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The Impact of Industrial Robots on the Skill-Based Wage Gap

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Abstract

In recent years, with the disappearance of the demographic dividend of the aging society and the requirements for high-quality economic development under the new normal, the application of industrial robots has rapidly advanced in the Chinese market. As an emerging driving force of technological progress, artificial intelligence has its own technological bias, but the existing literature has not paid attention to whether this bias will widen the income distribution gap of labor with heterogeneous skills. Based on this, this paper uses the panel data of 30 provinces from 2006 to 2015 to describe the application level of industrial robots with the import volume of industrial robots, and establishes a macro proxy indicator of skill-based wage gap according to the data of different skill industries to test the industrial robots in the Chinese context, using real effects on skills wage gaps, and conducting an analysis of geographic heterogeneity. In addition, further investigate the mechanism by which intelligent equipment exacerbates the skill-based wage gap, and analyze the possible "substitution effect", "demand effect" and "asymmetric labor productivity effect" of the use of industrial robots on the skilled labor force. The results show that the use of industrial robots has a significant positive effect on the expansion of the skill-based wage gap. The use of industrial robots will exacerbate the wage gap between the high-skilled and low-skilled labor in the market. This effect comes from a combination of three effects: the "substitution effect"—the use of industrial robots will change the skill structure of employment, reducing the proportion of low-skilled workers; the "demand effect"—the use of industrial robots will change to some extent. The increase in demand for high-skilled labor has no significant impact on the demand for low-skilled labor.

Keywords

Industrial Robots, Skill-Based Wage Gap, Labor Productivity, Technology Bias

1. Introduction

At present, the rapid development of artificial intelligence technology has brought profound changes to the world economy. With the rise of knowledge research in related fields such as big data and deep learning, as well as the innovation of computer cloud computing functions and hardware devices, artificial intelligence technology has ushered in a period of rapid development and a wave of applications all over the world. As the most important technical application of artificial intelligence technology, industrial robots have also attracted widespread attention around the world, and have begun to be more and more integrated into industrial production links and show a rapid expansion trend. In 2020, the average density of global industrial robots is 126 units/10,000 workers. Compared with 66 units/10,000 workers in 2015, the global usage of industrial robots has almost doubled in five years. Such a strong momentum has made industrial robots an important representative of Industry 4.0, directly demonstrating the major historical development opportunity of the third technological revolution.

According to the definition of the International Federation of Robotics (IFR), an industrial robot is a machine that can be automatically controlled, reprogrammable, and can complete multi-purpose tasks, is a multi-joint manipulator or a multi-degree-of-freedom machine device for the industrial field. It can realize various industrial processing and manufacturing functions by relying on its own power energy and control capabilities, and can replace humans in some monotonous, complicated and long-term work. The "substitute" and "high efficiency, high precision and high adaptability" of industrial robots actually perfectly fit the current development needs of China.

First of all, the Chinese market in the context of aging faces the problem of labor shortage. Since entering an aging society in 2000, the proportion of my country's population aged 65 and over has reached 11.97% in 2020, and China is about to become a moderately aging country. The "lewis inflection point" has passed, and the era of domestic economic development relying on demographic dividends has come to an end. The change of labor structure and the increase of labor cost have prompted enterprises to continuously improve the level of automation to replace manpower, which has forced the rapid application and development of industrial robots. "Machine substitution", the adverse impact of population aging on the economy and society can be alleviated by robot substitution. By using robots to replace traditional jobs, the economy's requirements for labor input can be reduced, thereby compensating for the adverse impact of insufficient labor supply on economic growth caused by population aging.

Secondly, China urgently needs to improve the quality of economic development, the industrial development model needs to be updated urgently, and the industrial structure is facing optimization and upgrading. In March 2021, the "14th Five-Year Plan for National Economic and Social Development and the Outline of Vision 2035" put forward new requirements for promoting the digital and intelligent transformation of the industry. Since the reform and opening up, China's industrial restructuring has made remarkable progress, and the proportion of the output value of the tertiary industry will reach 56.5% in 2021. However, the problem of unbalanced and insufficient economic development is still prominent, and the adjustment, optimization and upgrading of the industrial structure is still an inevitable requirement and an important task for transforming the development mode and achieving high-quality development. The technological advantages of industrial robots have brought "subversive breakthroughs" to the industrial development model in the industrial field, which is conducive to improving product quality, increasing production efficiency, enhancing scientific and technological innovation capabilities, and promoting the transformation and upgrading of traditional industries and the derivative development of new industries.

