The Effect of Artificial Intelligence (AI) on Firm Labor Structure

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Abstract

This paper aims to study the effect of AI on firm labor structure. Using a unique panel data of over 1300 publicly listed companies in China from 2007 to 2018, we study the effect of AI on firms' labor composition measured by labor force's education levels. We further compare the effect of AI on firms in the manufacturing sector to the effect on firms in the service sector. Our analysis generates two major findings. First, the use of AI leads to a larger labor demand increase for jobs requiring lower education levels than those requiring higher education levels. Second, the effect is stronger in the service sector than in the manufacturing sector. These findings contradict predictions of the "skill-biased technological change" (SJTB) and U-shaped "job polarization" effects proposed in the prior literature. We propose that "technology-enabled deskilling" effect is driving the effect of AI on labor structure.

1. Introduction

Artificial intelligence (AI) has become a driving force of many technology and business innovations in recent years. AI is believed to have multiple and often conflicting influence on labor forces. On the one hand, it can augment a worker's skills and hence improve the worker's productivity and thus increase labor demand. On the other hand, it can replace certain jobs traditionally carried by human workers through automation, including some white-collar jobs that traditionally require more sophisticated and advanced knowledge and skills, a distinction that separates AI from previous generations of automation technologies (e.g. IT-enabled manufacturing systems) that mostly affect simple and repetitive jobs. However, to the best of our knowledge, research that empirically analyzes the effects of AI on labor force structure at the firm level has been scarce [1][2].

In this study, we investigate the following research questions with an empirical study of a panel data set of over 1300 companies in China from 2007 to 2018: 1) How does AI affect the labor structure of a firm? 2) How does AI's effect on labor structure in the manufacturing industry differ from that in the service industry? As noted in Frank et al [3], "lack of empirically informed models of key microlevel processes (e.g., skill substitution and human-machine complementarity) and insufficient understanding of how cognitive technologies interact with broader economic dynamics and institutional mechanisms" are among "the barriers that inhibit scientists from measuring the effects of AI and automation on the future of work." By exploring the questions above, this study adds valuable understanding about the "microlevel processes" and the "institutional mechanisms" discussed herein.

2. Literature Review

Following the literature [4], we define AI as "intelligent (machine) agents, which are machines, software or algorithms that act intelligently by recognizing and responding to their environment." This definition highlights an important characteristic of AI – its ability to recognize and respond to its environment. This ability allows AI to provide customized or individualized responses, while earlier generations of automation technologies are more known for automation of routinized responses and processes. The distinction of the two different automation technologies has great implications for their impact on labor demands.

Several theories and models had been proposed to explain the impact of automation technologies on labor demand, with the following two theories arguably discussed the most: the skill-biased technological change (SBTC) and the task-based framework.

2.1. The Skill-biased Technological Change

The Skill-biased Technological Change (SBTC) was developed based on the finding of a strong correlation between the adoption of automation technologies and the increased use of better educated (e.g. college-educated) labor since the late 1970s [5][6][7]. According to this theory, labor forces can be divided into two groups based on their skills and how automation technologies enhance the capability or efficiency of human labor. One important hypothesis is

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that technology change is "skill-biased" [8]. That is, the complementary effect technology advancement is stronger for jobs requiring higher skills. Thus, the gain in productivity of high-skilled and better-educated workers due to technology advancement will be larger than that of the low-skilled and less educated workers. As a result, technological advancements drive employers to hire more high-skilled and better-educated workers and fewer low-skilled and less-educated workers [9]. This period witnessed a demand surge for high-skilled IT workers and a supply shortage of such workers due to the burst of newly created IT related job positions [8].

2.2. Task-based Framework (Job Polarization)

However, later studies found evidence of a U-shaped job polarization effect in the employment trends from the 1980s to 1990s in the U.S, the United Kingdom, and Europe [10][11][12]. The term "job polarization" refers to the finding of growth in employment in both the highest-skilled and paid (professional and managerial) and lowest-skilled (personal services) and paid occupations, with declining employment in the middle of the distribution (manufacturing and routine office jobs typically).

" Skill-biased" framework could not be used to explain this phenomenon effectively. Thus, some researchers extended the framework of "skill-biased" theory and proposed a task-based framework for explanation [13][14]. This stream of research suggests that IT and other automation technologies is not suitable to take on non-routine cognitive tasks that requires context-specific analysis, in-person communications or creativity. The workers that are the most suitable to take on these jobs are typically those with higher education and analytical skills. Meanwhile, IT and other automation technologies are also not suitable to take on the non-routine manual tasks, such as cleaning and personal health care. Meanwhile, the strong positive impact on overall productivity of IT and other automation technologies led to an explosive growth of businesses, which in turn lead to more demand for labors for non-routine cognitive tasks and non-routine manual tasks, thus the U-shape polarization effect.

