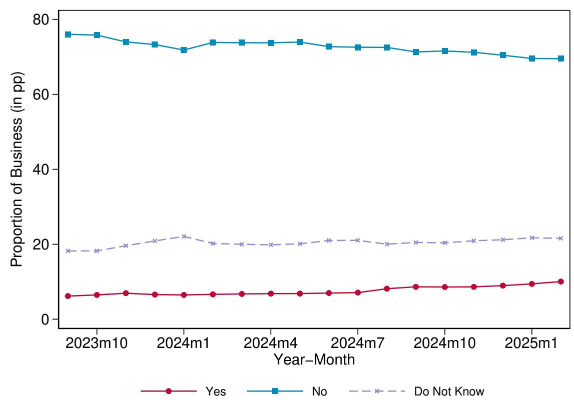
(a) Current AI Adoption, Raw Numbers (in pp)



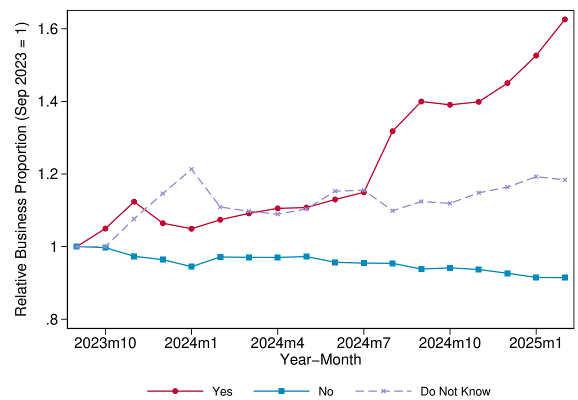
(b) Current AI Adoption, Relative to Sep. 2023



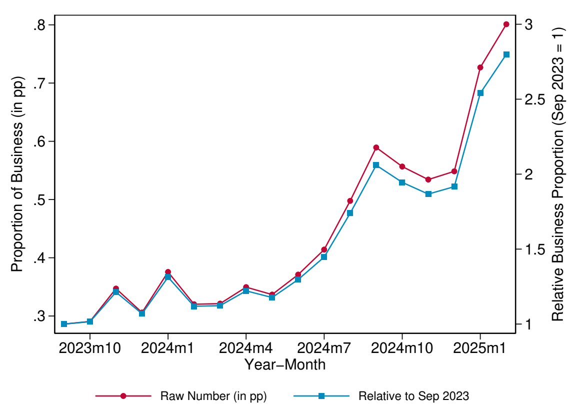
(c) Expected AI Adoption, Raw Numbers (in pp)



(d) Expected AI Adoption, Relative to Sep. 2023



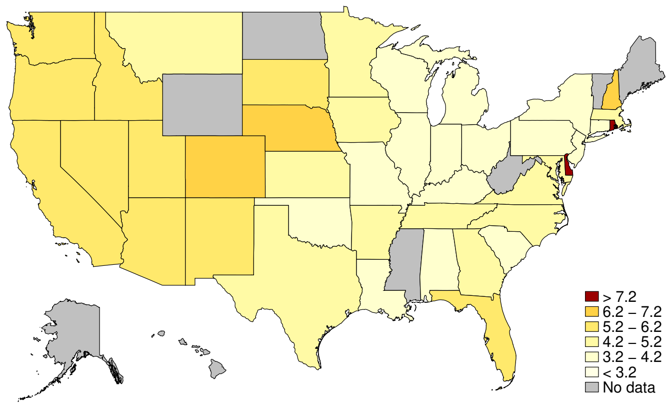
(e) Continuing AI Adoption



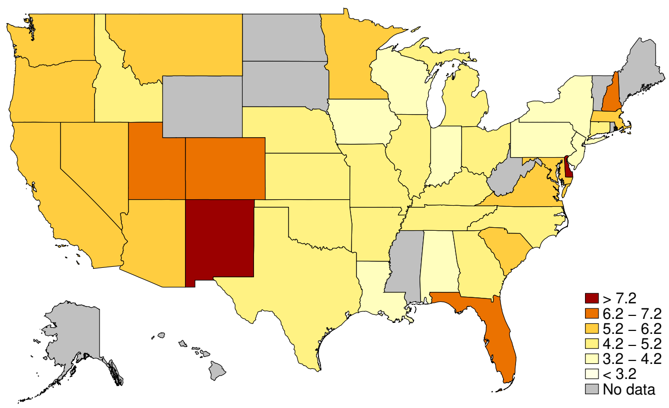
Data: Business Trends and Outlook Survey (BTOS)
Notes: In Subfigure 3.1e, the unconditional share of businesses that used and will use AI in producing goods or services is computed by multiplying the proportions of businesses that answered "Yes" to both Question 7 ("Did this business use AI in producing goods or services?") and Question 26 ("During the next six months, will this business use AI in producing goods or services?") in the BTOS.

Figure 3.2 Geographic Distribution of Current AI Adoption by State

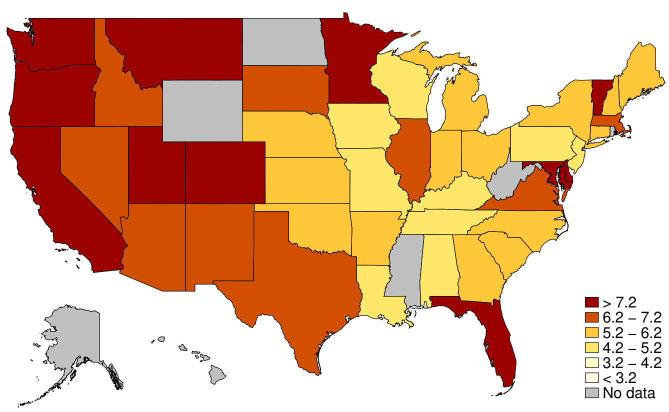
(a) Sep. 2023 - Feb. 2024



(b) Mar. 2024 - Aug. 2024



(c) Sep. 2024 - Feb. 2025



Data: Business Trends and Outlook Survey (BTOS)
Notes: Scales are in percentage point. These figures show the proportion of businesses that answered "Yes" to Question 7 ("Did this business use AI in producing goods or services?") in the BTOS. States with no data indicate that, according to BTOS, their estimate "does not meet publication standards because of high sampling variability, poor response quality, or other concerns about the estimate quality."

in Appendix Figures 3A.3 to 3A.5. The information industry experienced the highest level of AI adoption, showing an upward trend in the proportion of businesses answering "Yes" and a downward trend in the proportion answering "No" to both the current and expected AI adoption questions. The finance, real estate, professional and scientific services, management, education, and healthcare industries also show a trend of narrowing the gap between the proportion of businesses answering "No" and "Yes" to AI adoption questions, particularly for the expected adoption question.

3.2.2 Gender Wage Gaps

The data source to construct the hourly wage from September 2023 to December 2024 is from the Current Population Survey (CPS) data sourced from Integrated Public Use Microdata Series (IPUMS). My sample includes individuals aged 18 to 64 and excludes all individuals who are unemployed or never worked.[6] Since the CPS does not directly provide the hourly wage for each individual, I compute it using their usual hours worked per week and rounded weekly earnings[7] in the CPS data.

To ensure consistency in usual hours worked per week, I take several steps using the CPS data. First, I drop individuals with missing values or those reporting "hours vary." Second, I exclude individuals who report working 168 hours or more per week, as this is the theoretical maximum of hours per week. Finally, I restrict the sample to full-time workers by excluding individuals who report working fewer than 35 hours per week.[8]

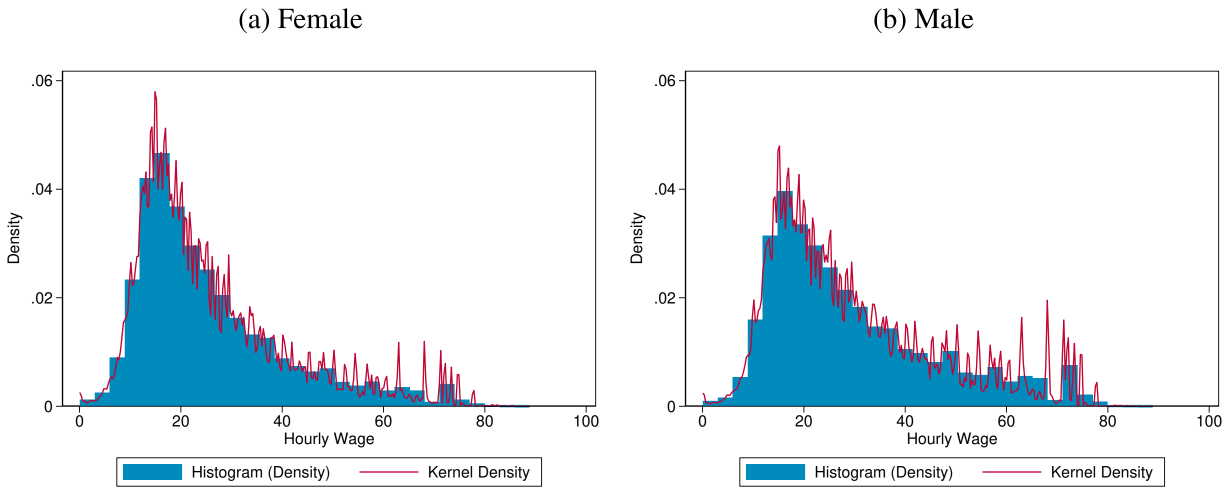
I apply the following restrictions to create a consistent wage series in the CPS data. First, I drop individuals with "Not in Universe (NIU)" values in weekly earnings. Second, I adjust weekly earnings to 2019 U.S. dollars using the Consumer Price Index for All Urban Consumers (CPI-U) provided by the Bureau of Labor Statistics. Finally, I apply a Winsorization approach to cap earnings at the 99th percentile instead of relying on the CPS topcoding system. This is due to changes in the Census Bureau's topcoding system during my sampling period. From April 2023

[6]Individuals who are unemployed or never worked are coded as "Not in Universe (NIU)" in the CPS data.

