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Original Research Article

Research on the Impact of Industrial Robots on China's Regional Industrial Structure

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ABSTRACT

The large-scale deployment of industrial robots and the technological innovation brought by artificial intelligence promote the development of local high industrialization and modernization. Industrial robots are going through the process of changing from automatic tools to intelligent tools, and even to innovative tools. Theoretical analysis shows that its universal characteristics and technological progress effect contribute to the transformation and upgrading of industrial structure. The panel smooth transition regression (PSTR) model is constructed based on the data of the international robotics Union. The results show that the following facts. (1). The impact of industrial robots on the upgrading of China's regional industrial structure has a single threshold effect, which can be roughly divided into an impact area bounded by Hu Huanyong line and high in the east and low in the west. (2). With the increasing impact, the positive effect of material capital agglomeration on the upgrading of regional industrial structure is restrained, and the negative effect of industrial labor agglomeration on the upgrading of regional industrial structure should be enhanced. (3). Affected by the impact, the elasticity of material capital agglomeration and industrial labor agglomeration increases marginally in the west of Hu Huanyong line, decreases marginally in the east of Hu Huanyong line, and finally converges. (4). Industrial robots have no significant impact on the industrial structure in the process of attracting human capital agglomeration, technological factor agglomeration and guiding the change of consumption structure.

Keywords: *Industrial Robot; Upgrading of Industrial Structure; Spatial Heterogeneity; Threshold Effect*

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1. Introduction

China is by far the world's largest industrial robot market. According to the public data of the International Federation of Robotics (IFR) in 2019, the average annual installation of industrial robots in China reached 140,500, while Japan ranked second with only 49,900. With the breakthrough of artificial intelligence in vision system, mobility and simple programming system, more intelligent cooperative robots are gradually emerging among the traditional industrial robots. However, as the leader of industrial robot end users, China has lacked detailed research in this field for many years. For example, Yang Guang and others[1] found that total factor productivity is an important transmission mechanism for industrial robots to affect economic growth. Emphasizing the role of total factor productivity in promoting economic growth dose not mean the deny of the impact of this technology on the labor market, that is, through attracting and replacing labor, technology biased unemployment and talent agglomeration occurred. According to the Petty-Clark theorem, this flow will drive the adjustment of regional industrial structure. In addition, whether the spillover effect brought by flow and its effect on regional innovation ability will indirectly affect the regional industrial structure needs to be summarized. Based on this, this study explores the impact mechanism of industrial robots on regional industrial structure through theoretical and case analysis.

It is found that industrial robots have two characteristics. (1). As a kind of technological progress[2], it can directly affect the regional industrial structure through the creation of new industrial clusters, the elimination of backward industries and the change of industrial status, or indirectly generate labor selection and substitution through technology biased unemployment to promote the change of industrial structure[3]. (2). As an innovation tool, knowledge production can be carried out by recombining the original knowledge[4], so as to improve the regional innovation ability and promote the upgrading of regional industrial structure. The literature retrieved with industrial robots and industry as the key words mostly starts from the application of industrial robots in heterogeneous industries, such as M. Hengstler *et al.*[5], E. Karabegovic *et al.*[6] and P. Tubaro *et al.*[7] respectively studied the application of industrial robots in medical industry, metal manufacturing industry and automobile industry, in order to explore the role and effect of industrial robots in industrial correlation effect. But their research do not involve the impact of industrial robot as a tool for technological progress and innovation. As the country that uses the most industrial robots in the world, it is necessary for China to anatomize the fuzzy field.

The upgrading of industrial structure is an important way to promote high-quality development in China, and industrial robots are important tools to drive industrial upgrading and promote local high-quality development. However, the use of industrial robots in different regions is very different, and its effect will also be affected by this. This study focuses on the relevant issues of industrial robots and regional industrial structure, shows the application characteristics of industrial robots, micro analyzes how they act on economic factors and then reflect on structural changes, combing out the main ways, internal logic and effects of this process. Considering that industrial robots have the characteristics of strengthening employment spatial polarization and technology polarization[8], we choose to explore the effect, trend and spatial characteristics of this impact on the upgrading of China's regional industrial structure from the perspective of factor agglomeration. Finally, it is proposed that the provinces at different stages of industrial robot development should pay more attention to the formulation of policies to help the systematic layout and full implementation of China's industrial robot development plan.