3. Hypothesis Development

3.1 AI and Labor Structure

With the observation of overall job increases in the past two decades, and the advances of new automation technologies such as AI and robotics, some researchers have started to question whether job polarization, that has been found widely exist from the 1980s to 1990s in the developed countries, will persist [15][16][17]. For the period 2000-2007, Autor [18] and Acemoglu and Autor [19] show that the share of low-skilled jobs increased rapidly while the shares of high-skilled or middle-skilled jobs did not. This is in contrary to the predictions of both the SBTC theory and the "Job Polarization" theory.

In this study, we argue that the effect of AI on labor structure can be explained by neither the SBTC theory nor the "Job Polarization" theory. Rather, AI leads to *technology-enabled deskilling*, which benefits disproportionally the low-skilled labor force. Technology-enabled deskilling was first noted in the early days of the industrial revolution. Reviewing the history of industrialization makes it clear that technology advances released a strong demand for low-skilled workers. In the textile industry, low-skilled sewing machine operators took the jobs of the high-skilled loom workers [20]. In the shipping industry, because of the adoption of the steam engines, middle-skilled professional sailors were replaced by the low-skilled engine operators [21]. In the manufacturing industry, with the prevalence of assembly lines, low-skilled assembly line workers replaced the craftsmen who possess more comprehensive set of skills [22]. Technology-enabled deskilling argues that, by taking over the part of a job that requires more skills and education, automation technologies can lower the skill thresholds of workforce for the job, since the rest of the job can now be completed by workers with less skills and education.

The surge of high demand for low-skill jobs has emerged again in the era of AI, as it did in the era of industrialization. For example, it used to be that a taxi driver had to master a complex set of knowledge about the streets and locations of a city in order to perform well in his job. Today, map and navigation applications have made it a job essentially that could be handled by anyone who knows how to drive. As a result, the high skill requirement of the job has been reduced to a low skill level. We therefore propose:

H1: AI has a stronger positive impact on the demand for low-skill labors than the demand for high-skilled labors.

3.2. Manufacturing versus Service Industries

Acemoglu and Restrepo [4] argues that AI is an "intelligent replacement" technology that can operate by recognizing and responding to its environment automatically. This feature makes AI capable of dealing with non-routine jobs. Non-routine jobs are particularly prevalent in the service industry, as all services require interactions between a service provider and a customer and the ability to responding to a customer's individual needs is critical. As AI enables such individualized response, it reduces the skill requirement for service workers. Such reduction in skill requirement could lead to a significant increase in labor supply due to the high elasticity of labor supply at the lower end [30]. Bryjolfsson et al. [31] conducted a detailed analysis on "suitability for machine learning" (SML) of 18,156 tasks, and 964 occupations in the O*NET database. Four out of the top five high SML occupations are in the service industries. We thus expect the phenomenon of "technology-enabled-deskilling" associated with AI to affect service industries more than manufacturing industries.

H2: AI has a stronger positive impact on the demand for low-skill labors in service sector than in the manufacturing sector.

4. Data and Analysis

4.1. Data and Measurement

Our empirical analysis uses a panel data set of 1387 publicly listed firms in China from 2007 to 2018, a total of 12 years. Our original sample has all the 3597 companies publicly traded in the Chinese Share-A stock market and it has 24,265 observations for the time span. We then delete a firm if it meets one of the followings: 1) firms whose stock trading was halted for more than half of total trading days in a year; 2) firms with abnormal variations (more than 5 times of standard deviation); or 3) firms with missing data. The final sample we use for the study has 1387 companies and 4563 observations. The data set is assembled from several data sources.

Labor Structure: The impact of AI on labor demand varies by the required skill levels [16][19]. As education required for a job is highly related to the required information processing and analysis skills for the workers, we focus on the impact of automation technology on the education structure of the labor force. We obtain the educational levels of employees of each firm. We further classify them into three categories: Category 1 are employees with highest education at the PhD level. Category 2 are those with highest education at the bachelor's or master's level. Category 3 are those with highest education below the bachelor's level. We use the log count value of the three types of employees to capture the labor structure of the firm. The data comes from the RESSET database.

IT Deployment: For IT deployment, we use a company's annual IT expenditure/investment to measure its deployment of IT, including investment and expenses in electronic devices, computers and their accessories. This measure is consistent with prior IS literatures that investigate the effect of IT on labor demand using IT investment or expenditure to measure IT inputs [23][24]. The data also comes from the RESSET database.

