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ROBOT ADOPTION AND URBAN TOTAL FACTOR PRODUCTIVITY: EVIDENCE FROM CHINA

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Abstract. Industrial robots are having a profound and lasting impact on China's economy. This research examines the deployment of industrial robots and their effects on urban total factor production from theoretical and empirical angles. It is created using panel data from 286 cities at the prefecture level between 2003 and 2017. It is found that: First, robot adoption promotes urban total factor productivity. Second, adopting robots has a more positive influence on urban total factor productivity development in western, underdeveloped, and less market-oriented areas compared to the developed and market-oriented areas in the east. Third, adopting robots could enhance urban innovation vitality, increase total factor productivity, boost industrial agglomeration, and improve technological progress or technical efficiency. Policy enlightenment provided by these findings can guide future technological advancements and promote high-quality city development.

Keywords: industrial robot, urban total factor productivity, technological progress, technical efficiency.

JEL Classification: O33, O47.

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1. Introduction

A new round of technological and industrial changes is being sparked by artificial intelligence, which is a key driving force behind the advancement of science and technology. Therefore, whether we can take advantage of it is a strategic concern. Consequently, China treats artificial intelligence technologies as a development strategy that enhances comprehensive national competitiveness and highly values their contribution to economic growth. Most importantly, a national strategy for building an innovative and powerful country in science and technology should include artificial intelligence. As part of China's Made in China 2025 initiative to become a manufacturing power, the State Council emphasized intelligent manufacturing as one of five major projects. Over the next three years, the Ministry of Industry and Information Technology will develop a new generation of artificial intelligence industry, as announced in 2017 by the Ministry of Industry and Information Technology. In the report, agglomeration areas for the artificial intelligence industry are being explored as a means of encouraging breakthrough development of the industry. Artificial intelligence is a new science and technology and application system that researches and develops theories, methods and technologies that simulate, extend and expand human intelligence (Wang, 2019; Liu et al., 2020). With the rise of new technologies and concepts such as artificial intelligence in various industries, various industries have gradually transformed into digitalization, intelligence, and automation, and entered a new stage of modern industry. At the same time, one of the major scenarios for the application of artificial intelligence technologies is the industrial robot, which are intelligent machines that can be controlled, repeated, and accomplished with multiple objectives, replacing humans in repetitive, complex, and time-consuming tasks (International Federation of Robotics [IFR], 2020). Traditional industrial robots only replace some tedious manual labor with robots and become an extension of human physical strength. Still, the intelligence level of robots is not enough to complete some relatively easy work.

In contrast, integrating artificial intelligence technology makes up for this shortcoming. The addition of artificial intelligence makes industrial robots respond in a similar way to human intelligence, giving the robot new vitality so that it can not only replace most of the manual labor of humans, but also take the place of the mental labor based on the program setting, improve production efficiency, and significantly reduce factory production costs. Therefore, with strong national policy support, industrial robots are rapidly adopted in production and manufacturing. In this case, a noteworthy question is whether the rapid expansion of "quantity" is accompanied by the simultaneous improvement of "quality". Therefore, improving urban productivity is of important practical significance for our country to encourage the thorough integration of industrial robots and the actual economy and develop the urban economy at a high level of quality.

The application of industrial robots has become an essential power source to promote China's transformation from a "major manufacturing" to a "manufacturing power". Industrial robots are intelligent machines that can be controlled, repeated, and accomplished with multiple objectives, replacing humans in repetitive, complex, and time-consuming tasks. Industrial robots can be controlled, repeated, and executed automatically. According to the IFR (2020), about 2.7 million industrial robots are used worldwide, which makes a world record. As shown in Figure 1, 783000 industrial robots were in use in Chinese factories as of

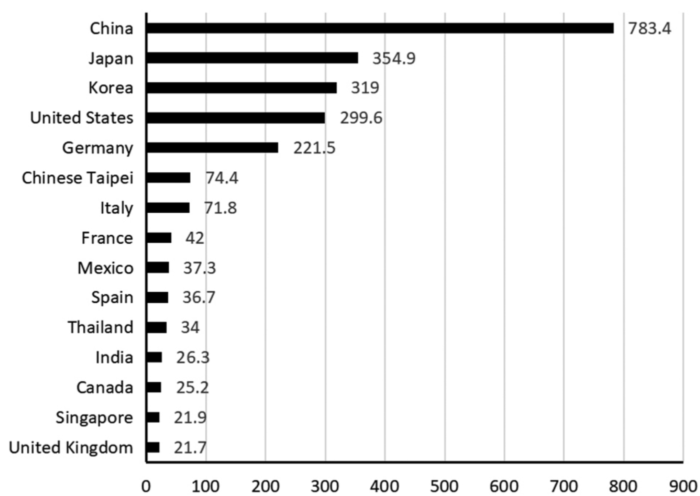

Figure 1. Cumulative installation of industrial robots in the top 15 countries (source: IFR, 2020)

the end of 2019, with more than 140000, an increase of nearly 21% compared with 2014. The chairman of IFR said that the global industrial robot market is currently dominated by China, with the most significant new imports in the world.

While stepping into the new normal, China is also faced with the practical problem of decreasing marginal returns to capital, labor, land, and other factors. Total factor productivity (TFP) is the output excluding capital, labor and land. High-quality development and medium and high growth rates can be achieved by improving TFP. Furthermore, China's TFP growth rate has slowed or even declined during the past decade (Huang et al., 2019). According to statistics, from 2005 to 2007, a total factor productivity growth rate of 3.7% was recorded in China on an annual basis. However, total factor productivity's average yearly growth rate fell to 1.8% from 2007 to 2013, at the lowest point of 0.96% in 2012 (Wang et al., 2013). Academics and industry are interested in how industrial robots affect urban total factor productivity since improving total factor productivity has always fueled economic growth in China and the world. Compared with the previous studies, there are several contributions to this paper.

