Does Artificial Intelligence Widen the Labor Income Gap? -- Based on China's Manufacturing Industry

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Abstract: In order to investigate the relationship between AI and labor income gap and deepen its intrinsic influence mechanism, the impact of AI application on labor income gap is empirically examined by constructing a task model of AI and labor income gap, taking Chinese manufacturing industry as the research object. It is found that AI has a significant widening effect on the labor income gap in China's manufacturing industry; the labor income gap in industries with different technology levels, factor intensity and monopoly degree also shows significant heterogeneity. The research in this paper reveals the income distribution effects of AI development and provides empirical evidence to support the promotion of common wealth in China.
Keywords: Artificial Intelligence; Labor Income Gap; Productivity Effect; Job Substitution Effect

1. Introduction

With the emergence of disruptive technologies such as autonomous driving, intelligent translation and ChatGPT, artificial intelligence is gradually becoming a new driving force for China's high-quality economic development in the future. So, will AI technologies affect labor force employment on a large scale? Will it affect the income gap of laborers? These questions have attracted wide attention from all walks of life. Early literature mainly focuses on developed countries such as Europe and the U.S. Using economic data from the U.S., Acemoglu and Restrepo (2017) found that for every percentage point increase in robot density, absolute wages would decrease by 0.25-0.5 percentage points[1]. bessen and Autor (2015) analyzed the employment of workers with different skills in the U.S. labor market by share trends, they found that the use of automated machines leads to a decrease in demand for low-labor jobs and an increase in demand for high-skilled labor jobs, which in turn induces a widening of the labor income gap[2]. However, some studies have argued that AI technology does not necessarily induce a widening labor income gap, and Stevenson (2019) argues that AI technology, like previous technological revolutions, is able to absorb more labor employment by increasing labor productivity and thus expanding the scale of manufacturers' production, and the labor income gap does not widen[3]. Recent literature on AI has also emerged in China, where Linhui Wang (2020) et al. measured the job turnover and productivity effects of AI technology based on a task model using China's provincial-level data from 2001-2016, and showed that AI technology induces a widening labor income gap between high- and low-skilled sectors[4].

Summarizing the above studies, it can be found that there is no unified opinion on the study of AI technology on labor income issues and there is a general lack of empirical evidence at the industry level in developing countries. Therefore, the marginal contributions of this paper to the existing literature are: first, to construct a static task model of AI technology affecting labor income gap, and to analyze the direction of AI technology affecting labor income gap according to the derived findings. Second, to empirically analyze the impact of AI technology on labor income gap by taking Chinese manufacturing industry as the research object and considering the issue of industry heterogeneity.

2. Theories and hypotheses

In this paper, based on Acemoglu and Restrepo (2018) study[5], we assume that there are n industries in a country, and the product of each industry i is obtained by combining intermediate goods produced by a series of jobs j on the interval $N_{in}, N_{in}+1$, and the production function of industry i is set as:

$$Y_i = \left[\int_{N_{in}}^{N_{in}+1} y_i(j)^{\frac{\mu-1}{\mu}} dj \right]^{\frac{\mu}{\mu-1}} \quad /(1)$$

where, $y_i j$ denotes the intermediate goods input of production industry i to job j and μ is the elasticity of substitution between different jobs.

Assume that the intermediate goods of different jobs j can be obtained from the production of AI or labor inputs. The positions N_{in}, I_{im} can be undertaken by AI and the productivity of AI machines among each position is set to a standard value of 1.$I_{im}, I_{in}$and$I_{in}, N_{in}+1$positions are taken up by low-skilled and high-skilled labor, respectively, and their respective labor productivity is A_{il} and A_{ih}, respectively. Eventually, the intermediate goods production function on job j is:

$$y_i(j) = \begin{cases} M_i(j), & \text{if } j \in [N_{in}, I_{im}] \\ A_{il} L_{il}(j), & \text{if } j \in (I_{im}, I_{in}] \\ A_{ih} L_{ih}(j), & \text{if } j \in (I_{in}, N_{in}+1] \end{cases} \quad /(2)$$

where $M_i j$ is the amount of AI machine input in the job, and $L_{il} j$ and $L_{ih}\ j$ are the amount of low-skilled labor input and high-skilled labor input in the job, respectively.

