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Robot Imports and Employment Location Choice:

Evidence From the Survey of Labor Dynamics in China

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ABSTRACT

As the "pearl at the top of the manufacturing industry," the widespread use of robots is affecting the employment decisions of individual workers. This paper contributes to our understanding of this subject by analyzing the impact of imports of industrial robots on employment location choice at the inter-provinces level in China. The analysis applies a logit approach to microdata from the China Customs Database and China Labor Dynamics Survey. The results suggest that robot import positively affects employment location choice, supporting the theory of "coexistence" between intelligent robots and the labor force. Specifically, industrial robots attract skilled workers via the creation effect and drive away routine labor via the substitution effect, but the creation effect is greater than the substitution effect. Finally, the authors discuss the channels from the perspectives of "skill-biased" and "routine-biased."

KEYWORDS

China Labor Dynamics Survey, Employment, Floating Population, Import, Industrial Robot, Location Selection, Routine-Biased, Skill-Biased

INTRODUCTION

Modern information technology, such as the internet, big data, and artificial intelligence (AI), has been rapidly developing, and industries taking advantage of AI vias the implementation of robots have been flourishing. To further strengthen the integration of AI into daily life, expand the use of intelligent applications, realize the new development pattern of the "dual circulation" and elevate the growth of the open economy, AI is a significant topic[1] that we cannot ignore.

AI is inseparable from the robotics industry, which forms the core of intelligent manufacturing. Given that it is a prominent trend in global automation and that China is going through an important period of intelligent transformation of manufacturing, the industrial robotics market seems to be booming. According to the Chinese Institute of Electronics and the International Federation of Robotics

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(IFR), China's industrial robot sales reached $5.73 billion in 2019, up 5.7% year-on-year; these sales account for about one-third of the global market share, making it the largest industrial market for robot applications in the world.[2] According to the *China Robot Industry Development Report* (2022), the operating revenue of China's robot industry in 2021 exceeded 130 billion yuan, and the output of industrial robots reached 366,000 units, a 10-fold increase over 2015, still ranking the first market. At the same time, the *White Paper on the Development of China's Robotics Industry* points out that the degree of automation in China's manufacturing industry is not high, and the density of industrial robots is still lower than the world average. The domestic industrial robots are mainly concentrated in the middle and low-end product fields, while the industrial robot market in high-end industries is dominated by Japanese, European and American enterprises; moreover, the core components in high-end fields are still mainly dependent on imports. There remains a significant gap between the overall level of local enterprises and foreign advanced technology. To pursue the goals described in the 14th Five-Year Plan regarding economic globalization, develop China's middle and high-end industrial chain, value chain, and international competitiveness, and promote the realization of the "double cycle" of the new development pattern, the National Development and Reform Commission and the Ministry of Commerce jointly revised the "*Catalogue of Industries Encouraging Foreign Investment (2020 Edition)*" on December 28, 2020.[3] This revision encourages foreign investment in advanced manufacturing industries. In the new *Catalogue*, several national entries point directly to the robotics industry, and the development of industrial robots will become the highlight of future foreign direct investment. In 2021, 15 departments including the Ministry of Industry and Information Technology and the National Development and Reform Commission officially issued the *"14th Five-Year Plan" for the Development of Robot Industry* (hereinafter referred to as the *Plan*). According to the *Plan*, China will become a source of global robotics innovation, a cluster of high-end manufacturing and a new plateau of integrated application by 2025.

There's no denying that with the weakening of China's demographic dividend, the widespread use of industrial robots will inevitably lead to the phenomenon of "machines replacing people" (Zhao, 2019). Meanwhile, according to the China Mobility Development Report 2018, the size of China's migrant worker population reached 241 million in 2018, and the migrant worker population is gradually becoming a key driver of regional economic growth. According to the 2010 national census data, the proportion of the urban labor force accounted for by the domestic migrant worker population labor force is about 42%, most prominently in Shenzhen and Dongguan in Guangdong Province and Xiamen and Quanzhou in Fujian Province, where the proportion of the migrant population labor force exceeds 90% and 73%, respectively.[4] It can be seen that the floating population, a very large labor force in cities, has a pivotal influence on local labor markets. These migrant laborers, a considerable number of whom work in labor-intensive industries, are vulnerable to the impact of intelligent robot technology. As trends in location choice for employment change, people will be influenced by many factors, and the ideal location will no longer be limited to the cities traditionally preferred for employment. Will the presence of industrial robots in cities have an impact on the employment and location selection behavior of the floating population? Does the use of industrial robots in cities facilitate the migration of migrant worker populations? This paper examines this central question. The results found that robot import does have an impact on labor employment location. The more imported robots, the more attractive the skilled and non-routine biased workers are, while the routine-biased and unskilled workers will choose to leave these cities. Understanding of how the migrant population decides on employment locations and a study of how industrial robots affect the migrant population's behavior in the context of the new era will help each region in China understand its own labor market allocation and improve resource allocation, which is important for promoting China's regional economic growth. This study also provides empirical evidence for city governments to use while developing policies to attract migrant workers, alleviating the polarization of employment, promoting local economic growth, and improving employment.

LITERATURE REVIEW

The purpose of this paper is to explore how industrial robot imports affect the employment site-selection behavior of migrant workers and thus have an impact on spatial mobility in the labor market. Therefore, this paper reviews and critiques the literature both on the employment site-selection behavior of migrant workers and on robotics, AI, and labor force employment.

Employment Location Choice of the Migrant Population

According to Roback's (1982) spatial equilibrium theory, when workers choose an employment location, the following factors influence their decision making: self-fulfillment, which comes from job opportunities and income, and urban livability, which comes from the natural environment and public services. In terms of job opportunities, the employment options and wage income that a city can provide are often the main factors attracting workers to that city. This observation is supported by Florida's (2004), which found that skilled immigrants tend to move to areas with high levels of social openness, diversity, and creativity. The vast majority of migrants in China gather in the Pearl River Delta, the Yangtze River Delta, Beijing-Tianjin-Hebei and other places, which directly reflects the tendency of the floating population to choose employment addresses. Therefore, Wei et al. (2020) pointed out that when a city introduces a large number of industrial robot production lines, it will inevitably mean an increase in the demand for advanced skills and the corresponding job opportunities, while the demand for low-level skills and the corresponding job opportunities decrease, thus affecting the employment location behavior of floating population.

The influence of urban livability on workers' choice of employment location depends on both the natural environment and public services of the city. Rappaport (2007) found that cities with better climatic conditions and living environment contribute positively to mobile migration. Graves and Regulska (1982) found that cities with mountains, rivers, lakes and seas are more effective in attracting labor migration. Whisler (2008) found that based on Tiebout's "voting with feet" theory, the labor force tends to work and live in cities with higher quality of life and a more beautiful environment. On the contrary, Sun (2019) found that air pollution has a negative impact on labor migration, and Zhang et al. (2017) found that high urban housing prices also have a certain inhibitory effect on the immigration of skilled immigrants. However, the high cost of living indirectly reflects that the city has high quality schools and a good level of social security. Diamond (2016) argued that in general, migrant workers are willing to bear higher costs to move to cities with better public services.

It is worth noting that the development potential of a city and the job opportunities it can provide are more influential in the employment decisions of the migrant worker population than the livability of the city.

Robotics, AI, and Labor Employment

When it comes to understanding the impact of AI on labor force employment, two main theories dominate the academic community: employment promotion theory and employment hindrance theory.

Employment promotion theory argues that the changes in technology symbolized by the development of robotics do not disrupt the job market, but rather benefit the employment prospects of the workforce. He et al. (2020), it is believed that artificial intelligence has a job-creating effect, and technological progress will create new jobs while replacing some jobs. Nnanna et al. (2021) and Alex et al. (2021) argued that artificial intelligence and other digital technologies can bring huge economic and social benefits and increase employment opportunities for young people. Autor (2015) stated that there are no jobs that are replaced by automation, only jobs that are complementary to automation. Compagni (2015) believed that the impact of the popularization of intelligence on a sector will extend to all sectors of the economy associated with it, thereby promoting the creation of new jobs. Gregory et al. (2016) found that although routine-biased technological did cause employment difficulties for middle-skilled workers in Europe, the spillover effect of demand created more employment opportunities due to the increase in product demand, so that technological progress did not have a negative impact on total employment. When Bessen (2015) used computers as a research object to explore whether employment was impacted, he found that the use of computers did not cause a large number of unemployment, but instead led to the growth of employment in the industry that used a large number of computers. Li (2021) summarized the role of AI in increasing total employment, arguing that technology promotes employment by improving enterprise productivity and social productivity. From the perspective of employment quality, Zhao and Zhao (2017) believed that the popularization of intelligence creates more leisure time and reduces the work intensity of the labor force, which is conducive to improving the employment quality of laborers.