First, several existing studies investigate the impact of income gaps, industrial structures, and structural changes on urban TFP without considering technological innovation, such as the application of industrial robots (Krüger, 2008; Bárány & Siegel, 2018; Beugelsdijk et al., 2018; Amri et al., 2019; Van Neuss, 2019). In cities that improve total factor productivity quickly, most cities introduce more industrial robots adoption (Zhao et al., 2022). Although estimating robots has significant practical value for urban total factor productivity, it has not been thoroughly discussed in the previous literature. This paper enriches the research on urban TFP using industrial robots as a framework for investigating urban TFP.

Second, this paper not only calculates and analyzes the TFP of cities from the perspective of industrial robots, but also includes manufacturing agglomeration, productive service industry agglomeration, and their collaborative agglomeration, which are easily overlooked and essential factors facing China's economic transformation in the analysis framework. This is also the theoretical implications that distinguish this study from previous studies.

Finally, we discover that spatially heterogeneously using industrial robots in cities affects total factor productivity. For example, western underdeveloped areas benefit more from industrial robots than eastern developed areas when it comes to improving urban TFP. The findings of this research not only contribute to the high-quality potential for urban economic growth in China, which is defined by urban total factor productivity, and policy recommendations for advancing the coordinated application of industrial robot use and urban economy, this is also the practical implications that distinguishes this study from previous studies.

2. Literature review and theoretical framework

2.1. Literature review

After reviewing existing literature, there will continue to be a lot of controversy in the academic community for a long time to come about how China's total factor productivity can be developed and changed (Brynjolfsson et al., 2019; Acemoglu & Restrepo, 2018a, 2018b, 2020; Petralia, 2020; Pan et al., 2022; Luo et al., 2022). The focus is on whether new technology can effectively increase total factor productivity for a long time. Industrial robots are an important application field of China's emerging technologies to promote the improvement of TFP. The research on the impact of industrial robot use on TFP mainly focuses on the following two categories (Brynjolfsson et al., 2019; Acemoglu & Restrepo, 2018a, 2018b, 2020; Petralia, 2020). According to one view, by increasing work efficiency and reducing labor costs, industrial robots can increase TFP. Chinese total factor productivity will substantially increase by applying the Internet, big data, artificial intelligence, and blockchain technologies (Pan et al., 2022; Luo et al., 2022). First, industrial robots will promote technological progress, significantly enhancing total factor productivity (Acemoglu & Restrepo, 2018a). Second, applying industrial robots to replace unskilled workers is conducive to increasing total factor productivity by improving enterprise production efficiency (Acemoglu & Restrepo, 2018b). Third, industrial robots are conducive to achieving the refinement and precision control of the product production process, reducing adequate labor time, improving management efficiency and product quality, and thus promoting total factor productivity (Acemoglu & Restrepo, 2020).

However, there is an opposing view that artificial intelligence is incapable of generating rapid economic growth and does not increase total factor productivity in a significant way (Brynjolfsson et al., 2019). Scholars who hold the opposite view believe that industrial robots suppress total factor productivity. Promoting total factor productivity with industrial robots, but the conclusions are biased because of measurement errors in production efficiency. For example, the multi-factor productivity of the science and technology industry brings comprehensive indicators such as output, labor, and capital into the growth analysis framework and finds that the contribution to total factor productivity growth is 10.9%, rather than the official 3.1% (Petralia, 2020). It is found that industrial robots do not promote total factor productivity, which may be caused by misexpectations and lag in factor reorganization. Additionally, there may be a time delay effect caused by industrial robots on TFP growth (Brynjolfsson et al., 2019).

The above views are hotly debated, but neither is backed up by empirical evidence. However, it is also possible to find studies that the relationship between industrial robot application density and total factor productivity was U-shaped (Du & Lin, 2022). The conclusions of the existing studies are quite different or even opposite. This provides valuable insight into industrial robot adoption's role in developing high-quality urban economies.

2.2. Theoretical framework

By adopting industrial robots, production efficiency can be directly improved and enhanced by integrating them with traditional production factors. Furthermore, robotics can accelerate the improvement of total factor productivity when the demand for other factors increases rapidly (Acemoglu & Restrepo, 2018b). Next, we mainly analyze the mechanism by which the industrial robots affects urban TFP from several aspects, including urban innovation at the urban level, industrial agglomeration at the industrial level, and technological progress and efficiency (by decomposing urban total factor productivity). Urban innovation aims to optimize resources through intelligent methods using industrial robots at the urban level, create new economic growth points, improve the conversion rate of innovation achievements, and thus stimulate innovation vitality. Industrial agglomeration is from the industrial level, focusing on the use of industrial robots that require the use of platforms for production and operation, and then the use of massive data for prediction to improve quality and improve processes. It can better meet the needs of data storage and analysis in production, effectively achieve connectivity between infrastructure and public services, and promote maximum utility.

2.2.1. Urban innovation

With the rapid development of information technology, the deep integration of industrial robots and the real economy has infused new vitality into the advancement of the city's innovative development (Caragliu & Del, 2019). The industrial robots can accelerate the innovation of network information technology, optimize resources through intelligent methods, create new economic growth points, reduce "asymmetric" public services, promote enterprises to achieve "customer-driven" innovation research and development, improve the conversion rate of innovation results, and stimulate innovation vitality, thereby promoting urban innovation (While et al., 2021).