2. Theoretical Analysis

2.1 Characteristic analysis of industrial robots

At present, the most common industrial robot is manipulator, which is mainly used in automobile industry and electronic industry. It takes chips, sensors and other equipment as the carrier and relies on artificial intelligence technologies such as machine learning, computer vision and cloud computing. Among them, robotics, as a discipline, focuses on the development and training of robots to interact with people and the world in a universal and predictable way. According to the literature, three trend characteristics of industrial robots are summarized.

2.1.1 Industrial robots as automation tools

Traditional industrial robots mainly play the role of automation tools to learn existing coding knowledge. P. Aghion *et al.*[4] regarded automation and "Ballmer's disease" as two main effects of technological progress on economic growth. (1). Automation departments invest in automation machines to improve productivity. When the return on capital increases more than the return on labor, the departments further improve the automation level, reduce product prices to win the market, and stimulate peer enterprises to buy automation machines[2], thus increase industrial output. (2). Technological progress will also increase the cost of non-automated sectors and reduce the return on capital, thus reducing industrial output. (3). The substitution effect of labor force selection brought by technological progress cannot be ignored. On the one hand, the effect of technology biased income distribution will aggravate the income gap. High-tech personnel are equipped with high salaries, and talent inflow are attracted from the aspect of space. On the other hand, the stylized work is replaced by automation and the labor force is lost, but whether it is absorbed by other local industries or flows into other places remains to be studied.

2.1.2 Industrial robots as intelligent tools.

In recent years, robots have gradually shown the characteristics of intelligent tools represented by cooperative robots: They are trying to learn more complex tacit knowledge than coding knowledge. IFR data show that the use of cooperative robots worldwide increased by 63.3% from 2017 to 2019. On the one hand, the impact of intelligent industrial robots on industrial output is also reflected in productivity and replacing programmed work. On the other hand, they can also replace non- programmed work to make up for the labor gap and even create new jobs. For example, industrial robots will be supplemented when there are no people in bad jobs such as waste disposal and working in high temperature environment. While intelligent robots participate in garbage disposal and other work, they also need to be supervised by corresponding employees. The "inspector" here is a new post.

2.1.3 Industrial robots as innovative tools

The impact of industrial robots as innovative tools on industrial output is also reflected in productivity, labor selection and substitution and making up for labor shortages. In addition to learning the existing coding knowledge and some tacit knowledge, it can also reorganize the original knowledge for knowledge production, so as to improve the regional innovation ability and drive the adjustment and upgrading of regional industrial structure. According to the endogenous growth theory, industrial robots change from reaction oriented to consciousness oriented, and human capital tends to be replaced by intelligent capital[9]. However, since the development of robots now depends on "weak" artificial intelligence, this point is yet to be realized technically.

To sum up, industrial robots are in the process of changing from automatic tools to intelligent tools and even to innovative tools. Although intelligent tools represented by cooperative robots have been put into application, they are rarely used, accounting for about 5% of the annual use of industrial robots. However, there are still difficulties in technical operation to realize the function of innovation tools. Therefore, this study takes the use of industrial robots as the research object, analyzes the action mechanism between industrial robots and regional industrial structure from the perspective of space, and tests the mediating effect.

2.2 Analysis of influencing factors

How can the economic effects of industrial robots in the three roles be reflected in the structural changes? It is found that technology biased unemployment, consumption structure, human capital, material capital and technological factor agglomeration play a major role. The main ways, internal logic and effects of industrial robots affecting regional industrial structure are to be further explored from a spatial perspective.

2.2.1 Industrial robots and technology biased unemployment

The development of automation and innovation and reconstruction brought by robots have greatly improved labor productivity, and the return on capital is gradually greater than the return on labor. In order to maximize profits, manufacturers replace part of the labor force with intelligent machines. Early robotics can replace low skilled workers in programmed work and complement high skilled workers[10], but low skilled and high skilled workers are needed in non-programmed work[11]. Most of the robots put into use today are traditional robots, and their neural networks are relatively single, so they can't learn deeply and draw inferences about other cases from one instance. Optimistic scholars believe that while automation cancels some low skilled jobs, it will create new jobs and alleviate the unemployment crisis[12]. The impact of this labor loss on the regional industrial structure is not necessarily a negative effect. Liu Yue and others[13] believe that the number of labor force is a double-edged sword and needs to be treated dialectically. In short, technology biased unemployment may promote the transfer of some industrial unemployed people to the service industry[14,15]. Re-employment through technical training and education is possible, and some may flow to other places. In addition, this technology biased unemployment is reflected in the trend of spatial agglomeration in industrial layout and market structure[16].