In such an overall environment, the application of industrial robots has increased rapidly in China. According to the data of industrial robot stocks in various countries in the world according to IFR statistics, the stock of industrial robots in China is growing exponentially, and has surpassed the United States, Japan, Germany, etc. around 2016. Developed countries have become the world's largest market, with installed capacity accounting for 40% of the global market. From the perspective of robot density data, compared with 228 units/10,000 people in the United States, 364 units/10,000 people in Japan, and 346 units/10,000 people in Germany, China's 187 units/10,000 units still have a gap with developed countries. The future development space of China's industrial robots is still very broad.

The prospects are bright, but risks and opportunities coexist, and disputes and doubts always exist. Many scholars have pointed out that while the application of industrial robots improves efficiency, it will also have a huge impact on the labor market. Statistics from the World Inequality Database (WID) show that in several major robot application countries, the income share of the top 10% of income earners has increased year by year, and the more obvious the increase in robot application, the more prominent this phenomenon is. The bias of technological progress has been widely discussed in recent years, and some scholars have attributed the increase in inequality in the economy to technological progress. As a representative of the progress of intelligent technology, industrial robots have the characteristics of automation and can directly replace low-skilled labor in industrial production such as welding, spraying, palletizing, etc. Instead, the market demand for low-skilled workers declines, which in turn leads to a decrease in the relative wages of low-skilled workers in their income share. In addition, industrial robots have the characteristics of job creation. The application of robots will give birth to new labor positions such as intelligent manufacturing engineering technicians, industrial robot system operation and maintenance personnel, and industrial robot system operators, and will also drive the derivative development of emerging industries such as robots, thereby increasing labor demand. But the new jobs created must adapt to the complexities of the new technology, and only for the high-skilled workforce. As an emerging driver of technological progress, artificial intelligence technology has the potential to increase income inequality while helping to promote high-quality economic growth. Whether the application of industrial robots with technical bias can achieve equal penetration and benefit all departments, elements and groups equally is an issue worthy of our constant attention and discussion.

Will the current large-scale application of industrial robots exacerbate income inequality in China? In particular, will the use of industrial robots widen the skills wage gap? If so, what is the underlying mechanism of this effect? Are there "substitution effects" and "demand effects"? Since the scope and depth of industrial robot applications in different regions are very different, is there a difference in the skill premium effect of industrial robot applications in different provinces and regions? The answers to these questions will help to evaluate the significance of the use of industrial robots to my country's social and economic development, and help to fully understand the impact of emerging technologies such as artificial intelligence on the labor market.

The research on the impact of the "AI revolution" on employment and income distribution is still in its infancy, lacking relevant empirical tests and quantitative evaluations, especially empirical evidence from developing countries. There are still many controversies and deficiencies in this kind of research, and its guiding significance to the real world, especially to China's reality is weak. This article attempts to discuss the impact of the application of industrial robots on China's labor market from a Chinese perspective, and attempts to provide empirical evidence from China through empirical testing and quantitative evaluation based on the latest data at the regional macro level.

Most of the existing literature focuses on the situation of developed countries, and there are few studies on developing countries. However, the labor force structure of developing countries is quite different from that of developed countries, and the application of artificial intelligence technology is also at different stages. From the perspective of China, this paper studies the impact of industrial robots on developing manufacturing powers, and provides empirical evidence that the income distribution effect of artificial intelligence comes from developing countries.

Most of the current research only focuses on the impact of artificial intelligence technology applications on the employment structure, and lacks attention to the effect of income distribution. On the issue of wealth distribution, it only pays attention to the distribution of capital and labor factors, and does not consider the internal division of labor. Based on the heterogeneity of labor skills, this paper will focus on the impact of the wage gap between low-skilled labor and high-skilled labor under the impact of intelligent technology applications. This paper attempts to measure the skills wage gap with macro-proxy and micro-integration methods, constructing provincial-level facial data in China, and providing concrete empirical experience.

Most of the existing research focuses on an industry perspective, putting the impact of robotics applications at the regional level on the back burner. But in fact the average effect at the regional level is just as important as the average effect at the industry level. Starting from the reality of unbalanced regional development, this paper fully considers the regional characteristics of intelligence, industrial upgrading, and population structure, and on this basis accurately reveals the profound impact of artificial intelligence technology applications on the labor market.

This paper mainly consists of the following six parts. The first part is the introduction. The research background and research significance of this paper are introduced. The second part is the literature review. According to the research objectives of this paper, the literature review is divided into three sections: Section one is the collation of relevant literature on the impact of artificial intelligence on employment structure and the induction of relevant theoretical analysis and empirical methods. The second panel is to sort out the literature related to artificial intelligence and income distribution, find the contradictions of the current research conclusions, and analyze the reasons for the contradictions in detail. The third section is to comment on the reading literature, summarize the past research context, and find the future development direction and the breakthrough of their own research. The third part puts forward its own research hypothesis based on theoretical summary and model deduction. Section IV details the empirical model, variable definitions and data sources used in this paper. The fifth part analyzes the empirical results, including the main regression analysis, the solution of the robustness validation endogeneity problem, and the mediation effect analysis. The sixth part is the conclusion and policy recommendations.