In contrast, employment hindrance theory views AI technology as a critical factor driving job market losses; such views are particularly prevalent among the traditional manufacturing industries. The research of Autor and Dorn (2013) demonstrated that the automation technology used in intelligent development promotes the improvement of productivity level, eliminates low-skilled laborers in industrial manufacturing, thus leading to the decline of total employment. Karabarbounis and Neiman (2014) pointed out that since the 1990s, the share of labor income in national income has shown a downward trend, and this decline was the result of the rapid decline in the relative price of ICT and labor. The research pointed out that the income of low-skilled and low-educated workers in countries such as the United Kingdom, the United States and Germany has been declining over the past few decades, which shows that technological progress has had a significant negative impact on the employment of low-skilled worker groups. Susskind's (2015) study also confirmed this view. Sachs et al. (2015) and Acemoglu and Restrepo (2017) emphasize that the use of industrial robots will cause unemployment and lower wages and negatively impact the quality of the labor market. By analyzing the characteristics of various occupations in China, Chen et al. (2018) found that more than 70% of the total employed population would be impacted by robots and artificial intelligence. Zhao (2019) believes that artificial intelligence cannot clearly influence the total employment in the short term, but there is asymmetry in the demand for labor with different skills, which aggravates the employment polarization problem.

In fact, scholars focus the impact of robot applications on the labor market for a long time and there is a voluminous literature on the subject. There are relatively few empirical studies about the employment market, however, and very little literature examines the employment site-selection behavior of the labor force from a micro-perspective. Even fewer studies focus on international imports of industrial robots. Therefore, compared with the existing literature, the marginal contribution of this paper lies in the following two areas.

The first is the innovative research perspective. Unlike most studies that explore the impact of robot applications on the labor market and its total volume and size from a macro-perspective, this paper takes a micro-perspective on the labor force and uses highly segmented micro-data to analyze the stock of the mobile labor force in each region to understand the changes in employment location decisions of migrant worker population under the surge of robot imports.

The second is the innovation in variable selection. This paper proposes new variables to stand as proxies for industrial robot applications. Using the robot imports data in the customs database and the data of the total industrial output value of the secondary industry in the Chinese industrial enterprise database, the number of inter-provincial industrial robot imports is obtained as a proxy for the level of manufacturing digitization, and it is used as the core explanatory variable. In addition, this paper, from the unique perspective of international trade imports, can provide not only a new view of the relationship between robots and labor force employment, but it can also enrich the relevant literature in the field by measuring the impact of domestic labor force spatial mobility by the application of intelligent robots more clearly and provide valuable practical suggestions for the government in formulating employment security policies.

The third is the innovation of the mechanism. This paper adopts the skilled-biased effect and the routine-biased effect to play a moderating role in the impact of robot import on the employment and location behavior of floating population. That is to say, the relationship between the import of robots and the employment and location behavior of the floating population is often affected by the skills of individual laborers. Robot technology has a skilled-biased feature, which attracts skilled labor to migrate to cities where robots are imported more and are more widely used. In addition, it is also affected by routine-biased work, that is, the more routine-biased jobs, the higher the possibility of robot importation. It is difficult for routine-biased workers to coexist with robots and will choose to leave the city rationally. Non-routine biased workers can complement robots, so they are more inclined to move to the city.

STYLIZED FACTS AND MECHANISMS

Intelligent Robotics Applications and the Job Market in China

According to statistics regarding industrial robots released by the International Federation of Robotics (IFR) in 2020, about 71% of the industrial robots in China are supplied by foreign robotics companies, and the cumulative installation of domestic industrial robots has reached 783,000 units,[5] ranking first in Asia, with an annual growth rate of 21%, much higher than the global average. Figure 1 shows the numbers of imported industrial robots for multifunctional machines in China between 2012 and 2017, and it can be clearly seen that the overall trend is positive. Therefore, as the areas for application of industrial robots continue to expand, the labor market will face greater opportunities and challenges.

According to the data of China Migrants Dynamic Survey (CMDS), Zhejiang, Jiangsu, Guangdong, Shanghai, and Beijing are provinces with large net population inflows, while Anhui, Jiangxi, Henan, Hunan Province and Sichuan Province are provinces with a large net outflow of population, but the above-mentioned provinces basically show a slowing trend in terms of population inflow and outflow. Figure 2 reflects the data of the net inflow of population in each province from 2014 to 2016. It is not difficult to find that there are huge differences in attracting floating population between provinces.

How do robots affect the labor market in China? Will the "machine substitution" or "machine expansion" effect drive the employment and location selection behavior of the floating population?

Figure 1. Number of multifunctional industrial robots imported to China (HS84795010), 2012-2017

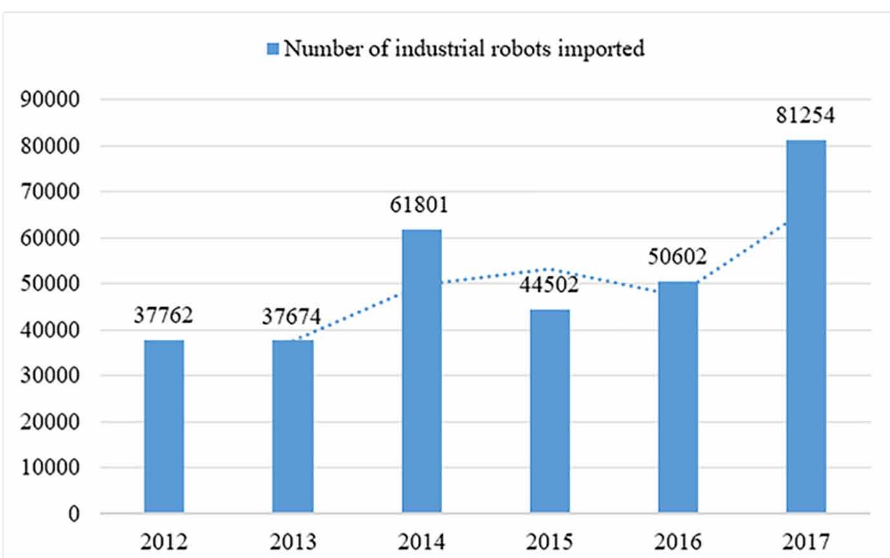
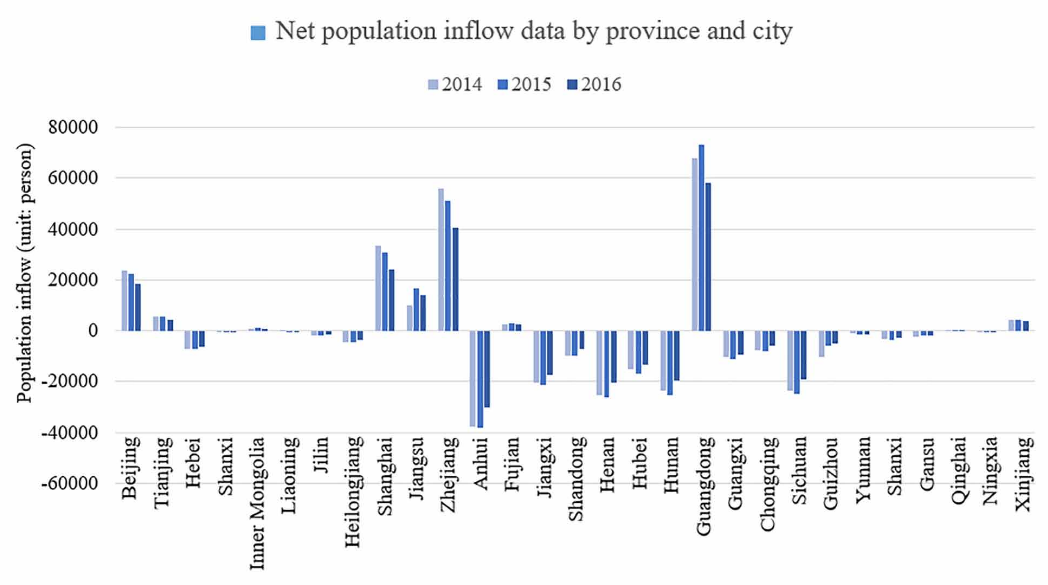