Since Solow's pioneering research, people have recognized the positive impact of innovation in promoting economic development (Solow, 1957; Aghion et al., 2009). As a result of innovation, urban development can improve total factor productivity and become more sustainable (Saleem et al., 2019; Pan et al., 2022). Although, in theory, innovation has a particular opportunity cost and spillover effect, according to empirical analysis, urban innovation can be said to be a recombination of factors of production, technological conditions, and mode of production. It is reflected in the continuous improvement of high-quality labor and scientific and technical investment, resulting in more technological achievements. Interactions between them result in changes in economic development modes and urban total factor productivity improvements. Therefore, we put forward hypothesis 1:

H1. *Robot adoption may promote urban total factor productivity through urban innovation.*

2.2.2. Industrial agglomeration

Industrial agglomeration is the carrier for microeconomic subjects to engage in technological innovation or efficiency improvement activities. This is because its supporting capacity determines the efficiency of technological progress or technical efficiency improvement to a large extent (Wei et al., 2020; Ramachandran et al., 2020).

First, high-tech industries such as industrial robot research and development need to generate a large amount of data with the help of platform production and operation, and then use massive data for prediction to improve quality and processes. Second, industrial agglomeration is a robust bearing platform for high-tech industries, including industrial robot adoption research and development, which can better meet the data storage and analysis in production and effectively realize the connectivity of infrastructure and public services. Third, promoting factor sharing, optimal allocation of resources, and utility maximization may improve urban total factor productivity (Ge & Chang, 2021).

Second, through urban development, the manufacturing industry, producer services, and collaborative agglomerations that are associated with them gradually developed, fostering the healthy development of the application of the industrial robotics industry through its deep integration with other sectors (Nguyen & Nguyen, 2018). Meanwhile, by integrating AI talents,, and cooperative communication, geographical industrial agglomerations can realize knowledge, technology, and information spillover among different enterprises and then the growth of urban TFP will be induced. Therefore, we put forward hypothesis 2:

H2. *Through industrial agglomeration, robot adoption could improve urban total factor productivity.*

2.2.3. Technological progress and technical efficiency

Progress in technology and technical efficiency is essential for total factor productivity (Du & Lin, 2022). By dividing TFP into technical progress and technical efficiency, this paper explores the influence mechanism of industrial robot adoption on urban TFP.

From the perspective of scientific and technological development, first of all, the use of industrial robots has made a lot of understanding and scientific and technological investment, especially the research and development of basic chips. The manufacturing process of the application of industrial robotics involves a series of technical links, such as equipment improvement, program, algorithm breakthrough, process control, etc. In particular, China's transformation from the first generation robot to the second generation industrial robotics, along with technological breakthroughs, service intelligence, and super bright-end transformation, contains a lot of technological progress. Second, industrial robotics brings knowledge and technological progress through the "learning by doing" effect (Roszko-Wójtowicz et al., 2019). With the wide use of industrial robots in actual production, a huge amount of raw data has been produced. Extensive data analysis helps enterprises produce valuable data and information and develop new knowledge from the data. Meanwhile, the application of industrial robotics based on mobile internet has to some extent, reduced the cost of information between different regions and firms, strengthened the connections between enterprises in different regions, and thus promoted technological progress between different enterprises (Huang et al., 2019; Du & Lin, 2022).

In terms of technological efficiency, compared with manual manufacturing, the use of industrial robots has become more intelligent and easy to manage. First, the use of industrial robots to replace those repetitive and low-skilled employees reduces the labor costs of enterprises and helps to improve the efficiency of capital allocation and economic benefits of the company (Dakpo et al., 2019). Second, in the production process, industrial robots can help enterprises realize decision-making, analysis, and design more quickly, ensure refined management work, and achieve an advanced production process, thus improving management efficiency and promoting enterprise production efficiency. Third, the robots adoption can grasp the situation of the consumer side through big data to meet consumers' demand for product quality and diversification. At the same time, they can match supply with demand, promote the practical configuration of means of production and products, and then promote product upgrading (Rawat & Sharma, 2021). As a result of the above analysis, we propose hypothesis 3:

H3. *Robot adoption might increase urban total factor productivity by advancing technology and improving technical efficiency.*

In Figure 2, we can see the theoretical framework of the mechanisms illustrated with diagrams.

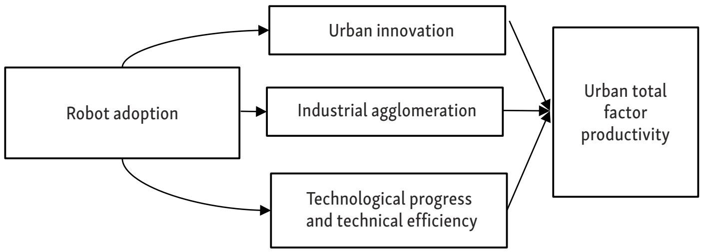

Figure 2. The mechanisms of robot adoption on urban TFP

3. Model, variables description and data

3.1. Model

Are they aiming at the research question raised in this paper: How do industrial robots affect urban total factor productivity? This paper establishes the following econometric model.

$$TFP_{it} = \alpha + \beta_1 \text{Robot}_{it} + \beta_2 X_{it} + \lambda_i + \mu_t + \varepsilon_{it}, \tag{1}$$

where i represents the city and t represents the year. TFP_{it} represents total factor productivity. Robot_{it} represents the application of industrial robots, which is the core explanatory variable. β_1 is the coefficient to be estimated for the impact of industrial robot application on urban total factor productivity, and it is the estimated coefficient focused on in this paper. X_{it} represents a set of control variables to minimize the impact of omitted variable bias. λ_i represents the urban fixed effect, μ_t represents the year fixed effect, and ε_{it} represents a random disturbance term.

3.2. Variables description

3.2.1. Total factor productivity (TFP)

Output indicator: Gross domestic product (GDP). The data is derived from Chinese urban Statistical Yearbook from 2003 to 2017 (National Bureau of Statistics in China, n.d.), and the nominal GDP of each year is converted into real GDP with 2002 as the base year.