Assuming that the wage rates of low-skilled labor and high-skilled labor in industry i are W_{il} and W_{ih}, respectively, and the respective supply is exogenously given, $W_i = W_{ih} W_{il}$ is the labor income gap in industry i. According to the factor market clearing condition, it is obtained that:

$$\mathrm{d}\ln W_i = \underbrace{\frac{\mu-1}{\mu} \mathrm{d}\ln \frac{A_{ih}}{A_{il}}}_{\text{productivity effect}} + \underbrace{\frac{1}{\mu} \mathrm{d}\ln \left(\frac{N_{in}+1-I_{im}}{I_{in}-I_{im}} \right)}_{\text{job substitution effect}} \quad /(3)$$

Equation shows that the use of AI brings about changes in the structure of skill efficiency and labor jobs, and further affects the income distribution between high-skilled and low-skilled labor, and the direction of the impact of AI on the labor income gap depends on the relative size of the productivity effect and the job turnover effect. Considering that the overall technology level of manufacturing industry in China is low （$\mu>1$） and the variability of sub-sectors is large. As a result, this paper proposes the hypothesis that:

Hypothesis 1: AI technologies are more conducive to increasing the productivity and job demand of high-skilled labor, which in turn widens the labor income gap.

Hypothesis 2: There may be industry heterogeneity in the impact of AI technologies on the labor income gap.

3. Empirical design

3.1 Model setting

Based on the inference of the theoretical model, to test the effect of AI on the labor income gap, the underlying regression model is set as follows:

$$\ln W_{it} = \alpha_0 + \alpha_1 \ln AI_{it} + \alpha_2 X_{it} + \delta + \lambda + \varepsilon \quad (4)$$

where i is the industry, t is the year, W_{it} is the labor income gap, AI_{it} is the industry intelligence level, and X_{it} is a set of control variables. δ is the industry fixed effect term, λ is the year fixed effect term. ε is the random error term.

3.2 Variable selection and data sources

The explanatory variable is labor income gap W, which is characterized by the ratio of the average wage of high-skilled labor to low-skilled labor in this paper ; the core explanatory variable is industry AI level. this paper uses industrial robot installation density to measure manufacturing AI level; the control variables this paper uses environmental regulation intensity Er, trade openness Ope, foreign investment dependence Fc, nationalization Na, and Industry profitability Pr is used as control variables.

Due to the availability of data, this paper uses the panel data of 29 manufacturing industries in China from 2006 to 2016 as the sample for the econometric test. Manufacturing and labor force data are obtained from the China Labor Statistics Yearbook, China Science and Technology Statistics Yearbook, China Industrial Statistics Yearbook, and China Environment Statistics Yearbook. Robotics data were obtained from the International Federation of Robotics (IFR).

4. Empirical Results and Analysis

4.1 Basic regression

Table 1 shows the results of the underlying regression. Among them, column (1) shows the regression results of using industry AI level directly on labor income gap without adding any control variables, and the results show that the effect of industry AI level on labor income gap is significantly positive at the 5% level, which indicates that the use of AI in manufacturing industry will tend to widen the labor income gap. Column (3) shows the regression results with the inclusion of industry-level control variables, and the results similarly show that the use of AI in the manufacturing industry widens the labor income gap, and that for every 1% increase in the use of AI, the labor income gap will widen by 0.021%. Hypothesis 1 is verified. In addition, to further ensure the robustness of the findings, the industry AI level indicator, measured by the density of industrial robot installations, is replaced with the number of industrial robots installed $LnAI\_num$ and the labor income gap is regressed again. Column (2) and column (4) show the regression results of industrial robot installation on labor income gap, respectively. The results show that the effect of industrial robot installation on labor income gap is still significantly positive and the findings are robust.

Table 1 Base regression results

Variables	(1)	(2)	(3)	(4)
	lnW	lnW	lnW	lnW
lnAI	0.020**		0.021***	
	(0.008)		(0.007)	
lnAI_num		0.017**		0.022***
		(0.008)		(0.007)
Er			-2.574	-2.485
			(2.831)	(2.833)
Ope			1.287***	1.400***
			(0.382)	(0.381)
Fc			0.568**	0.511**
			(0.255)	(0.249)
Na			0.300	0.296
			(0.342)	(0.342)
lnPr			-0.072**	-0.076**
			(0.032)	(0.032)
Constant	0.255***	0.255***	0.0865	0.066
	(0.042)	(0.049)	(0.142)	(0.143)
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	129	129	129	129
R^2	0.900	0.875	0.929	0.910

Note:* * *, * *, * indicate significant at the levels of 1%, 5%, and 10%, respectively. The standard error in parentheses is limited to space. This article only reports the core explanatory variables with significant regression coefficients.

