The Impact of Artificial Intelligence on Occupations*

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Abstract

Complementarity matters for the impacts of AI on occupations. AI possesses the potential to enhance the productivity of certain tasks while automating others. Leveraging a commonly used measure of occupational AI exposure, I create an innovative metric for occupational exposure to AI complementarity. This metric is derived by aggregating the AI exposure of coworkers, identified through China's online job posting data. Results indicate that exposure to AI correlates with a notable decline in occupational hiring growth between 2015 and 2019, a period marked by the widespread adoption of AI, signifying a pronounced displacement effect. Interestingly, occupations complemented by AI demonstrate growth in both wage and hiring. The skill level of the occupation and the capacity of firms to adopt AI emerge as pivotal factors influencing the impact of AI on jobs. Notably, both AI-exposed and AI-complemented jobs undergo significant changes in skill requirements following the AI surge.

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1. Introduction

Artificial intelligence (AI) refers to intelligence demonstrated by machines, as opposed to the natural intelligence of animals and humans. The mid-last decade saw a rapid surge in AI due to advancements in technology, the widespread availability of big data, and enhancements in computer hardware. As highlighted by Zhang et al. (2022), the number of publications on machine learning, a subset of AI algorithms, has more than doubled since 2015. Concurrently, the percentage of AI job postings in the U.S. rose from 0.4% of all job postings in 2015 to 0.9% in 2019, with a concentration on skill areas like machine learning, artificial intelligence, and neural networks. Supporting this trend, Acemoglu et al. (2022), using an expansive dataset of U.S. online job postings, find that the takeoff of AI vacancy postings significantly accelerates after 2015. On the application front, industries have been quick to adopt and innovate with AI. Google released TensorFlow [1] in 2015, and one year later, AlphaGo by DeepMind triumphed over Lee Sedol, one of the world's top Go players at that time. ChatGPT, an AI chatbot built on large language models, was released in November 2022 and rapidly became a center of discussion and interest.

Due to the rapid advances in AI and its great power of undertaking human tasks, the implications of AI on jobs have become increasingly pertinent. Theoretically, there are two directions of AI developments, automating existing tasks and creating new ones (Acemoglu and Restrepo 2019; Acemoglu and Restrepo 2020). Regardless of the direction, AI's introduction can boost labor demand in tasks not directly influenced by it, primarily via heightened total factor productivity (TFP). This impact is especially salient for non-automated tasks closely intertwined with automated and emergent ones, such as those that either produce inputs for, or utilize outputs from, the latter categories. Given the conflicting nature of AI's displacing effects on automated tasks, its complementary influences on new and non-automated tasks, and its overall productivity enhancements, what are the sign and magnitude of AI impacts on labor markets has been an empirical question.

This paper studies the impacts of AI on occupations. Occupations can be treated as bundles of tasks, abilities, and skills (Autor et al. 2003; Autor and Handel 2013; Acemoglu and Restrepo 2018). The influence of AI on any given occupation hinges

[1] TensorFlow is a foundational open-source platform and library for machine learning.

on which of its tasks are automated and which receive complementary benefits. Acemoglu and Restrepo (2018) use a Cobb-Douglas function to characterize the production of a final good by integrating different tasks, and assume that the development of AI automates some tasks previously handled by labor and creates new tasks where human labor has comparative advantages. Within this model, tasks that are complemented by AI are only the newly-created ones, not the pre-existing non-automated tasks. This distinction arises because the Cobb-Douglas function inherently suggests an elasticity of substitution value of 1 between automated and non-automated tasks. Consequently, the increased labor demand for non-automated tasks is expect to by driven solely by enhancements in TFP rather than through direct collaboration with high-efficiency automated tasks.

Compared to the theoretical literature, current empirical studies on the occupational impacts of AI have mainly focused on automation. A prevalent empirical approach is to construct occupational AI exposure measures based on occupational task structures and investigate how exposed occupations change. The metric introduced by Felten et al. (2018) and their subsequent modifications aggregates ability-level AI application scores using importance or level of abilities as weights. Webb (2019)'s index is based on the overlap between the text of job task descriptions in O*NET database and the text of AI patents. Brynjolfsson et al. (2018) develop a rubric for systematically scoring the suitability of any given job task for machine learning and in doing so, score each occupation for its suitability for machine learning. While these measures do assess the likelihood of automation, they overlook AI's potential to augment or complement human labor in non-automated roles. Employing the above three metrics, Acemoglu et al. (2022) find no discernible impact of AI on employment or wages at the occupation or industry level. While the null result can be explained by that AI has not been advanced enough to have detectable aggregate labor market influence, it is plausible that the not-captured complementing effects mitigate the explanatory power of these measures.

This paper attempts to add to the AI impacts literature by allowing AI to supplement existing non-automated tasks. To do so, I create an occupational exposure to AI complementarity metric by measuring the average AI exposure of coworkers using China online job posting data. Subsequently, I delve into how such between-occupation complementarity shapes our understanding of AI's

occupational impacts.

Based on a conceptual framework built on Acemoglu et al. (2022), I predict that given the same level of automation, occupations whose non-automated tasks are complemented by automated tasks have higher employment and wage growth than occupations without such complementarity. There has been evidence for between-occupation and between-skill complementarity. For instance, Jäger and Heining (2022) observe that the deaths of high-skilled professionals or managers lower wages of their peers, implying a complementary relationship. In contrast, Weinberger (2014) shows increasing complementarity between cognitive and social skills from the 1980s to 2000s. This paper adds to the labor complementarity literature by utilizing coworkers to measure labor's complementarity with AI technology.

Using Felten et al.'s occupational AI exposure index alongside China's online hiring data, I find that more exposed occupations witness modest positive wage growth but experience significantly larger negative hiring growth. One standard deviation (SD) increase in occupational exposure to AI corresponds to 2 percent increase in wage growth and 21 percent decrease in hiring growth, indicating a pronounced displacement effect outweighing productivity enhancements and direct complementary effects. Conversely, as hypothesized, occupations with coworkers exposed to AI exhibit higher growth in both wage and hiring. One SD increase in occupational exposure to AI complementarity results in 3 percent increase in wage growth and 34 percent increase in hiring growth, the latter being statistically significant at the 5% level. To ensure the robustness of exposure measures and rule out confounding factors, I test their predictive power on occupational changes in education and employment before 2015, and find no clear pre-trend. Additionally, my main results remain robust across various alternative specifications.

To investigate the mechanism underlying AI's impact on occupations, I segment my sample based on occupational education and experience requirement and labor market concentration, and investigate whether AI induces changes in the specific skills demanded by exposed occupations. Overall, lower-skilled jobs appear less affected by AI, suggesting that AI enhances the productivity of these roles more than their higher-skilled counterparts. In contrast, higher-skills occupations tend to benefit more when working with exposed counterparts. The ability of firms to adopt AI and displace workers emerges as a crucial factor as well, with greater monopsony

power leading to more displacement of exposed occupations and reduced hiring in other occupations. Besides, I find that exposed occupations are more likely to require skills in writing, management, finance, and specialized software, while showing lower demand for customer service skills, potentially explaining the positive wage effects of AI. Although the specific individual skills demanded or eliminated in AI-complemented occupations remain unclear, these jobs exhibit a higher degree of gross skill change.

The results of my paper contribute to our limited understanding of the impacts of AI on occupations (Acemoglu et al. 2022; Felten et al. 2019; Webb 2019). Using a similar approach to Acemoglu et al. (2022) but for an earlier period, Felten et al. (2019) find small positive effects of AI exposure on occupational wages without discernible employment effects. Notably, the positive correlation wage effects are mainly driven by occupations demanding elevated software skills. Conversely, Webb (2019) extrapolates the negative wage impacts of previous automation technologies including software and robots to the impacts of AI and forecasts that AI will reduce wage inequality since it is high-income occupations that are more exposed to AI by Webb's criteria. Overall, the evidence has been mixed and still developing. Since current measures are biased towards automation, my paper provides a new perspective to this literature by studying the role of AI in complementing human labor.

In addition to employment and wage, I am interested in the impacts of AI on occupational skill requirements. AI reshapes occupations through task restructuring, which consequently alters skill demands. This is supported by Acemoglu et al. (2022), which discovers that AI-exposed establishments are phasing out previously-posted skills while introducing new skills. Moreover, recent studies indicates a tight linkage between skill prerequisites and job earnings. Statically, Deming and Kahn (2018) find that there is substantial heterogeneity in skill requirements and skill demands have explanatory power for wage differentials across firms. Dynamically, Deming and Noray (2020) illustrate sluggish wage growth in careers undergoing rapid skill transitions, while Braxton and Taska (2023) measure technological change in occupations using the share of vacancies listing computer or software requirements and find that technological change can account for 45% of the decline in earnings post job loss. Recognizing the pivotal role of skill demands, I investigate which

skills AI is demanding and which skills AI is eliminating, and the implication of such skill requirement change on employment and earnings.

The findings of this paper carry significant implications for policymakers seeking to reconcile the development of AI with sustained labor force participation. Despite concerns about AI leading to a jobless future, the potential evidence of AI supplementing the labor force offers a reassuring perspective. To effectively leverage AI's capabilities in enhancing human tasks, policymakers are encouraged to promote investments in skills and capabilities that AI complements, and direct resources towards AI innovations with high complementarity potential. This study provides an initial guide on where to focus attention, but the design of effective policies requires further in-depth research.

The rest of the paper is followed by six sections. Section 2 introduces the conceptual framework. Section 3 describes the empirical setting and data sources. Section 4 outlines my empirical strategies and Section 5 presents main results of the study. Section 6 investigates potential mechanisms underlying the impacts of AI. Finally, section 7 offers concluding remarks and discusses additional implications stemming from this research.

2. Conceptual Framework

To motivate my empirical strategy, this section provides a conceptual framework that shows how AI shocks can influence occupations based on their exposure to AI and potential of being complemented by AI. Here I focus on the demand of occupations since AI shocks are quite recent and workers might be slow in changing their education and skills to have a significant supply shift across occupations in the short run.

