Proceedings of the 7th International Conference on Economic Management and Green Development
DOI: 10.54254/2754-1169/37/20231847

An Analysis of the Impact of Industrial Robots on Employment of College Students

Shiheng Chen[1,a,*]

[1]*The University of Warwick, Coventry, United Kingdom, CV4 7AL*
a. chenshiheng_2001@outlook.com
**corresponding author*

Abstract: With the development of artificial intelligence technology and the promotion and application of industrial robots, it has had a profound impact on economic behavior and reform, as well as on the job market. As an important part of the labor market, the impact of AI and industrial robots on the employment situation of college students is also a topic worth studying. This paper investigates the impact that AI and industrial robots will have on the overall employment number as well as the employment number of college students through the data of the employment market in 30 Chinese provinces from 2015 to 2019 with the OLS and fixed effect model. The empirical research results prove that the development of AI technology and the promotion and application of industrial robots will have the impact of the promotion effect on the overall employment number as well as the employment number of college students.

Keywords: artificial intelligence, industrial robots, employment, college students, promotion effect

1. Introduction

Artificial intelligence, abbreviated as AI, is the research and development of human intelligent activity laws and the construction of intelligent simulations of artificial systems that can make the machine capable of some complex work that previously required human intelligence to complete [1]. Industrial robots and big data are very representative of intelligent production elements in AI [2]. China has enacted many policies since 2013 to promote the development of industrial robots in the country, including the Made in China 2025 strategy, and data from the International Federation of Robotics shows that China will ship 16.84 million robots in 2020 with sales reaching 42.25 billion yuan, making it the world's largest robotics market [3]. In recent years, the number of college graduates in China has been increasing, but the employment rate of college students has been decreasing year by year, and the employment situation is not optimistic. With the promotion and application of artificial intelligence technology and industrial robots, whether it will have an impact on the employment market of college students has become a very worthy research problem. This paper uses the employment rate data of 30 provinces in China from 2015 to 2019 and uses OLS and fixed effect models to estimate the model.

DOI: 10.54254/2754-1169/37/20231847

2. Literature Review

The existing research on how the application of AI technology and industrial robots affects the job market mainly focuses on how the application of AI technology and industrial robots will cause changes in the job market, but there is no agreed-upon view. There are two prevailing views: one that the substitution effect is greater than the creation effect, that is, the application of AI technology and industrial robots will significantly increase labor market demand, and the other that the creation effect is greater than the substitution effect, that is, the application of AI technology and industrial robots will significantly reduce labor market demand.

Acemoglu and Restrepo based on data from the U.S. labor market from 1990-2007, found that the use of industrial robots reduces overall employment, where an increase of one robot per 1,000 people would reduce employment by 0.2% [4]. In the research of the relationship between AI and economic development, Furman and Seamans state that the job promotion effect of AI will ultimately lead to an increase in the size of labor force employment [5]. This means that the cost reduction effect and job promotion effect of AI technology will simultaneously lead to the expansion of existing industries and the birth of new industries, thus leading to an expansion of employment demand.

There are two different views on the impact of AI on the employment market of college students. One is the substitution effect, ie., AI has a negative effect on the employment of college students. Therefore, this part of the study believes that AI will replace some of the social labor jobs. For example, Alibaba has replaced traditional human positions through AI in its smart hotels and smart supermarkets [6]. Therefore, the popularization and promotion of AI will increase the difficulty of choosing college students' employment as well as the job selection of college students' employment.

Second, the promotion effect and the forecast analysis and research of the 2014 Washington Pew Research Center on 2025 artificial intelligence, including robotics, on the labor market impact point that, according to the actual situation of human history and industrial revolution development, although artificial intelligence will replace some labor positions to a certain extent, it can also create new employment industries as well as employment positions and therefore promote the employment of college students [7]. PwC 2017 report published at the Davos Forum in China said that by 2030, AI The economic value created will reach $1.6 billion by 2030, which will greatly boost the world economy, and China will be one of the countries that benefit the most from the development of AI [8]. Such a huge economic volume will also create more jobs, of which 5% of the economic value will be reflected in employment. The additional wealth created will promote China's employment rate, which rose by 12%, so artificial intelligence will also promote the employment of college students [9].