Figure 2. Net population inflow data by provinces and cities, 2014-2016 (China Migrants Dynamic Survey, 2014)



The China Development Report 2018 shows that the size of China's migrant worker population reached 241 million in 2018, and in terms of geographical scope, the Pearl River Delta, Yangtze River Delta, Beijing-Tianjin-Hebei Region, the middle reaches of the Yangtze River, and the Chengdu-Chongqing urban agglomerations are the main gathering places for the floating population.[6] As for the employment location choice of the labor force, according to the *2020 China College Student Employment Report*, the proportion of college graduates choosing to work in new first-tier cities increased from 22% in 2015 to 26% in 2019, while the proportion of graduates choosing to work in first-tier cities decreased from 26% in 2015 to 20% in 2019. In addition, 38% of the 2019 college graduates who chose to work in the new first-tier cities come from foreign provinces, up 10% from 28% in 2015, and the gap is gradually narrowing compared to first-tier cities, with 68%. As emphasized in the *Report*, the proportion of migrant workers in central cities is decreasing and the proportion of migrant workers in non-central cities is increasing.

Thus, the ideal employment location of the contemporary labor force is gradually shifting from former first-tier cities to new first-tier cities, demonstrating the new situation of "ideal employment city sinking." As a very large labor force in a city, the migrant population has a significant influence on the local labor market. These migrants, many of whom work in labor-intensive industries, are vulnerable to the impact of intelligent robot technology.

Mechanism Analysis of Effect of Robot Imports on Location of Labor Force Employment

In this paper, the effect mechanism of robot imports on the employment of the floating population is summarized as "Skill-Biased Technological Changes" and "Routine-Biased Technological Changes."

Skilled-Biased Technological Changes

Regardless of whether the application of AI creates a demand for labor with different work abilities, a theory that once dominated in economics is the "Skill-Biased Technological Changes" (SBTC) hypothesis. Bao (2017) proposed that jobs with high flexibility, complexity, and creativity and that require situational interactions are difficult to replace with AI, as are jobs requiring logical reasoning and creative ability, such as R&D personnel and development engineers. In addition, some lower-level jobs requiring social and emotional skills, such as caregiving and community work, are also not easily replaced. Thus, the widespread use of robots will further enhance the employment level of these positions, so the impact of robot imports on labor force employment will be moderated by SBTC, which is consistent with Duan (2018). Using provincial panel data from 2012-2020, Ming and Hu (2022) explored the impact of robots on labor with different skills, and found that robots promoted the employment of highly skilled labor and realized their coexistence. Based on this, the authors argue that the relationship between robot imports and the employment location selection behavior of the migrant population tends to be influenced by the skills of individual laborers. Robotics has skill-biased characteristics that attract skilled laborers to cities with more robot imports and more extensive applications.

Routine-Biased Technological Changes

According to the characteristics of industrialized firms, scholars have proposed a new hypothesis based on "skill-biased technological changes", namely "routine-biased technological changes (RBTC)". This hypothesis makes up for the defect of the default mapping relationship between task and skill in SBTC hypothesis. In fact, task is a kind of work activity, while skill is the ability endowment of workers to engage in various tasks. Autor et.al (2003) found that computers can perform repetitive tasks by setting specific programs, which have a degree of substitution utility for programmed tasks and complementary utility for non-programmed tasks. Autor et.al (2006) explained the decline in employment and wage levels in the American labor market by explaining that the substitution effect of ICT for programmed work has led to a reduction of many procedural work carried out by the middle income class. Thus, for the recurrent population, the relationship between their employment site-selection behavior and robot import is influenced by procedural jobs, i.e., the more procedural jobs there are, the higher the likelihood of robot import, which in turn can have an impact on workers engaged in such jobs.

Therefore, the employment decisions of micro-workers regarding advanced technologies such as robots usually depend on a contest between technology and skills; in other words, the interaction between robots' and workers' capabilities and their job content can influence the employment site-selection behavior of migrant workers through both SBTC and RBTC, mainly from the substitution between robot imports and the labor force. Robots achieve coexistence with skilled workers through the creation effect and are repelled from programmed labor through the substitution effect, attracting employment from non-programmed labor, thus promoting the inflow of skilled labor and repelling the migration of programmed workers.

DATA, VARIABLES, AND MODEL

Data Sources

This paper explores whether the import of industrial robots affects the employment location of the labor force and involves three main data sources.

1. Data regarding the importation of industrial robots came from the China Customs Database. According to the definition of IFR (2014), industrial robots refer to "multi-purpose machines and equipment that can be automatically controlled and repeatedly programmed in three or more axes"; imported industrial robots can, to a certain extent, be regarded as a reflection of the application of robotics in Chinese industrial enterprises. The classification of industrial robots is based on the HS Code of Customs, and the industrial robots included in the statistics are mainly divided into two categories. The first category code is 84795010, which denotes multifunctional industrial robots, and the second category code is 84795090, which includes other industrial

robots. Based on this, this paper selects the import data of these two types of industrial robots from the Chinese Customs Database for a total of three years from 2014-2016 at the national level, with the main indicator being the number of imports.

2. Data on industrial enterprises above the scale were obtained from the China Industrial Enterprise Database and the National Bureau of Statistics of China. At the provincial level, data regarding industrial enterprises in 29 provinces except Hong Kong, Macao and Taiwan, and Hainan and Xizang were selected, covering the total import and export volume, gross domestic product, number of industrial enterprises, level of industrial employment, and gross output value of the secondary industry for each province in 2014, 2015 and 2016; this data formed the basis for later calculations of the number of industrial robot imports, trade openness, and other control variables.
3. Labor migration data were obtained from the China Labor-Force Dynamic Survey (CLDS) conducted by the Social Science Research Center of Sun Yat-sen University. The survey focuses on the current situation of and changes to China's labor force. The sample covers 29 provinces and cities in China (except Hong Kong, Macao, Taiwan, Tibet, and Hainan), which is nationally (regionally) representative, and the survey targets all workers aged 15–64 in the sampled households. In the CLDS, the migrant worker population is defined as the population that spans administrative units at the county level and above and has resided continuously in an area for six months or more. A total of three surveys were conducted, in 2012, 2014, and 2016. In this paper, we investigated whether imported industrial robots from 2014-2016[7] affected the employment site-selection behavior of the labor force, so we selected two versions of CLDS 2014 and 2016, retaining only the cross-provincial mobile labor force population sample that covered 29 provinces and cities in China (except Hong Kong, Macao, Taiwan, Tibet, and Hainan) during the three-year period from 2014 to 2016. Some samples with missing values in the questionnaire were excluded when processing the migrant worker population data. Finally, the sample sizes of population flow from 2014 to 2016 were 283, 154, and 87, respectively, and the sample cities involved in the floating population were 27, 22, and 16, respectively.

Model Setting and Variables

We refer to the existing literature that offers research methods on migrant worker employment location choice (Sun et al., 2019) and use a conditional logit model to identify the impact of imported industrial robots on migrant worker location choice decisions. The specific empirical model is set as follows:

$$Choice_{ijt} = \alpha_0 + \alpha_1 Robot_{jt} + Z_{jt} + \mu_i + \delta_t + \varepsilon_{ijt}$$

The subscript *i* represents the individual migrant worker, *j* represents the province and city of employment, and *t* represents the year. $Choice_{ijt}$ denotes whether migrant worker individual *i* chooses province and city *j* as the employment location in year *t*. The core explanatory variable $Robot_{jt}$ denotes the industrial robot imports in province and city *j* at year *t*. Z_{jt} denotes the economic characteristics variable of province and city *j* at year *t* also is the control variable. The data used in this paper are mixed cross section data. In order to reduce the influence of missing variables, the individual effect μ_i and the time effect δ_t are controlled simultaneously. ε_{ijt} is the residual term.