The conceptual framework is a variation of the model in Acemoglu et al. (2022) with two important distinctions. Firstly, instead of looking at the impacts of AI on establishments, I start from the production process of a representative producer using a series of tasks, and then draw implications on occupations based on occupation-specific tasks. Secondly, instead of assuming the elasticity of substitution between any two tasks to always be 1, I allow a part of tasks to have higher pair-wise complementarity. For simplification, I assume those tasks with high

complementarity are perfect complements.

By the analysis of AI effects in the model, I have the following predictions on occupational demand changes after AI shocks. On one hand, conditional on the same exposure to AI, occupations requiring more AI-complemented tasks will be in higher demand. On the other hand, given the same level of AI-complementarity, the effects of AI on more exposed occupations are ambiguous depending on how strong negative displacement effects are compared to positive productivity and direct complementary effects.

2.1. Environment

Suppose a representative producer produces a final good y by combining the inputs, $y(x)$, of tasks $x \in \mathcal{T}$

$$\ln y = \ln A + \beta \ln(\min\{\alpha(x)y(x) : x \in \mathcal{T}^C\}) + (1-\beta)\int_{\mathcal{T}^{NC}} \alpha(x) \ln y(x) dx, \quad (1)$$

where A is the total factor productivity (TFP) in the whole economy. $\mathcal{T}^C$, a subset of $\mathcal{T}$, indicates the set of tasks perfectly complementing each other, while $\mathcal{T}^{NC}$ is the complement of set $\mathcal{T}^C$, where between-task elasticity of substitution is unit. β and $\alpha(x)$ are used to measure the importance or efficiency of each task $y(x)$. I restrict $\int_{\mathcal{T}^{NC}} \alpha(x)dx$ to be 1 to ensure that the production function exhibits constant return to scale.

Let $y^C = \min\{\alpha(x)y(x) : x \in \mathcal{T}^C\}$. The production procedure is equivalent to a two-step process. In the first step, the intermediate good y_c is produced using a perfect-complements technology, while in the second step, the final good is produced out of y^C and $y(x)$, of non-complemented tasks $x \in \mathcal{T}^{NC}$, with a Cobb-Douglas technology.

Before AI takes off, all tasks are produced by human labor $l(x)$:

$$y(x) = \gamma_l l(x), \quad (2)$$

where γ_l denotes the productivity of labor. After AI shocks, AI can be applied in the production of a set of tasks $\mathcal{T}^{AI}$. These tasks are generated through human

labor $l(x)$ or by AI-powered algorithms or machines $a(x)$:

$$y(x) = [(\gamma_l l(x))^{\frac{\sigma-1}{\sigma}} + (\gamma_a a(x))^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}}, \tag{3}$$

where σ is the elasticity of substitution between human labor and AI, and γ_a represents the productivity of AI technology. As Acemoglu et al. (2022), AI services are provided by combining AI capital $k(x)$ and labor specific in AI $l^{AI}(x)$:

$$a(x) = \min\{k(x), l^{AI}(x)\}. \tag{4}$$

I assume throughout the section that the whole market is competitive, and prices for AI capital, AI labor, and other normal labor are taken as given, denoted by R, w^{AI}, and w respectively.

2.2. AI Shocks and Labor Demand

To illustrate how AI can influence the labor demand, let us first assume that $\sigma = \infty$ so that labor and AI services are perfect substitutes for tasks $\mathcal{T}^{AI}$. In addition, AI shocks make these tasks more profitable to be performed by AI. Let w^C be the unit cost of producing y^C, and C be the unit cost of producing the final good y. By Cobb-Douglas shortcut, to minimize the cost, the total production cost is spent on each component in the production function proportional to their powers. For example, a β fraction of total cost falls on y^C. Therefore, without AI, the demand for perfect-complement labor $l^C = \int_{\mathcal{T}^C} l(x)dx$ and non-complement labor $l^{NC} = \int_{\mathcal{T}^{NC}} l(x)dx$ would be (in logarithm):

$$\begin{cases} \ln l^C & = \ln yC + \ln\beta - \ln w^C + \ln \int_{\mathcal{T}^C} \frac{1}{\alpha(x)\gamma_l(x)} dx \\ \ln l^{NC} & = \ln yC + \ln(1-\beta) + \ln \int_{\mathcal{T}^{NC}} \alpha(x)dx - \ln w \end{cases} \tag{5}$$

When AI takes over tasks $\mathcal{T}^{AI}$, the change of labor demand depends on productivity effects, displacement effects, and complementary effects:

$$\begin{cases} \Delta \ln l^C = & \underbrace{\Delta \ln yC}_{\text{productivity (+)}} \quad \underbrace{-\Delta \ln w^C}_{\text{complementary (+)}} \underbrace{-\ln \int_{\mathcal{T}^C} \frac{1}{\alpha(x)\gamma_l(x)} dx + \ln \int_{\mathcal{T}^C \setminus \mathcal{T}^{AI}} \frac{1}{\alpha(x)\gamma_l(x)} dx}_{\text{displacement (-)}} \\ \Delta \ln l^{NC} = & \underbrace{\Delta \ln yC}_{\text{productivity (+)}} \underbrace{-\ln \int_{\mathcal{T}^{NC}} \alpha(x) dx + \ln \int_{\mathcal{T}^{NC} \setminus \mathcal{T}^{AI}} \alpha(x) dx}_{\text{displacement (-)}}, \end{cases} \tag{6}$$

where the positive productivity effects come from expanded production, the negative displacement effects come from direct replacement by AI in tasks $\mathcal{T}^{AI}$, and the positive complementary effects come from lower cost of perfect-complements technology y^C. Therefore, the net demand shifts are ambiguous for both types of labor. However, it is clear that when the displacement effects on perfect-complement labor and non-complement labor are the same, demand for complemented labor would exceed demand for non-complemented labor due to extra complementary effects.

2.3. Occupational Impacts

The final good could also be considered as being produced using inputs from different occupations, which are collections of tasks. Tasks of each occupation can be classified into three groups, AI-automated tasks, AI-complemented tasks, and other tasks. More AI-automated tasks indicate stronger displacement and productivity effects. This is true when more exposure to AI leads to greater reduction in the unit production cost C and $\Delta \ln yC$ is increasing in $|\ln C|$. Since $\Delta \ln yC = (1 + \epsilon_D \frac{d \ln P}{d \ln C}) \Delta \ln C$, when the demand elasticity ϵ_D is high enough so that $\epsilon_D \frac{d \ln P}{d \ln C} < -1$, $\Delta \ln yC$ becomes increasing in $|\ln C|$. Furthermore, more AI-complemented tasks mean stronger complementary effects. Note that AI-complemented tasks within one occupation can be complemented not only by own occupational AI-automated tasks, but also by AI-automated tasks in other occupations.

Remark 1: Given the same amount of AI-complemented tasks, occupations with a

higher prevalence of AI-automated tasks will experience increased demand during an AI surge, provided that the productivity gains outweigh displacement effects. Conversely, in the opposite case, their demand will decrease.

Proof. Maintaining a constant level of AI-complemented tasks implies an unchanged cost reduction for the intermediate good y^C. Consequently, the variability in AI-automated tasks arises solely from $\mathcal{T}^{NC} \cap \mathcal{T}^{AI}$, which only influences the productivity and displacement effects. Assuming that $\Delta \ln yC$ increases with $|\ln C|$, the impacts of AI-automated tasks on occupational demand hinge on the relative dominance of productivity gains versus displacement effects. □

Remark 2: In a scenario where AI-automated tasks are equally available, occupations with more AI-complemented tasks will see an increased demand after AI shocks.

Proof. Increasing AI-complemented tasks while maintaining the level of AI-automated tasks implies that the occupation involves more tasks in the set $\mathcal{T}^C \backslash \mathcal{T}^{AI}$, leading to a more substantial decrease in w^C. Note that the unit cost of the final good C is positively related to w^C through the equation:

$$\ln C = \beta \ln w^C + (1-\beta) \ln \int_{\mathcal{T}^{NC}} \alpha(x) \ln(\frac{w}{\gamma_l(x)}) dx - \beta \ln \beta - (1-\beta) \ln \int_{\mathcal{T}^{NC}} \alpha(x) \ln(\alpha(x)) dx.$$

Therefore, a more significant decrease in w^C is associated with a greater decline in C, thereby intensifying productivity effects. Consequently, both increased complementarity and productivity effects will augment the demand for occupations with more AI-complemented tasks following AI shocks. □

2.4. Direct Complementarity

Once I relax the assumption of perfect substitutes between labor and AI within a task and allow AI to directly complement human labor in performing the same task, displacement effects disappear and direct complementary effects emerge. In section 2.3, AI-automated tasks are now in general AI-impacted tasks, and AI-complemented tasks are those not directly impacted by AI but closely related to AI-impacted tasks. Nonetheless, the arguments in section 2.3 still hold, although

increased demand for exposed occupations may be evidence for both direct complementarity and productivity effects.

2.5. The Role of Skills and Market Power

In the environment, I assume that workers are homogeneous except the specialty of AI-specific workers, and the economy is competitive. However, in the real world, workers vary by skill level and firms vary by their market power in the labor market.

The impacts of AI may differ by skill level. However, it is unclear whether the impacts are greater for high-skilled jobs or low-skilled jobs. On one hand, low-skilled occupations may be less likely to be affects because firms may have a lower incentive to replace jobs with low skills due to low wages or for training purposes, or AI is more likely to create new tasks in these areas. On the other hand, low-skilled jobs may be easier to be replaced because workers are more homogeneous.

The extent to which jobs can be replaced by AI may also depend on firms' monopsony power. The impacts of AI might be stronger in competitive labor markets due to the heightened incentives to adopt cutting-edge technologies for competitive advantage. It is also likely to be the other way around since firms with greater powers often find it easier to displace workers.

3. Empirical Setting and Data

3.1. Empirical Setting: China and AI

China has a large AI market. AI index report 2022 by Zhang et al. (2022) shows that 30% AI journal publications are from Chinese authors, and China ranks second in private investment in AI in the world. By 2022, two of the top thirty firms, in terms of market capitalisation, were AI-focused Chinese giants: Tencent and Alibaba [2] (Goldfarb and Trefler, 2018). China also has a big labor market. According to the National Bureau of Statistics of China, total employment by the end of 2022 is 733.51 million, with urban employment constituting 63% of this figure.