3. Methodology

3.1. Data Set

Table 1 is the summary statistics table, and the table shows the data used in this study from 2015 to 2019 of 30 provinces in mainland China (excluding Tibet). The data source is the Chinese Labor Statistics Yearbook and the International Federation of Robotics (IFR) [10].

This paper uses two variables as dependent variables, employment, which represents the number of employed people in each province in each year, and undergraduate, which represents the number of college students employed in each province in each year. For ease of interpretation as well as calculation, the dependent variables are to be taken as the natural logarithm, denoted as lnemployment and lnundergraduate, respectively.

The independent variable is lnrobots, which represents the density of robot installations in each province in each year.

DOI: 10.54254/2754-1169/37/20231847

Table 1: Summary Statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
id	150	15.5	8.684438	1	30
year	150	2017	1.418951	2015	2019
employment	150	2745.714	1775.868	321.41	7150.25
lnemployment	150	7.670988	0.7691419	5.772717	8.874903
undergraduate	150	223.8638	136.5109	25.06998	700.7245
lnundergraduate	150	5.193601	0.7241591	3.221671	6.552115
robots	150	14171.09	19817.91	263.7075	143562.1
lnrobots	150	8.82618	1.341421	5.574841	11.87452
wage	150	72977.17	20237.8	45403	166803
lnwage	150	11.16737	0.236534	10.72333	12.02457
urban	150	0.6105641	0.1104165	0.4293373	0.8923821
gdp_growth	150	8.380405	3.643249	-3.950439	21.24406
trading	150	9265.002	14777.63	37.58406	71763.06
lntrading	150	8.081215	1.564309	3.62658	11.18112

The control variables contain variables that can affect the employment status of each province in each year, including urban, which represents the urbanization level in each province in each year; wage, which represents the average wage in each province in each year; lnwage, which represents the natural logarithm of the average wage in each province in each year; trading, which represents the import and export trade volume in each province in each year; and lntrading, which represents the gdp_growth represents the GDP growth rate of each province in each year.

3.2. The Model

The model is as follows [11].

$$Y_{i,t} = \alpha_0 + \beta_1 lnrobots_{i,t} + \beta_2 urban_{i,t} + \beta_3 lnwage_{i,t} + \beta_4 lntrading_{i,t} + \beta_5 gdp\_growth_{i,t} + \varepsilon_{i.t}$$

Where $Y_{i,t}$ represent two different dependent variables respectively, $lnemployment_{i,t}$ and $lnundergraducate_{i,t}$. α_0 is the intercept term, and $\varepsilon_{i.t}$ is the error term.

3.3. Empirical Results

Table 2 shows the regression results of the OLS method. Columns (1) and (2) are the natural logarithm of the number of employed persons in each province in each year as the dependent variable, and columns (3) and (4) are the natural logarithm of the number of college students employed in each province in each year as the dependent variable.

Table 2: OLS model Results.

	(1)	(2)	(3)	(4)
	lnemployment	lnemployment	lnundergraduate	lnundergraduate
lnrobots	0.4333***	0.3102***	0.4803***	0.2415***
	(0.0309)	(0.0297)	(0.0203)	(0.0342)
urban		-4.5459***		-1.4481***
		(0.3365)		(0.3882)
lnwage		-0.3770***		0.2050
		(0.1353)		(0.1560)
lntrading		0.2948***		0.2807***
		(0.0292)		(0.0337)
gdp_growth		-0.0078		-0.0209***
		(0.0059)		(0.0069)
_cons	3.8467***	9.6016***	0.9542***	-0.4367
	(0.2756)	(1.3614)	(0.1808)	(1.5702)
N	150	150	150	150
R^2	0.571	0.909	0.792	0.864

