Industrial Robot Application, Productive Services Clustering and TFP

Fang Wang[a], Shuang Li[b], Wei Hu*

School of Economics, Wuhan University of Technology, Wuhan, Hubei, 430070, China

[a]837806777@qq.com; [b]2081491760@qq.com;
*Corresponding Author: 15056750999@163.com

Abstract. This paper discusses the impact of industrial robot application on total factor productivity using panel data from 30 regions in China from 2013 to 2019, and studies the threshold effect of productive service industry agglomeration on the relationship between the two based on the panel threshold model. It is found that:① industrial robot application has a significant promotion effect on total factor productivity, and this effect is greater for the western region of China;② productive service industry agglomeration has a single-threshold effect in the impact of industrial robot application on total factor productivity, and along with the productive service industry agglomeration crossing the threshold value, the impact of industrial robot application on total factor productivity turns from negative to positive. In the future, China should accelerate the application of industrial robots in the whole industry, promote the development of industrial integration with industrial agglomeration, and realize high-level scientific and technological self-reliance and self-improvement.

Keywords: Industrial Robots, Productive Services Agglomeration, TFP, Threshold Effect

1 Introduction and Literature Review

With the development of big data as well as intelligence, the application of industrial robots is becoming more and more common. According to the Global Robotics 2019 released by the International Federation of Robotics (IFR), a total of more than two million industrial robots are now in existence in various industries around the world, and the data shows that the operational stock of industrial robots in China has tripled over the past decade, and by the end of 2022, the number of industries using the The number of robots is close to 4 million units. Industrial robots as an important invention in the era of intelligence and automation represents the application of artificial intelligence and automation technology, leading a new round of scientific and technological and industrial revolution, and becoming an important driving force for industrial development, both at the macro level and at the micro level, which will form a new demand for intelligence, thus comprehensively enhancing the productivity of our society[4] .

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As for the impact of industrial robots on total factor productivity, the academic community has not yet reached a unanimous consensus. Part of the literature argues that the application of industrial robots can improve social productivity and promote rapid economic growth. First, robots can replace human labor thus improving productivity and realizing efficient production. Second, robots can form a complementary relationship with labor power and capital, increasing the productivity of labor and capital[2] . However, some economists have also raised concerns about the negative impacts of emerging production methods, arguing that automated production methods may act as an obstacle to economic development, for example, Gasteiger and Prettner[3] argue that the substitution effect of robots and labor will lower labor wages, reduce laborers' incomes and savings, and lead to a reduction in overall investment in the society, which will inhibit economic Growth. The productive service industry, endogenous to manufacturing and embedded across the value chain, enhances industrial robot application through agglomeration, thereby boosting total factor productivity (TFP). Simultaneously, the versatility of industrial robotics, such as collaborative robots in logistics and retail, drives innovation in modern service industries. Given the rapid advancement of industrial robots, studying their impact on TFP and the role of productive service industry agglomeration in shaping this relationship holds significant theoretical and practical importance[12].

2 Theoretical Analysis and Hypothesis

2.1 Industrial Robot Application and Total Factor Productivity

The application of industrial robots can realize the optimization of regional labor force skill structure, and then improve regional total factor productivity. The application of industrial robots can improve the skill structure of labor force through the joint action of employment substitution and creation effect[7] . Secondly, the application of industrial robots as an emerging technology will promote technological exchanges between enterprises in the same industry in the region, accelerate the accumulation of knowledge factors in the region through knowledge sharing, and form technological spillover effects, thus enhancing regional total factor productivity[8]. Based on this, this paper proposes hypothesis 1.

Hypothesis 1: Industrial robots can significantly increase total factor productivity.

2.2 Threshold Effect of Productive Services Clustering

The productive service industry has emerged with the changes in the production mode of modern manufacturing industry, and its characteristics include high technological content, significant economies of scale, low energy consumption and low pollution, etc., and it can promote economic growth in the form of spatial agglomeration development, which is mainly achieved by deepening the division of labor, extending the industrial value chain, and promoting technological innovation, etc[11] . The diversified agglomeration of productive service industries fosters economies of scale and knowledge spillovers, facilitating cross-border integration of knowledge and technology across industries. This enhances technological innovation, technical efficiency, and total factor productivity (TFP) [6]. However, the effect of industrial robot adoption on TFP depends on the degree of productive service industry agglomeration. In regions with low agglomeration, firms adopting robots may lack financial, technical, and logistical support, raising short-term costs and reducing efficiency, thereby hindering TFP growth [5]. Conversely, when the synergistic agglomeration of productive services and manufacturing reaches a threshold, factor coupling strengthens market linkages, enabling free factor flows[9]. Firms can access intermediate inputs from productive services, lowering costs, improving efficiency, and boosting TFP. Thus, productive service industry agglomeration exhibits a threshold effect in the relationship between robot adoption and TFP. This leads to Hypothesis 2.