AI Deployment: For AI deployment, we use the proxy AI ratio identified using TALWEM from each firm's annual report as described below. Since AI application is still at its early stage, the type of data similar to what we use to measure IT deployment is not available for the firms in our sample. As a result, the AI deployment proxy derived from the firm's annual report is the only feasible option here. Our assumption is that the more AI related terms appear in a firm's annual report, the more AI is deployed by the firm [25]. For identification, we use a dictionary to count numbers of AI terms in the firms' annual reports. Unlike the previous practice of subjective choice of terms used in the dictionary, we use a machine learning method (Word Embedding) to create our AI dictionary. Word Embedding uses neural network to develop models used for text search and identification automatically and thus is considered as more objective and accurate [26][27]. In particular, we use a Chinese Word Embedding model developed by Tencent AI Lab. Tencent AI Lab Word Embedding Model (TALWEM) includes over 8 million Chinese words and idioms with 200 dimensions. The training data covers contents available on the Internet, news, novels and other text sources as well words and idioms used by Wikipedia and Baidu Baike. Song et al. [28] provides the details about the algorithm of the TALWEM. We use "artificial intelligence" in Chinese as the seed word for the TALWEM model to find all the words that have a correlation with the word "artificial intelligence" above 0.75. A total of 45 such words[1] were identified according to the model. We then calculate the AI deployment ratio using equation (1) below:

$$AIDptRatio_{i,t} = \frac{The\ number\ of\ AI\ related\ terms\ in\ annual\ report_{i,t}}{The\ number\ of\ total\ words\ in\ annual\ report_{i,t}} \times 1000 - Industry\_year\_average_{AI,t} \quad (1)$$

We also use TALWEM to find the ratio of IT terms in the firms' annual reports and use it as a control variable in the model.

$$ITDptRatio_{i,t} = \frac{The\ number\ of\ IT\ related\ terms\ in\ annual\ report_{i,t}}{The\ number\ of\ total\ words\ in\ annual\ report_{i,t}} \times 1000 - Industry\_year\_average_{IT,t} \quad (2)$$

We start with the seed word "information system" in Chinese, using TALWEM we found 40 words[2] having a correlation with the word "information system"

[1] See Appendix Table 1.

[2] See Appendix Table 2.

above 0.75. We use these dictionaries to search the annual reports of the companies to calculate the proxies for IT deployment and AI deployment.

Control Variables: To control for local labor supply with complementary skills (Tambe's [24]), we include the number of local skilled workers measured by the annual number of college graduates in the province as a control variable in our empirical model. Other control variables including firm size, age, financial data including financial leverage and capital expenditure, and annual stock return for their potential influence on labor force structure of the firms. The number of annual undergraduate graduates comes from the National Bureau of Statistics of China, the financial data comes from the RESSET database and other data comes from the WIND database.

Table 1 below show the summary statistics of the variables used in our empirical model. (For variable definitions see Appendix Table 3) .

Table 1. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Labor Structure					
ln(PhD)	4,195	0.40	0.97	0.00	6.46
ln(BMDegrs)	4,195	5.43	2.11	0.00	9.91
ln(Others)	4,195	7.18	1.42	0.00	11.22
AI Deployment & IT Deployment					
AIDptRatio	4,194	0.01	0.25	-0.63	2.29
ln(ITUse)	4,195	17.02	1.55	10.30	22.07
Control Variables					
ITDptRatio	4,194	0.00	0.07	-0.22	0.62
ln(BAGrads)	4,195	2.58	0.60	-1.51	3.27
ln(Assets)	4,195	21.95	1.32	17.67	28.29
ln(Age)	4,195	8.70	0.34	7.11	9.93
FinLev	4,195	2.42	2.41	1.01	44.85
ln(Capex)	4,195	18.34	1.75	7.50	23.72
Returns	4,195	0.09	0.51	-0.95	3.47

4.2. Empirical Strategy

We match the firms in our sample using Propensity Score Matching (PSM). Using whether the company uses AI, company's total assets and industry as the matching criteria and its total number of employees as the dependent variable, with 1:4 ratio, we match the firms in the sample. We are able to match 1353 firms in our sample.

To estimate the effects of AI use and IT use on firm labor structure, we run a panel data regression model with time and firm fixed effects below:

$$Labor\ Structure_{i,t(t+1)} = \alpha + \beta_1 AIDptRatio_{i,t} + +\beta_2 ln(ITDpt)_{i,t} + \beta_3 ITDptRatio_{i,t} + \xi_{Firm} + \eta_{Year} + \sum_j \gamma_j Control_{i,t} + \varepsilon_{i,t} \quad (3)$$

To assess the differential effects of AI and IT use on firms in the manufacturing industries versus those in the service industries, we divide the sample into subsamples based on the firms' industry sectors, i.e. we divide all firms into the first, second and third sectors (agriculture, manufacturing and service sectors). As less than 2% of all public firms are in the agriculture sector, we remove them from the analysis. We run individual fixed effect panel data analyses of the subsamples based on equation (3) below.

$$Labor\ Structure_{i,t(t+1)} = \alpha + \beta_1 AIDptRatio_{i,t} \times IndMfg_{i,t} + \beta_2 AIDptRatio_{i,t} \times IndSvc_{i,t} + \beta_3 \ln(ITDpt)_{i,t} \times IndMfg_{i,t} + \beta_4 \ln(ITDpt)_{i,t} \times IndSvc_{i,t} + \beta_5 IndMfg_{i,t} + \beta_6 IndSvc_{i,t} + \beta_7 ITDptRatio_{i,t} + \xi_{Firm} + \eta_{Year} + \sum_j \gamma_j Control_{i,t} + \varepsilon_{i,t} \quad (4)$$

5. Results

Table 2 shows the correlations among the variables. Note that correlation between AIDptRatio and ln(ITDpt) is relatively insignificant at only 0.05.