Input indicators: The input indicators selected in this paper are capital and labor. The labor input indicator adopts the data of employees in the whole society, which is represented by the sum of employees in the unit and private individuals. The calculation method of capital stock is the perpetual inventory method, and the specific formula is shown in Equation (2) :

$$K_t = I_t + (1 - \delta_t) K_{t-1}. \tag{2}$$

It mainly involves three essential indexes in the calculation process: base share capital, price index and depreciation rate. According to the availability of data, we take the year 2002 as the base period, and the base capital stock at the city level is determined by the fixed capital stock of each province in 2002 according to the proportion of each city in the total social fixed asset investment of each province in that year. The capital stock at the provincial level is converted to the municipal level according to the city size to determine the base capital stock at the city level. In addition, the period estimated in this paper is from 2003 to 2017, and the capital stock at the provincial level in 2002 (Zhang, 2008). Investment in fixed assets adopts provincial fixed asset investment price index where prefecture-level cities are located, which was reduced to the same price in 2002. We assume a depreciation rate of 9.6% (Zhang, 2008).

The radial DEA model can't effectively solve the invalid value caused by the relaxation problem. Based on this theoretical defect, the Slack Based Measure (SBM) model directly introduces the relaxation variable into the production function, which can effectively solve the relaxation problem in the DEA model. The implementation process is as follows:

$$\min p = \frac{1-\frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{ik}}{1+\frac{1}{q}\sum_{r=1}^{q} s_r^+ / y_{rk}}; \tag{3}$$

$$\text{s. t} \quad \begin{aligned} X\lambda + s^- &= x_k \\ Y\lambda - s^+ &= y_k \\ \lambda, s^-, s^+ &\geqslant 0 \end{aligned}. \tag{4}$$

Where p represents the efficiency value of the evaluation decision-making unit, and m and q represent inputs and outputs, respectively. X and Y respectively represent the input and output matrix of the decision-making unit; s^- and s^+ represent the slack variables of input and output, respectively. If both are 0, there is neither input redundancy nor output deficiency. λ represents the weight coefficient of input and output.

Under the premise of constant returns to scale, the decomposition of total factor production efficiency into technological changes and technological efficiency changes better reflects the technological efficiency changes of the research object. Therefore, the use of this method has been vigorously promoted and applied in many fields (Dakpo et al., 2019). Considering the Slack Based Measure (*SBM*) model, this article will use this method to analyze changes in total factor productivity. Therefore, Total factor productivity (*TFP*) can be divided into technological progress (*TC*) and technical efficiency change index (*EC*) (Wang & Feng, 2021):

$$TFP(m^{t+1}, n^{t+1}, m^t, n^t) = \frac{D^{t+1}(m^{t+1}, n^{t+1})}{D^t(m^t, n^t)} \times \sqrt{\frac{D^t(m^{t+1}, n^{t+1}) \times D^t(m^t, n^t)}{D^{t+1}(m^{t+1}, n^{t+1}) \times D^{t+1}(m^t, n^t)}}; \tag{5}$$

$$EC = \frac{D^{t+1}(m^{t+1}, n^{t+1})}{D^t(m^t, n^t)}; \tag{6}$$

$$TC = \sqrt{\frac{D^t(m^{t+1}, n^{t+1}) \times D^t(m^t, n^t)}{D^{t+1}(m^{t+1}, n^{t+1}) \times D^{t+1}(m^t, n^t)}}, \tag{7}$$

where $D^t(m^t, n^t)$ is the decision unit in period t, $D^t(m^{t+1}, n^{t+1})$ is the decision unit in period $t + 1$; $D^{t+1}(m^t, n^t)$ and $D^{t+1}(m^{t+1}, n^{t+1})$ are the decision unit in period t and $t + 1$.

3.2.2. The application of industrial robots (Robot)

The core explanatory variable is the application of industrial robots (Acemoglu & Restrepo, 2018a, 2018b, 2020; Huang et al., 2022; Li et al., 2022), which reflects the distribution density of industrial robots at the city level, that is, the number of industrial robots per thousand people. The data used here comes from the International Federation of Robotics (IFR, n.d.), and the calculation formula is as follows:

$$\text{Robot}_{st} = \sum_{i \in I} l_{si}^{t} \frac{R_i^t}{L_i^t}, \tag{8}$$

where $l_{si}^{t} = L_{si}^{t} / L_{s}^{t}$, l_{si}^{t} denotes the number of employment in i industry of s area during t period. R_i^t indicates the number of robots in the i industry during the t period. L_i^t represents the total number of national employment in the industry i of period t. R_i^t / L_i^t denotes robot density at the national level in industry i of period t. We can get the robot density of s area in period t by adding up the robot density of all related industries in s area.

3.2.3. Industrial agglomeration

As for industrial agglomeration, we adopt the location entropy method to measure manufacturing agglomeration (*magg*) and producer service agglomeration (*sagg*), and its calculation formula is:

$$agg_i = \left(q_i / q\right) / \left(Q_i / Q\right), \tag{9}$$

where, agg_i represents the agglomeration index of manufacturing or producer services; q_i is the number of employees in an industry in the city i, and q is the number of employees in this industry nationwide. Q_i is the number of employees in the city i, and Q is the total number of employees in the country. Therefore, the calculation formula of collaborative agglomeration between the manufacturing industry and producer service industry ($coagg_i$) is as follows (Aleksandrova, 2020; Wang et al., 2022):

$$coagg_i = 1 - \frac{| magg - sagg |}{magg + sagg} + magg + sagg. \tag{10}$$

3.2.4. Control variables

Referring to relevant literature, we have selected the following control variables (Du & Lin, 2022; Huang et al., 2022; Li et al., 2022). Economic development level (*pgdp*), which is expressed as the proportion of GDP to registered population; Government intervention (*gov*), which is measured by the proportion of fiscal expenditure to GDP; Human capital (*human*), which is expressed by the number of college teachers and students per 10,000 people; Financial efficiency (*fe*), which is represented by the proportion of loans to deposits of financial institutions at the end of the year; Foreign direct investment (*FDI*), which is expressed as the proportion of foreign direct investment to GDP; Unemployment rate (*unem*), which is defined as the proportion of registered unemployed people in urban areas to registered population.