2.2.2 Industrial robots and consumption structure

Industrial robots improve productivity to increase of local overall income, and reduce the proportion of agricultural products in residents' consumption structure, so as to promote the land premium and the rise of price level. The biased effect of technology will also bring biased income distribution and aggravate the income disparities in the region[17]. The diffusion effect of low skilled personnel at a disadvantage will further improve the overall local income level. The widening income gap and the rising price level will promote the demand to shift from low-income elastic products to high-income elastic products, and change the local consumption structure under the circular cumulative causality mechanism. In addition, industrial robots may trigger a social revolution in the concept of consumption. Taking the concept of "vehicle as service" as an example, consumers' desire to buy private cars is weakened, and the structure of customer group of the automobile industry will also change.

2.2.3 Industrial robots and human capital

Industrial robots attract human capital to gather in terms of space, which can be explained by two theories. (1). Education, training and "learning by doing" theory: The high-tech industry has the trend of cultivating high-tech talents with local educational resources and internal resources of the company, and the training and education oriented human capital is deepening. (2). Spatial mobility of labor force: On the one hand, industrial robots raise the overall income level of the region, so as to attract more labor force to flow to the region in different ways. However, even in high-tech fields, there are still different levels of labor force, so the number of labor force in this industry may not be greatly reduced. On the other hand, the introduction of industrial robots into the production and operation of enterprises requires senior employees rather than ordinary labor force. However, high-quality talents in the region are often limited. Enterprises use high salaries to attract talents from different regions to gather in the location of the company. To sum up, industrial robots play a positive role in attracting human capital agglomeration, and demand-oriented market forces are further deepening the agglomeration of human capital in the region.

2.2.4 Industrial robots and material capital

(1). Technological progress will stimulate manufacturers to concentrate material capital. The rise of productivity brings strong market competition to enterprises and obtains the advantage of high productivity in market competition. However, the high fixed cost investment of industrial robots will bring threshold effect to some small and medium-sized enterprises. The superposition of the two effects enables the enterprises with technological first-mover advantage and certain capital accumulation in the region to quickly occupy the market and gain profits, so as to further purchase robots, expand the scale of enterprises, and deepen and concentrate material capital in terms of space. (2). Technological progress will create a number of new enterprises or departments[18]. It is usually realized in the place where technological progress takes place. The emergence of new departments will increase the spatial agglomeration of material capital through purchase or self-production.

2.2.5 Industrial robots and technical elements.

Industrial robots are in the technical stage of transition from automation to intelligence. The technology of the robots is not mature, and the corresponding technical support is not keeping up. A large amount of R & D capital must be invested to give full play to their full potential. Science and innovation resources are unevenly distributed among regions, with obvious spatial agglomeration[19]. Low developed regions have difficulties in terms of education level, talent reserve and financial support. IFR data show that in 2019, 73% of industrial robots went to China, Japan, the United States, South Korea and Germany. The spatial polarization of industrial robot terminals is obvious, which is manifested as "technology attracts technology" under Matthew effect.