[2]As of March 2022, data on the market capitalization of the largest public companies can be accessed at PWC: https://www.pwc.com/gx/en/audit-services/publications/top100/pwc-global-top-100-companies-by-market-capitalisation-2022.pdf

While existing studies have shown a surge in AI job postings in the U.S. post-2015 (Zhang et al. 2022; Acemoglu et al. 2022), the evidence on the trend within China has been limited. Using the China online job posting data, which will be introduced later, I find that similar to the U.S., the share of AI job postings increases from 0.2% in 2015 to 0.7% in 2019, with a rapid growth in late 2017, as shown in panel (a) of Figure 1.

3.2. Data

In this section, I introduce the main data I use for analysis and the basic steps to process these data.

3.2.1 China online job posting data

I use China online job posting data web scraped from three main Chinese online recruitment websites (Zhaopin, 51 Job, and Liepin) to characterize labor demand. It includes around 130 million daily job postings from 2007 to 2020. However, some of these websites experienced major adjustments in early 2014 and after December 2019, which lead to disproportionately low data volume in these periods (see Figure 2). For this reason, I focus on full-time jobs from July 2014 to November 2019. Each observation in this dataset records the posting firm, the job title, an occupation classification as defined by the websites, a detailed job description, the number of vacancies, wage, and requirements on age, experience, and education.

The job description variable describes the task contents of each job. I follow Deming and Noray (2020) to categorize the required skills for each job by identifying relevant keywords and phrases within these job descriptions. This results in 14 distinct skill categories: social, cognitive, character, creativity, writing, management, finance, business systems, customer service, office software, technical support, data analysis, specialized software, and ML/AI. Figure 3 illustrates the trend of jobs with all individual skill requirements except for AI skills. The skill requirements have remained relatively stable over time, with a noticeable increase in the demand for data analysis and a slight decrease in the requirement for specialized software, encompassing various traditional non-office software such as Java and Python. AI

jobs are those requiring the ML and AI skills[3]. Panel (b) of Figure 1 demonstrates the evolution of AI jobs concerning different AI technologies. In general, job postings mentioning Artificial Intelligence, Machine Learning, and Neural Networks or Deep Learning have exhibited the most substantial growth around 2017.

A potential problem with this data is that firms may post the same vacancies across platforms and over time. While efforts have been made to remove some duplicates prior to merging data from the three websites, it remains essential to ensure the exclusion of all potential redundancies. To distinguish unique job postings, I classify job advertisements based on the firm, job title, job location, and the week of posting, and subsequently discard any duplicates.

The occupation classification in this data is not standard because it is designed by the three job websites and each of them uses slightly different classification. Furthermore, for a study focusing on the impact of AI on occupations, it is crucial to ascertain which professions are most susceptible to AI interventions. Previous work that attempts to measure occupational compatibility with current AI capabilities has been based on the U.S. Standard Occupational Classification (SOC) system. To align with a standardized occupation classification and leverage pre-existing measures of occupational AI exposure, I manually map Chinese occupations with the most detailed 6-digit SOC codes wherever feasible. Out of 2,052 Chinese occupations in the dataset, 2,032 of them are matched with 353 6-digit SOC codes, 13 with 5-digit SOC codes, 9 with 3-digit SOC codes, and 6 with 2-digit SOC codes. The remaining professions, such as civil servants, trainees, and consultants, are too broad to be associated with a specific SOC code.

Of the total observations, 4% do not possess a specific occupation designation and 7% of those designated with occupations are not aligned with SOC codes[4]. For those postings, I use job titles to match with SOC codes. The idea is to identify the closest job title within matched entries for each unmatched posting and subsequently assign the corresponding SOC codes. Unlike English texts, words in a Chinese sentence are not separated by spaces. Following Li et al. (2019), I use the R version of Python package *jieba* to parse job titles into individual words and phrases. Next I

[3]See appendix of Deming and Noray (2020) for the relevant English keywords. I employ both these keywords and corresponding Chinese synonyms to identify skills.

[4]In scenarios involving multiple occupations, I pick the most specific one that appears first in the occupation list.

follow Atalay et al. (2020) to employ a continuous bag of words (CBOW) model to convert each word and phrase into a vector that capture their contextual meanings, and then search for the closest job titles in matched postings to those in unmatched postings based on the cosine similarity between associated vectors. The accuracy rate of my approach in a test set of size 10,000 is similar to that of Atalay et al. (2020)[5]. See Appendix A for details of my implementation.

In addition to occupations, I also need a corresponding definition for commuting zones in China to better define a local labor market. Counties in mainland U.S. are clustered into 722 commuting zones, which are formed based on commuting connections to portray the local economy. The mainland of China encompasses 31 provinces, 333 prefectures, and 2844 counties. Unfortunately, China currently lacks nationwide commuting flows data between counties, which makes it unfeasible to construct commuting zones as seen in the U.S.. However, this gap is being addressed by commuting flows data derived from cellphone locations. Employing location information gathered by a leading digital map provider, Chen et al. (2022) delineate commuting-based metropolitan areas in China. They find that in fact, commutes overwhelmingly occur within administrative boundaries [6]. Therefore, I choose the median size of administrative regions, prefectures, as the unit of local labor market[7].

Table 1 provides a comprehensive overview of the data for the year 2015. The upper panel delineates the occupational composition of online job postings across 22 main groups in the SOC system, excluding military-specific occupations. In comparison with China's national survey, certain occupations, such as managers, business and financial workers, computer workers, art workers, and office and administrative workers, are over-represented on online job platforms, whereas service workers, sales workers, agricultural workers, production workers, and transportation workers are under-represented. Furthermore, online job postings exhibit a disproportionate emphasis on higher education requirements compared

[5]My predictions are correct 41.9% of the time at 6-digit SOC level and 49.9% of the time at 4-digit SOC level, while Atalay et al. (2020) assign the same 6-digit SOC code 36% of the time and the same 4-digit SOC code 53% of the time in their test set.

[6]Chen et al. (2022) demonstrate that 91% of workers work in the county they live, in contrast to the U.S. where the figure is 72%.

[7]In addition, I include four province-level municipalities (Beijing, Tianjin, Shanghai, and Chongqing), and five counties directly under provincial government to cover the whole country. As a result, the maximum number of local labor markets is 342.

to the broader population. On average, the posted yearly wage is approximately $12,000 in 2015 US dollars, and the average experience requirement is around one year. Additionally, each firm, on average, posts 379 job advertisements in 2015, spanning across 22 distinct occupations.

3.2.2 AI exposure

I adopt the AI Occupational Exposure (AIOE) measure developed in Felten et al. (2021). This score is calculated based on two databases. The first is occupational ability structure derived from the O*NET database[8]. It defines 52 abilities covering cognitive, physical, psychomotor, and sensory categories. Moreover, it measures the importance or level of each ability for each O*NET-SOC occupation by surveying workers and experts[9]. The O*NET database is updated at least once a year. I use O*NET 19.0 version released in July 2014 to track occupational ability structure prior to the AI surge in 2017. Another is Electronic Frontier Foundation (EFF) AI progress measurement dataset that tracks the pace of progress across AI categories from 2010 onwards. The AI categories tracked include abstract strategy games, real-time video games, image recognition, visual question answering, generating images, reading comprehension, language modeling, translation, speech recognition, and instrumental track recognition.

The measure of occupational AI exposure involves a weighted sum of ability-level AI exposure scores, with weights assigned based on the importance or level of each ability within the occupation. There are two ways of calculating ability-level AI exposure scores. One is a forward-looking approach by Felten et al. (2021), that links from AI categories tracked by the EFF to abilities through survey responses from Amazon's Mechanical Turk (mTurk). Another is a backward-looking approach introduced by Felten et al. (2018) and Felten et al. (2019), that additionally weights each AI category by its progress from 2010 to 2015 on the basis of the first method. Since the measure based on the second approach accounts for historical AI progress, it is also called AI Occupational Impact (AIOI) index. However, since the AIOI index only considers AI progress during a short period of time, I adopt AIOE as the occupational exposure to AI measure in my main analysis, although the two

[8]https://www.onetonline.org/find/descriptor/browse/1.A

[9]Ultimately, the data is consolidated to correspond with the 6-digit SOC codes.

measures are highly correlated (correlation of 0.97) and results remain robust to using AIOI. Felten et al. (2021) scale the AIOE measure by occupational gross ability requirement, which is the sum of the prevalence and importance of all abilities used in the occupation. Whether the index is scaled determines if it measures absolute or relative AI exposure. Overall, cognitive and sensory abilities are much more exposed to AI than psychomotor and physical abilities. By scaling the index, the exposure level of some occupations with high requirements for cognitive and sensory abilities will be under-estimated if these occupations also have high requirements for psychomotor or physical abilities, such as surgeons. Therefore, I choose not to scale the index, while the scaled AIOE is tested in a robustness check.

Occupations with higher AI exposure are expected to undergo more substantial shifts in work content. This is validated by Felten et al. (2018), who find a statistically significant correlation between the occupational exposure measure and whether the Bureau of Labor Statistics was planning to change the official occupational definition in 2018. This implies adjustments in the nature of exposed occupations, with reorganization or redesign of job tasks. Similarly, establishments with higher exposure are expected to experience more changes as well. Acemoglu et al. (2022) show that AI-exposed establishments, based on AIOI, hire more AI-related positions from 2010 to 2018 and witness greater skill requirement changes in non-AI positions.

Table 2 presents the top and bottom 5 occupations by AIOE, along with their standardized AIOE scores in columns (1) and (2). Given the higher exposure of cognitive and sensory abilities to AI compared to psychomotor and physical abilities, it turns out that the AIOE measure is higher for professionals and managers and lower for service and production workers. For instance, surgeons are ranked in the top 5, reflecting their high demand for cognitive and sensory skills. Current AI technologies, particularly in pattern recognition and reinforcement learning, have the potential of impacting diagnoses, predicting treatment risks, and assisting in surgeries. AI, combined with robotics, may even be able to execute operations independently. Conversely, agricultural product graders and sorters, which might also be replaced by AI and robotics, have a low AIOE, emphasizing the measure's focus on AI exposure rather than robotics. The possibility of creating a combined measure for exposure to both AI and robotics, accounting for their complementarity, remains a potential avenue for future research.