Table 3 shows the results of regression analysis based on equation (2). Column 1, 3 and 5 indicate the impact of AI and IT deployment on the count of employees of different education levels at the firm at period T. Column 2, 4, and 6 show the results of the same analysis for period T+1.

We first examine the impact of IT deployment. From Column 1,3, and 5, IT deployment is shown to have significant positive effects on the labor demands of employees across different education levels including those with highest education below the bachelor's, at bachelor's and master's, and at Ph.D.'s. The finding is consistent with the finding in Dixon, Hong and Wu [29] - the use of robots results in an overall increase of employment using a novel data of Canadian firms. It is also consistent with Autor [15][17] which finds overall growth of jobs in almost every sector of our economy following major technology innovations after a period of time.

We next focus on the impact of AI deployment on labor structure. The results in Table 3 show that AI deployment has a significant positive effect on the firm's labor demand for employees with highest education level below the bachelor's, but a negative, albeit insignificant, effect for employees with highest education level above the bachelor's.

To compare the effects of AI deployment on the labor demand for different education levels, we conducted SUR test of the regression coefficients (V) in Column 1, 3, and 5 in Table 3 and the results are shown in Table 4 (Value 1 and Value 2 in Table 4 are the regression coefficients of the corresponding models). The default assumption is Value 1 is equal to value 2. Based on Panel A in Table 4, the regression coefficient value (0.21) of AIDptRatio on low education level labor (below bachelor's) amount is significantly larger than those of AIDptRatio on high education level labor (Ph.D.) amount (-0.143) and middle education level labor (bachelor's or master's) amount (-0.24).

That is, the deployment of AI has a stronger positive impact on the demand for low-skill labors than the demand for high-skilled labors. Our finding is consistent with Hypothesis 1. Based on Panel B in Table 4, IT shows positive effects on labor amount across all education levels in the firms. And its effect on low education level labor demand in the firm seems to be the strongest.

As the required education level for a job represents the complexity and difficulty of the part of the job that requires "brain work," our finding indicates that, with the use of AI and IT, this part ("brain work") are essentially "outsourced" to AI or IT, resulting in an effective separation of the "brain work" and the "physical work." As a result, it lowers the required education level for a worker to perform the job, as the worker now only needs to take care of the "physical work" part of the job. Eventually, this leads to the surge of creations of jobs that only deal with the "physical work" to a large degree and corresponding labor demand for low-education level workers in the firms.

Table 2. Correlation Analysis

	AIDptRatio	*ln(ITDpt)*	*ITDptRatio*	*ln(Assets)*	*ln(BAGrads)*	*ln(Age)*	*FinLev*	*ln(Capex)*	*Returns*
AIDptRatio	1.00								
ln(ITDpt)	0.05	1.00							
ITDptRatio	0.27	0.10	1.00						
ln(Assets)	0.01	0.64	0.00	1.00					
ln(BAGrads)	0.08	0.07	0.03	0.06	1.00				
ln(Age)	-0.01	0.12	-0.01	0.22	0.13	1.00			
FinLev	-0.01	0.18	-0.02	0.46	-0.02	0.14	1.00		
ln(Capex)	0.01	0.55	0.01	0.60	0.08	-0.01	0.14	1.00	
Returns	0.00	-0.02	0.00	-0.05	-0.11	-0.18	0.02	-0.02	1.00

Table 3. The Impacts of AI Use and IT Use on Labor

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(PhD)	*ln(PhD)*	*ln(BMDegrs)*	*ln(BMDegrs)*	*ln(Others)*	*ln(Others)*
	T0	T1	T0	T1	T0	T1
AIDptRatio	-0.143	-0.168	-0.240	-0.242	0.210**	0.182*
	(-1.20)	(-1.34)	(-1.54)	(-1.32)	(2.50)	(1.92)
ln(ITDpt)	0.058**	0.072*	0.145***	0.137***	0.269***	0.238***
	(2.04)	(1.94)	(2.95)	(2.63)	(4.66)	(4.83)
ITDptRatio	-0.015	-0.478	0.126	-0.322	-0.163	-0.175
	(-0.05)	(-1.30)	(0.17)	(-0.42)	(-0.51)	(-0.64)
ln(BAGrads)	0.087	0.004	0.051	0.081	-0.279	-0.393*
	(0.36)	(0.02)	(0.11)	(0.14)	(-1.36)	(-1.68)
ln(Assets)	0.195***	0.188***	0.587***	0.623***	0.356***	0.375***
	(3.54)	(2.83)	(6.06)	(5.60)	(4.73)	(5.29)
ln(Age)	-0.307	-0.350	-1.322*	-1.093	0.569*	0.329
	(-0.86)	(-0.86)	(-1.94)	(-1.31)	(1.84)	(1.06)
FinLev	-0.002	-0.023	-0.021	-0.047	-0.004	-0.016
	(-0.16)	(-1.30)	(-0.80)	(-0.95)	(-0.43)	(-1.08)
ln(Capex)	0.007	0.021	0.041	0.057*	0.045***	0.029**
	(0.52)	(1.20)	(1.34)	(1.89)	(3.03)	(2.03)
Returns	0.052**	0.013	-0.000	0.057	0.022	0.039*
	(2.14)	(0.55)	(-0.01)	(0.87)	(1.10)	(1.96)
Cons	-2.516	-2.198	1.230	-1.763	-10.521***	-7.548***
	(-0.80)	(-0.61)	(0.20)	(-0.25)	(-3.90)	(-2.76)
N	4194	3449	4194	3449	4194	3449
R-sq	0.0703	0.0785	0.1780	0.1884	0.3289	0.2793