Following the survey design of CLDS, the sample provinces and cities were divided into six different strata as follows: eastern provinces with a large population, central provinces with a large population, western provinces with a large population, eastern provinces with a small population, central provinces with a small population, and western provinces with a small population. The hierarchical distribution of sample provinces and cities is shown in Table 1.

The variables in this paper are designed as follows:

1. **Explained Variable:** The explained variable $Choice_{ijt}$ indicates whether individual *i*, the migrant worker, chooses province and city *j* as the place of employment in year *t*. It is a dummy variable. If one chooses to go to province and city *j* for employment, then $Choice_{ijt}$ takes the value of 1; if individual *i* chooses not to go to province or city *j* for employment, then $Choice_{ijt}$ takes the value of 0. All the sample provinces and cities included in the 2014 and 2016 versions of CLDS are selected as alternative provinces and cities for possible employment locations of the migrant worker, and each migrant worker *i* and each alternative province and city *j* are treated as one observation, so the actual number of observations is equal to the product of the sample number of migrant worker and the sample number of provinces and cities. *J* represents the number of alternative provinces and cities for employment, and there are a total of 29 provinces and cities except for Hong Kong, Macao and Taiwan, Tibet and Hainan—that is, the value of *j* is 29. The data structure of the conditional logit model is shown in Table 2.

Table 1. Provincial and municipal level distribution table

Hierarchy Distribution	Province Name
Eastern provinces with small population 1	Beijing, Fujian, Liaoning, Shanghai, Tianjin, Zhejiang
Eastern provinces with large population 2	Guangdong, Jiangsu, Shandong
Central provinces with small population 3	Anhui, Guangxi, Hubei, Jilin, Jiangxi, Shanxi, Chongqing
Central provinces with large population 4	Hebei, Henan, Heilongjiang, Hunan, Sichuan
Western provinces with small population 5	Gansu, Ningxia, Xinjiang
Western provinces with large population 6	Guizhou, Inner Mongolia, Shaanxi, Yunnan, Qinghai

Table 2. Data structure of the conditional logit model

Sample	Mobility *i*	Alternative Provinces and Cities *j*	Select Results $Choice_{ijt}$
1	1	1	1
2	1	2	0
...	...	...	0
J	1	*J*	0
J+1	2	1	0
J+2	2	2	1
...	...	...	0
2*J*	2	*J*	0
...	...	...	...

The probability that migrant worker *i* chooses to go to city *j* for employment is:

$$Prob\left(Choice_{ijt}=1\right)=\frac{\exp\left(\alpha_0+\alpha_1 Robot_{jt}+\beta Z_{jt}+\varepsilon_{ijt}\right)}{\sum_{j=1}^{J}\exp\left(\alpha_0+\alpha_1 Robot_{jt}+\beta Z_{jt}+\varepsilon_{ijt}\right)}$$

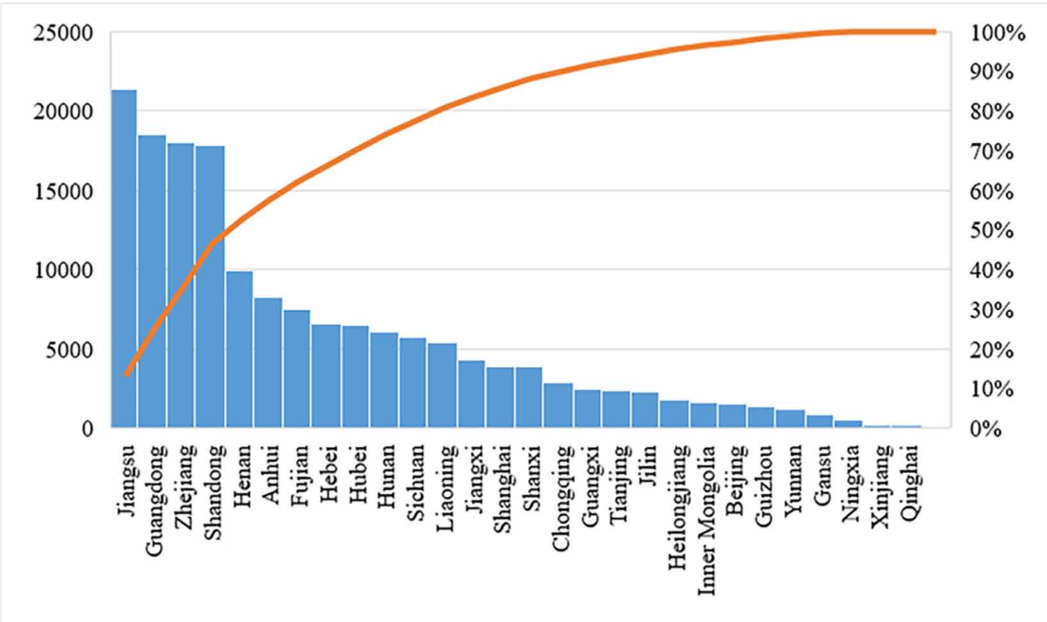
2. **Core Explanatory Variable:** The core explanatory variable $Robot_{jt}$ denotes the number of imported industrial robots in province and city *j* at year *t*. Since the data from the General Administration of Customs of China records only the import data of industrial robots at the national level from 2014 to 2016 and lacks data at the provincial level, we drew on the prevailing approach in the established literature (Wei et al., 2020) to calculate the import density of industrial robots at the provincial level through the Bartik instrumental variable method, to represent the reflection of robot technology applications in Chinese industrial enterprises. First, we selected the data regarding gross industrial output value of the secondary industry from the Database of Chinese Industrial Enterprises and related them with 29 provinces one by one to obtain the gross industrial output value data of the secondary industry in 29 provinces from 2014 to 2016. Then we selected a base year and used 2014 as an example to calculate the proportion of the total industrial output value of each province in the base year to the total national output value. Based on this, we further calculated the import quantity of industrial robots in this province in this year. The specific calculation method is as follows:

$$Robot_{jt}=\frac{Company_{jt}}{\sum_{j=1}^{J}Company_{jt}}\cdot Robot_t$$

$Robot_t$ denotes the total number of domestic industrial robots imported in year I, the $Company_{jt}$ denotes the number of industrial enterprises above the scale in province and city *j* in year *t*, and *J* is the total number of sample provinces and cities. After the calculation, it is possible to know the distribution of industrial robots imported in various provinces and cities in China in different years. The results show that the most prominent provinces and cities for industrial robot imports are Jiangsu, Zhejiang, Shandong, and Guangdong. and all of them are concentrated in the eastern part of China. The distribution of robot imports in each province and city is shown in Figure 3.

3. **Control Variables:** Many other factors need to be considered when exploring the employment site-selection behavior of the migrant worker population. Therefore, in the process of empirical analysis, we need to include the economic characteristics of cities as control variables, such as GDP per capita representing the level of local economic development, scale of investment introduction, and population density. Variables such as industrial value added and industrial employment were also selected to reflect the scale of the local industrial industry. Since the employment site-selection behavior of the migrant worker population is also affected by the quality of the local environment, provincial and municipal green coverage rate is further selected as a control variable. In order to control the influence of individual characteristics, we also included individual characteristic variables such as age, gender, foreign language proficiency, education level and household registration nature in the subsequent empirical research. We did not choose to include individual characteristics such as "whether to migrate" and "whether to have cross-county migration experience for more than half a year", because "whether to migrate" is a result variable and a bad control variable. The variable "whether there is cross-county flow experience for more than half a year" contains many missing values. Therefore, in order to ensure the stability and

Figure 3. Provincial and municipal distribution of robot imports



effectiveness of sample results, we did not include these two variables in the regression model. In the CLDS data from 2014 and 2016, the sample numbers of migrant worker population for 2014, 2015, and 2016 were 283, 154, and 87 respectively, totaling 524. In addition, the number of inflow provinces involved in each year is 29, and the overall number of samples available for research is 15,196.

The specific definitions of the migrant worker population characteristic variables and provincial and municipal characteristic variables involved in this paper and their descriptive statistics are shown in Tables 3 and 4, respectively. When processing the sample data of migrant worker population, we normalized the samples with missing values.