4. Empirical Strategy

4.1. Occupational Metrics

According to section 2, occupational AI-complemented tasks are defined as those perfectly complementing AI-impacted tasks. I assume that occupations whose coworkers are highly exposed to AI are more likely to have AI-complemented tasks. This aligns with findings by Jäger and Heining (2022), who provide evidence on the complementarity between coworkers in different occupations. Therefore, I calculate occupational exposure to AI complementarity by averaging the AI exposure scores of coworkers. Note that this approach only captures between-occupation complementarity instead of within-occupation complementarity. In China online job posting data, coworkers of an occupation are jobs posted in different occupations in the same firm during 2014 to 2015.

A caveat of my data is that it records new hires and may not fully represent the actual workers in a specific firm. On one hand, occupations with high turnover rates or those where workers tend to leave the job after a short period are likely to appear more frequently in online recruitment websites. On the other hand, as highlighted by Chen and Luo (2022), online job platforms disproportionately serve firms targeting young and high educated applicants in the private sector. However, two facts help alleviate the concern. First, the sample size of my data is large. For example, there are around 14 million observations in 2015, accounting for 3% of total urban employment in China. Second, the occupational distribution in online job platforms is generally similar to that of nationally representative samples. Specifically, the occupational share correlation at the 2-digit SOC level between my 2015 data and the 2015 China 1% population sample survey is 0.56 with a p-value less than 0.01. To further address the concern, I construct an alternative coworker measure that weights coworkers by their vacancies and turnover rate, to account for the possibility that multiple vacancies are created for a single advertisement and jobs with high turnover rate tend to be hired more frequently. The occupational turnover rate is calculated as the reciprocal of twice the tenure based on the China Family Panel Studies 2012 and 2014, assuming that subjects are halfway through their jobs.

4.2. Occupational Impacts of AI

4.2.1 Main specification

To estimate the effects of AI on occupations, I use an occupation-prefecture level regression given by:

$$\Delta y_{oi} = \beta_1 (\sum_k X_{ko} AI_k) + \beta_2 Comp_o + U'_{oi}\mu + \alpha_i + \eta_{b(o)} + \epsilon_{oi}, \tag{7}$$

where y_{oi} represents skill requirements, wages, or job hiring for occupation o in prefecture i, while Δ symbolizes the logarithm change from 2015 to 2019. AI_k denotes AI application index of ability k, and $\sum_k X_{ko} AI_k$ is Felten et al.'s index that measures the extent of AI exposure by weighting AI_k by the important or level of ability k in the occupation (X_{ko}). $Comp_o$ is the occupational exposure to AI complementarity. Both exposure measures are standardized. Controls U_{oi} include occupation-prefecture level education and experience requirements in 2015 (e.g., the share of associate and bachelor degrees, and average experience years), and occupational degree of automation that considers progress in computer software and robotics[10]. α_i and $\eta_{b(o)}$ refer to fixed effects for prefectures and 3-digit SOC code. Each observation is weighted by its hiring level in 2015. Standard errors are two-way clustered at occupation and prefecture level[11]. According to section 2.3, the sign of β_1 is not certain, but a positive β_2 is expected for both wage and job hiring since, given the same extent of AI exposure, occupations whose non-automated tasks are complemented by AI should experience higher demand than those without such complementarity.

4.2.2 Robustness check

The causality of the results might be questionable because occupational exposure measures are potentially correlated with other unobservable characteristics influencing labor market outcomes. The controls and 3-digit SOC fixed effects are

[10] In detail, it includes occupational *Degree of Automation* in July 2014 from the O*NET database, and exposure to software and robot scores from Webb (2019). I do not use Webb (2019)'s exposure to AI index because it is correlated with occupational employment trends before 2015.

[11] Abadie et al. (2023) show that when clustering at the treatment assignment level, standard errors are conservative with heterogeneous treatment effects.

aimed to deal with this issue. Additionally, considering the acceleration of AI after 2015, a test for any pre-trend in outcomes before the AI surge is conducted using data from the 2000 and 2010 China Census and the 2015 China 1% Population Sample Survey to measure occupational employment and average education changes from 2000 to 2010 and 2010 to 2015.

4.2.3 Heterogeneity analysis

According to the analysis in section 2.5, the impacts of AI may vary by skills and monopsony power. To test the role of skills, occupations are split into two groups based on experience or education requirements, and the main specification is run by groups. In terms of heterogeneity by market power, insights from Azar et al. (2022) are utilized to proxy monopsony power in Chinese local labor markets by quantifying labor market concentration across prefectures. Segmenting the sample based on these concentration levels allows for an analysis of whether market power significantly influences the scope and scale of AI's labor market effects.

5. Results

In this section, I will present the main findings concerning the effects of AI on occupational outcomes when considering AI's potential to complement non-automated tasks.

5.1. Occupational Metrics

Column (3) and (4) in Table 2 present the top and bottom occupations by their exposure to AI complementarity and the corresponding standardized scores. Occupations at the top, such as hospital workers, benefit significantly from AI complementarity as their coworkers, including surgeons and nurses, exhibit considerable exposure to AI. Conversely, service workers are least complemented by AI.

The occupational AI exposure and AI complementarity measures are significantly positively correlated. That implies that workers tend to collaborate with individuals who are similar to them. However, for a given value of AI exposure, substantial variation exists in the complementarity margin (see Figure 4). For in-

stance, First-Line Supervisors of Food Preparation and Serving Workers and Medical and Health Services Managers have similar AIOE measures (at the 42th and 65th percentile, respectively, relative to other occupations). However, the former is ranked at the 1st percentile in the coworker index, while the latter is ranked at the 96th percentile. This difference is due to First-Line Supervisors of Food Preparation and Serving Workers mainly collaborating with waiters and cooks, who have lower exposure to AI, while Medical and Health Services Managers collaborate with nurses or other types of managers, who have higher exposure to AI.

Later I interpret the effects of AI as the change in outcomes induced by one standard deviation (SD) increase of both occupational exposure measures. To be clearer about the magnitude, a 1 SD change in AIOE is approximately the difference between lawyers and media and communication workers, while a 1 SD change in the coworker index is about the difference between construction trades workers and media and communication workers.

5.2. Occupational Impacts of AI

5.2.1 Pre-trend test

I construct occupation-prefecture-level employment growth and change of the share of workers with some college education from 2000 to 2010 and 2010 to 2015 and regress them against occupational exposure measures. Table 3 shows that neither exposure index exhibits a significant relationship with occupational outcomes before AI takes off, providing some evidence for the exogeneity of my exposure measures. If anything, occupations with high exposure to AI and low complementarity with AI tend to experience faster employment growth from 2010 to 2015, and this relationship differs from that observed after 2015, as detailed in section 5.2.3.

5.2.2 AI jobs

Theory predicts that exposed occupations should have more tasks performed by AI when AI becomes prevalent. Surprisingly, Table 4 reveals that more exposed occupations do not significantly require more AI-related skills in their advertisements. To reconcile this result with Acemoglu et al. (2022)'s finding that more

exposed establishments hire more AI jobs, it is plausible that tasks highly exposed to AI in non-AI jobs are performed by computer occupations instead of the jobs themselves. In contrast, one SD increase in occupational exposure to AI complementarity leads to around 0.16 percentage point decrease in the share of AI jobs. This result holds robustly when restricting to occupation-prefecture pairs that experience strictly positive changes in AI job shares (see column (4)) and remains consistent when considering changes in the share of AI job openings, accounting for the number of vacancies in each advertisement (see columns (6) and (8)). Complemented occupations requiring fewer AI skills might suggest improved specialty between AI-impacted jobs and jobs that supplement AI-impacted jobs.

5.2.3 Wage and hiring

Table 5 demonstrates the effects of AI on wage and the level of job hiring. In column (1) and (3) where only exposure to AI is considered, one SD increase in the index leads to 2.2 percent increase in the growth rate of wages and 21.2 percent decrease in the growth rate of job advertisements posted. Both coefficients and standard errors hold relatively stable even when occupational exposure to AI complementarity is added. This indicates that, despite the positive correlation between AIOE and the coworker index, it does not substantially bias the estimation. Overall, the effects of AI exposure are significant at the 10% level. Given the much larger negative impacts on hiring, more exposed occupations are more likely to experience stronger displacement effects compared to productivity and any direct complementary effects. This seems contradictory to the results in Acemoglu et al. (2022), who find no significant effects of AI on occupational employment and wage growth. However, Table A.1 in the Appendix compares the effects of AI on occupational outcomes between this paper and Acemoglu et al. (2022), and columns 1-4 in this table show similar sign and magnitude for both wage and employment/hiring. Note that to make the two papers more comparable, I run the regressions at the occupation level when only controlling for 3-digit SOC fixed effects and restricting to the occupations that appear in China's online job boards.

In column (2) and (4), where exposure to AI complementarity is also considered, one SD increase in the coworker index leads to 2.7 percent increase in wage growth and 34.2 percent increase in hiring growth, with the latter being significant at the

level of 0.05. This aligns with Remark 2 in Section 2.3, indicating that occupations whose non-automated tasks are complemented by AI are more likely to experience higher demand, resulting in higher wage and hiring levels.

Column (5) and (6) in Table A.1 present the results when the regressions are estimated at the occupation level and all controls are included. It still holds that exposed occupations experience a slight increase in wage growth but a much larger decrease in hiring growth, and being complemented by AI accelerates both wage and hiring growth. Additionally, the magnitudes are in line with the estimates in Table 5, although the effects of AI on hiring are estimated less precisely.

Furthermore, the results are robust to several alternative specifications at the occupation-prefecture level as presented in Table 6. I control for 3-digit SOC fixed effects in the baseline model to compare within more similar occupations. In column (1), I investigate the role of these fixed effects. Without them, there is more bias, but the overall pattern of AI impacts still holds. I also look at whether different choice of occupations included in the regression influences the results. In column (2), I focus on the most detailed occupations and it reduces the number of total occupations by 27, while in column (3), I exclude computer related occupations. It turns out that the choice of occupations included in the regression has minimal influence and the results are not mainly driven by computer jobs. Although Table 3 does not reveal any clear pre-trends of occupational outcomes with both exposure measures, adding occupational employment growth from 2010 to 2015 as a control in column (4) amplifies the displacement effects of AI, with one SD increase in AIOE leading to a 33.3 percent decrease in hiring growth. Moreover, column (5) indicates that the effects of exposure to AI complementarity do depend on whether observations are weighted. Without weights, being complemented by AI has barely any impacts on wage growth, and its effects on hiring growth also decrease significantly compared to the baseline.