2.3 Impact mechanism analysis

The impact of industrial robots on the above five elements will induce growth effect in the economy, expand economies of scale, strengthen local economy, promote technological progress while improving production efficiency and boosting capital accumulation, and then have a positive effect on the upgrading of industrial structure. The agglomeration of human capital contributes to the labor market for local industries. The agglomeration of material capital provides convenience for local industries to obtain intermediate products and save transportation costs. The agglomeration of technological elements forms a good atmosphere based on trust and cooperation among enterprises, and brings competition and platform sharing at the same time. Intelligent machines replace labor, which improves productivity, reduces costs and increases profits. In addition, as a tool of technological progress and innovation, the intelligent machine can play a technical effect and affect the emergence of new departments, the improvement of productivity and the acceleration of automation process. At the same time, it can strengthen regional innovation ability and directly promote the upgrading of industrial structure. Under the causal mechanism of circular accumulation, growth effect and technology effect continue to attract labor, technology, human capital and material capital to gather in space, further promoting the upgrading of industrial structure. When it develops to a certain extent, the choice of labor substitution leads to the rise of local prices and the bankruptcy of small and medium-sized enterprises, resulting in the loss of labor force. The "Baumol disease" caused by the deepening imbalance of material capital makes the deepening of capital in the industry seriously unbalanced, which is not conducive to the development of rationalization of industrial structure in the region. The biased effect of technology aggravates the local income disparities and increases the rental price, resulting in the rising rent cost for small and medium-sized enterprises and having them eliminated by the market. Excessive concentration of factors brings negative effects. All these will have an adverse impact on the upgrading of regional industrial structure. This is also closely related to the degree of industrial transformation and the failure of supporting facilities in society. According to this, the analysis model (**Figure 1**) is constructed, in which the solid lines with arrow represent positive effect and the dotted lines with arrow represent negative effect.

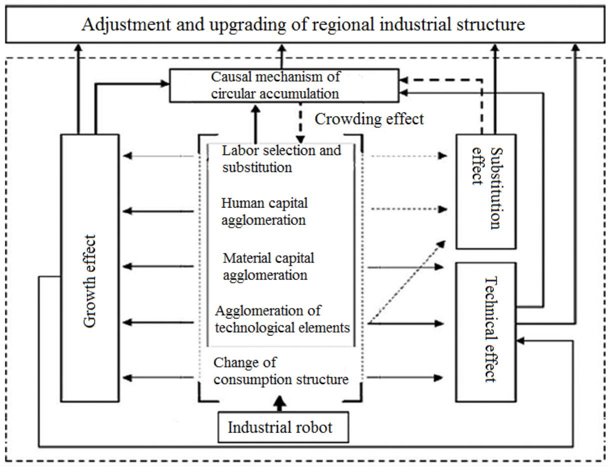

Figure 1. Theoretical model of industrial robots influencing the upgrading of regional industrial structure.

In short, industrial robots drive the upgrading of regional industrial structure through five influencing factors. The mechanism is as follows. (1). Under the action of the causal mechanism of circular accumulation, the growth effect and technology effect can continuously attract human capital, labor force, technology and material capital to gather in space and further promote the upgrading of industrial structure. (2). When it develops to a certain extent, due to labor loss, "Baumol disease", technology bias and crowding effect, it may be impossible to judge the impact of industrial robots on labor, technology and material capital, which will interfere with the judgment of the change direction of regional industrial structure. Based on this, the research hypothesis is put forward: The impact of industrial robots on labor force, human capital, material capital and technology may promote the upgrading of regional industrial structure.

3. Case Analysis

3.1 Data source and index selection

3.1.1 Data source

Internationally recognized robot density index is one of the standards to measure the development degree of manufacturing automation in a country. This study calculates the industrial robot impact index and regional industrial structure change index of 31 provinces in mainland China from 2009 to 2014. The required industrial robot density data is from the International Federation of Robotics (IFR), and other data are from *China Statistical Yearbook* and *China City Statistical Yearbook*.

3.1.2 Build the impact index of industrial robot

Generally speaking, the more robots are introduced into local areas, the greater the impact. The number of robots used in each region is affected by the scale of local labor force. In order to eliminate this heterogeneity, the industrial robot density index is selected to measure the impact of industrial robots. IFR has published the robot installation volume of various countries by industry since 2009, but it is only for the national level, and the inter-provincial data has been blank for a long time. Based on this, Chen Yongwei *et al.*[20] calculated the industrial robot density by industry with reference to the method of D. Acemoglu *et al.*[21], i.e. the average number of industrial robots per thousand people in each industry, and then constructed the inter-provincial industrial robot density by using the weighted average method to obtain the industrial robot density matrix covering 31 provinces for 6 years.

3.1.3 Build an upgrading index of industrial structure

It is known that the industries most impacted by robots are the tertiary industry and the secondary industry. The ratio of the two (Y) is used to measure the transformation and upgrading of industrial structure. This quantity clearly reflects the service-oriented trend of economic structure and the strength of the impact of industrial robots on the two types of industries is relatively low. Based on this, the path factors of industrial robots affecting the change of industrial structure are added to the model and set as explanatory variables (**Table 1**).