ESTIMATION

Baseline Estimation

We first inspected the impact of provincial and municipal imports of industrial robots on the location of employment for migrant workers, using an empirical estimation with a heteroskedasticity robust conditional logit; the benchmark estimation results are shown in Table 5. Only the core explanatory variable—the number of industrial robots imported—is included in column (1) of Table 5, and economic characteristics variables and industrial characteristics variables at the provincial level are included in column (2), including four control variables of GDP per capita, the size of capital attraction, industrial value added, and the number of people employed in industrial industries, to minimize the bias caused by omitted variables. Column (3) further considers the impact of control variables affecting quality of life, such as urban green environment and population density, on employment location choice.

From the estimated results in column (1), the estimated coefficient of industrial robot imports is 4.691 and the result is significant at the 1% level. According to the estimation results in column (2),

Table 3. Descriptive statistics of the characteristics variables of the migrant population

Variable Name	Definition	Number of Observations	Average Value	Standard Deviation	Minimum Value	Maximum Value
Age	Age (years)	524	37.06	12.46	20	73
Gender	Gender: Male=1, Female=0	524	0.500	0.500	0	1
Eng	Knowledge of foreign languages: Yes=1, No=0	524	0.292	0.455	0	1
Edu	Highest Education: Master's degree, undergraduate degree, college = 3. General high school, secondary school, technical school, vocational high school = 2. Elementary/private school, junior high school or below = 1	524	1.655	0.855	0	3
Resi	Household nature: Non-agricultural household = 1, agricultural household = 0	524	0.172	0.378	0	1
Migr	Whether the household is moved: Yes=1, No=0	524	0.193	0.395	0	1
Fluid	Whether there is cross-county mobility experience for more than six months: Yes=1, No=0	142	0.817	0.388	0	1

after adding GDP per capita, the size of capital attraction, industrial value added, and the employed population in industrial industries as control variables reflecting the economic and industrial situation, the estimated coefficient of industrial robot imports decreases in absolute value, but the result is still significant at the 5% level. Compared to column (2), column (3) further considers provincial and municipal green coverage and population density, and the absolute value of the estimated coefficient of industrial robot imports decreases but remains significant at the 5% level. This indicates that, all else being equal, for each additional unit of industrial robots imported by a province or city, the probability of the migrant worker choosing to be employed in that province or city will increase by 4.15%, which means that there is an employment-promoting effect of industrial robot imports on the employment location of the migrant worker population. Thus, robot imports promote the employment location willingness of the migrant worker population, and the productivity effect of robots is more dominant than the substitution effect. The widespread use of industrial robots positively affects the labor employment market of provinces and cities by creating new jobs, thus absorbing more migrant workers and changing the labor market structure, increasing the spatial inflow of migrant workers.

According to the estimation results in column (1), the estimated coefficient of industrial robot import is 0.327, and the result is significant at the 1% level. According to the estimation results in column (2), the estimated coefficient of industrial robot imports changes from positive to negative after adding the per capita GDP, scale of investment introduction, industrial added value and industrial employment reflecting the economic and industrial conditions as control variables. When we further control the individual characteristic variables and provincial fixed effect, the coefficient of robot imports changes to positive. As shown in column (4), it indicates that if the influence of omitted variables is not controlled, the coefficient of robot import will have a bias toward zero. Column (5) controlled the individual characteristics, province fixed effect and time fixed effect. The estimated coefficient of industrial robot import increased to 3.481, which was significant at the level of 10%.

Table 4. Statistical description of provincial and municipal characteristics variables

Variable Name	Definition	Number of Observations	Average Value	Standard Deviation	Minimum Value	Maximum Value
Choice	Whether the migrant population chooses the province or city	15,196	0.0345	0.182	0	1
Openness	Total imports and exports/GDP	15,196	0.0435	0.0478	0.00483	0.198
Ln(Robot)	Industrial robot imports, take logarithm	15,196	6.933	1.229	3.766	9.011
Ln(Rgdp)	Provincial and municipal GDP per capita, take logarithm	15,196	10.81	0.394	10.17	11.68
Ln(Invest)	The scale of investment, take the investment amount of foreign direct investment enterprises, and take logarithm	15,196	11.17	1.353	8.038	13.69
Ln(Plus)	Industrial value added, take logarithm	15,196	9.033	0.797	7.096	10.47
Ln(Emp)	Number of people employed in industrial sectors, take logarithms	15,196	5.342	0.983	2.738	7.080
GR	Greening coverage rate of urban built-up areas	15,196	0.391	0.0360	0.298	0.484
Ln(People)	Provincial and municipal population density, take logarithm	15,196	7.885	0.404	7.043	8.613
Ln(Air)	Air quality, take tons of sulfur dioxide emissions, take logarithm	15,196	12.72	0.970	8.500	14.12
Ln(LSW1)	Provincial first monthly minimum wage standard, take logarithm	15,196	7.280	0.130	7.060	7.690
Ln(Comp)	Number of industrial enterprises, take logarithm	15196	8.851	1.221	5.861	10.79
Ln(Inn)	Combined utility value of regional innovation capacity, take logarithm	15196	3.308	0.339	2.759	4.075

Meanwhile, compared with regression (1) - (4), regression (5) explained the sum of squares increased and the model fit was better. The result of benchmark regression shows that, under the same other conditions, if the import of industrial robots increases by 1%, the probability of floating population choosing to work in the province will increase by 3.481%, which means that the import of industrial robots has a promoting effect on the employment location of floating population, and the application of regional robot technology will not reduce the willingness of individuals to work in the region. Compared with the substitution effect, the productivity effect of robots should play a more dominant role, that is, the extensive application of industrial robots absorbs more floating population by creating new jobs, changes the structure of the labor market, increases the spatial inflow of floating population, and has a positive impact on the labor market of provinces and cities.

At the same time, the estimated results of the control variables can reflect the results of the existing literature studies. Taking the standard monthly minimum wage as an example, the income level of developed regions is higher, so people are more inclined to choose the regions with more developed

Table 5. Conditional logit estimation results of robotics influencing employment location choice for migrant workers

	(1)	(2)	(3)	(4)	(5)
Ln(Robot)	0.327***	-0.132**	-0.130**	2.265**	3.481*
	(8.17)	(-2.00)	(-1.97)	(2.06)	(1.90)
Ln(Rgdp)		-2.735***	-2.721***	-5.495	-7.096
		(-7.92)	(-7.87)	(-1.19)	(-1.25)
Ln(Invest)		0.605***	0.598***	-0.500	-0.900
		(4.00)	(3.95)	(-0.52)	(-0.82)
Ln(Plus)		1.109***	1.109***	6.610*	6.937*
		(3.87)	(3.86)	(1.94)	(1.90)
Ln(Emp)		0.297	0.301	-0.347	-0.669
		(1.01)	(1.02)	(-0.24)	(-0.43)
GR		0.731	0.771	15.653	14.295
		(0.29)	(0.31)	(0.98)	(0.87)
Ln(People)		0.481***	0.479***	0.341	0.464
		(2.84)	(2.83)	(0.41)	(0.55)
Ln(Air)		-0.498***	-0.496***	0.987**	0.935**
		(-6.70)	(-6.65)	(2.49)	(2.32)
Ln(LSW1)		4.697***	4.731***	-0.230	-0.754
		(6.97)	(7.02)	(-0.14)	(-0.42)
Personal Features	NO	NO	YES	YES	YES
Province FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	NO	YES
Observations	14,387	14,387	14,387	14,387	14,387
Chi2	71.99	767.04	769.42	1104.19	1105.10
Pseudo r-squared	0.0207	0.2206	0.2212	0.3175	0.3178

Note: Standard errors are in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Same below.

economic level and higher living standard as the ideal employment places. The value of industrial value-added reflects the production activities of industrial enterprises. The more productive the industrial enterprises are, the more the regions can create new jobs, promote employment, and drive the development of local employment levels, thus attracting the migration of other migrant workers.

Robustness Test

To verify the reliability of the findings further, the following efforts were made in this study. We conducted three robust estimation methods: first, from an econometric approach, we used Poisson regression and negative binomial estimation to examine further the impact of industrial robot imports on the location of labor force employment in industrial sectors; second, from a model setting perspective,we conducted a test of the independence of irrelevant alternatives assumptions (IIA) (McFadden, 1974) to justify the validity of the empirical model.And finally,from a variable perspective, we used an instrumental variable approach to replace the variables to overcome potential endogeneity problems as much as possible.