* p<0.1 ** p<0.05 *** p<0.01

Table 4. Comparisons of the Effects of AI Deployment and IT Deployment on Labor

	Value1	Value2	Chi2	P value
Panel A: AIDptRatio				
PhD VS BMDegrs	-0.143	-0.240	0.55	0.459
PhD VS Others	-0.143	0.210**	13.88	0.000
BMDegrs VS Others	-0.240	0.210**	10.95	0.001
Panel B: ln(ITUse)				
PhD VS BMDegrs	0.058**	0.145***	4.04	0.044
PhD VS Others	0.058**	0.269***	24.58	0.000
BMDegrs VS Others	0.145***	0.269***	5.42	0.020

Figure 1 visualizes the impact of AI and IT deployment on labor at period T. The horizontal axis shows the different education levels required by the jobs from the lowest to the highest. The vertical axis shows the value of the regression coefficients of AI deployment and IT deployment that indicates the impact of AI or IT deployment on the labor demand at various education levels. The blue curve shows the impact of the IT deployment and the orange curve shows the impact of AI deployment. A solid point means the impact is statically significant from zero ($p<0.1$ or less) and the hollow point means the impact is not statistically significant.

The results and the figure suggest a few important findings. First, IT has a positive effect on labor demand for all education levels. This suggests despite the potential negative replacement effects, IT, as a maturing automation technology, has led to the creations of enough new jobs to overcome it for all education levels. The new jobs are results of higher productivity. Second, the figure indicates that the impact of IT on the demands for workers of different education levels follows the declining pattern: the lower the education level, the stronger the impact. The results for T+1 period are consistent, which suggests such trends are not transient. This can be attributed the replacement of human "brain work" by IT. For the tasks requiring lower education level, which is typically routine tasks that can be programmed, IT replaces human "brain work" more effectively than for tasks requiring higher education level. The latter are typically non-routine jobs that require more complex knowledge and sophisticated cognitive or analytic skills. Consequently, IT lowers the level of education required for human labor to complete the rest of the task more effectively and thus stimulates more demand for such low education labors.

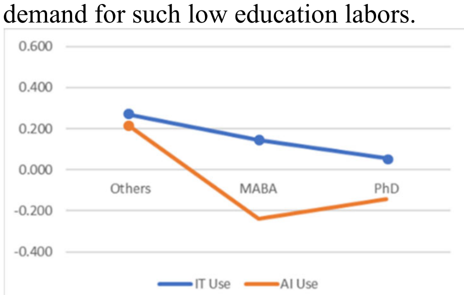


Figure 1. Impact on Labor Structure

Meanwhile, AI shows a significant positive impact only for demand of low education level labor. AI shares much similarity to IT as an automaton technology, which explains their similar positive effects on labor demand for the low-education level through the replacement effect of "brain work". As for jobs requiring middle and high-level educations, AI shows no significant effect. The major differences between IT and AI is AI's ability to perform non-routine cognitive tasks. As such, AI is more capable of replacing human for jobs requiring complex cognitive skills, creativity and decision making than IT. This suggests AI has stronger replacement effect for human labors for jobs requiring higher education levels and consequently a stronger negative effect on demand for labor with higher education level. We also note that AI is not as mature as IT in its applications. IT as a mature automation technology has stimulated significant amount of new products, services and businesses and consequently creations of a wide spectrum of jobs requiring different levels of skills and education. The resulted new jobs are more than enough to compensate the jobs loss due to IT's replacing human. AI, on the other hand, is just at its dawn of applications. In fact, so far the most significant commercial applications of AI in terms of scales have focused on the jobs requiring low education levels (e.g. AI customer service agents). AI's applications for tasks requiring middle or high education are yet to reach the depth, width and scale. Consequently, AI are yet to stimulate sufficient new services, products and businesses that lead to new jobs requiring middle or high-level educations as IT. To summarize, on the one hand, AI is more powerful to replace human for jobs requiring middle and high education than IT. On the other hand, AI is currently less effective to stimulate new jobs requiring middle and high education than IT due to less mature applications. These two mechanisms then lead to the overall less positive effects of AI on the demands for workers with middle or high education. However, as AI matures in its applications, we could expect AI to demonstrate a stronger positive effect in stimulating new jobs requiring middle and high education. At that point, the pattern might change.