3.3. Descriptive statistics

The main variables and descriptive statistics are shown in Table 1 and Table 2, respectively.

Table 1. Description of primary variables

Variables	Code	Unit	Data description
Total factor productivity	TFP	–	It is calculated based on equations (3) and (4).
The application of industrial robots	Robot	–	It is calculated based on equations (5).
Economic development level	pgdp	Yuan/person	The proportion of GDP to the registered population.
Government intervention	gov	%	The proportion of fiscal expenditure to GDP.
Human capital	human	–	The number of college teachers and students per 10,000 people.
Financial efficiency	fe	%	The proportion of loans to deposits of financial institutions at the end of the year.
Foreign direct investment	FDI	%	The proportion of foreign direct investment to GDP.
Unemployment rate	unem	%	The proportion of registered unemployed people in urban areas to the registered population.

Table 2. Descriptive statistics of main variables

Variables	Obs.	Std. dev.	Min	Mean	Max
TFP	3953	0.9803	0.0272	0.6651	1.0835
Robot	3937	2.2012	0.9776	0.0583	5.5599
pgdp	3953	10.0591	0.8901	6.6378	13.1558
gov	3953	0.1759	0.1808	0.0154	3.7289
human	3953	0.0141	0.0169	0.0000	0.1411
fe	3953	1.2555	0.6371	0.0793	6.5784
fdi	3953	0.0044	0.0151	0.0000	0.3809
unem	3953	0.0063	0.0054	0.0000	0.1154

4. Empirical results

4.1. The evolution of urban total factor productivity and industrial agglomeration

4.1.1. The evolution of urban total factor productivity

We calculate the total factor productivity (TFP) index of 286 cities from 2003 to 2017 according to equations (2)–(7), and the results are shown in Figure 3.

As can be seen from Figure 3, from 2003 to 2017, China's TFP and its components (that is, the index of scientific and technological progress) showed a gradual increase. The overall urban TFP index was between 0.92 and 1, indicating that the general development level of urban TFP was relatively stable, with the highest development level appearing in 2015. However, after 2011, urban TFP gradually tended to increase, indicating that urban TFP increased due to China's emphasis on improving total factor productivity in recent years.

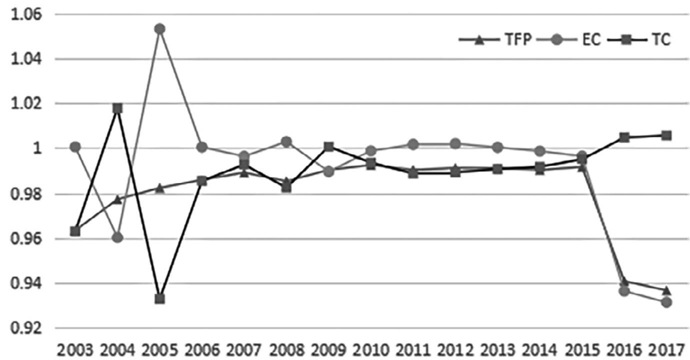

Figure 3. Evolution of total factor productivity from 2003 to 2017

Before 2016, the technical progress index (*TC*) was lower than the technical efficiency index (*EC*) in the observation period globally. However, after 2016, the contribution of *TC* to the TFP was gradually more significant than *EC*, indicating that the emphasis on technological innovation in China promoted the urban technical progress index.

The situation of robots in China in 2015 remained severe, with the most typical being the lack of overall breakthroughs in the core technology of robots. Because industrial robots mainly improve technical efficiency by supplementing and replacing the labor force, thereby improving urban Total factor productivity. From 2016 to 2017, the urban technical efficiency index (EC) and the urban TFP declined similarly. The urban technological progress index (TC) grew slowly, and the urban total factor productivity (TFP) decreased less than the urban technical efficiency index (EC). This indicates that the decline of the urban TFP in 2017 was mainly caused by the decline of the urban EC, And the slow growth of the urban technological progress index (TC). The reason may be the external policy environment or the decline of the industry's capital operation and management level during this period. In March 2016, the "Robot Industry Development Plan (2016–2020)" jointly released by the Ministry of Finance, the Ministry of Industry and Information Technology and the National Development and Reform Commission have mentioned that by 2020, the annual production of China's independent brand industrial robots will reach 100000 units. The yearly output of six-axis and above industrial robots will reach 50000 units. Under policy support and sustainable economic development, urban TFP and Total factor productivity and urban EC still declined in 2017, indicating that external policies do not cause it. Still, internal allocation problems, such as varying degrees of redundancy in using various input factors, and measures such as improving input, optimizing resource allocation, reducing enterprise production costs, and strengthening management are needed.