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2 shows the estimated results. The simple regression results in column (1) indicate that for every 1% increase in the installation density of robots, the number of employed people in each province will increase by 0.4333%, and the regression results in column (2) after controlling for the control variables indicate that for every 1% increase in the installation density of robots, the number of employed people in each province will increase by 0.3102%, and all of them are statistically significant at the 1% level. The simple regression results in column (3) indicate that for every 1% increase in the installation density of robots, the number of college students employed in each province rises by 0.4803%, and the regression results in column (4) after controlling for the control variables indicate that for every 1% increase in the installation density of robots, the number of employed in each province rises by 0.2415%, and both are significant at the 1% statistical level.

Table 3 represents the regression results of the fixed effect model controlling for both individual fixed effects and time fixed effects [12].

In table 3, the dependent variables in columns (1) and (2) are the natural logarithm of the number of employed persons in each province for each year, and the dependent variables in columns (3) and (4) are the natural logarithm of the number of college students employed in each province for each year.

The empirical results in Table 3 indicate that the fixed-effects model regression results in column (1) indicate that employment in each province increased by 0.0591% in each year when the density of robot installation increased by 1%, and the fixed-effects model regression results in column (2) after controlling for the control variables indicate that employment in each province increased by 0.0699% in each year when the density of robot installation increased by 1%, respectively significant at the 10% and 5% statistical levels.

Table 3: Fixed Effect Model Results.

	(1)	(2)	(3)	(4)
	lnemployment	lnemployment	lnundergraduate	lnundergraduate
lnrobots	0.0591*	0.0699**	0.2227***	-0.0413
	(0.0331)	(0.0340)	(0.0183)	(0.0767)
urban		0.0363		1.6825**
		(0.3588)		(0.8101)
lnwage		0.1684		0.1729
		(0.1484)		(0.3351)
lntrading		-0.0202		-0.0555
		(0.0171)		(0.0386)
gdp_growth		-0.0001		-0.0015
		(0.0011)		(0.0026)
_cons	7.1760***	5.3762***	3.2282***	3.0033
	(0.2741)	(1.6823)	(0.1612)	(3.7987)
N	150	150	150	150
R^2	0.058	0.085	0.556	0.721

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The fixed-effects model regression results in column (3) indicate that when the installation density of robots increases by 1%, the number of college students employed in each province for each year increases by 0.2227% and is significant at the 1% statistical level. The fixed-effects model regression results in column (4) after controlling for the control variables indicate that when the installation density of robots increases by 1%, there is a small but statistically insignificant decrease in the number of college students employed in each province for each year.

In the part of the robustness test, this paper adopted the methods of data winsorization and replacement of explanatory variables, respectively (Table 4). Columns (1) and (2) represent the regression results after winsorizing the data by 2.5% and 97.5%, respectively. Columns (3) and (4) represent the regression results after we replace the original explanatory variables with the explanatory variables lagging one period, because the explained variables are sometimes affected not only by the explanatory variables of the current period but also by the explanatory variables lagging one period. period impact. The results are still similar to the fixed effect results in Table 3. After

DOI: 10.54254/2754-1169/37/20231847

controlling for time fixed effects and individual fixed effects, the impact of robots on college students' employment is not statistically significant, thus proving that the model is robust.

Table 4: Robustness Test Results.

	(1)	(2)	(3)	(4)
	lnundergraduate_w	lnundergraduate_w	lnundergraduate	lnundergraduate
lnrobots	0.2076***	-0.1129		
	(0.0175)	(0.0739)		
L.lnrobots			0.2447***	-0.0543
			(0.0217)	(0.0997)
urban		2.0149**		1.9904*
		(0.7798)		(1.1205)
lnwage		-0.1960		0.7966*
		(0.3226)		(0.4199)
lntrading		0.0068		-0.0116
		(0.0371)		(0.0493)
gdp_growth		-0.0015		-0.0020
		(0.0025)		(0.0032)
_cons	3.3608***	6.9644*	3.0874***	-4.3233
	(0.1547)	(3.6566)	(0.1888)	(4.6503)
N	150	150	120	120
R^2	0.541	0.710	0.589	0.720