2. Literature Review

2.1. Artificial Intelligence and Employment Structure

Technological advances tend to bring about technical unemployment while improving productivity. Artificial intelligence as a revolutionary technology is no exception. Compared with previous technological revolutions, the impact of the "AI revolution" on employment will be broader, stronger and more lasting. At present, the potential impact of artificial intelligence on employment is a very important policy topic, attracting a large number of scholars and researchers to discuss. It should be pointed out that when discussing the impact of artificial intelligence on employment and income distribution, artificial intelligence is usually treated as an enhanced version of automation. Therefore, when reviewing artificial intelligence-related literature, this paper will also refer to the literature on the impact of automation.

Relevant literatures have carried out theoretical model deduction for this problem. Autor and others (2003) proposed the classic ALM model, which can be said to be a benchmark model for studying the impact of artificial intelligence on employment structure. The model assumes that production consists of two types of tasks, stylized tasks and non-stylized tasks, where stylized tasks only require low-skilled labor, while non-stylized tasks require high-skilled labor. Automation equipment can only be responsible for stylized tasks, not non-programmed tasks, so automation replaces low-skilled labor and complements high-skilled labor. Under this assumption, the impact of automation is obviously biased. It will crowd out the employment space of low-skilled labor. As the right-hand man of high-skilled workers, improving efficiency will bring benefits to high-skilled workers. Frey and Osborne (2017) extended the ALM model. In their model, unstylized tasks require both high-skilled and low-skilled labor. In this setting, the impact of automation on high-skilled workers is no longer certain, and high-skilled workers will also be impacted by automation technology under certain conditions. Benzel et al. (2015) discussed whether there is a "substitution effect" of robots on labor by establishing an intertemporal iteration (OLG) model. Model derivation shows that under certain conditions, robots can completely replace low-skilled jobs and partially replace high-skilled jobs, which will lead to a reduction in labor demand and a drop in wages. Although the price reduction brought about by the increase in productivity after the use of robots can improve the welfare of workers to some extent, it cannot fully compensate for the damage caused by the "substitution effect" to the labor force. As a result, the researchers suggest that the use of robots could lead to so-called Immiserizing Growth—economic growth but a decline in social welfare. Acemoglu and Restrepo (2016, 2018) construct models that include job creation. In the model, when automation eliminates some jobs, it also creates new jobs with more comparative advantages. Therefore, when discussing the net effect of automation on employment, it is necessary to compare the relative degrees of the two effects of substitution and demand. The conclusion shows that under the condition of long-run equilibrium, the effect depends on the use cost of capital and labor. If the cost of using capital is low enough compared to the cost of labor, that is, wages, then all occupations will be automated; otherwise, there will be boundaries to the impact of automation. In addition, the researchers also considered the heterogeneity of labor itself. When there are labors with different skill levels, the advancement of automation technology will also lead to the generation of income gaps within heterogeneous skilled labor.

In terms of empirical analysis, the conclusions are controversial. There are two different empirical results of existing research, and therefore two different attitudes and perspectives on the application of artificial intelligence technology. The view on the negative side is that the "substitute relationship" between industrial robots and human labor dominates, and the promotion and application of artificial intelligence technology will eventually crowd out employment opportunities and bring about an employment crisis.

Some literature even emphasizes that the AI revolution is a "race" between man and machine. Hanson (2001) uses a neoclassical economic growth model, and the measurement results show that intelligent robots may create new employment opportunities, but the higher production efficiency of machines will inevitably lead to the dominant substitution effect. Acemoglu and Restrepo (2016) argue that even if robots replace low-skilled workers, the emergence of new employment tasks will offset some of the impact and increase the wages of low-skilled workers in the long run. Acemoglu and Restrepo (2017) used data from the U.S. labor market from 1990 to 2007 and found that every 1% increase in robot density would reduce jobs by 0.28% - 0.34% and wages by 0.25% - 0.50%.

Yan Xueling et al. (2020) studied the impact of the application of industrial robots on employment in China's manufacturing industry. Through research on China's manufacturing industry data from 2006 to 2017, it is proved that the use of industrial robots will reduce employment opportunities in the manufacturing industry. For every 1% increase in the number of industrial robots, employment will decrease by about 4.6% (2020) combined regional and industry data to show that the expansion of the use of industrial robots will reduce the employment rate of the region in the next year, and the labor market structure in different regions will have an impact on this result. The higher the proportion of low-skilled labor in areas where there is more, the phenomenon of "technical unemployment" will become more prominent. In addition, the higher the degree of marketization, the more obvious the negative effect of intelligent employment in areas with weak labor protection.