Hypothesis 2: There is a threshold effect of productive services agglomeration in the impact of industrial robotics adoption on the total factor of manufacturing.

3 Research Design

In order to study the impact of industrial robot application on total factor productivity, the following model is constructed for empirical testing:

$$TFP_{it} = \alpha_0 + \alpha_1 AI_{it} + Z_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{1}$$

Where TFP_{it} denotes total factor productivity in i during the period of t ,AI_{it} denotes the level of industrial robot application in i during the period of t ,Z_{it} denotes the control variables,μ_i and δ_t denote the region and time fixed effects, respectively, and ε_{it} is the random error term.

A panel threshold effect model is constructed to examine the threshold effect of productive service industry agglomeration on the relationship between industrial robot application and total factor productivity, with a single threshold effect as an example:

$$TFP_{it} = \beta_0 + \beta_1 AI_{it} \times I(Agg_{it} \le \theta) + \beta_2 AI_{it} \times I(Agg_{it} > \theta) + \beta_3 Z_{it} + \varepsilon_{it} \tag{2}$$

where θ is the threshold value and $I(\cdot)$ is the indicator function.

3.1 Variable Measurement

(1) Explained variable: Total Factor Productivity (TFP)

Total Factor Productivity (TFP) is the explanatory variable of this paper. In this paper, the DEA-Malmquist index method is chosen to be used to calculate Total Factor Productivity (TFP) in each province. In calculating Total Factor Productivity, output, labor inputs and capital inputs need to be considered. Among them, output is expressed using the Gross Domestic Product (GDP) of each region, with price adjustments to eliminate the influence of price factors. Labor input is measured by the number of employed people in the whole society. Capital input, on the other hand, is measured by the amount of investment in fixed assets.

(2) Explanatory variables: industrial robot applications (Robot)

Industrial robot application, measured by industrial robot penetration rate. The core explanatory variables in this paper refer to the studies of Acemoglu et al. [1] and Wang Wen et al. [10] , and the data on industrial robots in various industries in China published by the International Federation of Robotics is used to construct the variable of installed density of industrial robots, which is computed as follows.

$$Robot_{it} = \frac{Installation_{it}}{Emp_{it}} = \frac{\sum_{n=1}^{N}(Emp_{int} \times Installation_{nt})}{Emp_{it}} \tag{3}$$

Where $Robot_{it}$ denotes the level of industrial robots in$t$ in$i$, which is the explanatory variable used in this paper. $Installation_{it}$In this paper,t is the industrial robots installed in$t$ in$i$,Emp_{it} is the total employment in$t$ in i ,$Installation_{nt}$ is the industrial robots installed in$n$ in$t$, which is classified according to the ISIC industry classification standard published by IFR. Due to the difference between the industry classification standard and the industry classification standard of the National Bureau of Statistics (NBS), this paper obtains the industrial robots installed in each region based on the employment data of the sub-region and sub-industry of the China Labor Statistical Yearbook by calculating the proportion of employment in$t$ in each region in the$n$ industry.Emp_{int} is the total industry to be summed up. The data on the number of industrial robots installed in each region is obtained, and$N$ is the total number of industries that need to be summed up.

(3) Threshold variable: agglomeration of productive services (Agg)

This paper uses the agglomeration index of productive service industry as the threshold variable. In this paper, according to the guidance of the Outline of the Eleventh Five-Year Plan for National Economic and Social Development and the National Economic Industry Classification and Codes (2002), the productive service industry includes the following industries: wholesale and retail trade, transportation, warehousing, and postal service, information transmission, software, and information technology service, finance, Real Estate, Leasing and Business Services, Scientific Research and Technology Services, and Water Conservancy, Environment and Public Facilities Management[9].

In this paper, the location entropy method is selected for calculation based on the existing research, and the specific formula is as follows:

$$Agg_{ijt} = \frac{q_{ijt}/q_{jt}}{q_{it}/q_t} \tag{4}$$

Among them,Agg_{ijt} is the entropy of location of$j$ industry in$i$ region in the period of$t$,q_{ijt} is the employment of$j$ industry in$i$ region in the period of$t$,q_{jt} is the employment of$j$ industry in the whole country in the period of$t$,q_{it} is the employment of$i$ region in the period of$t$, andq_t is the employment of$t$ industry in the whole country in the period of .