We next explore whether and how the impact of AI and IT on labor structure of a firm is related to the sector it belongs to. Table 5 demonstrates the summary statistics of AI deployment, IT deployment and counts of employees of the three different education levels at firms in manufacturing and service sectors. The variable "AIDptRatio Raw" is the ratio of AI terms in the firm's annual report before adjusted with the industry average. Based on "AIDptRatio Raw", AI deployment is lower in the manufacturing sector and higher in the service sector.

Table 5 Summary Statistics of the Manufacturing and Service Sectors

Variable	Obs	Mean	Std. Dev.	Min	Max
Manufacturing Sectors - IndMfg					
AIDptRatio	2,862	0.02	0.26	-0.22	2.29
AIDptRatio Raw	2,862	0.13	0.27	0.00	2.36
ln(ITUse)	2,863	16.97	1.47	11.66	22.05
ln(PhD)	2,863	0.38	0.94	0.00	6.46
ln(BMDegrs)	2,863	5.39	2.03	0.00	9.85
ln(Others)	2,863	7.38	1.24	0.00	11.22
Service Sectors - IndSvc					
AIDptRatio	1,275	0.01	0.23	-0.63	1.67
AIDptRatio Raw	1,275	0.16	0.30	0.00	1.94
ln(ITUse)	1,275	17.16	1.72	10.30	22.07
ln(PhD)	1,275	0.44	1.04	0.00	6.15

ln(BMDegrs)	1,275	5.58	2.25	0.00	9.91
ln(Others)	1,275	6.72	1.67	0.00	11.19

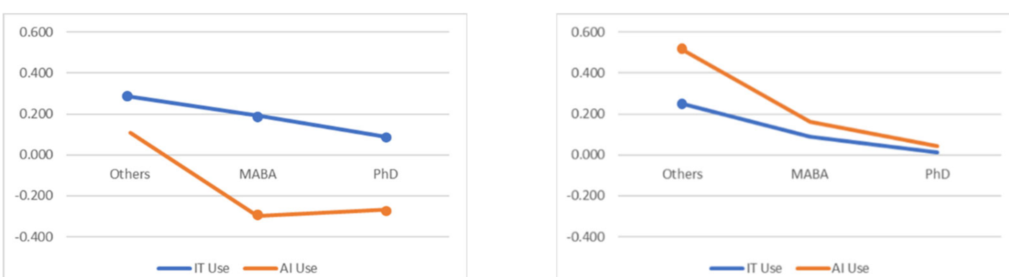
Table 6 shows the results of the regression model in equation (3). Column 1, 3, and 5 indicate the effect of AI deployment and IT deployment on the count of firm employees of different education levels in period T. Column 2, 4 and 6 indicate these effects in period T+1. Figure 2 shows how AI and IT influence labor demand in manufacturing and service sectors.

For the manufacturing sector, IT deployment has a similar pattern of impact on labor demand for different education levels consistent to that of the full sample analysis: (1) positive effects for all types of labor demands and (2) that the less education required, the stronger the positive effects. However, AI deployment has significant negative impact on demand for labors requiring middle and high-level education in manufacturing sector. The finding suggests that AI has a more powerful replacement effect for human labors for jobs requiring higher educations in manufacturing. In sectors like manufacturing where robotics technology is more suitable and has more mature and wider applications, AI has gained more power in replacing human labors. This result also reminds us that, in order for AI to be more effective to automate the "brain work" part of a job task, application and advancement in robotics that automates the "physical work" part is necessary.