The positive view is that the "complementary relationship" between robots and humans dominates, and the promotion and application of artificial intelligence technology will eventually increase employment opportunities (2016), through empirical analysis of the European Union, believed that industrial robots can create new employment opportunities by increasing product demand, and the demand effect will exceed the negative impact of the substitution effect, which will eventually lead to employment growth. Furman (2018) summarized labor economic data in the United States over the past decade when automation technology began to be adopted, and found that employment growth actually exceeded expectations, and the reality proved the improvement in employment levels brought about by technological change. Empirical analysis by Abeliansky and Prettner (2017) argue that countries with lower population growth rates will take the lead in adopting and inventing new automation technologies to overcome the negative economic impact of declining population growth. Chen Yanbin et al. (2019), Deng Zhou (2016), Lin Chen et al. (2020), and Lv Jie et al. (2017) also emphasized the complementary relationship between industrial robots and labor, all of which demonstrate that artificial intelligence technology has an impact on China in the age of aging. Economic growth and capital structure improvement are of great significance.

Although there are differences in the estimates of the impact of the "AI revolution" by different researchers, most scholars represented by West (2014), Brynjolfsson and Mc (2007), Seamans and Raj (2018) believe that although short-term employment substitution, the effect is outstanding. In the long run, artificial intelligence is still enough to create enough employment opportunities to make up for the losses caused by the substitution effect. The government needs to formulate corresponding policies to smooth the short-term impact caused by the application of artificial intelligence technology and provide for the smooth transition of the employment structure enough time. The most important policy recommendation is to strengthen education and improve the skills structure of the workforce. Kaplan (2015) and Furman (2018) studies have proved that the greatest impact of artificial intelligence applications on employment is not to reduce the absolute number of jobs, but the low-skilled workers who are squeezed out are simply not suitable for new jobs. The government can help low-skilled workers adapt to new jobs by providing career guidance and related skills training. In order to make this training guidance continuous and able to cope with the short-term shock of technology, the government can consider establishing job mortgage loans for unemployed low-skilled workers, allowing them to take loans against future work income from new jobs to pay related reemployment training.

2.2. Artificial Intelligence and Income Distribution

There are several paths through which artificial intelligence could have an impact on income distribution. First, in theory, artificial intelligence is a biased technology, and its use will have different effects on the marginal product of different groups, leading to differences in their income status. This effect is reflected in two aspects: One is between different production factors, which mainly affects the distribution of different factors; The other is within heterogeneous labor, which is mainly reflected in the impact on the income distribution of workers with different skill levels. Second, the "artificial intelligence revolution" will also change the market structure, allowing some companies to gain higher market power and business owners to gain higher residual income. The research in this paper focuses more on the labor income distribution of skill heterogeneity within workers, so only this part of the literature is summarized.

Many scholars believe that the difference in factor returns is one of the main reasons for the uneven distribution of income. The research of Piketty (2014) shows that the artificial intelligence revolution in recent years has further increased the return on capital, income distribution has become more and more inclined to capital owners, the concentration of wealth has led to further aggravation of imbalance, and the gap between the rich and the poor has become increasingly serious. Technological progress will obviously intensify the unequal returns to labor and capital factors. Acemoglu and Restrepo (2016, 2017) also believe that the technological progress has obvious bias, and the popularization of industrial robots will reduce the return on labor. But as a capital-intensive technology, it can provide a significant return on capital. Sachs (2017) and Stevenson (2017) empirically show that in the application environment of industrial robots, the return gap between the two elements of capital and labor will continue to widen, resulting in a continuous increase in the income gap.

When there is skill heterogeneity among workers, the bias of technology will also be reflected within the group. Acemoglu and Autor (2011) believe that under the impact of automation changes, the income changes of different skilled workers will be very different. The reasons for this difference can be explained by the following three paths:

First, industrial robots "replace" low-skilled labor and "compensate" for high-skilled labor. At present, low-skilled workers are more vulnerable to the impact of intelligent technological changes due to the low difficulty, high repetition and stylization of their work, their incomes are reduced, and their jobs are crowded out. On the other hand, the non-stylized and high-tech jobs engaged in by high-skilled workers have been assisted and strengthened by intelligent technology, improving work efficiency and increasing income. Autor et al. (2003) analyzed the U.S. labor market from 1960 to 1998 and found that after 1970, computerization led to the emergence of a polarization effect, the market demand for stylized jobs dropped sharply, and the demand for non-stylized jobs decreased significantly. Demand has increased massively. Goos and Manning (2007) tested the conclusions of the ALM model using UK data and found that technological progress also triggered polarisation effects in the UK. Autor and Dorn (2013), Goos et al. (2014), etc. also obtained the same results on the basis of US and European data. Hemous et al. (2016) introduced artificial intelligence technology to reconstruct the horizontal innovation model, and confirmed that automation technology will affect income distribution by replacing low-skilled labor and increasing the demand and remuneration of high-skilled labor, thereby increasing labor income inequality. Bughin et al. (2018) predicted that by 2030, the application of artificial intelligence technology will further reduce the market demand for low-skilled labor and increase the market's demand for high-skilled labor, so that about 13% of total income will flow from low-skilled labor to high-skilled labor. The low-skilled labor income share will drop from 33 percent to 20 percent.