3.2 Data Sources

The data on GDP, number of employees and fixed asset investment in each province required for the calculation of total factor productivity come from the China Statistical Yearbook and the statistical yearbooks of each province, respectively. The data on industrial robots in China required for calculating the level of industrial robot application are from the International Federation of Robotics (IFR), and the number of patent applications for industrial robots are from PatentHub. Among the control variables, the R&D investment intensity is from the National Science and Technology Investment Statistics Bulletin of each year; the data in the level of economic development, trade openness, population density and urbanization rate are from the CSMAR Cathay Pacific database. The descriptive statistics of the variables are analyzed in the following table 1.

Table 1. Description of variables

variant	**sample size**	**average value**	**(statistics) standard deviation**	**minimum value**	**maximum values**
TFP	300	1.286	0.240	0.613	2.382
Robot	300	2.525	2.954	0.00300	18.78
Agg	300	1.302	0.524	0.617	3.049
EDL	300	0.0330	0.0260	0.00300	0.111
STR	300	0.0330	0.0300	0.00200	0.126
R&D	300	0.0100	0.00600	0	0.0220
FDI	300	0.0220	0.0200	0	0.121
SIZE	300	4577	2813	563.5	12489
GOV	300	0.261	0.115	0.113	0.758

Source: Organized by the author

4 Analysis of Empirical Results

4.1 Benchmark Regression

Table 2 presents the empirical results based on the panel fixed effects model. Columns (1)-(4) are regressed on the application of industrial robots, controlling for the fixed effects of province and time. The results show that in column (1), the regression coefficient of industrial robot application is positive and significant at the 1% significant level, indicating that industrial robots have a significant contribution to total factor productivity; columns (2)-(4) are the regression results of progressively adding control variables affecting total factor productivity, and it can be seen that the regression coefficient of industrial robot application is still significant and positive at the 1% level, further confirms its positive impact on total factor productivity.

Table 2. Benchmark Regression Results

	(1) TFP	(2) TFP	(3) TFP	(4) TFP	(5) TFP	(6) TFP	(7) TFP
Robot	0.162 ***	0.161 ***	0.178 ***	0.177 ***	0.193 ***	0.198 ***	0.215 ***

	(0.020)	(0.020)	(0.022)	(0.022)	(0.025)	(0.025)	(0.032)
EDC		-22.891	68.908	64.532	62.361	42.557	54.935
		(36.210)	(63.124)	(63.665)	(63.543)	(63.840)	(65.400)
STR			-72.464*	-73.720*	-78.348*	-76.494*	-76.001*
			(40.933)	(41.062)	(41.116)	(40.798)	(40.827)
R&D				24.983	3.686	2.833	7.226
				(41.979)	(44.801)	(44.445)	(44.750)
FDI					7.229	10.093*	10.909*
					(5.398)	(5.551)	(5.631)
GOV						-4.800*	-4.752*
						(2.451)	(2.454)
SIZE							-0.001
							(0.001)
constant	1.011 ***	1.778	1.072	1.005	1.254	3.070*	5.050*
	(0.081)	(1.216)	(1.273)	(1.280)	(1.291)	(1.581)	(2.744)
Fixed Effect	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
N	210.000	210.000	210.000	210.000	210.000	210.000	210.000
r2	0.270	0.272	0.284	0.286	0.293	0.308	0.311

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Organized by the author

4.2 Robustness Tests

To further ensure that the conclusions are robust, the paper performs the following tests.

(1) Replacement of core explanatory variables

The core explanatory variable is replaced with the number of industrial robot patent applications for testing, and based on the "Industrial Robot China Patent Technology Analysis Report" published by the National Center for Industrial Information Security Development, the logarithmic value of the number of industrial robot patent applications is used to estimate the number of industrial robot patents using the keywords of the seven types of technologies, namely natural language processing, deep learning, cloud computing, speech recognition, computer vision, intelligent driving, and intelligent robotics, for the industrial robots is estimated[8].

(2) Extension of the time interval

Extending the study sample interval to 2010-2019 for the test, the results are shown in column (2) of Table 3.

After replacing the core explanatory variables or changing the sample interval of the study, the coefficient of industrial robot application is still significantly positive, indicating that industrial robot application has a significant contribution to total factor productivity, proving the robustness of the conclusions of this paper.