Table 6 The Impact of AI and IT in Manufacturing and Service Sectors

	(1) *ln(PhD)* T0	(2) *ln(PhD)* T1	(3) *ln(BMDegrs)* T0	(4) *ln(BMDegrs)* T1	(5) *ln(Others)* T0	(6) *ln(Others)* T1
AIDptRatio × IndMfg	-0.267*	-0.227	-0.300*	-0.308	0.107	0.193*
	(-1.74)	(-1.40)	(-1.81)	(-1.53)	(1.27)	(1.91)
AIDptRatio × IndSvc	0.045	-0.179	0.161	0.297	0.515***	0.353*
	(0.23)	(-0.81)	(0.43)	(0.65)	(2.98)	(1.95)
ln(ITDpt) × IndMfg	0.087**	0.088*	0.194***	0.155**	0.284***	0.225***
	(2.37)	(1.89)	(2.96)	(2.40)	(4.48)	(4.16)
ln(ITDpt) × IndSvc	0.011	0.040	0.089	0.116*	0.252***	0.268***
	(0.30)	(1.05)	(1.39)	(1.67)	(3.66)	(4.44)
IndMfg	-0.805	-2.201	-19.427**	-19.686**	-4.683***	-5.042***
	(-0.49)	(-1.18)	(-2.03)	(-2.36)	(-3.38)	(-3.07)
IndSvc	0.222	-1.676	-17.148*	-18.513**	-4.044***	-5.460***
	(0.14)	(-0.90)	(-1.79)	(-2.22)	(-2.66)	(-3.19)
ITDptRatio	-0.203	-0.705*	0.474	0.046	-0.101	0.062
	(-0.67)	(-1.94)	(0.60)	(0.05)	(-0.30)	(0.23)
ln(BAGrads)	0.084	0.010	-0.044	-0.023	-0.311	-0.427*
	(0.35)	(0.04)	(-0.10)	(-0.04)	(-1.52)	(-1.83)
ln(Assets)	0.202***	0.191***	0.578***	0.621***	0.357***	0.375***
	(3.60)	(2.84)	(5.94)	(5.51)	(4.72)	(5.32)
ln(Age)	-0.361	-0.376	-1.118*	-0.784	0.612**	0.451
	(-1.01)	(-0.91)	(-1.79)	(-1.02)	(1.97)	(1.47)
FinLev	-0.001	-0.024	-0.018	-0.044	-0.003	-0.015
	(-0.08)	(-1.39)	(-0.69)	(-0.89)	(-0.31)	(-1.02)
ln(Capex)	0.007	0.021	0.040	0.055*	0.044***	0.027*
	(0.50)	(1.24)	(1.31)	(1.83)	(2.94)	(1.88)
Returns	0.053**	0.013	0.010	0.070	0.025	0.041**
	(2.20)	(0.58)	(0.17)	(1.07)	(1.23)	(2.07)
Cons	-1.779	-0.041	18.343	15.102	-6.412**	-3.329
	(-0.59)	(-0.01)	(1.58)	(1.37)	(-2.36)	(-1.18)
N	4194	3449	4194	3449	4194	3449
R-sq	0.0752	0.0832	0.1857	0.1966	0.3340	0.2887

* p<0.1 ** p<0.05 *** p<0.01



Manufacturing Sector   Service Sector

Figure 2. Labor Demand Growth Rate in Manufacturing and Service Sectors

In the service sector, both AI deployment and IT deployment have positive effects only for jobs requiring low education while their effects on jobs requiring middle or high-level education are not statistically significant. This finding suggests that, for service sector where non-routine jobs are typically an integral part of the service and the middle and high level jobs often require inter-person communication and cognitive skills (e.g. education and health care) or creativity, IT has a less prominent roles to play despite its mature applications. Also, if we compare the effects of AI or IT in manufacturing and service sectors, AI has a stronger impact in the service sector than in the manufacturing sector while IT has a similar level of impact for both the service and the manufacturing sectors. Our finding is consistent with Hypothesis 2, which notes that AI is especially powerful for non-routine jobs involving personalization and customization, which makes AI especially influential in the service sector than in the manufacturing sectors. where jobs are more likely to involve routine tasks.

6. Summary and Discussion

Since the inception of industrialization, a major concern of the society is whether automation will deprive humans of jobs and reduce the share of human labor in the whole production process of our society. Multiple theories offered competing explanations and predictions on this issue.

Our empirical study reported in this paper lends support to the “technology-enabled deskilling” effect theory – i.e. AI reduces the education level requirement for certain jobs and accordingly it shows a strong positive effect on jobs requires low education levels (below college). As AI is able to replace human for the relatively complex cognitive and analytic tasks, it essentially lowered the job entry requirement. This surprising strong complimentary effect of AI on labor demand for low-skill workers could have far-reaching implications for innovative business models and labor market landscape. Moreover, our study shows this effect is stronger in the service sector than in the manufacturing sector. We attribute this to the fact that in service sector there are more non-routine jobs than in manufacturing sectors. When AI overtakes the part of a non-routine job that requires sophisticated cognitive or analytic skills, it separates the high-skill part of the job to the low-skill part and increase the demand for low-skill workers. It does so more in the service sector than in the manufacturing sector. Finally, the study shows although AI is built on the traditional IT infrastructure, it differs from IT in their effects on labor demand in an organization in notable ways. This is due to their different stages in terms maturity of the technology and their applications and the unprecedented capacity of AI to overtake jobs requesting sophisticates cognitive and analytic skills.

This study has quite some limitations that we hope to explore further in our future research. One of such limitations is our measure of AI deployment, which is the count of AI related terms in the firms’ annual reports. We do not observe the actual application of AI in firms. Recent studies on task-technology fit (TTF) and affordance theory finds that AI is better fit for certain tasks than others. As such, a micro level analysis of the application of AI at the task level will be fruitful in better understanding the underlying mechanism of the effect of AI labor demand. The second limitation of this study is the challenge in establishing causality. While we try to establish (Granger) causality by analyzing response variables in the t+1 period, the relationships identified are ultimately associations rather than causal effects. There may also exist potential confounders that we did not control.