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4. Conclusion

The empirical results of this paper show that both the OLS estimation method and the fixed effects estimation method prove that the diffusion and application of AI technology and industrial robots have a promotion effect on the job market. Both for the overall job market and for the job market of college students, the diffusion and application of AI technology and industrial robots will have a significant and positive effect on the overall number of jobs and the number of college students employed, which also represents the possibility that AI and industrial robots will displace some labor jobs, but most of them will be concentrated in low-skilled jobs, while for high-end manufacturing, more jobs can be provided. At the same time, it is difficult for AI and industrial robots to be fully automated in practical applications, and in the daily operation of enterprises, there are many management tasks that require a high degree of cooperation between personnel and teams, which AI and industrial robots are unable to do for the time being. These are the reasons why AI and industrial robots have a creative effect on overall employment numbers and the number of college students employed. However, there are some limitations to this research. The data used in this study are from 2015 to 2019, and because the years of application and promotion of AI technology and industrial robots in China are still relatively few and the related statistics and data are also few, the author hopes to collect newer and more comprehensive data for future research. In addition, the current overall employment market and the employment market of college students have the effect of spatial spillover. In the future, spatial measurement-related econometric models can be introduced into the

DOI: 10.54254/2754-1169/37/20231847

research to study the spatial spillover effect of the promotion and application of artificial intelligence technology and industrial robots on the employment market.

Acknowledgements

I would like to sincerely thank my advisor and professors for their invaluable guidance, support, and encouragement throughout the development of this econometric study on the relationship between robots and the unemployment rate. Their expertise and insights have been indispensable in shaping the direction and quality of this research. Furthermore, I would like to extend my heartfelt appreciation to my family, whose unwavering love, support, and understanding have been a constant source of strength and motivation during the course of this project. Their belief in me has made it possible for me to persevere and succeed in this academic endeavor.

References

[1] *Strong, A. I. Applications of artificial intelligence & associated technologies. Science [ETEBMS-2016], 5(6). (2016).*
[2] *Cheng, G. J., Liu, L. T., Qiang, X. J., & Liu, Y. Industry 4.0 development and application of intelligent manufacturing. In 2016 international conference on information system and artificial intelligence (ISAI) (pp. 407-410). IEEE. (2016, June).*
[3] *Graetz G, Michaels G. Robots at Work [J]. Review of Economics and Statistics, 100(5) : 753 - 768. 2018.*
[4] *Acemoglu D, Restrepo P. Robots and Jobs: Evidence from US Labor Markets [J]. Journal of Political Economics, 128(6) : 2188 - 2244. 2020.*
[5] *Furman J, Seamans R. AI and the Economy [J]. Innovation Policy and the Economy, 19 (1): 161-191. 2019.*
[6] *Zhang, D., Pee, L. G., & Cui, L. Artificial intelligence in E-commerce fulfillment: A case study of resource orchestration at Alibaba's Smart Warehouse. International Journal of Information Management, 57, 102304. (2021).*
[7] *Abuselidze, G., & Mamaladze, L. The impact of artificial intelligence on employment before and during pandemic: A comparative analysis. In Journal of Physics: Conference Series (Vol. 1840, No. 1, p. 012040). IOP Publishing. (2021, March).*
[8] *Tencent Research Institute, CAICT, Tencent AI Lab, & Tencent open platform. The Power of Capital. Artificial Intelligence: A National Strategic Initiative, 141-149.*
[9] *Ying, L. G. Measuring the spillover effects: Some Chinese evidence. Papers in regional science, 79(1), 75-89. (2000).*
[10] *IFR International Federation of Robotics. International Federation of Robotics. https://ifr.org/. (n.d.)*
[11] *Wooldridge, J. M. Introductory econometrics: A modern approach. Cengage learning. (2015).*
[12] *Wooldridge, J. M. Econometric analysis of cross section and panel data. MIT press. (2010).*