Table 3. Robustness Inspection

variant	(1)	(2)
Robot1	0.091 ***	
	(0.031)	

Robot		0.106 ***
		(0.029)
constant	-1.585	7.240 ***
	(2.637)	(1.849)
fixed effect	**YES**	**YES**
N	210.000	300.000
r2	0.210	0.111

Standard errors in parentheses
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$
Source: Organized by the author

4.3 Threshold Effect Test

From the results in Table 4, it can be seen that when the degree of agglomeration of productive services is below a threshold, the coefficient of industrial robot application is negative at the 1% significance level, which means that the application of industrial robots has an inhibitory effect on total factor productivity. However, when the degree of agglomeration of productive services exceeds a threshold, the coefficient of industrial robot application becomes positive at the 1% significance level, which means that the application of industrial robots has a promoting effect on total factor productivity.

Table 4. Threshold Effect Model Verification

variant	(1)
Robot	-0.249***
(Coagg≤ 0.8239)	(0.0585)
Robot	0.0676***
(Coagg> 0.8239)	(0.0124)
control variable	2.329***
	(0.559)

Standard errors in parentheses
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$
Source: Organized by the author

5 Conclusions and Policy Recommendations

5.1 Conclusions

This study analyzes data from 30 Chinese regions and industrial robot statistics from the International Federation of Robotics (2013–2019) to explore the relationship between industrial robot adoption and total factor productivity (TFP), including the threshold effect of productive service industry agglomeration. Key findings are as follows:

(1) Industrial robot application significantly enhances regional TFP, a result robust to endogeneity treatments and sensitivity tests.

(2) In western China, industrial robots play a more pronounced role due to low labor costs, which attract manufacturing firms, foster knowledge exchange, and reduce

operational costs with government support, further incentivizing innovation and TFP growth.

(3) Productive service industry agglomeration exhibits a single threshold effect. Below the threshold, insufficient inter-industry exchange leads to redundant knowledge inputs, hindering TFP. Above the threshold, enhanced knowledge and technology flows drive innovation, making robot adoption a significant contributor to TFP improvement.

5.2 Policy Recommendations

Based on the conclusions, the paper makes the following policy recommendations.

(1) Rapidly build a complete industrial robot industry chain and promote China's self-reliance in high-level science and technology. The country should speed up the establishment of a complete industrial robot industry chain from research and development to application, encourage enterprises to carry out independent research and development, master the core technology of industrial robots, and realize the industry's self-control.

(2)Accelerate the development of industrial robots and promote the deep integration of industries. The agglomeration of productive service industries can promote the coupling of elements and improve the application scope and effect of industrial robots. Therefore, each region should expand the information communication channels between industries on the basis of building an industrial interaction platform to open up the channels of the industrial chain.

Reference

1. Acemoglu D , Restrepo P .Artificial Intelligence, Automation and Work[J].Social Science Electronic Publishing, 2018.
2. Berg A , Buffie E , Zanna L F .Should We Fear the Robot Revolution?(The Correct Answer is Yes)[J].IMF Working Papers, 2018, 18(116):1.
3. Gasteiger, E., and K. Prettner. a Note on Automation, Stagnation, and the Implications of a Robot Tax [R]. School of Business & Economics Discussion Paper, 2017.
4. Goos M , Manning A , Salomons A .Job Polarization in Europe[J].
5. Guy,Michaels,Ashwini,et al.HAS ICT POLARIZED SKILL DEMAND? EVIDENCE FROM ELEVEN COUNTRIES OVER TWENTY-FIVE YEARS[J].Review of Economics & Statistics, 2014.
6. DU Chuanwen,LI Qing,RUI Mingjie et al. Substitution complementary relationship between large-scale industrial robot application and heterogeneous skilled labor[J]. China Science and Technology Forum,2018(08):174-182.
7. LI Lei,WANG Xiaoxia,BAO Qun. Employment effects of robots: mechanisms and Chinese experience[J]. Management World,2021,37(09):104-119.
8. LI Lianshui,BAO Yifa,LIU Jun. Research on the impact of intelligence on total factor productivity of Chinese manufacturing industry[J]. Science Research,2020,38(04):609-618+722.
9. LIU He-Dong,ZHANG Gui-Jing. Impact of collaborative industrial agglomeration on high-quality economic development[J]. Science and Technology Progress and Countermeasures,2022,39(01):69-77.

10. WANG Wen, NIU Zedong, SUN Zao. The service industry under the impact of industrial robots:Structural upgrading or low-end lock-in[J]. Statistical Research, 2020, 37(7):12.
11. YAN Chuan,HE Haokai. Productive services agglomeration, fiscal decentralization and urban industrial eco-efficiency[J]. Economic and Management Review,2019,35(03):92-107.
12. Zhang He,Xu Ning. Industrial Agglomeration Specialization, Diversification and Green Total Factor Productivity--Based on the Externality Perspective of Productive Service Industry Agglomeration[J]. Economic Issues,2022(05):21-27.