7. References

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8. Appendix

Appendix Table 1. Dictionary of AI terms

AI terms in Chinese	AI terms in English
人工智能	**Artificial Intelligence**
AI	AI
AI+	AI+
AI+医疗	AI+ Medical Care
AI 技术	AI Technology
AI 领域	AI Field
AI 人工智能	Artificial Intelligence
AI 时代	AI Age
AI 芯片	AI Chip
大数据	Big Data
大数据和云计算	Big Data and Cloud Computing
大数据与人工智能	Big Data and Artificial Intelligence
发展人工智能	Developing artificial intelligence
机器人和人工智能	Robot and Artificial Intelligence
机器人技术	Robotics
机器学习	Machine Learning
机器智能	Machine Intelligence
计算机视觉	Computer Vision
人工智能 AI	Artificial Intelligence
人工智能产业	Artificial Intelligence Industry
人工智能的发展	Development of Artificial Intelligence
人工智能的未来	The future of Artificial Intelligence
人工智能和机器学习	Artificial Intelligence and Machine Learning
人工智能化	Artificial Intelligence
人工智能机器	Artificial Intelligence Machine
人工智能机器人	Artificial Intelligence Robot
人工智能技术	Artificial Intelligence Technology
人工智能领域	Artificial Intelligence Field
人工智能深度学习	Artificial Intelligence and Deep Learning
人工智能时代	Artificial Intelligence Age

人工智能算法	Artificial Intelligence Algorithm
人工智能芯片	Artificial Intelligence Chip
人工智能研发	Research and Development of Artificial Intelligence
人工智能应用	Artificial Intelligence Application
认知计算	Cognitive Computation
认知技术	Cognitive Technology
深度学习	Deep Learning
深度学习算法	Deep Learning Algorithm
图像识别	Pattern Recognition
物联网	Internet of Things
新兴科技	Emerging Technology
云计算	Cloud Computing
智能	Intelligence
智能机器	Intelligent Machine
智能技术	Intelligent Technology

Appendix Table 2. Dictionary of IT terms

IT terms in Chinese	IT terms in English
信息系统	**Information System**
服务系统	Service System
管理平台	Management Platform
管理系统	Management System
管理信息系统	Management Information System
平台系统	Platform System
企业信息系统	Enterprise Information System
软件系统	Software System
实现信息	Realization of information
数据共享	Data Sharing
数据互联互通	Interconnection in Data
数据集成	Data Integration
数据系统	Data System
数据信息	Data Information
统一平台	Integrated Platform
网络系统	Network System
网络信息系统	Network Information System
系统平台	System Platform
系统数据	System Data
相关系统	Related System
信息管理	Information Management
信息管理平台	Information Management Platform
信息管理系统	Information Management System
信息互联互通	Interconnection in Information
信息化管理	Informatization Management
信息化管理系统	Informatization Management System
信息化平台	Informatization Platform
信息化系统	Informatization System
信息数据	Information Data
信息网络系统	Information Network System
信息系统建设	Information System Construction
信息系统平台	Information System Platform
业务管理系统	Operation Management System
业务系统	Operation System
业务信息系统	Operating Information System
业务应用系统	Business Application System
应用系统	Application System
云平台	Cloud Platform
综合管理系统	Comprehensive Management System
综合信息系统	Integrated Information System

Appendix Table 3. Description of Key Measures and Data Sources

Measure	Description
Labor Structure	
ln(PhD)	Number of employees with doctor degree and in natural logarithm.
ln(BMDegrs)	Number of employees with bachelor's and master's as the highest degree in natural logarithm.
ln(Others)	Number of employees whose highest education is high school, vacation school or lower in natural logarithm.
AI Deployment & IT Deployment	
AIDptRatio	AI deployment proxy: the ratio of AI related terms in the firm's annual report adjusted with industry average.
AIDptRatio Raw	The ratio of AI terms in the firm's annual report before adjusted with the industry average.
ln(ITDpt)	IT deployment proxy, using the firm's IT related fixed assets, including electronic equipment and computers and auxiliary equipment, in natural logarithm.
Control Variables	
ITDptRatio	IT deployment proxy: the ratio of IT related terms in the firm's annual report adjusted with industry average.
ln(BAGrads)	Number of undergraduate graduates in each province (x 10,000) in natural logarithm.
ln(Assets)	Total assets in natural logarithm.
ln(Age)	The age of listed firms (days) in natural logarithm.
FinLev	Financial Leverage, using equity multiplier as a proxy indicator, calculated by dividing the ending balance of total assets by the ending balance of owner's equity.
ln(Capex)	Capital expenditures: cash paid for the purchase and construction of fixed assets, intangible assets and other long-term assets in a year.
Returns	The annual returns of individual stocks adjusted by market returns.
Sector Structure	
IndMfg	The second sectors: manufacturing sector.
IndSvc	The third sector: service sector.