4.1.2. The evolution of industrial agglomeration

Based on equations (8)–(10), we calculate the correlation between the concentration index of manufacturing and producer services and cities from 2003 to 2017. According to the theory of location entropy, the larger the location entropy index, the higher the industrial agglomeration level. In contrast, the smaller the location entropy index is, the lower the industrial agglomeration level. Figure 4 shows that the manufacturing agglomeration level

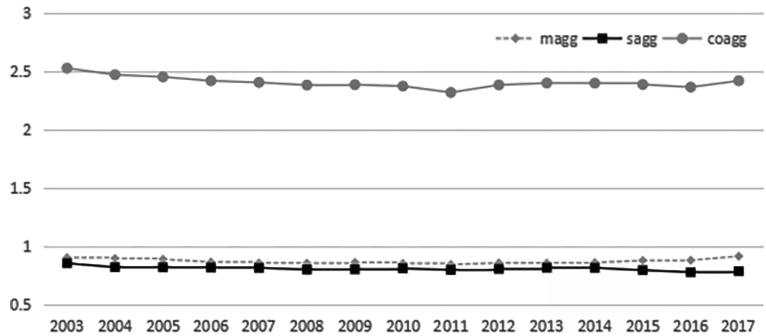

Figure 4. The trend of Industrial Agglomeration from 2003 to 2017

of 286 cities in China from 2003 to 2017 was in a slightly slow fluctuation trend during the sample period. However, after 2013, it was somewhat rising, indicating that the manufacturing agglomeration development was relatively gentle.

Alternatively, producer services are agglomerating in the opposite direction. Still, the overall agglomeration level is slightly lower than that of the manufacturing industry, which shows a slight downward trend after 2013. Manufacturers and producer services, however, have relatively high levels of collaborative agglomeration, which was in a downward trend from 2003 to 2011. Still, it is in an upward trend after 2011. The above evolution aligns with the general characteristics of China's transition economy and the evolution law of advanced industrial structure. Especially since 2011, the increasing degree of collaboration between manufacturing and producer services shows that China has made great progress. Meanwhile, in this process, the coordinated development of manufacturing and services is gradually established, which also creates a good industrial foundation for high-quality development and a new round of reform and opening up.

4.2. Basic results

To examine the impact of industrial robots on urban total factor productivity, we adopt a fixed effects model to estimate Equation (1), and the results are shown in Table 3. Column (1) reports the results of only controlling for city and year fixed effects, while columns (2)–(7) report the results of adding the corresponding control variables are reported in turn. We take column (7) as the reference for discussion. The results show that at the statistical level of 1%, the estimated coefficient of robots is significantly positive, indicating that the application of industrial robots improves the urban total factor productivity. Therefore, it is necessary to optimize further the ecological environment of talents who "come from far away" and improve urban human capital.

4.3. Endogeneity and robustness test

A possible problem in this paper is that cities with high total factor productivity are more inclined to use industrial robots. That is, cities with high total factor productivity take the initiative to choose industrial robots for production instead of industrial robots, increasing

Table 3. The impact of robot adoption on urban TFP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Robot	0.0142*** (0.0022)	0.0091*** (0.0017)	0.0090*** (0.0015)	0.0089*** (0.0015)	0.0089*** (0.0015)	0.0089*** (0.0015)	0.0090*** (0.0016)
pgdp		0.0188*** (0.0018)	0.0111*** (0.0022)	0.0114*** (0.0023)	0.0115*** (0.0023)	0.0125*** (0.0023)	0.0125*** (0.0024)
gov			–0.0363*** (0.0075)	–0.0360*** (0.0075)	–0.0361*** (0.0075)	–0.0374*** (0.0082)	–0.0375*** (0.0082)
human				–0.0370 (0.0337)	–0.0391 (0.0339)	–0.0576* (0.0342)	–0.0555 (0.0346)
fe					0.0015 (0.0011)	0.0017 (0.0011)	0.0018 (0.0012)
fdi						0.0059 (0.0155)	0.0065 (0.0156)
unem							–0.0821 (0.0807)
_cons	0.9360*** (0.0045)	0.7750*** (0.0173)	0.8495*** (0.0204)	0.8466*** (0.0212)	0.8444*** (0.0214)	0.8342*** (0.0222)	0.8349*** (0.0223)
City-FE	YES	YES	YES	YES	YES	YES	YES
Year-FE	YES	YES	YES	YES	YES	YES	YES
N	4131	4130	4129	4129	4127	3951	3937
R^2	0.4662	0.5097	0.5325	0.5326	0.5320	0.5546	0.5533

Notes: Robust standard errors clustered at the city level are in parentheses; *, ** and *** denote significance at 10%, 5% and 1% levels, respectively. The same below.

urban total factor productivity. There may be a reverse causality between industrial robot use and urban TFP. We use the instrumental variable method to alleviate the endogenous problems mentioned above. We chose WD-Robot as the instrumental variable and constructed it as follows: The total number of global robots is subtracted from the number of domestic industrial robots, and then the number of urban workers is used as the weight (Acemoglu & Restrepo, 2018b, 2020). Instrumental variables must meet the two assumptions of correlation and homogeneity (Acemoglu & Restrepo, 2018a). Since there are already a considerable number of industrial robots in the world, the use of industrial robots among countries is competitive. On the other hand, the number of industrial robots in other regions is inversely proportional to their own numbers.

In addition, the invention and application of light industrial robots in 2006 were also selected to construct instrumental variables (Du et al., 2010). For the correlation of the instrumental variable, the emergence of light industrial robots is not only a technology shock but also has different impacts on different regions. Because of the fewer restrictions on the application of light industrial robots and the lower relative cost, it is especially suitable for application in religions with weak industrial foundations and lacking industrial capital. Since 2006, the industrial robots in various regions has gradually increased, and a considerable proportion of them are light industrial robots. Like industrial robots, light industrial robots transmit data and information quickly on the internet, and the scale of the network

Table 4. 2SLS estimation results

	(1)	(2)
Panel A: Second-stage estimation		
Robot	0.0159*** (0.0017)	0.0168*** (0.0019)
Controls	YES	YES
City-FE	YES	YES
Year-FE	YES	YES
N	3933	3933
R-squared	0.242	0.199
Panel B: First-stage estimation		
WD-Robot (IV)	–1.8187*** (0.0010)	
Post2006×Industry (IV)		0.0212*** (0.0023)
Controls	YES	YES
City-FE	YES	YES
Year-FE	YES	YES
KP F-statistics	324.27	156.86

can be rapidly expanded, providing faster response speed, richer information content and smarter application mode. For the externality of this instrumental variable, the invention and application of young industrial robots in 2006 can be used as a good natural test. The appearance of light industrial robots is a relatively exogenous technological impact. Therefore, besides the channels of industrial robots, we hold that this instrumental variable is relatively exogenous to urban total factor productivity.