4.2 Heterogeneity analysis

In this paper, China's manufacturing industry segments are classified into high technology and low technology industries, capital-intensive and labor-intensive industries, and high degree of monopoly and low degree of monopoly industries. The regression results are shown in Table 3.

Among them, column (1) and column (2) show the regression results for industries with different technology levels. It can be seen that the effect of AI on labor income gap is significantly positive in low-tech industries, while the regression results are not significant in high-tech industries. The reason is that the labor force in low-skilled industries has weaker expertise and environmental adaptability, and the work tasks are mostly repetitive manual labor. The substitution effect caused by AI is able to squeeze out part of the low-skilled labor force from the job market, thus widening the labor income gap in low-skilled industries. Columns (3) and (4) show the regression results for different intensive industries. It can be seen that AI has a significant widening effect on the labor income gap in both capital-intensive and labor-intensive industries, but the effect is more pronounced in labor-intensive industries. Columns (5) and (6) show the regression results for industries with different degrees of monopoly. It can be found that AI has a positive and significant effect on the labor income gap in low monopoly degree industries. This is because the market competition is fierce in low-monopoly industries, and firms are more willing to apply AI in their production processes in order to pursue more profits, so that the productivity effect and job turnover effect of AI can widen their labor income gap.

Table 2 Results of industry heterogeneity analysis

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	lnw	lnw	lnw	lnw	lnw	lnw
lnAI	0.010	0.015**	0.017*	0.023**	-0.021	0.020*
	(0.016)	(0.007)	(0.010)	(0.011)	(0.014)	(0.011)
Er	5.132	-2.467	3.574	-1.031	-3.197	-1.998
	(28.650)	(2.867)	(4.230)	(4.523)	(9.539)	(3.544)
Ope	1.985**	2.468***	2.807	1.482***	-0.723	1.839***
	(0.792)	(0.538)	(1.959)	(0.499)	(1.334)	(0.630)
Fc	-0.009	0.307	-0.249	0.135	0.406	0.222
	(0.584)	(0.282)	(0.450)	(0.314)	(0.576)	(0.291)
Na	1.140	0.280	0.238	-0.203	-0.280	0.944
	(1.245)	(0.347)	(0.555)	(0.752)	(0.623)	(0.749)
lnpr	0.828	-0.097**	-0.092**	0.367	-0.065	-1.341*
	(0.564)	(0.040)	(0.038)	(0.362)	(0.052)	(0.774)
Constant	-2.023*	0.126	0.134	-0.704	0.727	2.677*
	(1.162)	(0.110)	(0.268)	(0.738)	(0.442)	(1.594)
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	47	82	41	87	44	84
R^2	0.967	0.913	0.858	0.933	0.698	0.940

Note:* * *, * *, * indicate significant at the levels of 1%, 5%, and 10%, respectively. The standard error in parentheses is limited to space. This article only reports the core explanatory variables with significant regression coefficients.

5. Conclusions and Recommendations

Based on the findings, the following conclusions are obtained: first, the use of AI in China's manufacturing sector widens the labor income gap, and the findings remain robust after including the density of the U.S. robot stock with a one-period lag of AI levels as an instrumental variable. Second, there is industry heterogeneity in the impact of AI on the labor income gap across technology levels, factor intensities, and monopoly degrees.

This paper has the following policy implications: First, China should increase investment in higher education and improve the factor market system. Based on the productivity effect and job turnover effect of AI on the labor income gap, the government should further promote the universalization of education, and for the technically unemployed due to AI and other automated technologies, the government can set up special funds to provide special subsidies for their unemployed, for example, the Singapore government provides $500 digital skills training for citizens over 25 years old to avoid ordinary employed people from employment difficulties caused by lack of digital skills. Second, the Chinese government should reasonably guide the development of AI and formulate AI policies that match the stage of development. Currently, low-skilled industries, low-monopoly industries and labor-intensive industries are the main employment fronts for low-skilled labor, and these industries are more strongly affected by AI, and if these industries blindly use AI technology, not only will it not promote industrial upgrading and economic development, but also will bring massive unemployment and social instability.

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