Poisson Regression and Negative Binomial Regression Estimation

Since Poisson regression and negative binomial regression are like logit regression in that they can handle models in which the dependent variable is a dichotomous variable, we chose these two regression methods for further analytical validation. Table 6 reflects the results of Poisson and negative binomial regressions, with column (1) for Poisson regression and column (2) for negative binomial regression. Results of both estimations show that the estimated coefficient of industrial robot imports is significantly positive at the 10% level, indicating that industrial robot imports are conducive to attracting more migrant workers into the region for employment. This result is consistent with the previous findings based on micro-individual provincial and municipal employment choices and can corroborate the presence of the creation effect of industrial robot imports on the employment of the migrant workers.

Table 6. Results of Poisson regression and negative binomial regression estimation of the impact of industrial robot imports on employment in industrial sectors

	(1)	(2)	(3)	(4)
	Poisson	**NB**	**Two-Step Poisson**	**Two-Step NB**
Ln(Robot)	3.412*	3.412*	6.026***	6.026***
	(1.88)	(1.88)	(10.59)	(10.59)
Robot_Resid			-1.604***	-1.604***
			(-2.71)	(-2.71)
Ln(Rgdp)	-6.761	-6.761	-8.953***	-8.953***
	(-1.20)	(-1.20)	(-16.39)	(-16.39)
Ln(Invest)	-0.972	-0.972	-1.729***	-1.729***
	(-0.90)	(-0.90)	(-12.58)	(-12.58)
Ln(Plus)	6.789*	6.789*	6.816***	6.816***
	(1.86)	(1.86)	(13.48)	(13.48)
Ln(Emp)	-0.640	-0.640	-0.484***	-0.484***
	(-0.41)	(-0.41)	(-3.02)	(-3.02)
GR	15.191	15.191	9.797***	9.797***
	(0.93)	(0.93)	(5.77)	(5.77)
Ln(People)	0.508	0.508	0.590***	0.590***
	(0.60)	(0.60)	(6.43)	(6.43)
Ln(Air)	0.971**	0.971**	1.086***	1.086***
	(2.41)	(2.41)	(19.95)	(19.95)
Ln(LSW1)	-1.103	-1.103	3.005***	3.005***
	(-0.62)	(-0.62)	(10.68)	(10.68)
Personal Features	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	15,196	15,196	13,187	13,187
Chi2	1085.50	1085.50	39108.78	23515.88
Pseudo r-squared	0.2379	0.2379	0.473	0.352

Unrelated Option Independence Hypothesis Test

In order to make the estimation results of conditional logit more reliable, we adopted the approach of Xia and Lu (2015), and added the independence of irrelevant alternatives assumptions (IIA) (McFadden, 1974). This assumption requires that the ratio of the occurrence probability of any two options is independent of the existence of other options. For example, in this paper, the assumption requires that relative to the province (city) of A, the relative probability of the labor force choosing city B for employment is related to the alternative destination province C (province C). The existence of the city is irrelevant, that is, the estimation results obtained before and after excluding a certain option are statistically consistent. We use the Hausman method to test the reliability of the estimated results of the conditional Logit model. Specifically, for the Beijing-Tianjin-Hebei, Yangtze River Delta and Pearl River Delta regions with obvious floating population characteristics, Beijing, Shanghai, Guangdong and Fujian are respectively excluded sample data for comparison. The results of Hausmann test showed that compared with the estimated parameters of the original sample, the estimated parameters did not change systematically after excluding the data of a certain province, and most chi-square values were very small or negative, which could not reject the null hypothesis, so the results obtained by the conditional Logit model had credibility. There are several tables of Hausmann test results, and the paper is limited in space, so we have attached the test results for display.

Potential Endogeneities and Processing

As known that while the importation of industrial robots by cities certainly affects the employment migration behavior of migrant workers, it is also worth noting that the extent to which cities import industrial robots may also be an adaptive response to labor supply and costs. Thus, the core variable, industrial robot imports, then encounters possible endogeneity problems that must be mitigated by seeking instrumental variables.

Referring to Acemoglu and Restrepo (2020), this paper uses the development frontier of industrial robot technology as the instrumental variable to separate the confounding factors affecting the application of domestic industrial robots. That is to say, the instrumental variable is constructed by using the distribution of industrial robots in various industries of countries with higher application density of industrial robots than China at the same period. Based on the method proposed by Chen (2022), industrial robots located in five countries: the United States, the Netherlands, Portugal, South Korea and Germany, represent the forefront of instrumental variables in the construction of industrial robot science and technology. These five countries have a strong positive correlation with China in the growth of industrial robots. Theoretically speaking, the frontier of robot technology development in the five countries will not affect the employment location of the floating population in China, which satisfies the exogeneity condition of the instrumental variables. In order to avoid possible simultaneous errors, refer to Autor (2013), the values of $Emp_{s,j,t=2013}$, $Emp_{j,t=2013}$ and $Emp_{s,t=2013}$ are measured using the values of one stage lag.

The specific construction form of Bartik tool variables is as follows:

$$Robot_{jt}^{foreign} = \frac{1}{5}\sum_{c}\sum_{s}\frac{Emp_{s,j,t=2013}}{Emp_{j,t=2013}} * \frac{Robot_{st}^{c}}{Emp_{s,t=2013}}$$

$Robot_{st}^{c}$ represents the operation volume of industry s in Country c in t years, $Emp_{s,t=2013}$ represents the employment number of industry s in Country c in 2013, $Emp_{s,j,t=2013}$ represents the employment number of industry s in province and city j in 2013, and $Emp_{j,t=2013}$ represents the total employment number of industry in province and city j in 2013.

Due to the failure of two-stage least square method and correlation test in conditional Logit model, but the results of Poisson and negative binomial regression test are robust, this paper adopts Hilbe (2011) two-step method and uses instrumental variables to carry out two-stage Poisson and negative binomial regression. Specifically, in the first step, OLS estimation of instrumental variables (the frontier of industrial robot science and technology development) and other control variables was conducted using endogenous variables (robot import) to obtain the corresponding residuals. In the second step, the endogenous variables, the residual estimated in the first step and other control variables were used to carry out Poisson and negative binomial regression for the flow number(Zhang, 2019). In Table 6, model (3) and Model (4) respectively reported the results of two-step Poisson regression and two-step negative binomial regression. From the residual coefficient of the two-step regression, Poisson regression and negative binomial regression both passed the 1% significance test, and the coefficients of the two were consistent, indicating that endogenous bias did exist in the previous regression, and it is more appropriate to choose the instrumental variable of the development frontier of industrial robot science and technology. The estimation results of Hilbe two-step method show that the positive influence of core explanatory variables on labor location is still robust after the instrumental variable method.

In conclusion, this robustness check confirms that industrial robot imports drive the productivity level of enterprises and promote the widespread use of intelligent robots. In such a context, labor and robots are capable of coexisting, and although there is a substitution effect of robots on some workers' jobs, the creation effect is clearly superior in the overall context; the use of robotics can have a catalytic effect on the employment of migrant workers by creating more new jobs, thus attracting the transfer of migrant workers to the target provinces and cities.

Heterogeneity Analysis of the Impact of Industrial Robots

This paper examined the impact of industrial robot imports on labor force employment using a conditional logit model and instrumental variables but did not include the factor of individual heterogeneity of the migrant worker population as an influence on decision making. Therefore, to explore more precisely the employment site-selection behavior of the migrant worker population, we incorporated a heterogeneity analysis of the migrant worker population into the discussion.