In column (6) and (7), I try alternative ways of constructing the exposure to AI measure, and the coworker index are adjusted as well. Neither AIOI nor scaled AIOE changes the pattern, although the estimates using scaled AIOE are less precise. In the last three columns, I do not change the exposure to AI measure but explore three alternative coworker indices. To address concerns that occupations with high turnover appear more frequently in the data, I weight coworkers by the number

of vacancies and turnover rate when constructing the index in column (8). It does not change the results. In column (9), for each occupation, I only consider top 35 occupations that work with them to exclude rare coworkers. The results also remain consistent, which makes sense because rare coworkers are assigned with very low weights in my original coworker index. Lastly, taking the case where workers with the same occupation often work together into account, I include the same occupation as coworkers in column (10). All estimated coefficients become less significant, which may be due to higher correlation between AIOE and this coworker index. However, overall, the sign and magnitude of coefficients do not change.

6. Mechanism

In this section, I investigate the influence of education, experience, and labor market concentration on the effects of AI on occupations. Additionally, I explore detailed skill requirements and examine how they are impacted by AI progress.

6.1. Role of Education and Experience

The results for heterogeneity by education and experience are presented in Table 7. All observations are divided by two groups according to occupational education and experience requirements. Column (1) and (2) show that jobs with low education requirements benefit from AI, while it is high-education jobs that are more affected. For low-education jobs, one SD increase in occupational exposure to AI results in 3.8 percent increase in wage growth and 31.5 percent increase in hiring growth, while one SD increase in AIOE within high-education jobs leads to 37.7 percent decrease in hiring growth. This suggests stronger productivity or direct complementary effects among low-education jobs, or firms have higher incentives to replace jobs with high wage. The former may be because AI is easier to be scaled up or create new tasks that complement human labor in areas where expertise is not highly required. Similarly, according to column (3) and (4), jobs with high experience requirement are more affected than their low-experience counterparts. Low-experience jobs often involve simpler tasks and are at a lower position on the job ladder. While firms may find it easier to replace low-experience jobs, they still prefer to retain these

jobs for training purposes. As for the effects of AI complementarity, high-skilled jobs (with higher requirements for education or experience) seem to benefit more from working with exposed occupations in terms of hiring. This indicates that the productivity of high-skilled AI-coworkers improves more when AI-exposed jobs are more productive, in line with the complementary relationship between the two types of jobs.

6.2. Role of Labor Market Concentration

In column (5) and (6) of Table 7, I categorize occupation-prefecture pairs into two groups by the HHI index. According to Azar et al. (2022), a higher HHI implies greater labor market concentration and, therefore, greater monopsony power of firms. The positive wage effects of AI are concentrated in lower concentrated market, while the negative hiring effects are concentrated in markets with more monopsony power. That suggests firms with high HHI are more adept at displacing workers while keeping wages low. Additionally, by comparing the coefficients of the coworker index in panel B, it suggests that when firms have high HHI for AI-complemented jobs, they also hire fewer of these jobs.

6.3. Skill Requirement Change

The results presented in Table 4 indicate that exposed jobs do not undergo any significant change in the requirement for AI skills, while AI-complemented jobs require fewer AI skills compared to other occupations. Consequently, the alteration in AI skill requirements does not account for the observed negative hiring effects of AI exposure and positive effects of AI complementarity. Instead, in this section, I explore the channel of changing requirements for other skills.

Figure 5 illustrates the effects of AI on the change in other individual skill requirements as specified in Deming and Noray (2020). Exposed occupations are more likely to require skills such as writing, management, finance, and specialized software, while less likely to require customer service skills. The former skills are typically considered as high-level skills, and the heightened requirement for these skills may explain the positive wage effects of AI. Similar skill requirement changes are found by Alekseeva et al. (2021) in firms that intensively demand

AI skills. Moreover, the decrease in the requirement for customer service aligns with the widespread use of AI in call centers nowadays. On the other hand, AI-complemented occupations do not show any significant change in individual skill requirements.

To gain further insight into the effects of AI on occupational skill requirements, I aggregate all individual skills into a gross measure for skill requirement change. Following the approach of Deming and Noray (2020) and Acemoglu et al. (2022), I define occupational gross skill requirement change as the sum of the absolute share change of individual skills over all skills, and positive and negative skill changes as the sum of the share change of growing skills and the sum of the absolute share change of declining skills respectively. The specific formula is as follows:

$$SkillChange_{oi} = 100 \sum_{s=1}^{S} \{Abs[(\frac{Skill_{oi}^{s}}{JobAds_{oi}})_{2019} - (\frac{Skill_{oi}^{s}}{JobAds_{oi}})_{2015}]\} \tag{8}$$

$$PositiveSkillChange_{oi} = 100 \sum_{s=1}^{S} \{max[(\frac{Skill_{oi}^{s}}{JobAds_{oi}})_{2019} - (\frac{Skill_{oi}^{s}}{JobAds_{oi}})_{2015}, 0]\} \tag{9}$$

$$NegativeSkillChange_{oi} = 100 \sum_{s=1}^{S} \{-min[(\frac{Skill_{oi}^{s}}{JobAds_{oi}})_{2019} - (\frac{Skill_{oi}^{s}}{JobAds_{oi}})_{2015}, 0]\} \tag{10}$$

Table 8 displays the effects of AI on gross skill requirement change. Although exposed occupations do not experience any significant gross skill change, AIOE is positively related to positive skill change and significantly negatively related to negative skill change, indicating that exposed occupations are more likely to require both growing skills and declining skills. Their requiring more declining skills is because they require more writing, management, and finance skills, which are becoming obsolete for average occupations. In comparison, AI-complemented occupations experience greater overall skill requirement change. More specifically, they are more likely to require growing skills while being less likely to require declining skills. Overall, both AI-exposed and AI-complemented jobs undergo more substantial transformations in terms of required skills when AI takes off, despite having different development directions.

7. Conclusion

Complementarity matters for the impacts of AI on occupations. However, prior theoretical and empirical work falls short in capturing occupational complementarity with AI. I assume that occupations that work with AI-exposed coworkers are more likely to be augmented by AI technology. Using Felten et al.'s occupational AI exposure measure and coworker data derived from Chinese online job postings in 2014 and 2015, I construct an occupational exposure to AI complementarity measure by averaging the AI exposure index of coworkers. Although both exposure measures show positive correlation, they have distinct implications on occupational outcomes. Being exposed to AI leads to significantly lower growth in hiring, signifying stronger displacement effects against positive productivity and direct complementary effects. However, occupations complemented by AI experience faster growth in wage and hiring, consistent with my theoretical prediction that, given the same level of AI automation, occupations more complemented by AI should be in higher demand post-AI shocks.

Delving into the mechanisms through which AI influences occupations, heterogeneity analysis based on occupational education and experience requirements, and local labor market concentration sheds light on the role of occupational characteristics and firms' incentives and capabilities to adopt AI in the production process. Lower-skilled jobs appear less susceptible to AI impacts, with less-educated jobs even benefiting from AI, suggesting that AI enhances the productivity of lower-skilled roles more than their higher-skilled counterparts. For the latter group, displacement effects dominate, as there might not be enough room for expansion. Moreover, firms may have stronger incentives to replace higher-skilled occupations when exposed, given the cost-saving benefits and the lack of protection conferred by the need for training. The ability of firms to implement AI and displace workers also plays a pivotal role. Greater monopsony power among firms leads to more displacement of exposed occupations and fewer hires in other occupations to work with them. Additionally, AI induces changes in other occupational dimensions, which may intertwine with wage and hiring changes. Exploring the specific skills demanded in job advertisements reveals that exposed occupations are more likely to require writing, management, finance, and specialized software skills, while

less likely to demand customer service skills. While the individual skills sought by AI-complemented occupations are not explicitly identified, they undergo more substantial gross skill changes. This underscores the endogeneity of occupational tasks to AI and emphasizes the importance of using task structure before AI shocks to estimate occupational exposure accurately. Furthermore, these skill changes may serve as an underlying factor influencing wage and hiring dynamics (Deming and Noray, 2020).

Note that my conceptual framework and empirical interpretation are based on the demand change after AI surge. Given the rapid integration of AI into the labor market around 2017, it is plausible that people may not have adjusted their labor supply quickly enough to drive the observed empirical results. However, for future research, understanding the dynamics of labor supply changes is crucial in comprehending the effects of AI on the labor market. Such changes might exacerbate the negative impacts of AI if workers shift from highly exposed jobs to less exposed ones. Conversely, it could alleviate negative effects if AI motivates exposed individuals to acquire new skills and deliver fresh value to firms. Importantly, AI-complemented jobs are likely to experience increases in labor supply as well.

The exposure measure I employ is forward-looking and not influenced by the actual AI progress. However, it is important to note that the estimated effects are confined to the period from 2015 to 2019. The implications of AI on more recent labor markets, even with the same exposure measure, might differ due to the varying development paces of different AI technologies. For instance, while Deep Learning made significant strides around 2017, Large Language Models like ChatGPT are currently experiencing rapid growth. Although a part of the exposure measure captures the differential exposure to language modeling technology, recent advancements may yield different labor market effects compared to technologies that progressed significantly before 2020.

Analyzing the effects solely of occupational exposure to AI may seem disappointing, as displacement effects from automation tend to dominate any positive productivity or direct complementary effects. However, when considering between-occupation complementarity, AI emerges as a boon for workers collaborating with exposed jobs. Since exposed workers are more likely to collaborate with others in the same category, they may not be as adversely affected as initially anticipated.

Exposed workers need not be more prone to replacement, as firms require them to collaborate with other exposed workers. As emphasized by Agrawal et al. (2023), AI-driven task automation has the potential to broaden employment opportunities for more workers by complementing other non-automated skills. Policymakers should focus on equipping workers with complemented skills and providing assistance in job transitions, rather than inhibiting AI from automating tasks.