3.2 Model construction

Considering the multiplicity of influencing factors, the complexity of action mechanism and the spatial heterogeneity of industrial structure change, and the impact of industrial robots on regional industrial structure has cumulative characteristics, it is impossible to determine whether the embodiment of this switch is the instantaneous transformation of threshold or continuous latent transformation. Therefore, select the PSTR model that can better interpret the threshold characteristics and characterize continuous changes, and then substitute the indicators in **Table 1** into the PSTR model to obtain the following model:

$$\ln Y_{it} = \alpha + \beta_{01}\ln K_{it} + \beta_{02}\ln H_{it} + \beta_{03}\ln L_{it} + \beta_{04}\ln T_{it} + \beta_{05}\ln C_{it} + (\beta_{11}\ln K_{it} + \beta_{12}\ln H_{it} + \beta_{13}\ln L_{it} + \beta_{14}\ln T_{it} + \beta_{15}\ln C_{it})\left\{1 + exp\left[-y(S_{it} - C_j)\right]\right\}^{-1} + \varepsilon_{jit}$$

In the formula: Y_{it} is the industrial structure upgrading index of i Province in t; K_{it} is the physical capital agglomeration index of i Province in t; H_{it} is the human capital agglomeration index of i province in t; L_{it} is the industrial labor agglomeration index of i province in t; T_{it} is the technological progress index of i province in t; C_{it} is the consumption level index of i Province in t; γ represents the slope of the conversion speed; S_{it} is the impact index of industrial robots in i province in t; C_j is the position parameter; ε is random disturbance term; α and β are intercept term and coefficient respectively.

Table 1. Descriptive statistics of dependent and independent variables

Variable	Calculation method	Observed value	Average value	Intra group standard deviation
Industrial structure change index (Y)	Ratio of tertiary industry output value to secondary industry output value	186	0.978	0.541
Industrial robot impact (S)	Installation amount of intelligent robots per thousand people	186	0.014	0.012
Physical capital agglomeration (K)	Proportion of provincial industrial material capital stock in the whole country/proportion of provincial total material capital stock in the whole country	186	3.108	8.072
Human Capital Agglomeration (H)	The labor force is classified according to the years of education and weighted and summed	186	69.520	9.352
Industrial labor agglomeration (L)	Proportion of provincial industrial employment in the whole country/proportion of provincial total employment in the whole country	186	1.008	0.936
Technological progress (T)	Stochastic frontier analysis	186	0.479	0.147
Consumption structure (C)	Per capita consumption level	186	13 539.370	7 199.169

Through the test, the explanatory variable and the explained variable are stable, and then take the impact of industrial robot as the threshold variable to test its nonlinear relationship with the change of industrial structure. The results show that the relationship between industrial robot impact and industrial structure optimization is nonlinear by rejecting the linear model assumption and PSTR model assumption with at least one threshold variable and not rejecting PSTR model with at least two threshold variables. The test statistics of AIC and SC show that under the condition of threshold variables, when the number of conversion functions is 2 and the number of position parameters in each conversion function is 1, the AIC and SC values are the best. This means that the model of industrial robot impact and regional industrial structure change is a single threshold model with two transfer functions.

3.3 Results and robustness test

3.3.1 Spatial distribution of industrial robot density index (Figure 2)

The development of the eastern and northeast regions is slightly better than that of the central and western regions. The leading areas of industrial robot density in the east, central, west and northeast regions are Tianjin, Hubei, Chongqing and Jilin respectively. Among them, the first and second gradient drop in the central, western and northeast regions is large, and the drop in each administrative section in the east region is small. The density distribution of industrial robots in China has obvious spatial heterogeneity and agglomeration characteristics.

3.3.2 PSTR model results of industrial robots affecting regional industrial structure (Table 2)

Except for the negative effect of labor selection and substitution, other explanatory variables are positive effects. Combined with the index composition, the alternative index of labor force selection is regarded as the agglomeration of industrial labor force. The reduction of its agglomeration degree means the transfer or spatial diffusion of some labor force to service industry. The former will effectively promote the development of tertiary industry and realize the optimization and upgrading of industrial structure, and the negative correlation can be explained. The synthesized model symbols are in line with the economic significance.