Differences in Impact by Gender and Age

Obviously, there are natural differences in employment preferences between men and women. Common sense suggests that men prefer to choose jobs with more rational thinking and skills that are more muscle-intensive, while women prefer to think more emotionally and choose skills that are more brain-intensive, so there are bound to be differences in employment location decisions by gender. Age reflects the life cycle of an individual and is also closely related to the stage of career development. Referring to Super's (1980) career development theory, an individual's career development will go through several stages, such as "growth, exploration, fixation, maintenance and decline." Persons aged 16 to 30 are usually in the growth and exploration period of career development, still struggling to cross the threshold of the industry; they have not yet formed a complete career skills system. People aged 31 to 45 are usually at the peak of career development; the content of their work has become fixed and procedural and they have developed a complete career skills system. People aged 46 and above occupy the maintenance and decline period; they lack the ability to adapt to new things. Therefore, different ages imply that workers are at different stages of career development and have different levels of acceptance of new things; thus, the impact of robots on the employment location of the workforce may vary depending on their age. For this reason, we conducted an empirical test.

Table 7 shows the estimated results of the heterogeneity analysis by gender and age. The results in column (1) and (2) show that the estimated coefficient of industrial robot import is significantly negative at the level of 10% of male samples, but not significant in female samples, indicating that

Table 7. Heterogeneity analysis of robot impact (I): by gender and age

	(1)	(2)	(3)	(4)	(5)
	Male	Women	16 to 30 Years Old	31 to 45 Years Old	46 Years Old and Above
Ln(Robot)	-0.171*	-0.145	0.185	-0.337***	-0.347***
	(-1.80)	(-1.51)	(1.42)	(-2.86)	(-2.86)
Ln(Rgdp)	-2.838***	-2.860***	-3.189***	-3.234***	-2.283***
	(-5.51)	(-5.60)	(-4.85)	(-5.25)	(-3.22)
Ln(Invest)	0.515**	0.544**	0.945***	0.568**	0.070
	(2.32)	(2.46)	(3.42)	(2.10)	(0.24)
Ln(Plus)	1.680***	0.645	2.398***	1.870***	0.320
	(4.08)	(1.63)	(3.85)	(3.68)	(0.77)
Ln(Emp)	-0.131	0.954**	-0.918	0.073	1.390***
	(-0.31)	(2.37)	(-1.51)	(0.14)	(3.04)
GR	1.418	0.454	2.657	-4.591	3.468
	(0.40)	(0.13)	(0.58)	(-0.98)	(0.80)
Ln(People)	0.333	0.501**	0.720**	0.516*	0.046
	(1.35)	(2.06)	(2.31)	(1.67)	(0.14)
Ln(Air)	-0.587***	-0.683***	-0.694***	-0.719***	-0.788***
	(-5.04)	(-5.82)	(-4.96)	(-4.64)	(-4.50)
Ln(LSW1)	6.034***	3.865***	4.589***	5.125***	4.601***
	(6.07)	(3.89)	(3.55)	(4.22)	(3.41)
Observations	6,865	6,971	4,739	4,776	3,487
Pseudo r-squared	0.2258	0.2389	0.2820	0.2554	0.1652

industrial robot import has a more obvious exclusion of male, and labor-intensive jobs are easy to be replaced, which reflects the gender difference in industrial manufacturing employment. Columns (3)(4)(5) show the estimation results by age, where only the samples in the age group of 31 to 45 years old and 46 years old above are significant at the 1% level, while the samples in the age group of 16 to 30 years old do not pass the significance test. At the same time, we can also find that the import of robots to 31 to 45 years old and 46 years old and above group exclusion effect is more serious. This suggests that the younger workforce can quickly learn and adapt to new environments and embrace a wider range of jobs beyond the industrial sector, thus mitigating the impact of robot imports to a certain extent. The older workforce is more experienced, and most of them are already engaged in leadership, management, and communication jobs. Their job preferences tend to be more stable and less affected by industrial robots. Therefore, the population at the peak of their career development is more able to perceive the employment boosting effect from industrial robot imports.

Differences in the Impact of Different Foreign Language Level

At present, with the surging trend of internationalization, foreign language level is an important indicator that affects the quality of employment and job opportunities. Therefore, in the heterogeneity analysis of individual education level, this paper adopts two indicators to measure whether one knows a foreign language or not. Table 8 shows the empirical results of heterogeneity analysis.

Table 8. Heterogeneity analysis of robot impact (II): By foreign language level

	(1)	(2)
	Inability	**Ability**
Ln(Robot)	-0.246***	0.043
	(-3.12)	(0.33)
Ln(Rgdp)	-2.875***	-2.619***
	(-6.81)	(-3.85)
Ln(Invest)	0.559***	0.479*
	(3.06)	(1.68)
Ln(Plus)	1.182***	1.502***
	(3.55)	(2.61)
Ln(Emp)	0.365	0.298
	(1.05)	(0.52)
GR	0.266	1.493
	(0.09)	(0.33)
Ln(People)	0.327	0.836***
	(1.57)	(2.67)
Ln(Air)	-0.555***	-0.959***
	(-5.83)	(-5.59)
Ln(LSW1)	4.940***	3.760***
	(6.00)	(2.87)
Observations	9,897	4,010
Pseudo r-squared	0.2248	0.2468

Column (1) and (2) indicate whether the employment location behavior of the floating population is affected by the difference of foreign language level. The results show that the import of robots has a significant negative impact on the floating population who do not know a foreign language, and it is significant at the level of 1%, while the floating population who know a foreign language does not pass the significance test. The results show that the import of industrial robots will crowd out more workers who do not speak foreign languages and exclude the less skilled.

Differences in Impact Across Urban and Rural Areas and Mobility

The employment location choice behavior of the migrant worker population may be influenced by the family of origin and whether an individual has experience with migration. Therefore, we examine the differences in the impact of robot use on employment location choice of the migrant worker population group by splitting the sample between urban and rural households and asking whether they have had experience with household migration.

The conditional logit regression results for the subsample are shown in Table 9, where we can see that there is also a household preference for the employment impact of industrial robot imports on heterogeneous groups. Robot imports have a negative effect on the migrant worker population with agricultural households and are significant at the 10% level, while there is no significant effect on the migrant worker population with non-agricultural households. The last two columns of Table 9 represent the migration experience of heterogeneous groups, and the results show that industrial robot

Table 9. Heterogeneity analysis of robot impact (III): Urban-rural household and migration experiences

	(1)	(2)	(3)	(4)
	Non-Agricultural Household	**Agricultural Household**	**Household Migration Over**	**Household Registration Has Never Been Moved**
Ln(Robot)	-0.194	-0.137*	-0.267*	-0.086
	(-1.37)	(-1.80)	(-1.83)	(-1.12)
Ln(Rgdp)	-0.706	-3.286***	-1.213	-3.132***
	(-0.83)	(-8.31)	(-1.38)	(-7.90)
Ln(Invest)	-0.231	0.760***	-0.120	0.765***
	(-0.65)	(4.41)	(-0.33)	(4.40)
Ln(Plus)	0.262	1.560***	-0.196	1.772***
	(0.53)	(4.50)	(-0.40)	(4.98)
Ln(Emp)	1.273**	-0.022	1.832***	-0.279
	(2.33)	(-0.06)	(3.42)	(-0.78)
GR	3.027	0.365	5.481	-1.008
	(0.60)	(0.13)	(1.08)	(-0.34)
Ln(People)	0.569	0.516***	0.670*	0.494**
	(1.47)	(2.67)	(1.72)	(2.52)
Ln(Air)	-0.644***	-0.562***	-0.684***	-0.524***
	(-3.10)	(-6.79)	(-3.58)	(-5.97)
Ln(LSW1)	3.929**	4.893***	3.498**	5.076***
	(2.52)	(6.38)	(2.27)	(6.52)
Observations	2,390	11,705	2,545	11,538
Pseudo r-squared	0.1301	0.2536	0.1664	0.2479

imports have a significant negative effect on the population whose household has never migrated and is significant at the 10% level, while the population that has never moved a family does not pass the significance test. Thus, we can find that the perceived effect of industrial robot importation is more pronounced for the group of agricultural households and the group without household migration experience, and the impact from the level of intelligent robot development is greater. The population with urban origins and the population whose household registration is not fixed are more likely to migrate to areas with more developed industrial levels and better industrial facilities, while the population with rural origins and does not have migration experience are less likely to be affected by industrial robots. This may be because they would like a more stable life.

Differences in Impact on Sectors

Since industrial robots are widely used in the service industry, some financial and educational industries basically do not come into contact with industrial robots. Therefore, the impact on the migrant worker population is bound to vary depending on their own work industries. We divided the industries in the population sample into industrial manufacturing, service industry, and other industries including science, education, culture, and health; the conditional logit regression results of the subsample are shown in Table 10.