[7]Beginning in April 2023, the Census Bureau began rounding weekly earnings as a privacy protection measure.

[8]Without this restriction, the mean hourly wage may be overestimated or the wage distribution may be skewed due to observations with extremely high weekly earnings but very low reported weekly hours worked. For example, some CPS observations show weekly earnings exceeding $2,000 with only 0 or 1 hour worked per week.

Figure 3.3 Distribution of Hourly Wage by Gender, 2019-24



Data: the Current Population Survey (CPS)

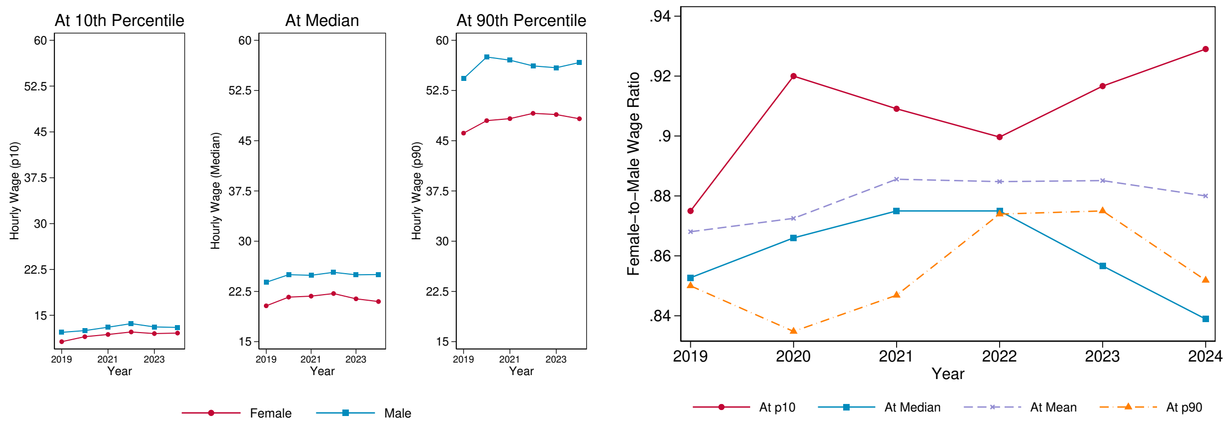
to March 2024, weekly earnings were topcoded at $2,884.61 (nominal). Starting from April 2024, the Census Bureau used the weighted average of the reported earnings of the top 3% of earners as the "dynamic" topcode. Winsorized mean hourly wage had a consistent trend over time (Appendix Figure 3A.6a), while uncapped one disproportionately increased after April 2024 (Appendix Figure 3A.6b), especially for high-skilled groups (Appendix Figure 3A.7).

Figure 3.3 presents the distribution of hourly wages for female (Figure 3.3a) and male (Figure 3.3b) workers from 2019 to 2024. Both distributions exhibit a right-skewed shape, indicating that most workers earn lower hourly wages, while a smaller proportion earns substantially higher wages. However, the wage distribution for male shows a slightly wider right tail and is less right-skewed than the female wage distribution, suggesting that men are more likely than women to earn higher wages and have more access to high-paying jobs. The male wage distribution also has a lower peak and a relatively wider spread, suggesting that men have a more even distribution of wages compared to women. The kernel density estimates (red lines) reinforce these patterns by smoothing out the histogram.

To visualize gender wage gaps across the wage distribution, Figure 3.4a displays hourly wages by gender at the 10th percentile, median, and 90th percentile over time. From 2019 to 2024, the hourly wages for male were consistently higher than female. The gender wage gap is much wider

Figure 3.4 Hourly Wage across Percentiles, 2019-24

(a) Hourly Wage by Gender (b) Female-to-Male Wage Ratio



Data: the Current Population Survey (CPS)

at the top of the wage distribution compared to the bottom, but it shrinks at both ends. Figure 3.4b shows the female-to-male wage ratio at the 10th percentile, median, mean, and 90th percentile, highlighting a non-uniform gender wage gap across the distribution. The gap was the narrowest and showed a tendency to close at the bottom of the distribution, where women's hourly wages increased from 88% to 92% of men's hourly wages. The female-to-male wage ratio is lower at the top of the wage distribution, indicating that women tend to be underrepresented in high-paying jobs. The trend where the ratio at the mean is higher than at the median is consistent with Figure 3.3, suggesting that the wage distribution for female is more right-skewed.

3.3 Empirical Strategy

I study the relationship between AI adoption and gender wage gaps using the following specification:

$$\begin{aligned}\ln(Wage_{o4,s,t,g}) = \alpha + \beta Female_g + \tau AI\ Adoption_{s,t} + \gamma(Female_g \times AI\ Adoption_{s,t}) \\ + \mathbf{X}_{s,t}\mathbf{\Phi} + \mu_{o4} + \delta_s + \theta_t + \varepsilon_{s,t},\end{aligned} \tag{3.1}$$

where $o4$, s, t, and g denote 4-digit OCC2010 occupation, state, time period (year-month), and gender, respectively. The time period used in my sample is from September 2023 to December 2024. $Wage_{o4,s,t,g}$ is the mean hourly wage (in 2019 U.S. dollars) measured at the occupation-by-state-by-year-month-by-gender level. $Female_g$ equals one if g is female and zero otherwise. $AI\ Adoption_{s,t}$ measures the state-year-month level current, expected, or continuing AI adoption by firms. It represents one of the following: (1) the proportion of businesses in state s using AI to produce goods or services during the current time period t; (2) the proportion of businesses in state s at time t expecting to use AI in producing goods or services within the next six months; or (3) the proportion of businesses in state s at time t that reported both currently using and expecting to use AI.[9] These shares are multiplied by 100; thus the unit of measurement is a percentage point (pp). $\mathbf{X}_{s,t}$ contains state-year-month control variables that may affect individuals' hourly wages: the share of female employment; the share of Black population; the share of Hispanic population; and the share of population who earned a Bachelor's degree or above. Standard errors, $\varepsilon_{s,t}$, are clustered at the state-year-month level to account for the fact that the AI adoption variable is an aggregated measure.

The coefficient of interest, γ, captures how the relationship between wages and AI adoption in firms differs for females compared to males. By including occupation, state, and year-month fixed effects, coefficients are identified using within-occupation variation, while accounting for state-specific time-invariant differences in wages and general time trends.

To test this relationship in both the short term and long term, I include the lagged and lead AI adoption variables in the following specification:

$$\begin{aligned}\ln(Wage_{o4,s,t,g}) = \alpha + \beta Female_g &+ \sum_{k\in\{t-3,t,t+3\}} \tau_k AI\ Adoption_{s,k} \\ &+ \sum_{k\in\{t-3,t,t+3\}} \gamma_k (Female_g \times AI\ Adoption_{s,k}) + \mathbf{X}_{s,t}\mathbf{\Phi} + \mu_{o4} + \delta_s + \theta_t + \varepsilon_{s,t},\end{aligned} \tag{3.2}$$

where $AI\ Adoption_{s,t-3}$ and $AI\ Adoption_{s,t+3}$ represent the AI adoption three months prior and three months ahead, respectively. I only include the $t-3$, t, and $t+3$ terms for $AI\ Adoption_{s,k}$ to mitigate potential multicollinearity.

[9] Due to the lack of the firm-level data, the measurement of continuing AI adoption is an unconditional share computed by multiplying the proportions of businesses that answered "Yes" to both Question 7 ("Did this business use AI in producing goods or services?") and Question 26 ("During the next six months, will this business use AI in producing goods or services?") in the BTOS.

To better capture the distributional effects of AI adoption on gender wage gaps, I construct wages at the industry-by-state-by-year-month-by-gender level for different percentiles of the wage distribution and include industry, state, and year-month fixed effects:

$$\ln(Wage^{p}_{ind,s,t,g}) = \alpha + \beta Female_g + \tau AI\ Adoption_{ind,t} + \gamma(Female_g \times AI\ Adoption_{ind,t}) \\ + \mathbf{X}_{s,t}\boldsymbol{\Phi} + \mu_{ind} + \delta_s + \theta_t + \varepsilon_{ind,t}, \tag{3.3}$$

where ind denotes 2-digit NAICS code and p represents the p^{th} percentile. This approach allows me to analyze how AI adoption influences wage dispersion within industries while maintaining between-occupation variation. Compared to the previous specification, equation (3.3) employs industry-year-month AI adoption to better reflect sector-specific technological adoption patterns. In this way, this specification better captures how AI impacts gender wage gaps at different percentiles of the wage distribution within industries, rather than relying on state-level measures which may absorb industry-level heterogeneity. Standard errors are clustered at the industry-year-month level to align with the industry-year-month level AI adoption variable.