Consequently, we construct the instrumental variable *Post2006×Industry*, where *Post2006* is a virtual variable, indicating whether the external impact of light industrial robots has occurred. The current year is greater than or equal to 2006, and the value is assigned to 1; otherwise, it is 0. *The industry* is the proportion of local industrial output value, representing the difference in industrial base among cities.

The results of instrumental variables are shown in Table 4. The application of industrial robots still positively promotes urban total factor productivity.

4.4. Expand the coverage of industrial robots and help underdeveloped areas

Suppose the application of industrial robots affects urban total factor productivity through technological progress. In that case, the backward areas in the past can enjoy the service of modern technology through the application of industrial robots, thus promoting the urban total factor productivity of these areas. However, while the technology in developed areas is more advanced, the role of the introduction of industrial robots is more "icing on the cake". Therefore, in the empirical study, we consider the influence of different regions, developed and underdeveloped areas and regions with other degree of marketization and study whether industrial robots in underdeveloped areas have a more significant impact on urban TFP.

Specifically, we group the sample by east, middle, west, and northeast to investigate the spatial heterogeneity impact of industrial robot use on urban total factor productivity. Table 5 reports the results. The coefficient of *Robot* in the eastern region on urban total factor productivity pass the statistical level test of 5% and is significantly positive. The coefficient of *Robots* in the middle and western areas is significantly positive at the statistical level of 1%, and coefficients of eastern, central and western regions increase. It indicates that the application of industrial robots in these three regions improved urban total factor productivity, and the promotion effect on the western region is more obvious. However, the application of industrial robots in the Northeast region has no significant impact on urban total factor productivity, possibly due to the severe brain drain in Northeast China in recent years. Compared with other areas, there is a particular gap between high-level talents. Therefore, although industrial robots have a specific first-mover advantage, the industry's overall performance in recent years has been relatively limited.

Table 5. Heterogeneity test: Different regions

	(1)	(2)	(3)	(4)
	East	Middle	West	Northeast
Robot	0.0047** (0.0022)	0.0092*** (0.0029)	0.0139*** (0.0034)	0.0091 (0.0070)
Control	YES	YES	YES	YES
City-FE	YES	YES	YES	YES
Year-FE	YES	YES	YES	YES
N	1266	1167	1021	483
R^2	0.5436	0.5938	0.5133	0.4643

In addition, the level of economic development is different in the region, such as per capita GDP and marketization, can significantly promote total factor productivity growth (Beugelsdijk et al., 2018; Wu et al., 2020). We refer to the "2021 China City Business Charm Ranking List" published by the New First-tier Cities Research Institute, and we divide cities into five aspects: the first is the concentration of commercial resources, the second is the urban hub, the third is the urban activities, the fourth is the diversity of lifestyle, and the fifth is the future plasticity (Tao et al., 2023; Lan et al., 2023; Zhou & Li, 2023). According to all five dimensions[1], we divide groups as follows, cities below the median are backward areas, and cities above the median are developed areas[2] (Cui et al., 2023). For marketization, the current literature usually adopts the marketization index to characterize the marketization process, and we use the marketization index to measure the marketization degree by grouping the median. According to Fan et al. (2012), regarding the calculation of the marketization index,

[1] Please see the https://www.datayicai.com/ for details.

[2] According to our calculations, there are a total of 337 cities on the 2021 China City Business Charm Ranking List, with a median ranking of 169th.

we define the maximum and minimum provincial values of each positive primary indicator in the base period year as 10 points and 0 points, respectively (for negative indicators, 0 points and 10 points respectively), and determine their scores based on the relative positions of the indicator values in each province's base period year with the maximum and minimum indicator values, thus forming the corresponding primary index for that indicator. The five aspect indices are combined to form a marketization index, which reflects the relative marketization process in different provinces based on the base year. To avoid data incompatibility in additional years due to changing the weight of indicators, the arithmetic mean method is used to calculate each sub-index and aspect index for the latest marketization index over the years, thus maintaining the comparability of cross-year data[3]. Cities below the median have a low degree of marketization, while cities above the median have a high degree of marketization (Fan et al., 2011; Zhang, 2021).

In Table 6, columns (1)–(2) present results of industrial robots' impact on total factor productivity in backwards and developed regions, while columns (3)–(4) present results of industrial robots' impact on total factor productivity in markets with low and high levels of marketization. In regions with varying levels of economic development, there is typically heterogeneity in the induced effects of industrial robot use on urban TFP growth. Among them, industrial robots have played a huge role in promoting the development of underdeveloped areas. In addition, in areas where the level of marketization is not high, the use of industrial robots can significantly improve urban TFP. The above results show that applying industrial robots will help underdeveloped areas.