Second, the productivity effect of artificial intelligence technology. While artificial intelligence technology has caused job turnover, it also has a prominent productivity effect. Graetz and Michaels (2018) estimated the impact of changes in industrial robot density on labor productivity on the basis of industry panel data from 17 countries from 1993 to 2007. The empirical results show that for each level of robot density increase, the average annual growth rate of labor productivity ranges from 2.60% - 4.10%. This productivity-boosting effect of industrial robots can have an impact on factor income distribution. The research of Sachs and Kotlikoff (2012) and Guo Kaiming (2019) show that artificial intelligence technology will asymmetrically change the productivity of different production factors in the process of combining with machinery and equipment. Cao

Jing and Zhou Yalin (2018) analyzed the promotion effect of artificial intelligence on TFP, and further discussed the impact of artificial intelligence on the labor market, arguing that the growth of total factor productivity will lead to aggravation of income inequality. When Du Chuanwen et al. (2018) found that the relationship between industrial robots and low-skilled workers is a substitute and a complementary relationship with high-skilled workers, they used the country's total factor productivity as a control variable to measure the impact of neutral technological progress. The possible impact of factor income, the results show that the improvement of total factor productivity can increase the proportion of high-skilled labor and the income share of high-skilled labor; reduce the proportion of low-skilled labor and the income of low-skilled labor.

Third, the application of artificial intelligence will change the functions of workers themselves. Some literature studies believe that the application of intelligent technology may change the function of workers themselves, thereby affecting their income distribution as a labor factor. Trajtenberg (2018) divides the direction of technological progress into two categories: "labor-enhancing innovation" and "labor-substituting innovation". If artificial intelligence technology develops in the direction of labor-enhancing, it will help improve workers' own skills and improve their skills. Labor efficiency, promote their labor employment and income increase. Research by Korinek and Stiglitz (2017) expects that without government intervention, artificial intelligence technology will increase the inequality of income distribution by enhancing the ability of workers, among which the rich are more likely than the poor to obtain training and education through financial resources, or have a certain Workers with similar skills are more likely to use technology to improve labor productivity and widen the income distribution gap.

The income distribution effect of technological change is bound to be affected by policy factors. Reasonable policy measures can make the process of technological change more inclusive and enable everyone to better share the fruits of technological change.

Korinek and Stiglitz (2017) discuss distribution policies in the "AI revolution". They pointed out that although the progress of artificial intelligence technology can increase the total wealth of society, it is difficult for the free market to achieve Pareto improvement due to the impossibility of cost-free income distribution in the real world. While some people benefit from technology, there will inevitably be others suffered damage. To reverse this situation, policy intervention is necessary. The advancement of artificial intelligence technology will bring two effects, the concentration of residual wealth and the change in the relative price of factors, and policies must respond to these two effects. Specifically, taxation, intellectual property policy, and anti-monopoly policy can all play a corresponding role. Kaplan (2015) provides a comprehensive discussion of related income distribution policies. Given the different effects of AI on workers with different skills, he suggested taxing those who benefit from the technology and subsidizing those who suffer as a result.

2.3. Summarization and Analysis of Existing Literature

The existing literature on labor economics research on the "AI revolution" has the following characteristics:

1) There are great differences in the estimates of the employment impact of the "AI revolution" by different researchers, and a unified conclusion has not yet been reached in terms of theoretical models and empirical results. Hanson (2016), Acemoglu and Restrepo (2016, 2017), Yan Xueling et al. (2020) and Kong Gaowen et al. (2020) believe that robots mainly have a "substitute role" for humans, which will have a crowding out effect on workers; Gregory et al. (2016), Abeliansky and Prettner (2017), Deng Zhou (2016), Lv Jie et al. (2017) believe that robots and human labor complement each other and will create new jobs and increase employment.

2) The research on the impact of artificial intelligence technology on the distribution of heterogeneous labor income is still in its initial stage. At present, it only focuses on the heterogeneity of workers in terms of skill levels—workers with different skills will have significant differences in income changes after facing technological progress. However, this part of the research still lacks a quantitative assessment of the income gap between high-skilled and low-skilled labor caused by the "artificial intelligence technology revolution", how artificial intelligence technology in different sectors changes the employment structure through the "replacement" or "compensation" effect, and how Altering factor productivity affects labor compensation and has not resulted in systemic outcomes.