3.4 Results

3.4.1 AI Adoption and within-Occupation Gender Wage Gaps

I first look at the relationship between within-occupation gender wage gaps and AI adoption varying across states and over time. Columns 1-3 of Table 3.1 estimate equation (3.1) using current AI adoption. The Ordinary Least Squares (OLS) estimates in column 1 show that women earn, on average, 13.5% lower hourly wages than men in the absence of AI adoption in businesses, but there is no significant relationship between AI adoption and wages. Column 2 adds state and year-month fixed effects, while column 3 further controls for occupation fixed effect; thus, column 3 captures within-occupation effects. The coefficient on the interaction term, $Female_g \times AI\ Adoption_{s,t}$, is now significant and positive, implying that women may experience slightly more positive wage changes from current AI adoption compared to men. Specifically, a 1pp increase in the share of businesses currently adopting AI at the state-year-month level is associated with a 0.5% higher mean hourly wage for women relative to men. This result remains consistent regardless of the

Table 3.1 Effects of Current AI Adoption by State on Gender Wage Gaps

	Dep. Var.: Log Mean Hourly Wage				
	(1)	(2)	(3)	(4)	(5)
Female	-0.135***	-0.137***	-0.147***	-0.186***	-0.210***
	(0.017)	(0.017)	(0.015)	(0.022)	(0.023)
%Businesses Using AI[1] in Current Month (t)	-0.006***	-0.003	-0.004	-0.003	-0.002
	(0.002)	(0.004)	(0.003)	(0.004)	(0.005)
Female × %Businesses Using AI in Current Month (t)	0.005	0.005*	0.005**	0.001	0.004
	(0.003)	(0.003)	(0.003)	(0.005)	(0.007)
%Businesses Using AI 3 Months Ago (t-3)				-0.002	-0.003
				(0.005)	(0.006)
Female × %Businesses Using AI 3 Months Ago (t-3)				0.011*	0.016**
				(0.006)	(0.006)
%Businesses Using AI 3 Months later (t+3)					-0.002
					(0.005)
Female × %Businesses Using AI 3 Months later (t+3)					-0.002
					(0.006)
Observations	62,480	62,480	62,479	47,845	42,800
State FE		✓	✓	✓	✓
Year-Month FE		✓	✓	✓	✓
Occupation FE			✓	✓	✓
Outcome Mean	3.162	3.162	3.162	3.161	3.160
R^2	0.033	0.038	0.310	0.312	0.316

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

[1] The share of businesses currently using AI is measured as the average monthly share of businesses at the state level that answered "Yes" to Question 7 in the Business Trends and Outlook Survey (BTOS), which asked "Between MMM DD – MMM DD, did this business use Artificial Intelligence (AI) in producing goods or services? (Examples of AI: machine learning, natural language processing, virtual agents, voice recognition, etc.)." The unit is a percentage point.

inclusion of occupation fixed effect. Note that the OLS estimates underestimate gender wage gaps without AI adoption. After controlling for state, year-month, and occupation fixed effects, on average, women earn 14.7% less in hourly wages than men.

Column 4 estimates equation (3.2) by including the lagged term of AI adoption, which refers to the reported AI adoption from three months ago, to capture the short-term and long-term effects. The coefficient on the interaction between female and current AI adoption ($Female_g \times$

$AI\ Adoption_{s,t}$) is now statistically insignificant (0.001), while the coefficient on the lagged interaction term ($Female_g \times AI\ Adoption_{s,t-3}$) is significantly positive (0.011), indicating that AI adoption by business could have a delayed effect on female wages. This finding suggests a long-term effect of AI adoption on narrowing gender wage gaps, which is in contrast to the short-term effect shown in column 3. Several reasons could explain this contradiction. First, the current and lagged AI adoption variables might be highly correlated, leading to multicollinearity issue. Second, the lagged period's effect might explain more of the variation, leading to a weaker effect of the current period.

Column 5 further includes the lead term of AI adoption, the reported AI adoption from three months later. The relationship between lagged AI adoption and female wages is stronger: a 1pp increase in the state-year-month share of businesses using AI three months ago is associated with a 1.6% higher mean hourly wage for women compared to men at the current stage. This result strengthens the idea that there might be a delayed response in the labor market to the actual implementation of AI in businesses.

Table 3.2 estimates equation (3.2) separately for each of the following four skill groups proposed by Chapter 2 of my dissertation: high-skilled AI-complement, high-skilled not-yet-AI, middle-skilled, and low-skilled groups. Panel A only considers current and lagged AI adoption. Column 1 of Panel A is the same as column 4 of Table 3.1, which uses the full sample of occupations. Coefficients in Panel A show a significant relationship between lagged AI adoption and mean hourly wages for female from the middle-skilled group. Compared to middle-skilled men, mean hourly wages for middle-skilled women increase by 1.2% if the share of businesses reported using AI three months ago at the state-year-month level increases by 1pp. This could be explained by the substitutability effect of AI, where middle-skilled occupations, being routine-intensive, are particularly vulnerable to AI-driven displacement (Acemoglu and Restrepo, 2018, 2019; Huang, 2025). Since these middle-skilled, routine-intensive occupations tend to be male-dominated, their mean hourly wages are more negatively affected by AI adoption than females. In addition, women in routine-intensive roles were more likely to shift to high-skilled, high-wage occupations compared to men (Cortés et al., 2024), leading to a narrower gender wage gap within the middle-skilled occupations.

In Panel B of Table 3.2, I use the share of businesses reporting expected AI adoption during the next six months at time period t, which reflects businesses' future plans and strategies, instead of the share of businesses reporting using AI currently (t) and three months ago ($t-3$). In column 1 of Panel B, the expected AI adoption benefits female workers slightly more than male workers, reflecting the effect of forward-looking expectation on narrowing gender wage gaps in general. Same as Panel A, when decomposing occupations into the four skill groups, Panel B only shows a significantly positive correlation between gender wage gaps within middle-skilled occupations and expected AI adoption. Since BTOS asks businesses whether they expect to use AI in producing goods or services, it is possible that businesses plan to adopt AI for routine-intensive tasks to replace labor but have not yet implemented it.

Panel C of Table 3.2 uses the continuing AI adoption at the state-year-month level, which is an unconditional share computed by multiplying shares of businesses reporting both current and expected AI adoption. Since the AI adoption is likely to be an ongoing event, this continuing AI adoption measure captures how pervasive and sustained AI adoption is expected to be. Continuing AI adoption narrows gender wage gaps more than current or expected AI adoption. The coefficient on the interaction term in column 1 of Panel C indicates that a 1pp increase in the unconditional share of businesses reporting both current and expected AI adoption leads to a 3.2% increase in mean hourly wages for women compared to their male counterparts. Since the unconditional continuing AI adoption share reflects both current and expected AI usage, these findings suggest that businesses anticipating greater AI adoption are shifting their wage structures to favor women, thus narrowing gender wage gaps.

3.4.2 AI Adoption and within-Industry, between-Occupation Gender Wage Gaps

While Section 3.4.1 focuses on the mean hourly wage using within-occupation variations, Section 3.4.2 looks at the distributional effects of AI adoption. Table 3.3 presents estimates of equation (3.3), utilizing industry-year-month specific AI adoption and industry-by-state-by-year-

Table 3.2 Effects of AI Adoption by State on Gender Wage Gaps by Skill Group

	Dep. Var.: Log Mean Hourly Wage				
	(1) All Occ.	(2) High-Skilled AI-Complement Occ.	(3) High-Skilled Not-Yet-AI Occ.	(4) Middle-Skilled Occ.	(5) Low-Skilled Occ.
	Panel A. Current AI Adoption				
Female	-0.186***	-0.154**	-0.148***	-0.239***	-0.210**
	(0.022)	(0.060)	(0.037)	(0.028)	(0.094)
%Businesses Using AI in Current Month (t)	-0.003	-0.010	-0.013*	0.001	0.021
	(0.004)	(0.013)	(0.007)	(0.005)	(0.018)
Female × %Businesses Using AI in Current Month (t)	0.001	0.001	-0.003	0.009	-0.004
	(0.005)	(0.011)	(0.007)	(0.006)	(0.025)
%Businesses Using AI 3 Months Ago (t-3)	-0.002	0.001	-0.004	-0.000	0.003
	(0.005)	(0.014)	(0.009)	(0.006)	(0.016)
Female × %Businesses Using AI 3 Months Ago (t-3)	0.011*	-0.003	0.012	0.012*	0.018
	(0.006)	(0.015)	(0.010)	(0.007)	(0.025)
Observations	47,845	5,030	16,694	22,714	2,735
R^2	0.312	0.111	0.212	0.236	0.236
	Panel B. Expected AI Adoption				
Female	-0.147***	-0.143***	-0.112***	-0.181***	-0.194***
	(0.014)	(0.038)	(0.021)	(0.019)	(0.062)
%Businesses Reporting Expected AI Adoption	-0.004*	0.001	-0.005	-0.005*	-0.001
	(0.002)	(0.006)	(0.004)	(0.003)	(0.008)
Female × %Businesses Reporting Expected AI Adoption	0.004**	-0.002	0.002	0.008***	0.009
	(0.002)	(0.005)	(0.003)	(0.002)	(0.008)
Observations	69,417	7,258	24,293	32,943	3,998
R^2	0.312	0.106	0.208	0.231	0.239
	Panel C. Continuing AI Adoption				
Female	-0.132***	-0.145***	-0.103***	-0.158***	-0.173***
	(0.008)	(0.021)	(0.013)	(0.012)	(0.036)
%Businesses Continuing AI Adoption[1]	-0.016	0.044	-0.046	-0.012	-0.001
	(0.022)	(0.052)	(0.039)	(0.027)	(0.077)
Female × %Businesses Continuing AI Adoption	0.032**	-0.025	0.015	0.078***	0.104
	(0.015)	(0.032)	(0.023)	(0.023)	(0.066)
Observations	62,479	6,580	21,825	29,618	3,609
R^2	0.310	0.104	0.207	0.231	0.240
State FE	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓

Notes: Each observation is an occupation-state-year-month-gender cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS based on the 2010 Census Occupational Classification. The skill group indicators are constructed by Chapter 2 of my dissertation. All columns include a set of state-year-month controls. Standard errors shown in parentheses are clustered at the state-year-month level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The share of businesses continuing AI adoption is an unconditional measure, computed by multiplying the proportions of businesses that responded "Yes" to both Question 7 (currently using AI) and Question 26 (expecting to use AI) in the Business Trends and Outlook Survey (BTOS).

month-by-gender hourly wages at the 10^{th} percentile, median, mean, and 90^{th} percentile of the wage distribution. Coefficients on the binary indicator for women, $Female_g$, align with the trends in gender wage gaps shown in Figure 3.4. The gap is wider at the top of the wage distribution but narrower at the bottom.