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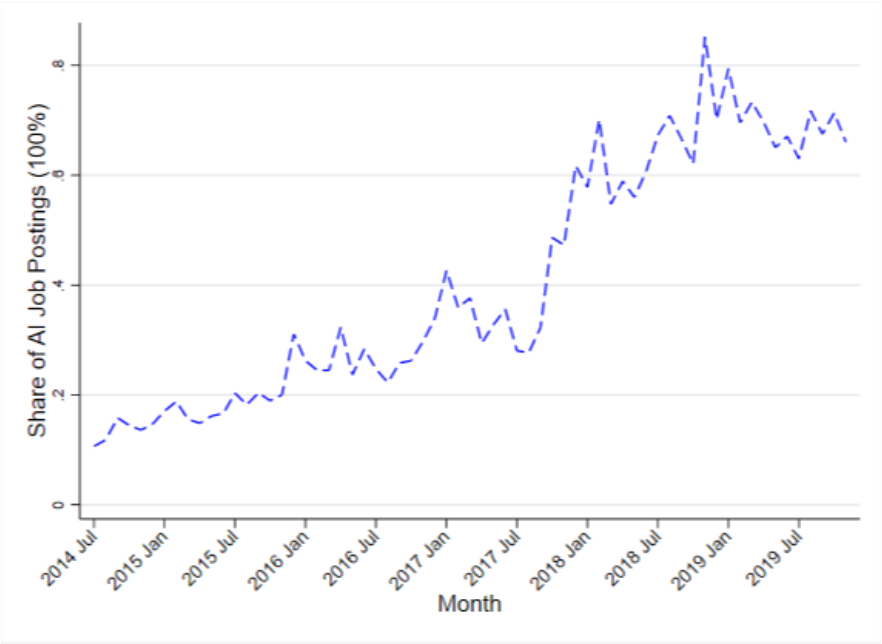
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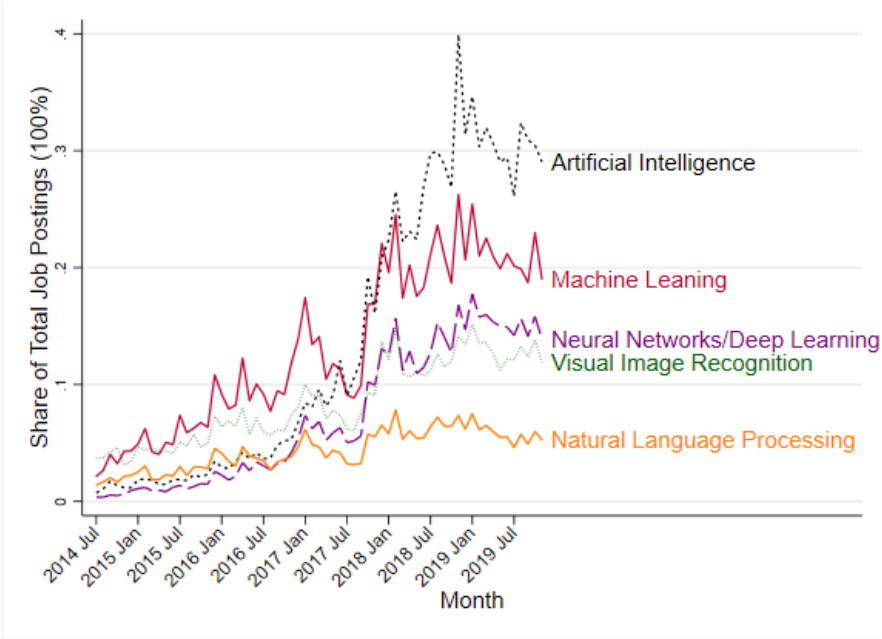
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Figures and Tables

Figure 1: Trend of AI jobs



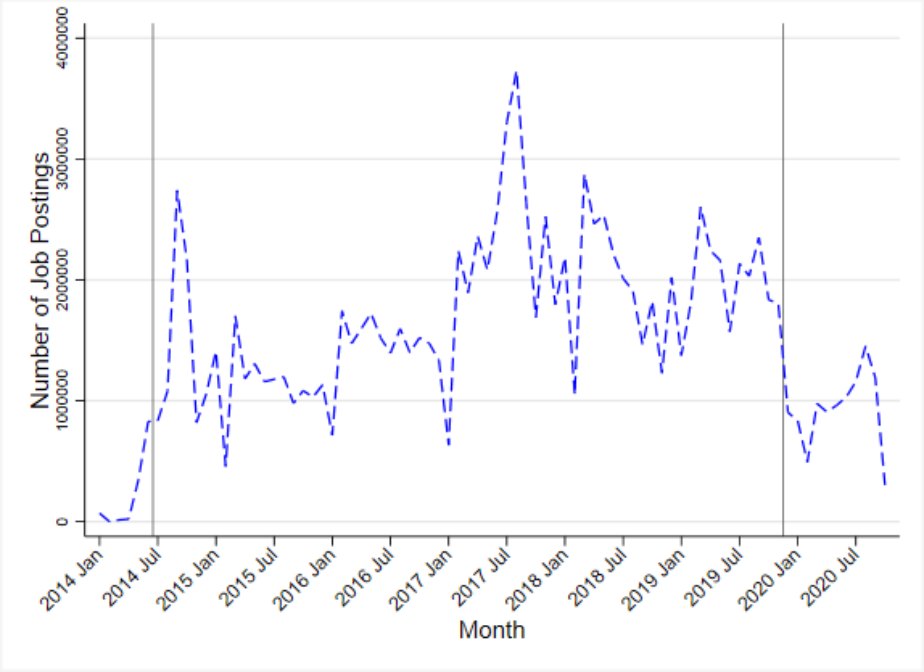
(a) Trend of share of AI job postings



(b) Trend of share of AI job postings by AI technology

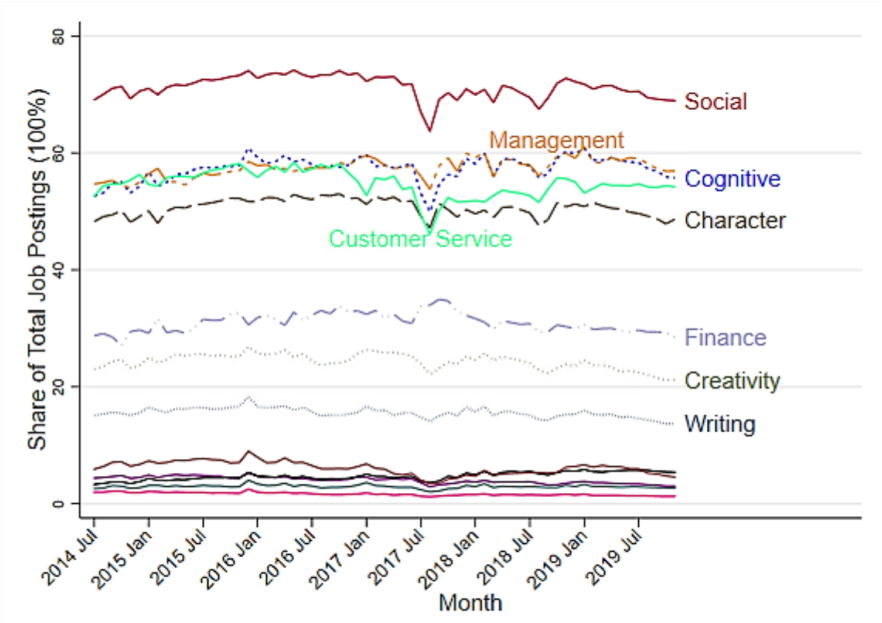
Note: Panel (a) shows the trend in the share of total AI job postings among all job postings from July 2014 to November 2019, and panel (b) illustrates the trend of job postings categorized by different AI technologies.

Figure 2: Trend of job postings

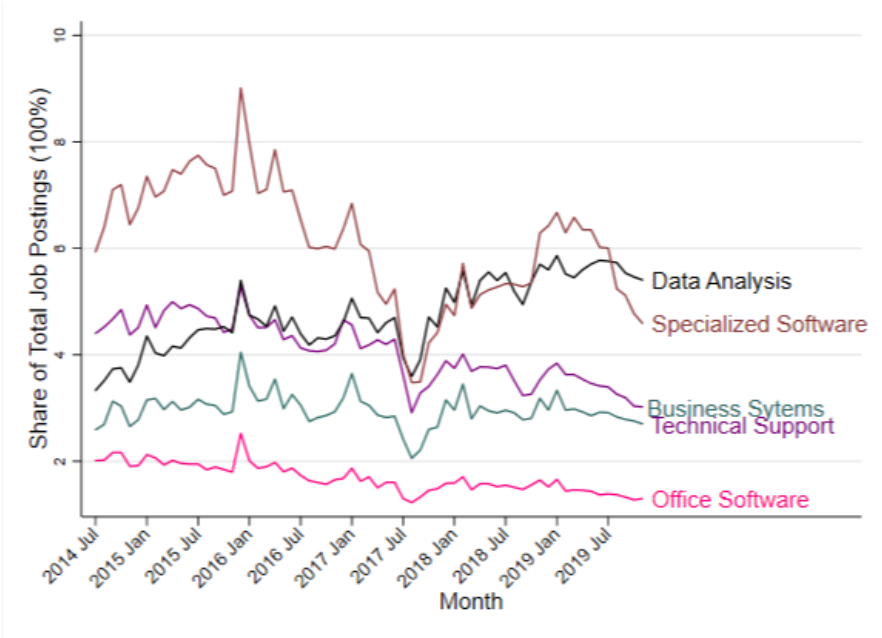


Note: This figure shows the monthly trend in the number of job postings in three main Chinese online recruitment websites. The time window between the two vertical lines will be my focus throughout my study.