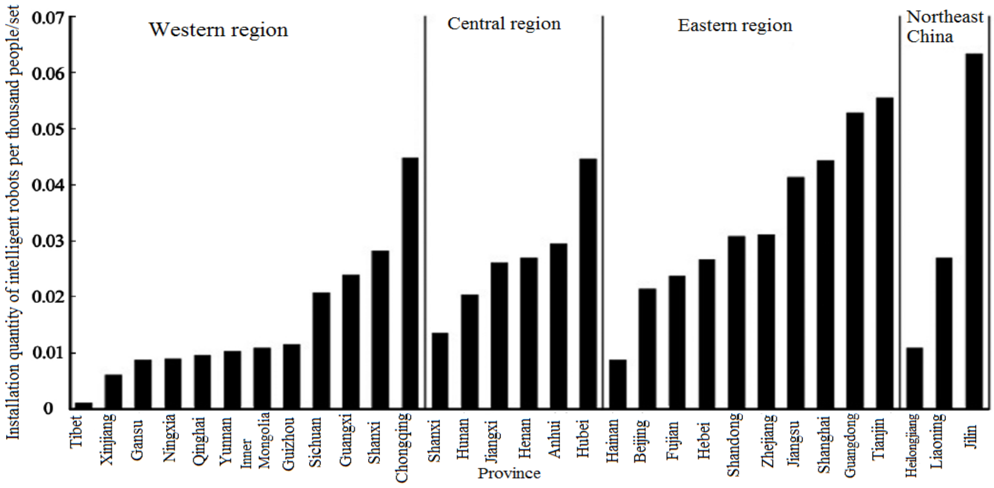

Figure 2. Density index of industrial robots in provinces of eastern, central, western and Northeast China in 2014.

Table 2. PSTR model results

Variable	Explanatory variable		Transfer function I		Transfer function Π	
	Coefficient β_0	T value	Coefficient β_1	T value	Coefficient β_2	T value
K	0.198***	6.233	0.194	2.042	-0.440***	-3.404
H	0.637***	3.179	0.855	1.383	-0.545	-0.594
L	-0.409***	-4.844	1.137***	9.164	-1.047***	-4.516
T	1.054***	8.969	-0.238	-0.885	-0.412	-1.016
C	0.742***	5.980	-0.413	-1.416	0.222	0.512

Note: *** means rejecting the original hypothesis at the confidence level of 1%.

The relationship between transfer function and threshold variable is shown as follows. The transfer function I is a (0,1) function, which shows the threshold effect. The transfer function II is a smooth function, which means that the influence of factor agglomeration and consumption structure on industrial structure varies due to cross-sectional heterogeneity, and this influence will transfer smoothly between high and low impact effects. Two similar position parameters of -4.373 and -4.544 are obtained from transfer functions I and II respectively, and their mean value of -4.459 is taken as the threshold parameter. When the impact of industrial robot is less than -4.459, the marginal effect of factors is slow first and then fast. When it is greater than -4.459, the marginal effect of elements is first fast and then slow.