Panel A of Table 3.3 focuses on the current AI adoption. The coefficients on the interaction term show a non-monotonic pattern in the relationship between current AI adoption and gender wage gaps across the wage distribution. At the 10^{th} percentile, the coefficient on the interaction term is significant and negative (-0.010), implying that a 1pp increase in the industry-year-month share of businesses currently adopting AI leads to a 1% decline in hourly wages for women at the 10^{th} percentile of the distribution compared to men. This result suggests that current AI adoption is associated with a wider gender wage gap at the bottom of the wage distribution. This negative effect persists but slightly diminishes at the median, where the estimate is smaller in magnitude (-0.005) but still statistically significant, indicating a weaker effect of current AI adoption on the gender wage gap at the median than at the bottom of the distribution. In contrast, the coefficient on the interaction term turns positive (0.009) and significant at the 90^{th} percentile, suggesting that high-wage women benefit more from current AI adoption relative to men in similar high-wage roles. This positive relationship reduces the gender wage gap at the top of the wage distribution. However, at the mean, the interaction term is insignificant (-0.001), indicating a lack of clear relationship between industry-specific AI adoption and the average gender wage gap within industries but across occupations. It is possible that the negative effects at the bottom of the distribution and the positive effects at the top appear to offset each other, resulting in an insignificant net effect at the mean. These results remain robust across different combinations of state, year-month, and industry fixed effects, as shown in Appendix Table 3A.1. However, they become insignificant after including lagged AI adoption terms, potentially due to multicollinearity.

These findings indicate that current AI adoption exacerbates gender wage gaps at the bottom of the wage distribution but reduces gaps at the top. This non-monotonic pattern occurs because AI adoption by business disproportionately disadvantages women in low- and middle-wage jobs

Table 3.3 Effects of AI Adoption by Industry on Gender Wage Gaps across the Wage Distribution

	Dep. Var.: Log Hourly Wage			
	(1) At p10	(2) At Median	(3) At Mean	(4) At p90
Panel A. Current AI Adoption				
Female	-0.068***	-0.143***	-0.129***	-0.230***
	(0.020)	(0.012)	(0.012)	(0.016)
%Businesses Using AI in Current Month (t)	0.005	0.002	0.000	-0.004
	(0.007)	(0.004)	(0.004)	(0.004)
Female × %Businesses Using AI in Current Month (t)	-0.010***	-0.005**	-0.001	0.009***
	(0.003)	(0.002)	(0.002)	(0.003)
Observations	13,478	13,478	13,478	13,478
R^2	0.121	0.331	0.346	0.331
Panel B. Expected AI Adoption				
Female	-0.056***	-0.131***	-0.125***	-0.236***
	(0.021)	(0.012)	(0.012)	(0.017)
%Businesses Reporting Expected AI Adoption	0.003	0.003	0.002	-0.001
	(0.006)	(0.003)	(0.003)	(0.003)
Female × %Businesses Reporting Expected AI Adoption	-0.008***	-0.005***	-0.001	0.007***
	(0.002)	(0.002)	(0.001)	(0.002)
Observations	13,478	13,478	13,478	13,478
R^2	0.121	0.332	0.348	0.331
Panel C. Continuing AI Adoption				
Female	-0.104***	-0.159***	-0.133***	-0.197***
	(0.016)	(0.009)	(0.009)	(0.012)
%Businesses Continuing AI Adoption[1]	0.022	0.014	0.006	-0.003
	(0.026)	(0.015)	(0.013)	(0.012)
Female × %Businesses Continuing AI Adoption	-0.028*	-0.017*	-0.005	0.030**
	(0.015)	(0.030)	(0.008)	(0.011)
Observations	13,478	13,478	13,478	13,478
R^2	0.120	0.331	0.346	0.330
State FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓

Notes: Each observation is an industry-state-year-month-gender cell. Industry is represented by 2-digit NAICS code. All columns include a set of state-year-month controls. Standard errors shown in parentheses are clustered at the industry-state-year-month level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

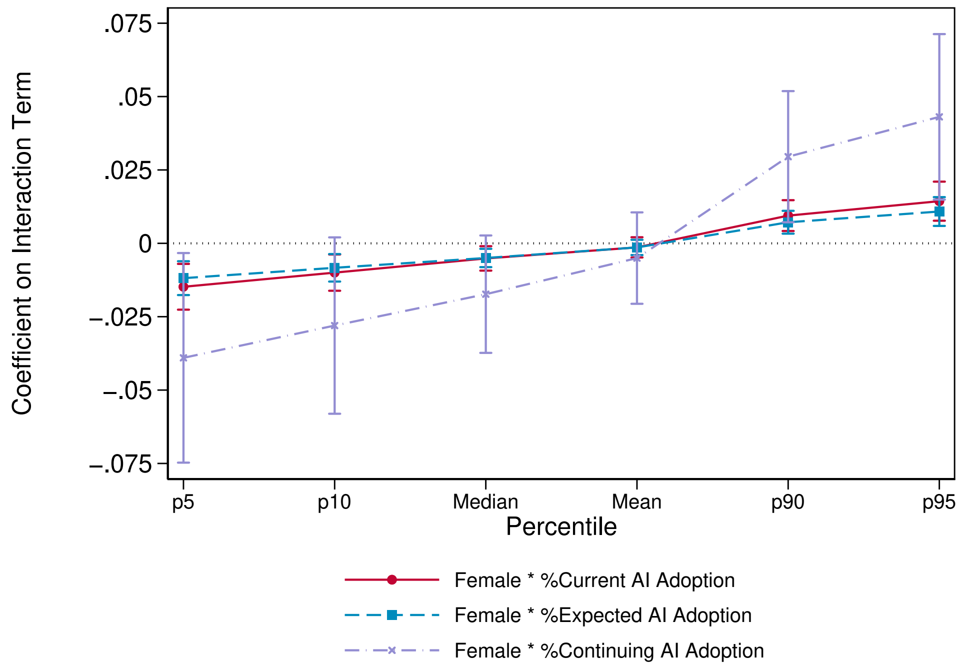
[1] The share of businesses continuing AI adoption is an unconditional measure, computed by multiplying the proportions of businesses that responded "Yes" to both Question 7 (currently using AI) and Question 26 (expecting to use AI) in the Business Trends and Outlook Survey (BTOS).

while benefiting women in high-wage jobs. AI adoption tends to replace routine tasks, which are primarily concentrated at the bottom or middle of the wage distribution (Acemoglu and Restrepo, 2018, 2022). On the one hand, women in low- and middle-wage jobs are overrepresented in routine-intensive roles like clerical and administrative occupations, which are highly likely to be replaced by AI-powered automation (Brussevich et al., 2019; Cazzaniga et al., 2024). This displacement effect of AI adoption may lead to stagnating or declining wages for women. On the other hand, men at the bottom or middle of the wage distribution tend to specialize in manual, non-routine tasks which are more AI-resilient than routine-intensive tasks. Thus, they might be less affected by AI adoption in businesses because these manual, non-routine tasks are not easily performed by current AI capabilities. At the upper end of the wage distribution, the complementarity or augmentation effect of AI dominates its substitution effect (Chapter 2 of my dissertation). Women in high-wage jobs may use AI to enhance their productivity, leading to greater wage gains or more promotion opportunities for high-paying women relative to men. This is consistent with Carvajal et al. (2024), which find that women with top grades can significantly enhance their job prospects by acquiring AI skills, and Cazzaniga et al. (2024), which suggest that women are more likely to benefit from the complementarity of AI.

Panels B and C of Table 3.3 show a similar non-monotonic pattern: both expected and continuing AI adoption widen gender wage gaps at the lower and middle parts of the wage distribution but narrow the gap at the top. Notably, the non-monotonic effect of continuing AI adoption is much larger in magnitude than the effect of current or expected AI adoption. Since continuing AI adoption is the unconditional share of businesses reporting both current and expected AI usage, it reflects the persistent AI use by business. This long-term adoption is likely to have larger effects on the labor market compared to one-time adoption or future plans.

I plot the coefficients on the interaction term between female and AI adoption estimated from equation (3.3) in Figure 3.5 to illustrate the heterogeneous impacts of AI adoption on gender wage gaps across the wage distribution. In addition to the estimates presented in Table 3.3, I also run regressions at the 5^{th} and 95^{th} percentiles to provide a more comprehensive overview of how AI

Figure 3.5 Effects of AI Adoption on Women Relative to Men in the Hourly Wage



Notes: The coefficient estimates plotted are the estimates of γ from equation (3.3). They represent the difference in the effect of current, expected, and continuing AI adoption, respectively, between women and men. The corresponding 95% confidence intervals are also shown.

adoption affects gender wage gaps at both the lower and upper ends of the wage distribution. The coefficient plot visualizes the non-monotonic trend in how the impact of AI adoption on women's hourly wages differs from men's across the wage distribution. It reveals that the lower an individual is in the wage distribution, the stronger the widening effect of AI adoption on the gender wage gap is. In contrast, at the upper end of the distribution, AI adoption is associated with a narrowing of the gap.

3.4.3 AI Postings and Gender Wage Gaps

Since the framing of the AI-related question in the BTOS does not clearly differentiate between measuring the substitutability or complementarity effect of AI adoption, I use the share of job postings requiring AI skills to better capture the complementarity effect of AI by adopting the following specification:

Table 3.4 Effects of AI Postings on Gender Wage Gaps by Skill Groups, 2019-24

	Dep. Var.: Log Mean Hourly Wage				
	(1) All Occ.	(2) High-Skilled AI-Complement Occ.	(3) High-Skilled Not-Yet-AI Occ.	(4) Middle-Skilled Occ.	(5) Low-Skilled Occ.
Female	-0.154***	-0.183***	-0.124***	-0.165***	-0.139***
	(0.005)	(0.016)	(0.011)	(0.007)	(0.024)
%AI Postings[1]	-0.032***	-0.026	-0.029**	-0.028***	-0.043
	(0.008)	(0.020)	(0.013)	(0.010)	(0.031)
Female × %AI Postings	0.033***	0.048***	0.029***	0.031***	0.002
	(0.005)	(0.013)	(0.009)	(0.006)	(0.021)
Observations	100,090	8,847	31,520	51,333	6,273
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓
Outcome Mean	3.136	3.580	3.260	3.006	2.986
R^2	0.408	0.168	0.364	0.330	0.326

Notes: Each observation is an occupation-state-year-gender cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS based on the 2010 Census Occupational Classification. The skill group indicators are constructed by Chapter 2 of my dissertation. All columns include a set of state-year controls. Standard errors shown in parentheses are clustered at the state-year level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
[1] The share of AI postings is measured at the state-year level. The unit is a percentage point. The data is from the AI Index Report by Stanford Institute for Human-Centered AI, who provides the Lightcast data on AI posting shares at the state-year level for the public.

$$\ln(Wage_{o4,s,yr,g}) = \alpha + \beta Female_g + \tau AI\ Postings_{s,yr} + \gamma(Female_g \times AI\ Postings_{s,yr}) + \mathbf{X}_{s,yr}\mathbf{\Phi} + \mu_{o4} + \delta_s + \theta_{yr} + \varepsilon_{s,yr}, \quad (3.4)$$

where yr represents year (from 2019 to 2024) and $AI\ Postings_{s,yr}$ is the state-year level share of job postings requiring AI skills (in percentage points), which is provided by Zhang et al. (2022), Maslej et al. (2023), and Maslej et al. (2024) from Stanford Institute for Human-Centered AI (HAI).[10] The coefficient of interest is still γ, which captures the changes in the mean hourly wage for women relative to men associated with a 1pp increase in the state-year level share of AI job postings.