Figure 3: Trend of AI jobs



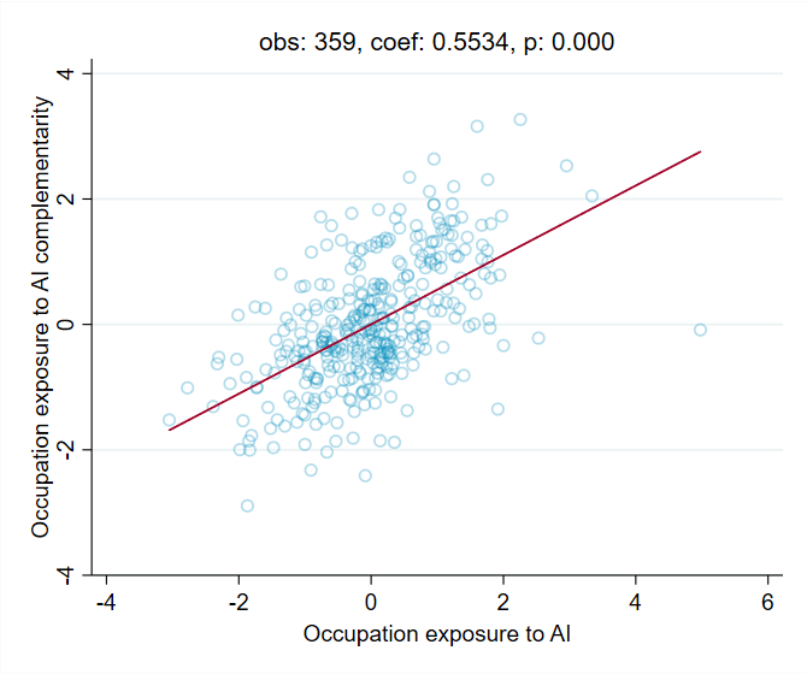
(a) Trend of individual skill requirement, part (a)



(b) Trend of individual skill requirement, part (b)

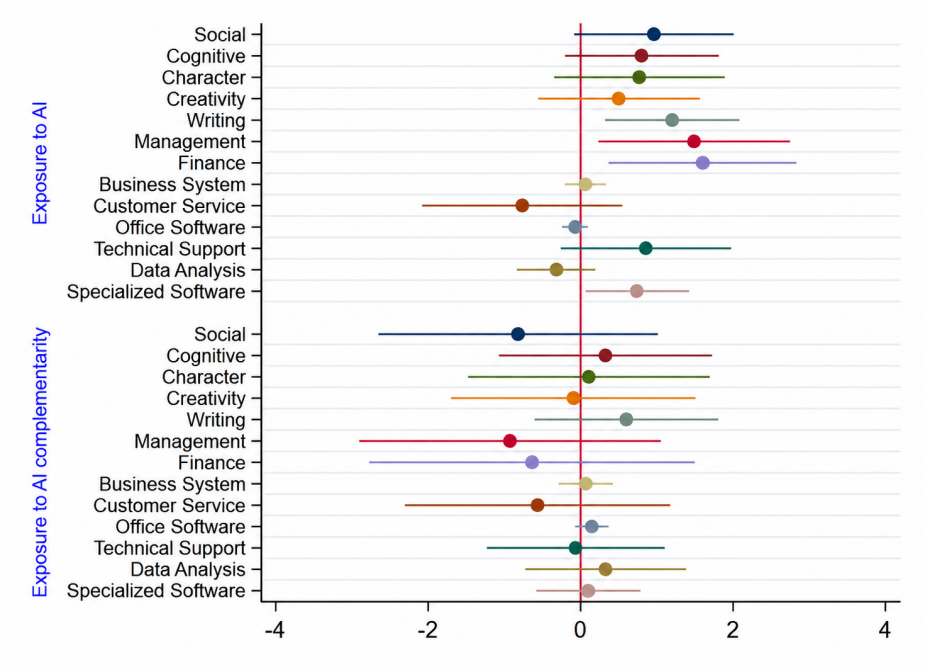
Note: Panel (a) illustrates the trend in the share of job postings mentioning skills with relatively higher demand, while panel (b) displays the trend for the remaining skills, which are positioned at the lower end of the demand spectrum in panel (a).

Figure 4: Occupational metrics



Note: This figure shows the relationship between occupational exposure to AI measure and occupational exposure to AI complementarity measure.

Figure 5: The effects of AI on individual skill requirement



Note: This figure displays the coefficients of both exposure measures in equation (10) when the explanatory variables are the changes of individual skill requirements.

Table 1: Summary statistics for 2015 data

	(1) Obs.	(2) Mean	(3) S.D.	(4) National Survey
Occupational shares, 2015 (in %)				
Management Occupations	13,819,669	20.62		4.79
Business and Financial Operations Occupations	13,819,669	12.76		5.23
Computer and Mathematical Occupations	13,819,669	7.58		0.12
Architecture and Engineering Occupations	13,819,669	5.16		5.70
Life, Physical, and Social Science Occupations	13,819,669	0.78		0.13
Community and Social Service Occupations	13,819,669	0.91		0.77
Legal Occupations	13,819,669	0.13		0.12
Education, Training, and Library Occupations	13,819,669	1.61		1.42
Arts, Design, Entertainment, Sports, and Media Occupations	13,819,669	7.11		0.45
Healthcare Practitioners and Technical Occupations	13,819,669	0.61		2.95
Healthcare Support Occupations	13,819,669	0.03		0.00
Protective Service Occupations	13,819,669	0.20		1.64
Food Preparation and Serving Related Occupations	13,819,669	0.84		10.16
Building and Grounds Cleaning and Maintenance Occupations	13,819,669	0.10		0.00
Personal Care and Service Occupations	13,819,669	0.52		1.43
Sales and Related Occupations	13,819,669	18.01		34.51
Office and Administrative Support Occupations	13,819,669	15.48		8.09
Farming, Fishing, and Forestry Occupations	13,819,669	0.05		3.11
Construction and Extraction Occupations	13,819,669	1.17		1.12
Installation, Maintenance, and Repair Occupations	13,819,669	0.81		1.52
Production Occupations	13,819,669	3.63		6.22
Transportation and Material Moving Occupations	13,819,669	1.88		10.51
Share of job postings, 2015 (in %)				
High school or less	13,819,231	10.14		86.6
Associate degree	13,819,231	38.70		7.35
Bachelor degree	13,819,231	19.16		5.57
Master and PhD	13,819,231	0.46		0.53
Wage (in 2015 USD)	5,087,885	12,340.72	10,136.31	
Experience	11,163,664	1.39	1.75	
Job postings per firm	13,819,669	378.69	2,203.12	
Occupations per firm	13,819,669	22.37	26.11	

Notes: This table reports summary statistics on occupations, education, wage, experience, and firm hiring in 2015. Column 1 shows the number of observations. Column 2 and 3 report the average and standard deviation of the variables, while column 4 shows the averages in the 2015 China's 1% Population Sample Survey.

Table 2: Top and bottom occupations by occupational exposure measures

	AIOE	Score	Coworker Index	Score
Top 5	Airline Pilots, Copilots, and Flight Engineers	4.67	Anesthesiologists	3.27
	Physicists	3.58	Pediatricians, General	2.64
	Air Traffic Controllers	3.33	Dentists, General	2.53
	Commercial Pilots	3.22	Medical and Clinical Laboratory Technologists	2.35
	Surgeons	3.18	Physicians and Surgeon	2.31
Bottom 5	Models	-3.12	Dishwashers	-2.89
	Graders and Sorters, Agricultural Products	-2.86	First-Line Supervisors of Food Preparation and Serving Workers	-2.41
	Locker Room, Coatroom, and Dressing Room Attendants	-2.82	Baggage Porters and Bellhops	-2.32
	Telemarketers	-2.58	Cooks, Institution and Cafeteria	-2.04
	Cleaners of Vehicles and Equipment	-2.54	Food Preparation Workers	-2.00

Notes: This table lists top and bottom 5 occupations by occupational AI exposure measures.

Table 3: Pre-trend test

	Employment Growth				ΔShare of Some College			
	2010-2015		2000-2010		2010-2015		2000-2010	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure to AI	0.170	0.168	-0.005	-0.004	-0.008	-0.007	-0.017	-0.018
	(0.115)	(0.115)	(0.042)	(0.043)	(0.014)	(0.015)	(0.015)	(0.015)
Exposure to AI complementarity		-0.017		0.015		0.009		-0.007
		(0.020)		(0.051)		(0.005)		(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3-digit SOC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,777	7,777	6,011	6,011	8,231	8,231	6,292	6,292
No. of prefectures	319	319	310	310	318	318	312	312
No. of SOC	88	88	84	84	88	88	85	85

Notes: Dependent variables are occupation-prefecture-level employment growth and change of the share of workers with some college education from 2010 to 2015 and 2000 to 2010. The independent variables of interest include occupational exposure to AI and AI complementarity. Controls include occupation-prefecture-level education and experience requirements and occupational degree of automation. Regressions are weighted by occupation-prefecture-level job postings in 2015. Standard errors, clustered two-way at occupation and prefecture level, are in parentheses. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Table 4: The effects of AI on share of AI jobs

	Share of AI Job Postings				Share of AI Job Openings			
	Full Sample		Change>0		Full Sample		Change>0	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure to AI	0.027	0.024	0.048	0.046	0.012	0.009	0.030	0.028
	(0.066)	(0.066)	(0.080)	(0.080)	(0.073)	(0.073)	(0.093)	(0.094)
Exposure to AI		-0.158**		-0.248*		-0.190**		-0.287*
complementarity		(0.079)		(0.146)		(0.085)		(0.170)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3-digit SOC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53,694	53,694	6,186	6,186	53,608	53,608	6,098	6,098
No. of prefectures	340	340	289	289	340	340	288	288
No. of SOC	338	338	261	261	338	338	266	266

Notes: Dependent variables are changes of share of AI job postings and AI job openings from 2015 to 2019. The independent variables of interest include occupational exposure to AI and AI complementarity. Controls include occupation-prefecture-level education and experience requirements and occupational degree of automation. Regressions are weighted by occupation-prefecture-level job postings in 2015. Standard errors, clustered two-way at occupation and prefecture level, are in parentheses. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Table 5: The effects of AI on growth of wage and hiring

	Wage Growth		Hiring Growth	
	(1)	(2)	(3)	(4)
Exposure to AI	0.022	0.023*	-0.212*	-0.205*
	(0.014)	(0.013)	(0.120)	(0.116)
Exposure to AI complementarity		0.027		0.342**
		(0.021)		(0.147)
Controls	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes
3-digit SOC FE	Yes	Yes	Yes	Yes
Observations	52,531	52,531	52,092	52,092
No. of prefectures	340	340	339	339
No. of SOC	338	338	337	337