3) The existing authoritative research literature is mainly based on western developed countries as research samples, and mainly uses data from 1990 to 2010 to conduct empirical research, which leads to a relatively lack of empirical evidence on the impact of robot applications on China's labor market. The guiding significance of China's reality is weak. In recent years, especially in the past two years, more and more Chinese scholars have begun to use Chinese data to try to give evidence of the impact of robot applications on China's labor market, but their research has the following problems:

a) Most of the research is limited to studying the impact of the number of employees and the proportion of labor income under the impact of robots, and on this basis, adds industry or regional heterogeneity analysis. These studies only focus on the relationship between the use of industrial robots and the overall labor income, and do not divide the labor force for skill heterogeneity, nor do they empirically evaluate the income gap within the labor force.

b) Most of the existing research focuses on the industry perspective, putting the impact of robot applications at the regional level on the back burner. But in fact the average effect at the regional level is just as important as the average effect at the industry level. Few studies start from the reality of unbalanced regional development, fully consider the regional characteristics of intelligent automation and industrial upgrading, and on this basis accurately reveal the profound impact of intelligent automation on the labor market.

Based on the literature review, the following research trends are proposed:

1) Provide further evidence that the "artificial intelligence revolution" has impacted China's labor market. On the one hand, artificial intelligence automation should be introduced in the design of theoretical models. At present, most models regard automation as capital that can supplement or replace labor and introduce them into the model for analysis. In practice, the role of artificial intelligence and its impact on the economy are much more complicated. Artificial intelligence itself is not only a kind of capital, but also affects the investment of other capitals, and may also become a new factor of production in the future. Based on this, it is also necessary to have a deeper understanding of the mechanism and development of industrial intelligent automation. On the other hand, it is necessary to strengthen the collection and arrangement of relevant statistical data, and break through the limited and single quantitative research.

2) Divide labor according to skills, further study the impact of artificial intelligence automation on the employment and income of laborers with different skills, and further study the changes in labor market structure under the impact of robots and the income gap among workers. At the same time, the specific mechanism of these effects will be studied. Whether through "substitution" "compensation" or through asymmetric changes in productivity, more rigorous and rational mechanism analysis is required to test.

3. Model and Hypotheses

Referring to the ideas provided by Graetz and Michaels in the paper ROBOTS AT WORK, we regard robots as a new production factor, and establish a model for analysis. Suppose that the entire social production is a three-factor production sector $Y = F(K, R, L)$, and the returns to scale remain unchanged. K represents traditional capital, R represents industrial robot capital, and L represents labor. Suppose Y is the Cobb Douglas production function with a CES-type production function nested in it:

$$Y = AK^{\alpha}\left[\gamma R^{\varepsilon} + (1-\gamma)L^{\varepsilon}\right]^{(1-\alpha)/\varepsilon} \tag{1}$$

Among them, the enterprise technological progress coefficient $A \in (0, +\infty)$, the distribution coefficient $\gamma \in (0,1)$, the substitution parameters $\alpha \in (0,1)$, $\varepsilon \in (-\infty, 1]$. The formula (1) is divided by the labor L at the same time, and the production function in per capita form is obtained by simplification:

$$y = Ak^{\alpha}\left[\gamma r^{\varepsilon} + (1-\gamma)\right]^{(1-\alpha)/\varepsilon} \tag{2}$$

where y represents labor productivity, and k and r represent the unit factor inputs of capital and industrial robots, respectively. When the elasticity of substitution between industrial robots and labor is $\varepsilon \in (0,1]$, that is, when there is a mutual substitution relationship between industrial robots and labor, then labor productivity y will increase with the increase of robot usage r.

According to Euler's theorem, the average wage w can be expressed as:

$$w = y - \frac{\partial y}{\partial k} k - \frac{\partial y}{\partial r} r \tag{3}$$

Differentiate k and r in Equation (2) and substitute them into equation (3), and simplify to get:

$$w = \frac{(1-\alpha)(1-\gamma)}{\gamma r^{\varepsilon} + (1-\gamma)} y \tag{4}$$

According to formula (4), the labor income share can be obtained:

$$\frac{w}{y} = \frac{wL}{Y} = \frac{(1-\alpha)(1-\gamma)}{\gamma r^{\varepsilon} + (1-\gamma)} \tag{5}$$

According to the result of Equation (5), when the substitution parameter of industrial robot and labor is $\varepsilon > 0$, that is, industrial robot and labor are in a mutual substitution relationship, then the share of labor income will decrease with the increase of industrial robot usage. On the contrary, when the substitution parameter $\varepsilon < 0$ of industrial robots and labor, that is, when industrial robots and labor are complementary, the labor income share will increase with the increase of robots.