Table 3.4 presents results estimated from equation (3.4) for all occupations and each skill group separately. The coefficient on the interaction term in column 1 indicates that, compared

[10] Stanford HAI aggregates online job postings data from Lightcast at the state-year level and provides free public access. However, more granular data is not publicly available.

to men, a 1pp increase in the share of AI postings at the state-year level leads to a 3.3% mean hourly wage growth for women. When restricting the sample to each one of the skill groups, women in high-skilled AI-complement jobs have the largest mean hourly wage growth relative to men, suggesting a narrower gender wage gap within high-skilled AI-complement occupations driven by the complementarity effect of AI. Note that for low-skilled group in column 5, the coefficient on the interaction term (0.001) is insignificant, implying that a higher demand for AI skills does not disproportionately benefit or disadvantage women in low-skilled jobs compared to men. Furthermore, the coefficient on the share of AI postings (-0.043) is not significant. These findings could be due to the fact that low-skilled occupations are less likely to require AI skills, as discussed in Chapter 2 of my dissertation, and therefore, the AI posting share does not significantly affect wages for low-skilled workers.

Appendix Table 3A.2 tests the short- and long-term effects of the AI posting share by including its lagged term, which represents the share from the previous year. The coefficient on the interaction term between female and AI postings in the current year is significantly positive, particularly for high-skilled AI-complement occupations. In contrast, the coefficient on the interaction between female and the lagged term is insignificant, except for low-skilled occupations. Since job postings requiring AI skills signal expectations for and anticipated changes in AI skills in the future, the share of AI job postings may have a more immediate impact on wages compared to AI adoption, which reflects the actual implementation of AI in firms.

Table 3.5 re-estimates equation (3.4) but replacing the outcome variable with the industry-by-state-by-year-by-gender hourly wage at the 10^{th} percentile, median, mean, and 90^{th} percentile of the wage distribution. Different from Table 3.3, coefficients on the interaction term in Table 3.5 show a monotonic trend in the relationship between the share of AI postings and gender wage gaps across the wage distribution, with coefficients plotted in Appendix Figure 3A.8. A higher demand for AI skills narrows gender wage gaps across the distribution, while the AI adoption by business widens the gap at the bottom of the distribution but narrows the gap at the top. This difference may arise because AI job postings and AI adoption reflect distinct aspects of AI. AI job postings

Table 3.5 Effects of AI Postings on Gender Wage Gaps across Wage Distribution, 2019-24

	Dep. Var.: Log Hourly Wage			
	(1) At p10	(2) At Median	(3) At Mean	(4) At p90
Female	-0.132***	-0.182***	-0.162***	-0.228***
	(0.016)	(0.016)	(0.012)	(0.013)
%AI Postings[1]	-0.033*	-0.019	-0.027	-0.018
	(0.018)	(0.017)	(0.017)	(0.018)
Female × %AI Postings	0.024*	0.028**	0.044***	0.056***
	(0.013)	(0.012)	(0.010)	(0.010)
Observations	9,144	9,144	9,144	9,144
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Outcome Mean	2.534	3.114	3.087	3.777
R^2	0.302	0.626	0.685	0.489

Notes: Each observation is an industry-state-year-gender cell. Industry is represented by 2-digit NAICS code. All columns include a set of state-year controls. Standard errors shown in parentheses are clustered at the industry-year level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The share of AI postings is measured at the state-year level. The unit is a percentage point. The data is from the AI Index Report by Stanford Institute for Human-Centered AI, who provides the Lightcast data on AI posting shares at the state-year level for the public.

capture expected demand for AI-related vacancies, which may benefit low-wage women more than men. It is possible that some female-dominated clerical or administrative jobs may require workers to use AI-powered tools rather than being fully automated, thus providing upskilling or reskilling opportunities that benefit women more than men. AI adoption indicates the implementation of AI in producing goods or services in business, leading to job displacement which disproportionately disadvantages low-wage women. However, low-wage men usually specialize in manual, non-routine jobs, which are less likely to be complemented by AI or be substituted by AI at the present stage.

Estimates in column 4 of Table 3.5 further supports the finding that, at the top of the wage distribution, AI narrows the gender wage gap by benefiting women more than men. These high-wage jobs are more likely to involve problem-solving, decision-making, and cognitive tasks that can be complemented by AI rather than being replaced. Women in high-paying jobs can utilize AI tools or acquire AI skills to enhance their productivity, leading to wage gains. The increasing demand for AI skills in these jobs may also provide women with greater opportunities for employment, upskilling, potential promotions, or transitions into higher-wage roles.

After including the lagged share of AI postings variable in Appendix Table 3A.3, the results align with those on within-occupation mean hourly wages in Appendix Table 3A.2. The AI posting share reflects labor market expectations, leading to quicker wage adjustments, particularly at the upper end of the wage distribution.

3.5 Conclusion

The rapid advancement of AI raises questions about its impact on labor market outcomes. While most of the existing literature focuses on how AI affects employment and wages from the perspective of the exposure to AI, my study explores the relationship between AI adoption in firms and gender wage gaps in the U.S. during September 2023 to December 2024. I first find that an increase in the share of businesses reporting current, expected, or continuing AI adoption in producing goods or services narrows the within-occupation gender gaps in mean hourly wage. Using the AI adoption data by industry to capture industry-specific patterns in technological changes, I document a non-monotonic pattern in the distributional effect of AI adoption on gender wage gaps: AI adoption widens gaps at the lower end and middle of the distribution but narrows the top. I further test the correlation between the complementarity of AI and gender wage gaps using the data on online job postings requiring AI skills. Results suggest that the higher demand for AI skills narrows gender wage gaps across the wage distribution, with more pronounced effects at the top of the distribution.

The real-time, high-frequency data on AI adoption at the state or industry level allows me to examine the differential effects of dynamic changes in AI adoption on wages for females versus males. However, due to the lack of more granular level data, such as the firm level, my paper is unable to compute the conditional share that firms adopting continuing AI usage to more accurately measure the persistence of firms adopting AI. In addition, the framing of survey questions regarding the AI usage makes it difficult to (1) distinguish between the substitution and complementarity effect of AI and (2) capture the extent workers use generative AI tools like ChatGPT during work. These remain important topics for future research.

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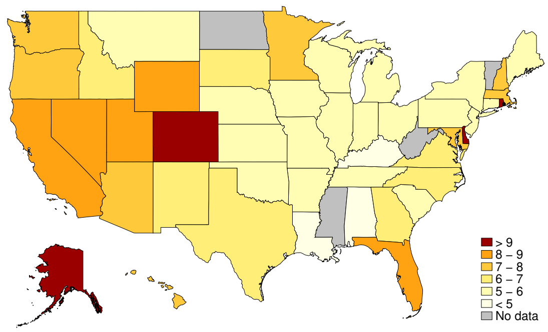
APPENDIX 3A

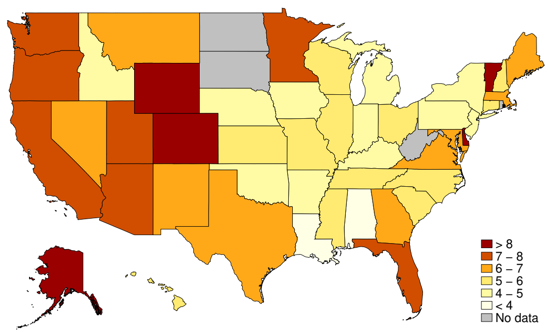
ADDITIONAL FIGURES & TABLES

Figure 3A.1 Geographic Distribution of Expected AI Adoption by State

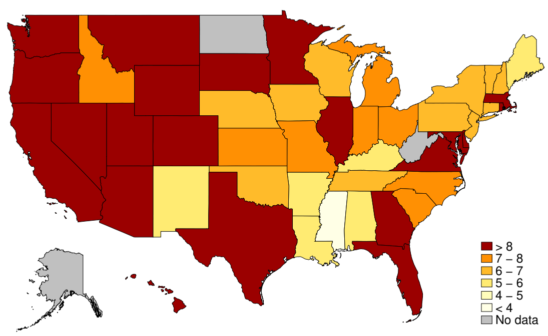
(a) Sep. 2023 - Feb. 2024



(b) Mar. 2024 - Aug. 2024



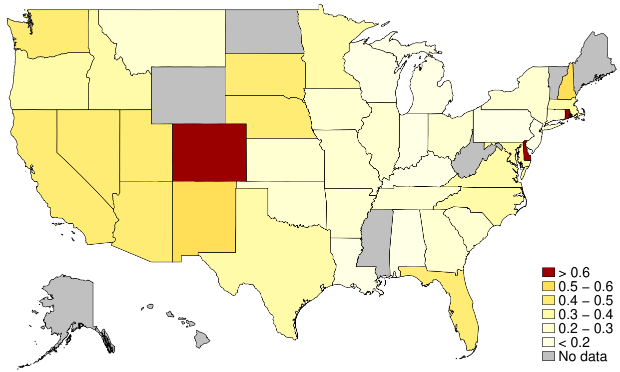
(c) Sep. 2024 - Feb. 2025



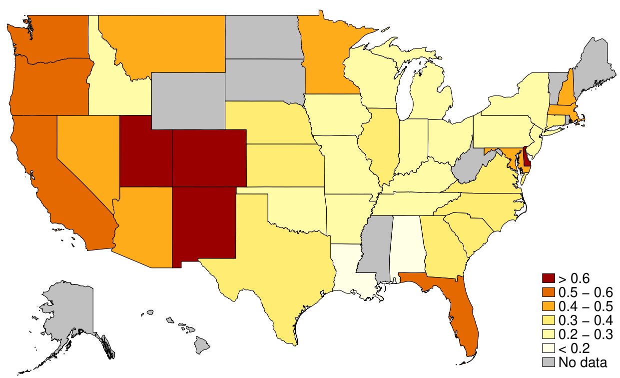
Data: Business Trends and Outlook Survey (BTOS)
Notes: Scales are in percentage point. These figures show the proportion of businesses that answered "Yes" to Question 26 ("During the next six months, will this business use AI in producing goods or services?") in the BTOS. States with no data indicate that, according to BTOS, their estimate "does not meet publication standards because of high sampling variability, poor response quality, or other concerns about the estimate quality."