Under the impact of industrial robots, the threshold effect of industrial structure upgrading on material capital accumulation (K) and industrial labor agglomeration (L) is significant, while the threshold effect on human capital agglomeration (H), technological progress (T) and consumption structure (C) is not significant. The possible reasons are as follows. (1). China is still in the initial stage of industrial robot application, and the effect of impact on some economic factors is not obvious. (2). The volume of relevant data of industrial robot is insufficient, which cannot fully reflect its long-term characteristics. (3). The implementation lags behind, i.e. the full play of new technology requires the support of complete supporting facilities and counterpart talents, which is lagging behind. Therefore, it is not necessary to discuss the coefficients of these three explanatory variables. The elastic changes of the other two significant factors show that the robot impact makes the upgrading effect of regional industrial structure in the face of high and low impact environments, the marginal effect of changing explanatory variables is a smooth transfer before and after the threshold. Specifically summarized in the following four aspects. (1). With the increase of impact, both high and low impact environments show the positive effect of restraining material capital agglomeration on the upgrading of regional industrial structure and the negative effect of promoting industrial labor agglomeration on the upgrading of regional industrial structure. The possible reason for the inhibition is that the low impact area is in the primary stage of applying industrial robots, so capital intensive automation products are mostly purchased by strong enterprises in the region to obtain high market competitiveness. Other enterprises in the same industry are damaged, and the structure in the industry is unbalanced, which is reflected in the negative effect of the imbalance of capital deepening on the optimization and upgrading of industrial structure. In addition, the increasing use of industrial robots also means that the material capital in the region flows to industry. (2). The speed of transfer is fast first and then slow. With the increase of impact, the elastic change of high and low impact areas corresponds to acceleration and deceleration, which can be explained by cyclic accumulation causal mechanism and crowding effect. (3). The industrial labor agglomeration that crosses the threshold and enters the high impact area has a reverse effect, which is manifested in that the industrial labor agglomeration has changed from a negative effect to a positive effect on the upgrading of industrial structure. The possible reason is that the industry uses high-tech talents to replace low-tech talents, which improves the degree of labor agglomeration. (4). According to the results of PSTR β_1=1, the spatial distribution of high impact area can be roughly obtained (**Table 3**). Firstly, the impact area of high industrial robots gradually appeared in 2010. The number of provinces newly entering the high impact area increased year by year, but the increase rate gradually decreased. In 2014, only Shanxi Province was added. It can be found that China is deepening the deployment of industrial robots, and its impact on the adjustment of regional industrial structure is becoming more and more obvious. From the perspective of space dimension, the impact area of high industrial robots is mainly concentrated in the east of Hu Huanyong line, especially in the East. This is because the quality of economic development in the eastern region is higher than that in the central and western regions[22], indicating that the use of industrial robots also depends on a good economic environment. At the same time, technology introduction and regional innovation capacity will also be affected by the local opening level, and low opening level may be detrimental to output[23]. Therefore, the eastern region with a high level of openness is more likely to enjoy the positive effect brought by technological progress and drive the adjustment and upgrading of regional industrial structure by improving innovation ability. Secondly, the high impact areas in Northeast China are only Jilin and Liaoning. This is because the automobile industry in Jilin and Changchun is developed, which drives the development of heavy industry in the surrounding areas, and the important flow of industrial robots application is the automobile industry. In addition, Chongqing in the west and Henan in the middle are also large enterprises in the development of automobile industry. To sum up, the provinces in the impact area of high industrial robots have a good foundation for the development of heavy industry and are in the forefront in the use of industrial robots.

3.3.3 Robustness test

(1). The above variables are analyzed by using the special form of panel transfer regression (PTR) model of PSTR model. It is concluded that the position parameter of industrial robot impact on industrial structure optimization and upgrading effect is 4.382, which is very different from the result of PSTR model analysis (4.459), and the coefficient symbol of each explanatory variable remains unchanged. (2). Under the condition that the impact of industrial robot is the threshold variable, five explanatory variables are removed from the original PSTR model to test the robustness of the model. The results show that except that the sign of human capital variable coefficient changes from positive to negative when excluding material capital variables, the signs of all explanatory variables are the same as the original coefficient in other cases, i.e. the elimination of explanatory variables has little impact on the nonlinear model of industrial robot and industrial structure upgrading effect. In conclusion, PSTR model is robust.

Table 3. China's provinces and cities in the high impact zone of industrial robots from 2009 to 2014

Particular year	High industrial robot impact zone			
	Eastern Region	Central region	Western Region	Northeast China
2009	—	—	—	—
2010	Jiangsu, Zhejiang, Guangdong, Tianjin, Shanghai	Hubei	Shaanxi, Chongqing	Jilin, Liaoning
2011	Jiangsu, Zhejiang, Guangdong, Tianjin, Shanghai, Shandong, Hebei and Fujian	Hubei, Anmei	Shaanxi, Chongqing, Guangxi	Jilin, Liaoning
2012	Jiangsu, Zhejiang, Guangdong, Tianjin, Shanghai, Shandong, Hebei and Fujian	Hubei, Anmei	Shaanxi, Chongqing, Guangxi	Jilin, Liaoning
2013	Jiangsu, Zhejiang, Guangdong, Tianjin, Shanghai, Shandong, Beijing, Hebei, Fujian	Hubei, Anmei, Henan, Hunan, Jiangxi	Shaanxi, Chongqing, Guangxi, Sichuan	Jilin, Liaoning
2014	Jiangsu, Zhejiang, Guangdong, Tianjin, Shanghai, Shandong, Beijing, Hebei, Fujian	Hubei, Anmei, Henan, Hunan, Shanxi, Jiangxi	Shaanxi, Chongqing, Guangxi, Sichuan	Jilin, Liaoning