Table 10. Heterogeneity analysis of the impact of robots (IV): Employment sector

	(1)	(2)	(3)
	Industrial Manufacturing	Service Industry	Other Industries
Ln(Robot)	0.628**	0.001	0.523
	(2.20)	(0.00)	(1.55)
Ln(Rgdp)	-5.506***	-2.648*	-0.953
	(-3.84)	(-1.75)	(-0.62)
Ln(Invest)	1.733***	0.990	0.942
	(3.05)	(1.45)	(1.35)
Ln(Plus)	0.790	3.730***	0.114
	(0.44)	(2.81)	(0.07)
Ln(Emp)	1.359	-2.426*	1.551
	(0.85)	(-1.91)	(1.11)
GR	11.201	0.135	-11.688
	(1.21)	(0.01)	(-0.89)
Ln(People)	0.515	1.180	1.648**
	(0.75)	(1.63)	(2.12)
Ln(Air)	-1.477***	-0.944*	-0.790*
	(-3.71)	(-1.84)	(-1.73)
Ln(LSW1)	5.539**	-0.446	-2.824
	(2.14)	(-0.15)	(-0.86)
Observations	2,782	678	869
Pseudo r-squared	0.6378	0.1260	0.3246

The results show that there is an industry preference for the impact of robots on the employment site-selection behavior of heterogeneous groups. The use of robots has a significant positive impact on the migrant worker population employed in industrial manufacturing, which is significant at the 5% level, and the estimated coefficient is greater than that of the total sample. Regarding the migrant worker population's employment site-selection behavior in the service and other industries, the impact is not significant. To conclude, the widespread use of industrial robots can attract the labor force in industrial manufacturing industries to choose employment locally by creating more jobs, and the employment promotion effect of robots on the labor force is more significant; these two points are mutually supportive. These findings are in line with theoretical expectations.

Mechanism Analysis of the Impact of Robot Imports on the Location of Labor Force Employment

The previous section has verified that robot imports have a significant effect on labor force employment location, and this section will further explore the situational mechanisms by which robot imports affect labor force employment location, focusing on both SBTC effect and RBTC effect.

Each adjustment variable is set as follows.

Skill-Biased Technological Changes Effect

This paper uses the method of Sun (2019), the proportion of education level of labor force in total employment in each province (edu), to represents the SBTC effect. Elementary school and below represent Low skill (ledu), middle school, high school and higher vocational representation Medium Skill (medu), and college, junior college and above represent high skill (hedu). The relevant data are obtained from the *Report on Evaluation of Regional Innovation Capability in China.*

Routine-Biased Technological Changes Effect

In this paper, innovation ability is used to measure the RBTC effect. The more robots are imported, the stronger local innovation ability is, and the more non-procedural workers can be attracted. Specifically, technological progress will increase the need for innovative workers, which will encourage the inflow of non-procedural workers. Relevant data are from *China Regional Innovation Capability Evaluation Report.*

Table 11 shows the regression results. Columns (1) to (3) are the moderating effects of low skill, medium skill and high skill, respectively. The results show that the interaction coefficient of "industrial robot imports × low skill labor" is -1.281, and the interaction coefficient of "industrial robot imports × medium skill labor" is significant at the level of 1% in the whole model (1), and the interaction coefficient of "industrial robot imports × medium skill labor" is 2.006. In the full model (2), the interaction coefficient is significant at the level of 1%. The estimated coefficient of the interaction term of "industrial robot import × highly skilled labor force" is 0.843, and in the full model (3), the interaction coefficient is significant at the level of 1%. Specifically, the import of robots promotes the employment of medium-skilled and high-skilled workers and has a crowding out effect on low-skilled workers. This indicates that the relationship between workers' mobile location selection behavior and robot import is largely influenced by their own skills. (4) is listed as the moderating effect of innovation ability. The estimated coefficient of the interaction term of "industrial robot import x innovation ability" is 1.650, and the interaction term coefficient in the whole model (4) is significant at the level of 1%, indicating that the increase of the number of imported robots in a province will improve the probability of non-procedural workers entering the region under the condition of other conditions being unchanged. Robots have an expanding employment effect on non-procedural immigration.

CONCLUSION AND POLICY RECOMMENDATION

This paper uses data from the China Customs Database and the CLDS and combines data from 29 Chinese provinces and municipalities directly under the central government to explore the mechanisms by which imported industrial robots affect the employment location of the migrant worker population. The conclusion of the study is as follows. First, provinces and municipalities with more imported industrial robots are more attractive to the migrant worker population, and the employment promotion of robots dominates over employment inhibition, when all other conditions remain the same. Second, the influence of robots is heterogeneous among the individual characteristics of the floating population. The impact on males is generally higher than that on females. Male groups in the golden age of career development are more affected by industrial robots. High-skilled workers and laborers engaged in industrial manufacturing jobs tend to enter provinces and cities with high levels of the industrial robot imports, and populations with different household registration and migration experiences also have different employment location preferences. Third, with other conditions unchanged, the location of employment of the floating population is regulated by their own skill level and regional innovation level, which verifies the existence of SBTC effect and RBTC effect.

Based on the above findings, this paper proposes the following policy recommendations. First, the government can make full use of the employment advantages of robots to attract more

Table 11. Mechanisms of effect of robot imports on labor force employment location choice

	(1)	(2)	(3)	(4)
Ln(Robot)	3.993***	-8.398***	-2.428***	-5.596***
	(7.66)	(-4.10)	(-4.59)	(-11.16)
Ln(Robot)*Ln(ledu)	-1.281***			
	(-7.81)			
Ln(ledu)	9.307***			
	(8.06)			
Ln(Robot)*Ln(medu)		2.006***		
		(4.04)		
Ln(medu)		-11.094***		
		(-3.16)		
Ln(Robot)*Ln(hedu)			0.843***	
			(4.48)	
Ln(hedu)			-7.149***	
			(-5.44)	
Ln(Robot)*Ln(inn)				1.650***
				(11.28)
Ln(Inn)				-9.129***
				(-7.42)
Ln(Rgdp)	-1.464***	-2.420***	-1.233**	-2.044***
	(-3.93)	(-6.73)	(-2.37)	(-5.64)
Ln(Invest)	0.620***	0.597***	0.727***	0.263
	(3.72)	(4.01)	(4.42)	(1.48)
Ln(Plus)	0.685**	0.476	0.928***	0.508**
	(2.38)	(1.48)	(2.91)	(2.00)
Ln(Emp)	0.149	0.533*	-0.040	0.062
	(0.49)	(1.86)	(-0.13)	(0.22)
GR	5.923**	-0.860	1.685	8.655***
	(2.21)	(-0.36)	(0.65)	(3.11)
Ln(People)	0.351*	-0.130	0.961***	1.344***
	(1.72)	(-0.65)	(4.71)	(6.82)
Ln(LSW1)	4.699***	5.056***	3.635***	1.223*
	(6.67)	(6.87)	(5.39)	(1.84)
Ln(Air)	-0.561***	-0.559***	-0.467***	-0.100
	(-7.32)	(-7.60)	(-5.98)	(-1.01)
Observations	14,387	14,387	14,387	14,387
Pseudo r-squared	0.2412	0.2297	0.2318	0.2690

floating population to move to the local area. In addition, in the case of a large number of imported industrial robots, it is necessary to pay attention to the unemployment problem caused by individual differences of workers, make an overall plan, pay more attention to education, and cultivate more labor force with creativity and communication ability. Second, the floating population should focus on improving their own skills, prepare for the crisis, promote their own comprehensive education and quality improvement, workers engaged in routine work tasks can moderately transfer to the post of non-routine work tasks, expand their employment possibilities, thereby expanding the possibility of fighting alongside intelligent machine technology; Thirdly, enterprises can train employees' professional skills to achieve human-computer interaction, improve the productivity of enterprises, and further attract the inflow of high-quality talents.

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CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

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ENDNOTES

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6 http://finance.eastmoney.com/a/201812221011810028.html
7 Data from the CLDS 2012 version of the questionnaire were excluded because the data on industrial robot imports in the China Customs database that could be obtained contained only the years 2014-2016.

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