Figure 3A.2 Geographic Distribution of Continuing AI Adoption by State

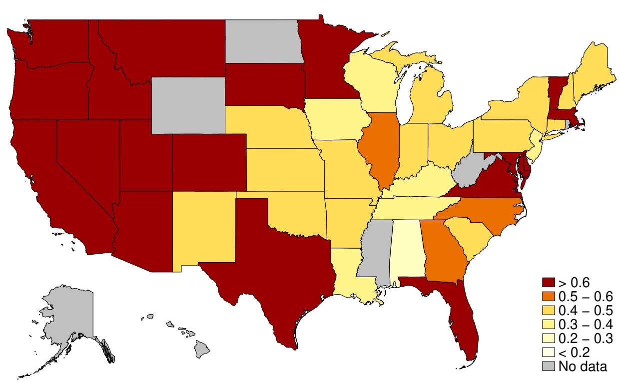
(a) Sep. 2023 - Feb. 2024



(b) Mar. 2024 - Aug. 2024

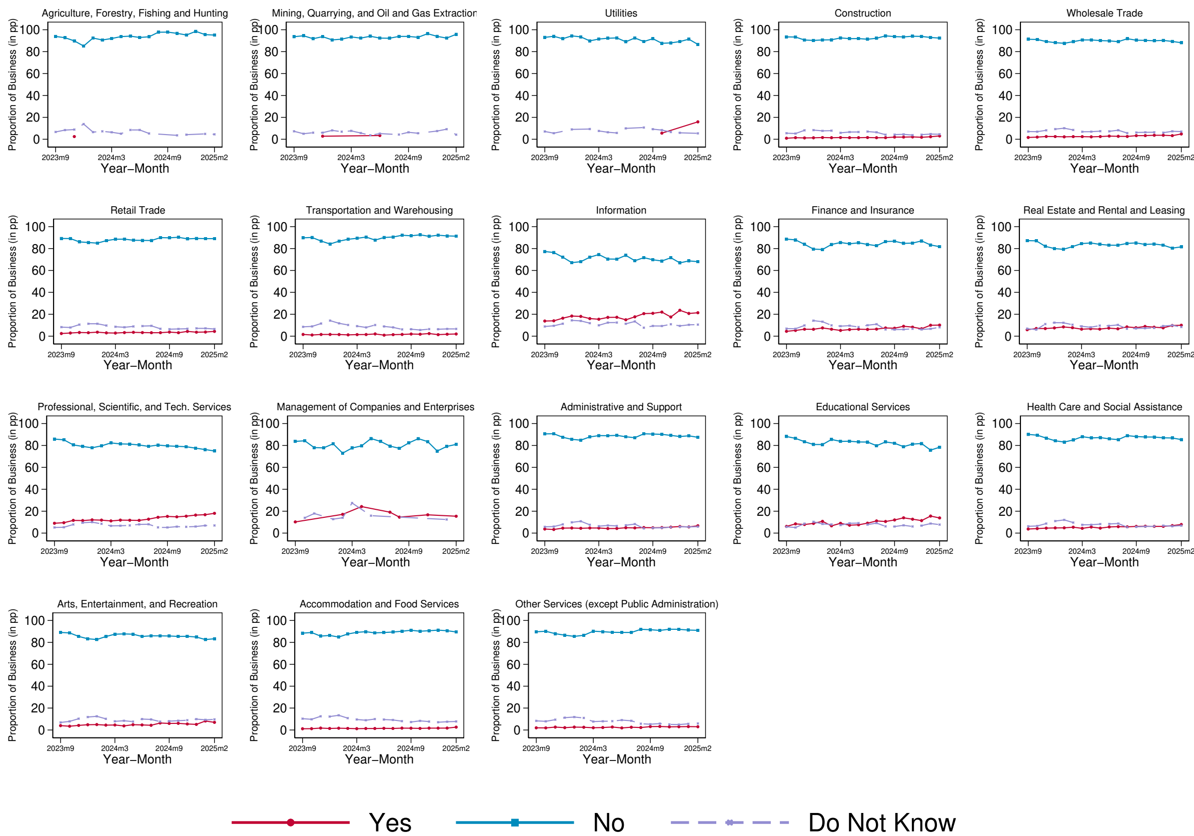


(c) Sep. 2024 - Feb. 2025



Data: Business Trends and Outlook Survey (BTOS)
Notes: Scales are in percentage point. These figures show the unconditional share of businesses currently using and expecting to use AI in producing goods or services, computed by multiplying the proportions of businesses that answered "Yes" to both Question 7 ("Did this business use AI in producing goods or services?") and Question 26 ("During the next six months, will this business use AI in producing goods or services?") in the BTOS. States with no data indicate that, according to BTOS, their estimate "does not meet publication standards because of high sampling variability, poor response quality, or other concerns about the estimate quality."

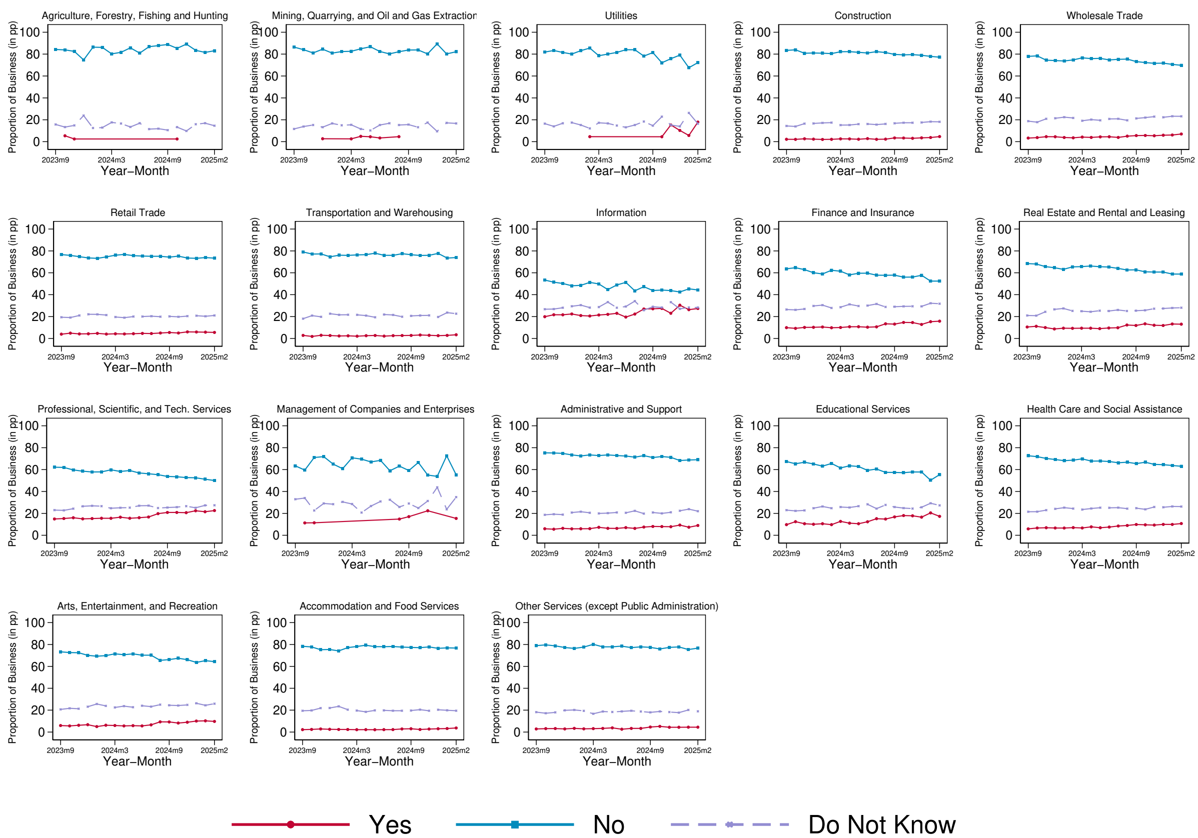
Figure 3A.3 Current AI Adoption by Industry (in pp), Sep. 2023 - Feb. 2025



Data: Business Trends and Outlook Survey (BTOS)