Notes: Dependent variables are occupation-prefecture-level growth in wages and hiring from 2015 to 2019. The independent variables of interest include occupational exposure to AI and AI complementarity. Controls include occupation-prefecture-level education and experience requirements and occupational degree of automation. Regressions are weighted by occupation-prefecture-level job postings in 2015. Standard errors, clustered two-way at occupation and prefecture level, are in parentheses. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Table 6: Robustness checks for AI impacts on occupational wage and hiring

	No 3-d SOC FE (1)	6-d SOC only (2)	No computer SOC (3)	Pretrend controlled (4)	No weights (5)	AIOI (6)	Scaled AIOE (7)	Coworker weighted (8)	Top 35 coworkers (9)	Same occ. coworkers (10)
					A. Wage					
Exposure to AI	0.024*	0.023*	0.023*	0.010	0.013	0.023*	0.004	0.022*	0.023*	0.019
	(0.014)	(0.013)	(0.014)	(0.015)	(0.014)	(0.014)	(0.018)	(0.013)	(0.014)	(0.014)
Exposure to AI	−0.001	0.030	0.022	0.008	−0.002	0.022	0.043*	0.026	0.021	0.026
complementarity	(0.022)	(0.022)	(0.022)	(0.020)	(0.005)	(0.021)	(0.023)	(0.020)	(0.013)	(0.020)
3-digit SOC FE	*No*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	52,531	48,972	50,276	33,648	52,531	52,475	52,204	52,531	52,531	52,531
No. of prefectures	340	340	340	332	340	340	340	340	340	340
No. of SOC	338	311	322	259	338	339	338	338	338	338
					B. Hiring					
Exposure to AI	−0.133	−0.184	−0.199	−0.333***	−0.255**	−0.194	−0.082	−0.212*	−0.207*	−0.234*
	(0.104)	(0.118)	(0.121)	(0.120)	(0.105)	(0.117)	(0.160)	(0.117)	(0.116)	(0.121)
Exposure to AI	0.259	0.364**	0.332**	0.336**	0.067**	0.375**	0.129	0.310**	0.230***	0.189
complementarity	(0.189)	(0.150)	(0.145)	(0.146)	(0.027)	(0.150)	(0.138)	(0.139)	(0.087)	(0.139)
3-digit SOC FE	*No*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	52,093	49,511	49,927	33,015	52,531	52,045	51,954	52,092	52,092	52,092
No. of prefectures	339	339	339	332	340	339	340	339	339	339
No. of SOC	338	311	321	258	338	338	337	337	337	337

Notes: This table presents robustness checks including: not controlling 3-digit SOC fixed effects in col. 1, focusing on 6-digit SOC occupations in col. 2, exclusing computer occupations (2-digit SOC=15) in col. 3, controlling for pre-trend employment growth from 2010 to 2015 in col. 4, not weighting observations in col. 5, using AIOI in col. 6, using scaled AIOE in col. 7, and using three alternative coworker indices in cols. 8-10. The three different alternative coworker indices are calculated respectively by weighting coworkers by job openings and occupational turnover rate, only considering top 35 coworker occupations, and including job advertisements in the same occupation as coworkers. All columns include common controls and prefecture fixed effects. Clustered standard errors at occupation and prefecture level are in parentheses. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Table 7: Heterogeneity analysis for the impacts of AI on wage and hiring

	Education		Experience		HHI	
	Below p50	Above p50	Below p50	Above p50	Below p50	Above p50
	(1)	(2)	(3)	(4)	(5)	(6)
			A. Wage			
Exposure to AI	0.038**	0.015	−0.012	0.049***	0.023*	−0.012
	(0.016)	(0.015)	(0.016)	(0.016)	(0.013)	(0.016)
Exposure to AI	−0.011	0.040	0.014	−0.008	0.031	0.006
complementarity	(0.018)	(0.027)	(0.022)	(0.030)	(0.024)	(0.006)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Prefecture FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
3-digit SOC FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	22,162	30,367	30,036	22,494	30,966	21,560
No. of prefectures	337	340	340	339	335	340
No. of SOC	169	169	169	169	324	336
			B. Hiring			
Exposure to AI	0.315**	−0.377***	−0.194	−0.407**	−0.208*	−0.337***
	(0.122)	(0.133)	(0.151)	(0.191)	(0.116)	(0.121)
Exposure to AI	−0.072	0.620***	0.076	0.640***	0.363**	0.070***
complementarity	(0.108)	(0.180)	(0.176)	(0.179)	(0.166)	(0.026)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Prefecture FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
3-digit SOC FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	22,048	30,044	30,019	22,073	30,359	21,729
No. of prefectures	338	339	339	339	335	339
No. of SOC	169	168	169	168	322	335

Notes: This table shows heterogeneous effects of AI by education, experience, and local labor market concentration. Dependent variables are occupation-prefecture-level growth in wages and hiring from 2015 to 2019. The independent variables of interest include occupational exposure to AI and AI complementarity. Controls include occupation-prefecture-level education and experience requirements and occupational degree of automation. Regressions are weighted by occupation-prefecture-level job postings in 2015. Standard errors, clustered two-way at occupation and prefecture level, are in parentheses. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Table 8: The impacts of AI on gross skill requirement change

	Skill Change		Positive Skill Change		Negative Skill Change	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to AI	-2.782	-2.374	2.470*	2.575*	-5.469***	-5.331***
	(1.853)	(1.958)	(1.484)	(1.502)	(1.934)	(1.954)
Exposure to AI complementarity		12.030**		5.035*		6.636*
		(5.088)		(3.034)		(3.981)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes
3-digit SOC FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	52,396	52,396	53,788	53,788	53,744	53,744
No. of prefectures	340	340	340	340	340	340
No. of SOC	338	338	338	338	338	338

Notes: This table presents the impacts of AI on occupation-prefecture level gross skill change, and categorize the impacts into both positive and negative components of gross skill change. The independent variables of interest include occupational exposure to AI and AI complementarity. Controls include occupation-prefecture-level education and experience requirements and occupational degree of automation. Regressions are weighted by occupation-prefecture-level job postings in 2015. Standard errors, clustered two-way at occupation and prefecture level, are in parentheses. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

A. Details on Textual Analysis

A.1. Text segmentation

As mentioned before, Chinese words in a sentence are not separated by spaces. Li et al. (2019) applies the Python package *jieba* to parse messages posted on a major online investor forum in China. Here, I use the R version of the package, called *jiebaR*[12], to segment job titles into individual words and phrases. The package *jiebaR* identifies words and phrases according to a dictionary, and I use the default dictionary. As Li et al. (2019), I remove 18 stop words in Chinese that are equivalent to the following words: *of, -ing, -ed, and, is/are, about, both/all, yet, or, a/an, we/us, you, they/them.*[13] Symbols are also discarded in the process. Figure A.1 shows the 100 most frequent words in 2014 and 2015. The top 5 words are *sales, manager, specialist, engineer, and assistant* in English. Although most words in Figure A.1 are associated with job functions, there are some words related to wage and benefits.

Figure A.1: Word cloud of the 100 most frequent words



[12]https://github.com/qinwf/jiebaR

[13]Chinese stop words are defined here: https://github.com/fxsjy/jieba/blob/master/extra_dict/stop_words.txt

A.2. Word embeddings

According to Gentzkow et al. (2019), it is crude to summarize documents by counting different words, since it does not take into account similarity between words syntactically or semantically. Instead, it is easier to capture relationships between words when words are mapped into a vector space. The word2vec method is commonly used to represent words by vectors. It transforms each word by a real vector with given dimensions. Words with similar meanings correspond to close vectors. The continuous bag of words model belongs to word2vec methods. The model is based on the idea that words are similar if they are surrounded by similar words in texts. I implement the CBOW model using the R package *word2vec* with type *cbow* developed by Mikolov et al. (2013). Due to the substantial scale of my dataset, I estimate the CBOW model in an annual base. This involves processing all segmented job titles within each year, while excluding words that appear less than 10 times. The goal is to convert individual word or phrase into a 30-dimension vector.

A.3. Match job titles with SOC codes

Job titles can be further depicted as vectors by taking the average of the constituent word vectors. As closely aligned numerical vectors denote semantic similarity, I leverage the cosine similarity metric to quantify the proximity between any two job title vectors. In cases where a posting lacks an assigned SOC code, I conduct a search for its nearest counterpart by computing the cosine similarity among job titles. Subsequently, I match it with the SOC code of the nearest posting. I test the performance of my approach by randomly picking up 10,000 postings with matched SOC codes and predicting their SOC codes using job titles. My predictions are correct at 6-digit SOC level 41.9% of the time, at 5-digit SOC level 45.5% of the time, at 4-digit SOC level 49.9% of the time, and at 2-digit SOC level 61.3% of the time. The accuracy rate is in line with Atalay et al. (2020), which assigns the same 6-digit SOC code 36% of the time and the same 4-digit SOC code 53% of the time.

B. Appendix figures and tables

Table A.1: Comparing the effects of AI on occupational outcomes between this paper and Acemoglu et al. (2022)

	Acemoglu et al. (2022)					
	2010-2018 Growth		2015-2019 Growth			
	Wage (1)	Employment (2)	Wage (3)	Hiring (4)	Wage (5)	Hiring (6)
Exposure to AI	0.036	-0.346	0.009	-0.140*	0.040**	-0.225
	(0.091)	(0.507)	(0.015)	(0.082)	(0.017)	(0.140)
Exposure to AI complementarity					0.037	0.342*
					(0.028)	(0.177)
Controls	No	No	No	No	Yes	Yes
3-digit SOC FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	296	312	329	329	284	286

Notes: The table compares the effects of AI on occupational outcomes between the US and China for the same set of occupations. The independent variables of interest include occupational exposure to AI and AI complementarity. In column 1 and 2, outcomes include wage and employment growth from 2010 to 2018 in the US, derived from Acemoglu et al. (2022), while in columns 3-6, outcomes include wage and hiring growth from 2015 to 2019 constructed from China online job posting data. All columns control for 3-digit SOC fixed effects and are weighted by initial occupational employment or hiring. Column 5 and 6 additionally control for occupational education and experience requirements and occupational degree of automation. Standard errors, robust against heteroskedasticity, are in parentheses. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.