4. Conclusion and Enlightenment

4.1 Conclusion

China has become a leader among the end users of industrial robots, driving the development of local industrialization, modernization and intellectualization. With the continuous innovation of technology, its universal characteristics and technological progress effect promote industrial transformation and upgrading. However, the support of this proposition in theory and case analysis is very limited. This study uses PSTR model to explore the impact of industrial robots on the upgrading of regional industrial structure. Theoretical analysis shows that industrial robots can promote the upgrading of regional industrial structure by attracting the agglomeration of human capital and technological elements. However, due to the loss of labor, "Baumol's disease", the use threshold of the platform, the high cost of R & D funds and time and the crowding effect, the impact of industrial robots on the upgrading of regional industrial structure in the process of labor selection and substitution, the change of consumption structure and the deepening of material capital agglomeration is uncertain, which may also stimulate the intensification of social contradictions caused by unemployment.

The impact of industrial robots on the upgrading of China's regional industrial structure has an obvious nonlinear relationship. It has a significant impact on the upgrading of regional industrial structure in the process of material capital agglomeration and labor force selection and substitution, but the impact of human capital agglomeration, technological factor agglomeration and consumption structure change on the industrial structure is not significant. The spatial distribution of industrial robot impact not only reflects the central peripheral structure, but also shows the gap between the East and the West.

The impact of industrial robots on China's regional industrial structure has a single threshold effect. The provinces in the high impact area are mainly concentrated in the east of Hu Huanyong line. With the increase of impact, the positive effect of material capital agglomeration on the upgrading of regional industrial structure is restrained, and the negative effect of industrial labor agglomeration on the upgrading of regional industrial structure should be enhanced. The upgrading effect of regional industrial structure reversed mutation at the threshold. The effect of regional industrial structure upgrading to the west of Hu Huanyong line is increasing marginally, showing divergent characteristics. In the east of Hu Huanyong line, the marginal effect decreases and eventually converges.

4.2 Enlightenment

The potential social contradictions triggered by technical unemployment in the process of industrial robots, as well as the structural imbalance and technological monopoly crisis caused by the deepening of biased capital, all need the government's assistance to guide and eliminate. It is suggested to make decisions about the layout of industrial robots according to regional differences. Western and Northeast China, except Guangxi, Chongqing, Sichuan, Shaanxi in the West and Jilin and Liaoning in the Northeast, are all in the impact area of low industrial robots. The impact of industrial robots takes labor force as the main transmission mechanism, and the elastic growth affecting the upgrading effect of regional industrial structure shows a divergent trend. If we can guide the labor force to flow into the service industry, we can solve the problems of bankruptcy and resource waste of non-automated departments, and use industrial robots to drive the upgrading of regional industrial structure. The eastern and central regions, except Hainan, are in high impact areas, and the effect of factor changes on the upgrading of industrial structure is gradually stable. At this stage, the breakthrough of industrial robot technology is particularly important to stimulate the positive effect of industrial structure upgrading. Its development focus is on the investment and test of industrial robot R & D.

There are common problems in high and low impact areas. The increase of impact will weaken the positive effect of material capital accumulation on the upgrading of industrial structure. The possible reasons are "Baumol's disease" and the rising cost of stagnant departments, resulting in the bankruptcy of small and medium-sized industries and the waste of resources. To this end, the following improvement suggestions are put forward. (1). Using test base mode to solve the problems of technology upgrading in high impact area and machine introduction in low impact area. The R & D department needs scenario application to achieve accurate improvement. Small and medium-sized enterprises lack funds. The two can realize the intelligent transformation of production through cooperation, accelerating the transformation and upgrading of small and medium-sized enterprises. (2). Bankrupt enterprises release the recycling of resources to solve the problem of "Baumol's disease" in high and low impact areas. (3). Solve the problem of the shortage of specific talents in high and low impact areas through the transformation from old to new and enclave training, including high-tech employees who operate and maintain robots and skilled workers who train robots.

Conflict of interest

The authors declare that they have no conflict of interest.

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