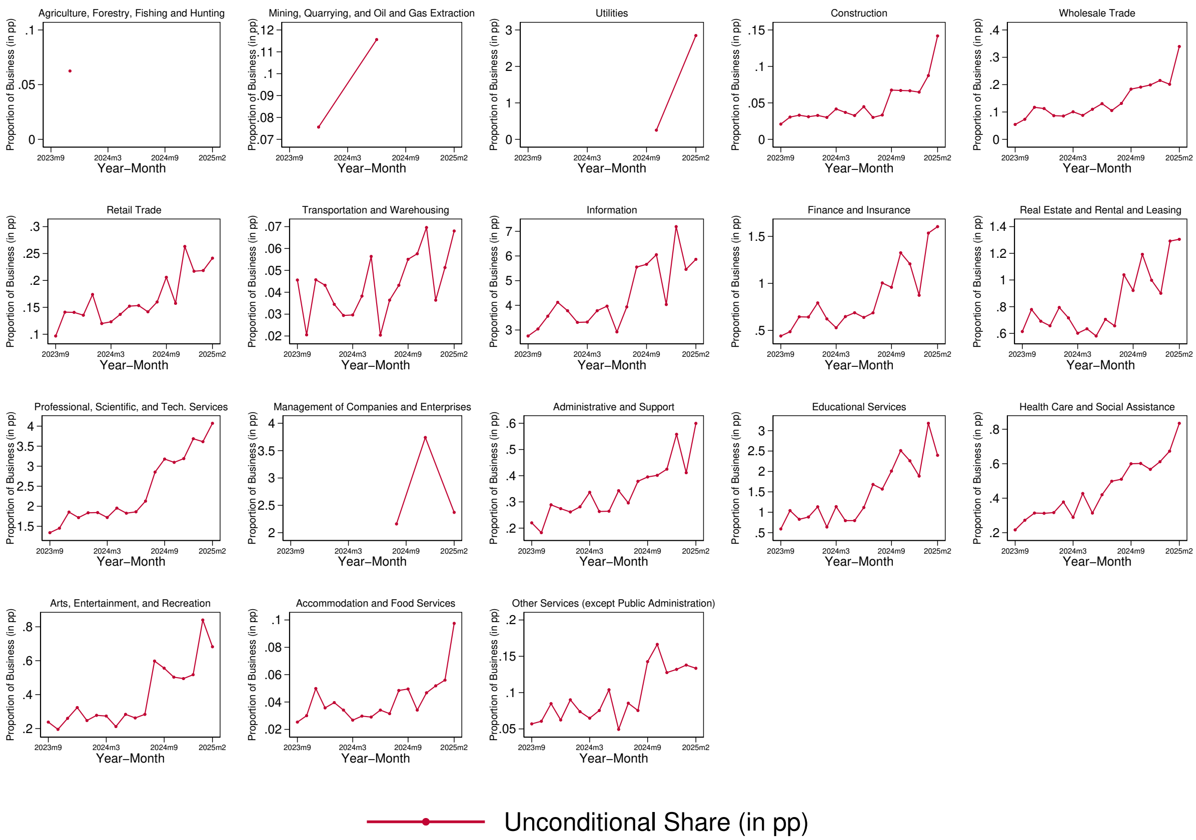
Notes: Scales are in percentage point. Industries are represented by the 2-digit NAICS code. Industries with missing data points indicate that, according to BTOS, their estimate "does not meet publication standards because of high sampling variability, poor response quality, or other concerns about the estimate quality."

Figure 3A.4 Expected AI Adoption by Industry (in pp), Sep. 2023 - Feb. 2025



Data: Business Trends and Outlook Survey (BTOS)
Notes: Scales are in percentage point. Industries are represented by the 2-digit NAICS code. Industries with missing data points indicate that, according to BTOS, their estimate "does not meet publication standards because of high sampling variability, poor response quality, or other concerns about the estimate quality."

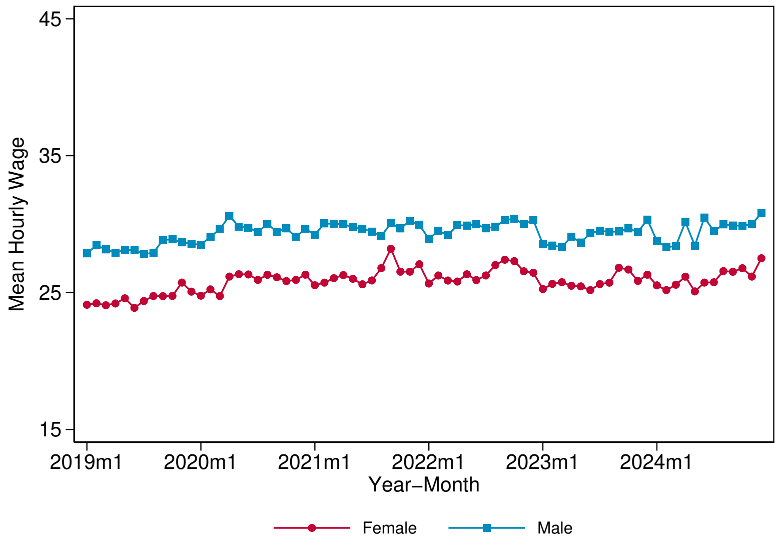
Figure 3A.5 Continuing AI Adoption by Industry (in pp), Sep. 2023 - Feb. 2025



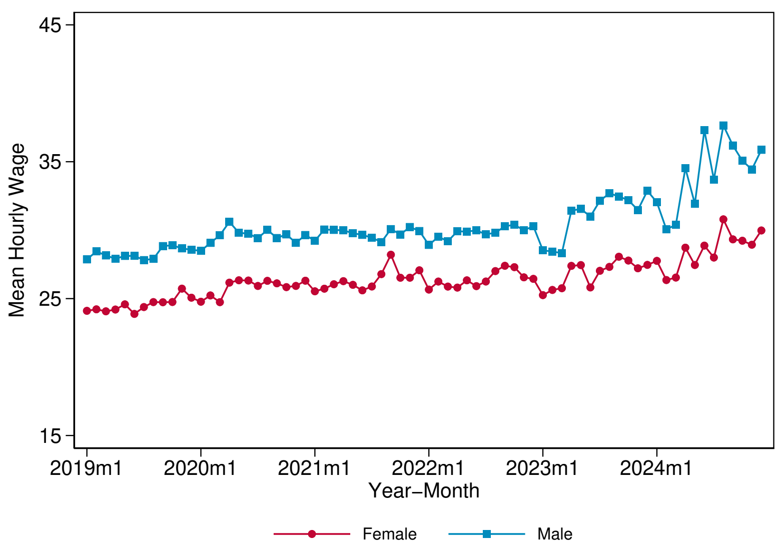
Data: Business Trends and Outlook Survey (BTOS)
Notes: Scales are in percentage point. Industries are represented by the 2-digit NAICS code. These figures show the unconditional share of businesses currently using and expecting to use AI in producing goods or services, computed by multiplying the proportions of businesses that answered "Yes" to both Question 7 ("Did this business use AI in producing goods or services?") and Question 26 ("During the next six months, will this business use AI in producing goods or services?") in the BTOS. Industries with missing data points indicate that, according to BTOS, their estimate "does not meet publication standards because of high sampling variability, poor response quality, or other concerns about the estimate quality."

Figure 3A.6 Mean Hourly Wage in the U.S. (in 2019 U.S. Dollars), 2019-24

(a) Earnings Capped at the 99th Percentile



(b) Uncapped Earnings

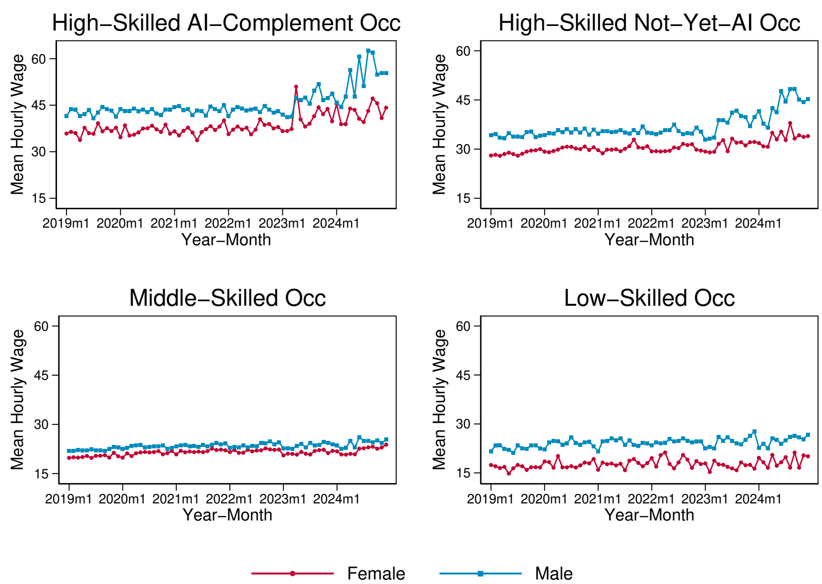


Notes: In Subfigure 3A.6a, earnings are winsorized at the 99th percentile to mitigate the influence of outliers. In Subfigure 3A.6b, earnings follows the Census Bureau's topcoding system: from April 2023 to March 2024, weekly earnings were topcoded at $2,884.61 (nominal); beginning in April 2024, the maximum value of weekly earnings is the weighted average of the reported earnings of the top 3% of earners during the reported month.