Referring to the ALM model proposed by Autor et al., production requires two kinds of tasks—stylized tasks and non-stylized tasks, where stylized tasks only require low-skilled labor, while non-stylized tasks require high-skilled labor. The use of industrial robots can only be used to complete programmed tasks, not non-programmed tasks, so the use of industrial robots replaces low-skilled labor and complements high-skilled labor. At this stage, those occupations that are more severely impacted by the artificial intelligence technology revolution are mainly those occupations that focus on stylized tasks and require low skills. The use of industrial robots mainly strengthens and assists those occupations that are not stylized and require higher skills. Under such circumstances, the income share of low-skilled labor will continue to decline with the development of intelligence, while the income share of high-skilled labor will continue to rise with the development of intelligence, resulting in a widening income gap between high-skilled labor and low-skilled labor.

According to the result of formula (5), we can also see $\frac{wL}{Y} = \frac{w}{y}$ = average wage/labor productivity, it can be seen that the difference of labor income share comes from the ratio of average wage to labor productivity. When the application of industrial robots makes the average wage increase more than the increase in labor productivity, the labor income share will rise; otherwise, it will decline. When high-skilled labor and low-skilled labor are impacted by intelligence, average wages and labor productivity may increase at different rates, resulting in different changes in the income share of high- and low-skilled labor, resulting in unfair income distribution within labor.

On the basis of literature research, combined with model deduction, the following hypotheses can be put forward: The use of industrial robots will further widen the skill-based wage gap. The application of industrial robots mainly produces a "substitution effect" for low-skilled labor, which will squeeze out the employment space of laborers performing low-skilled routine tasks; for high-skilled labor, it mainly exerts a "demand effect" ("compensation effect"), Through the use of industrial robots, production efficiency is improved, product prices are reduced, and market demand is increased, thereby driving enterprises to expand production scale and increase the demand for labor. Differences in the impact of industrial robot applications on labor with different skills will affect labor income distribution and widen the skill-based wage gap.

4. Measurement Model settings

Based on the theoretical analysis, to study the impact of the use of industrial robots on the skill-based wage gap, the following panel fixed-effects model will be set:

$$w_{it} = \beta_0 + \beta_1 \ln R_{it} + \beta_2 \ln SLS_{it} + \gamma X_{it} + \alpha_i + \alpha_t + \varepsilon_{it} \tag{6}$$

In the benchmark regression (6), w_{it} represents the skill income gap (skill premium); $\ln R_{it}$ represents the usage of industrial robots; $\ln SLS_{it}$ represents the skill structure of labor supply; X_{it} represents other control variables; the subscripts i and t represent the province and year, respectively; α_i represents the unobservable provincial fixed effect, which is added to control the characteristics of the province; α_t represents the time fixed effect, which is added to control the influence of specific events in the year; ε_{it} it is the random error term. If $\beta_1 > 0$, it means that when the skill structure of labor supply and other control variables are at the mean value, the increase in the use of industrial robots widens the skill income gap.

4.1. Explained Variable

The explained variable of this econometric model is the skill income gap. Skilled income gap refers to the income gap between high-skilled labor and low-skilled labor. With reference to past research, high-skilled labor and low-skilled labor can be classified from the perspectives of professional skills, positions, experience, and educational qualifications. This paper fully considers people's understanding of different skill levels in reality, and divides the labor force into high-skilled labor and low-skilled labor according to their educational level. The labor force with a college degree or above is regarded as a high-skilled labor force, and the labor force with other degrees is classified as a low-skilled labor force. Since there is no wage statistics according to occupational grades in China Statistical Yearbook, China Labor Statistics Yearbook and other economic census data, there is no wage data according to education level, and the unavailability of direct data is evidence of technical bias. Research brings difficulties.

Researchers in this direction often use the following two methods to refer to the skill-based wage gap. The first is the macro-level substitution method. Specifically, the wages of low-skilled labor are replaced by the average wages of industries with fewer skilled workers, and the wages of high-skilled labor are replaced by the average wages of industries with more skilled workers. The ratio of the two can be used as an approximate proxy for the true skill premium. Lan Liu (2010) used the ratio of the average wage in the science and technology industry to the average wage in the manufacturing industry to measure the skill income gap (2010) used the ratio of the average wage in the manufacturing industry to the average wage in agriculture, forestry, fishery and animal husbandry to measure the skill income gap. Lu Xueqin and Wen Yanbing (2013) used the ratio of the average salary of scientific research and technical service industry to the average salary of agriculture, forestry, animal husbandry and fishery. The second is the micro-level integration method, which uses micro-databases such as the census, the China Household Income Survey (CHIPS), and the China Urban Household Survey (UHS) to integrate information on the education level and wage income of the survey samples. For example, Wang Linhui et al. (2014), Dong Qingzhi et al. (2021) and others used the CHNS database to integrate high-skilled and low-skilled wage data in 1989, 1991, 1993, 2000, 2004, and 2006; and the 2008 China Household Income Survey (CHIP) data and provincial data to empirically examine changes in skill income gaps. Due to the inconsistency of data and limited coverage of this method, it is often obtained by fitting, which also cannot avoid the existence of bias. At the same time, this method of reference often ignores the perspective of geographical direction and cannot provide provincial skilled labor income gap.