Table 6. Heterogeneity test

	(1)	(2)	(3)	(4)
	Backward region	Developed region	High degree of marketization	Low degree of marketization
Robot	0.0079*** (0.0020)	0.0028 (0.0026)	0.0049** (0.0021)	0.0007 (0.0021)
Control	YES	YES	YES	YES
City-FE	YES	YES	YES	YES
Year-FE	YES	YES	YES	YES
N	2045	1892	1993	1944
R^2	0.5726	0.4770	0.4714	0.5419

4.5. Mechanism analysis

4.5.1. Urban innovation

First, the use of industrial robots, through scientific and technological innovation, promote the gathering of new industries and new technologies, enhance their innovation ability and competitiveness, thus promoting the economic growth of a region. Therefore, this project

[3] For more detailed calculation methods, please refer to "China marketization index: report on the relative progress of marketization in various regions in 2011", Fan et al., Economic Science Press, Beijing, China, 2011).

will take the number of patent applications per 10,000 people as an independent variable to study whether it can enhance the city's innovation power and then improve its TFP. The data on urban innovation vitality comes from the China City and Industrial Innovation Report 2017 (Kou & Liu, 2017). Table 7 shows the impact of industrial robots on urban innovation vitality in columns (1)–(4). Statistically, the coefficient of robots on patents with different types is significantly positive at the statistical level of 1%, indicating that industrial robots will boost urban innovation vitality, which also verifies hypothesis 1.

Table 7. Mechanism analysis: Urban innovation

	(1)	(2)	(3)	(4)
	Applied patents	Invention patents	Utility model patents	Appearance design patents
Robot	9.0755*** (1.9109)	1.1532*** (0.3295)	4.6834*** (1.1262)	3.2389*** (0.6292)
Control	YES	YES	YES	YES
City-FE	YES	YES	YES	YES
Year-FE	YES	YES	YES	YES
N	3937	3937	3937	3937
R^2	0.2999	0.2217	0.3278	0.1608

4.5.2. Industrial agglomeration

Through industrial agglomeration, which includes manufacturing, production service industry clusters, and industrial clusters, it is possible to grow urban TFP through learning, correlation and competition effects. To test hypothesis 2, columns (1)–(3) of Table 8 present the estimations of industrial robots' use in manufacturing, production service industry and their cooperative agglomeration, respectively. At the 1% statistical level, *Robots* are significantly associated with manufacturing agglomeration and collaborative agglomeration. On the contrary, in statistics, the contribution of robots to the aggregation effect of the service industry is obviously negative. The research results show that the use of industrial robots can effectively promote manufacturing agglomeration, manufacturing and production service industry linkage aggregation, and have a radiation effect on it. Under the superimposed effect of the promotion of industrial robot technology, productive services radiate outward, and then promote the collaborative agglomeration of the manufacturing industry, which is conducive to alleviating the imbalance of China's industrial structure and promoting the improvement of TFP in various regions of our country. The model tests hypothesis 2.

4.5.3. Technical progress and technical efficiency

Further decomposition of urban TFP into technological progress and technical efficiency is used to examine how industrial robots contribute to urban TFP. The effect of industrial robots on urban TFP is then studied. As can be seen from the column (4) of Table 8, statistically, applying industrial robots to improve technical efficiency yields a significant increase in technical efficiency at the statistical level of 1%. Column (5) of Table 8 shows that the coefficient is significantly positive at the statistical level of 1%.

The reasons for promoting technical efficiency and technological progress by applying industrial robots may be as follows: firstly, through robots adoption, the substitution of labor by industrial robots means technological progress, especially the substitution of low-skilled labor. Furthermore, R&D and production of the robot industry have high technical requirements, and the entire industrial robot industry will promote the technological level of other related industries. Secondly, robot adoption helps improve the technical level of the production process. Finally, robot adoption through reconstruction and reorganization, optimal resource allocation, and improving management efficiency to improve the scale efficiency play a constructive role in advancing technical efficiency. This also confirms hypothesis 3.

Table 8. Mechanism analysis

	(1)	(2)	(3)	(4)	(5)
	magg	sagg	coagg	Technical progress	Technical efficiency
Robot	0.3840*** (0.0260)	–0.0805*** (0.0198)	0.3095*** (0.0263)	0.0078*** (0.0015)	0.0013*** (0.0003)
Control	YES	YES	YES	YES	YES
City-FE	YES	YES	YES	YES	YES
Year-FE	YES	YES	YES	YES	YES
N	3937	3937	3937	3937	3937
R^2	0.4668	0.0274	0.2064	0.7438	0.9304

5. Conclusions and policy implications

5.1. Conclusions

According to this paper's econometric findings, the application of industrial robots fosters the increase of urban TFP. The results mentioned above are still valid when considering the model's endogeneity. Mechanism analysis shows that industrial robots may improve urban TFP by stimulating innovation vitality, boosting industrial agglomeration, and improving technological progress and technical efficiency. According to these results, industrial robots have played a major role in boosting China's urban economy's quality development.

5.2. Policy implications

The policy implications are as follows:

First, the industrial robots should be moderately expanded according to each city's factor endowment and industrial development reality to advance the growth of urban TFP more significantly. Support for industrial robot development through policy, optimize the industrial structure, raise the bar for human capital, advance modern education, foster the creation of industrial robots, promote the industrial robots and depth fusion, and play a better industrial robot lead role to the city's total factor productivity. While introducing an industrial robot development support policy to cultivate and create a good development environment for industrial robot development.

Second, considering the particularity of different regions and economic development levels, industrial robots, policy optimization, and industrial layout should be adopted. Therefore, a regional industrial robot industry development strategy should be implemented to enhance urban total factor productivity to complete regional coordination and superior regional economic development.

Finally, it is necessary to promote the deep integration of manufacturing and producer services and to improve their concentration level in order to increase urban total factor productivity through industrial robots. You can achieve this by integrating industrial robots into the supply chain, the value chain, and the industrial chain. For high-quality economic development, a government must emphasize the positive effect industrial agglomeration has on urban TFP.

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Data availability

All data included in this study are available upon request by contact with the corresponding author.

Conflict of interests

The authors have no conflicts of interest to declare that are relevant to the content of this article.

Compliance of ethical standard

The authors have declared that no competing interests exist.

This article does not contain any studies with human participants performed by any of the authors.

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