Figure 3A.7 Mean Hourly Wage in the U.S. by Skill Group (in 2019 U.S. Dollars), 2019-24

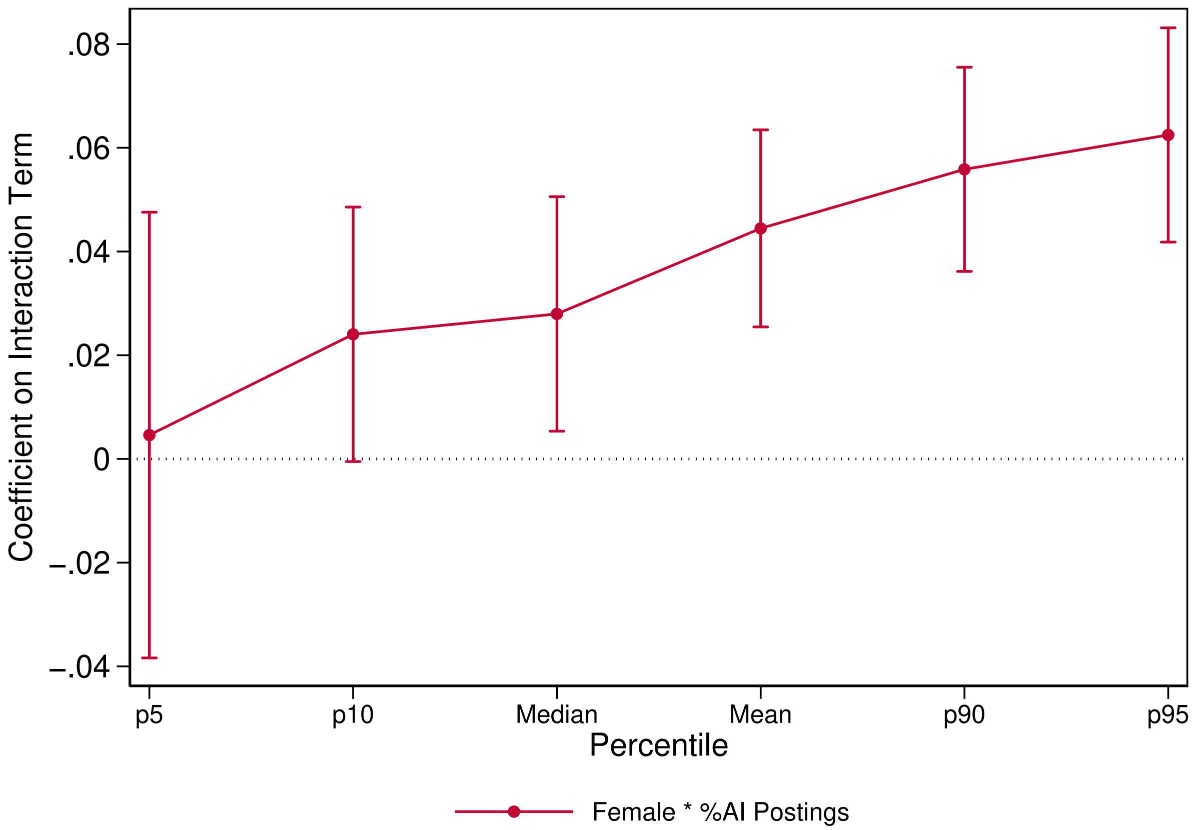
(a) Earnings Capped at the 99th Percentile

(b) Uncapped Earnings



Notes: The skill group indicators are constructed by Chapter 2 of my dissertation. In Subfigure 3A.7a, earnings are winsorized at the 99th percentile to mitigate the influence of outliers. In Subfigure 3A.7b, earnings follows the Census Bureau's topcoding system: from April 2023 to March 2024, weekly earnings were topcoded at $2,884.61 (nominal); beginning in April 2024, the maximum value of weekly earnings is the weighted average of the reported earnings of the top 3% of earners during the reported month.

Figure 3A.8 Effects of AI Postings on Women Relative to Men in the Hourly Wage



Notes: The coefficient estimates plotted are the estimates of γ from equation (3.4), but with one modification: replacing the outcome variable with the industry-by-state-by-year-by-gender hourly wage at the 10^{th} percentile, median, mean, and 90^{th} percentile of the wage distribution. The corresponding 95% confidence intervals are also shown.

Table 3A.1 Effects of Current AI Adoption by Industry on Gender Wage Gaps

	Dep. Var.: Log Hourly Wage			
	(1)	(2)	(3)	(4)
Panel A. At 10th Percentile				
Female	-0.068***	-0.068***	-0.068***	-0.064***
	(0.018)	(0.020)	(0.020)	(0.024)
%Businesses Using AI[1] in Current Month (t)	0.036***	0.037***	0.005	0.016**
	(0.002)	(0.003)	(0.007)	(0.008)
Female × %Businesses Using AI in Current Month (t)	-0.010***	-0.010***	-0.010***	-0.006
	(0.003)	(0.003)	(0.003)	(0.013)
%Businesses Using AI 3 Months Ago (t-3)				-0.021*
				(0.013)
Female × %Businesses Using AI 3 Months Ago (t-3)				-0.004
				(0.015)
R^2	0.066	0.081	0.121	0.114
Panel B. At Median				
Female	-0.143***	-0.143***	-0.143***	-0.142***
	(0.012)	(0.012)	(0.012)	(0.014)
%Businesses Using AI in Current Month (t)	0.044***	0.046***	0.002	0.004
	(0.002)	(0.003)	(0.004)	(0.008)
Female × %Businesses Using AI in Current Month (t)	-0.005***	-0.005**	-0.005**	0.002
	(0.002)	(0.002)	(0.002)	(0.011)
%Businesses Using AI 3 Months Ago (t-3)				-0.008
				(0.009)
Female × %Businesses Using AI 3 Months Ago (t-3)				-0.008
				(0.013)
R^2	0.220	0.236	0.331	0.324
Panel C. At Mean				
Female	-0.129***	-0.129***	-0.129***	-0.135***
	(0.012)	(0.012)	(0.012)	(0.013)
%Businesses Using AI in Current Month (t)	0.038***	0.040***	0.000	0.001
	(0.001)	(0.003)	(0.004)	(0.007)
Female × %Businesses Using AI in Current Month (t)	-0.001	-0.001	-0.001	-0.002
	(0.002)	(0.002)	(0.002)	(0.008)
%Businesses Using AI 3 Months Ago (t-3)				-0.009
				(0.008)
Female × %Businesses Using AI 3 Months Ago (t-3)				0.001
				(0.010)
R^2	0.192	0.217	0.346	0.349
Panel D. At 90th Percentile				
Female	-0.230***	-0.230***	-0.230***	-0.244***
	(0.014)	(0.016)	(0.016)	(0.018)
%Businesses Using AI in Current Month (t)	0.033***	0.035***	-0.004	-0.003
	(0.001)	(0.004)	(0.004)	(0.008)
Female × %Businesses Using AI in Current Month (t)	0.009***	0.009***	0.009***	0.002
	(0.002)	(0.003)	(0.003)	(0.011)
%Businesses Using AI 3 Months Ago (t-3)				-0.008
				(0.009)
Female × %Businesses Using AI 3 Months Ago (t-3)				0.010
				(0.014)
R^2	0.171	0.199	0.331	0.334
Observations	13,478	13,478	13,478	10,914
State FE		✓	✓	✓
Year-Month FE		✓	✓	✓
Industry FE			✓	✓

Notes: Each observation is an industry-state-year-month-gender cell. Industry is represented by 2-digit NAICS code. All columns include a set of state-year-month controls. Standard errors shown in parentheses are clustered at the industry-state-month level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The share of businesses currently using AI is measured as the average monthly share of businesses at the industry level that answered "Yes" to Question 7 in the Business Trends and Outlook Survey (BTOS), which asked "Between MMM DD – MMM DD, did this business use Artificial Intelligence (AI) in producing goods or services? (Examples of AI: machine learning, natural language processing, virtual agents, voice recognition, etc.)." The unit is a percentage point.

Table 3A.2 Short-Term Versus Long-Term Effects of AI Postings on Gender Wage Gaps by Skill Groups, 2019-24

	Dep. Var.: Log Mean Hourly Wage				
	(1) All Occ.	(2) High-Skilled AI-Complement Occ.	(3) High-Skilled Not-Yet-AI Occ.	(4) Middle-Skilled Occ.	(5) Low-Skilled Occ.
Female	-0.150***	-0.179***	-0.120***	-0.162***	-0.124***
	(0.006)	(0.018)	(0.012)	(0.009)	(0.031)
%AI Postings[1] in Year t	-0.027***	-0.012	-0.021	-0.021	-0.094***
	(0.010)	(0.025)	(0.017)	(0.014)	(0.035)
Female × %AI Postings in Year t	0.029***	0.047**	0.020	0.028***	0.032
	(0.007)	(0.021)	(0.016)	(0.009)	(0.029)
%AI Postings in Year $t-1$	-0.020*	-0.044*	-0.008	-0.029*	0.011
	(0.011)	(0.026)	(0.016)	(0.017)	(0.039)
Female × %AI Postings in Year $t-1$	0.001	0.001	0.008	-0.001	-0.052*
	(0.007)	(0.024)	(0.014)	(0.009)	(0.030)
Observations	78,956	7,039	25,036	40,294	4,922
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓
Outcome Mean	3.146	3.587	3.268	3.017	2.996
R^2	0.412	0.187	0.367	0.331	0.331

Notes: Each observation is an occupation-state-year-gender cell. Occupation is represented by 4-digit OCC2010, a harmonized occupation system constructed by IPUMS based on the 2010 Census Occupational Classification. The skill group indicators are constructed by Chapter 2 of my dissertation. All columns include a set of state-year controls. Standard errors shown in parentheses are clustered at the state-year level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The share of AI postings is measured at the state-year level. The unit is a percentage point. The data is from the AI Index Report by Stanford Institute for Human-Centered AI, who provides the Lightcast data on AI posting shares at the state-year level for the public.

Table 3A.3 Short-Term Versus Long-Term Effects of AI Postings on Gender Wage Gaps across Wage Distribution, 2019-24

	Dep. Var.: Log Hourly Wage			
	(1) At p10	(2) At Median	(3) At Mean	(4) At p90
Female	-0.118***	-0.176***	-0.156***	-0.225***
	(0.019)	(0.018)	(0.015)	(0.016)
%AI Postings[1] in Year t	-0.055**	-0.008	-0.033	0.005
	(0.022)	(0.025)	(0.022)	(0.022)
Female × %AI Postings in Year t	0.033	0.021	0.036**	0.040**
	(0.021)	(0.020)	(0.018)	(0.017)
%AI Postings[1] in Year $t-1$	0.026	-0.017	-0.021	-0.048**
	(0.034)	(0.027)	(0.023)	(0.022)
Female × %AI Postings in Year $t-1$	-0.024	0.003	0.006	0.015
	(0.019)	(0.020)	(0.018)	(0.018)
Observations	7,286	7,286	7,286	7,286
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Outcome Mean	2.549	3.125	3.083	3.785
R^2	0.302	0.638	0.693	0.488

Notes: Each observation is an industry-state-year-gender cell. Industry is represented by 2-digit NAICS code. All columns include a set of state-year controls. Standard errors shown in parentheses are clustered at the industry-year level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[1] The share of AI postings is measured at the state-year level. The unit is a percentage point. The data is from the AI Index Report by Stanford Institute for Human-Centered AI, who provides the Lightcast data on AI posting shares at the state-year level for the public.