This paper fully considers the availability of data and the compatibility with the research on provincial division, chooses to focus on macro-agents, and assists micro-integrated data for verification. According to the data on the input ratio of high-skilled and low-skilled labor in China's sub-sectors provided by the World Input-Output Database (WIOD) from 2006 to 2015, the average proportion of low-skilled labor in manufacturing is about 75%. The low-skilled labor force in the information transmission, software services accounts for about 30%. In the past 10 years, the proportion of skilled labor in the two industries has been basically stable. The information technology industry has always been an industry with high-skilled labor, and the manufacturing industry has always been an industry with low-skilled labor. Therefore, this paper uses the ratio of the average wage in the information transmission, software and information technology service industries to the average wage in the manufacturing industry to express the income gap between high-skilled labor and low-skilled labor.

Considering the possible bias of representing skilled labor in a single industry, on the basis of sufficient research on data and methods, we choose to further refer to the method of Lei Qinli and Wang Yang (2017) to measure the skill-based wage gap. According to the data on the proportion of skilled labor force in 16 industry categories in the "China Labor Statistics Yearbook" over the years, the study found that the ranking of the proportion of high-skilled labor and low-skilled labor in each industry is stable. The industries with a high proportion of high-skilled labor include scientific research and technical services, education, information transmission software and technical services, finance, health, culture and public services. The ratio of the number of employed persons is more than 50%. Industries with a high proportion of low-skilled labor include agriculture, forestry, animal husbandry, fishery, mining, manufacturing, construction, transportation, accommodation, and wholesale. The proportion of low-skilled labor is higher than 75%. Combine the top 7 industries with the highest concentration of high-skilled labor into high-skilled industries and the top 7 industries with the highest concentration of low-skilled labor into low-skilled industries, and calculate the wages of high-skilled labor, wages of low-skilled labor, and skilled wages gap. Specifically, according to the "employees in urban units by industry" and "the average wage of employees in urban units by industry" in the "China Statistical Yearbook", and the "educational level of urban employees by industry" in the "China Labor Statistical Yearbook" Make calculations based on the data. This method makes full use of existing data and mitigates the impact of industry differences on skill premiums.

Specifically, it is assumed that each province has two industries, the average wage of industry 1 is W_1, and the average wage of industry 2 is W_2. Each industry employs labor in the same labor market, so labor with the same skill level has the same wage. Suppose the wage of high-skilled labor is W_H and the wage of low-skilled labor is W_L. The proportion of high-skilled labor in industry 1 is P_{H1}, and the proportion of low-skilled labor is $(1-P_{H1})$; the proportion of high-skilled labor in industry 2 is P_{H2}, and the proportion of low-skilled labor is $(1-P_{H2})$. Then, the average wages of representative industries 1 and 2 can be expressed as a function of skilled labor wages and unskilled labor wages:

$$W_1 = P_{H1} \cdot W_H + (1-P_{H1}) \cdot W_L$$

$$W_2 = P_{H2} \cdot W_H + (1-P_{H2}) \cdot W_L$$

The derivation can be obtained, the wages of high-skilled labor and the wages of low-skilled labor are:

$$W_H = \left[W_1(1-P_{H2}) - W_2(1-P_{H1})\right] / (P_{H1} - P_{H2})$$

$$W_L = (W_1 P_{H2} - W_2 P_{H1}) / \left[P_{H2}(1-P_{H1}) - P_{H1}(1-P_{H2})\right]$$

The industry average wages of each province can be obtained and integrated from the provincial statistical yearbook, and the labor skill structure of each industry can be extracted from the World Input-Output Database (WIOD). After sorting out, it is found that the results of the number of wage gaps for different skills in different provinces calculated by the above two macro methods are similar, and finally the skills wage gaps in 30 provinces from 2006 to 2015 are sorted out.

We then consider micro-integrated proxies for skill-income gaps. This paper uses China's urban household survey data (UHS) to supplement and adjust the above skills wage income gap. The National Bureau of Statistics China Urban Household Survey (UHS) contains information on the income levels of individuals with different educational levels, which provides a good data basis for defining the wages of labor with different skills. It can be simply summed up by simply adding up the annual income of individual labor in the region. Average, construct the wage index of labor with different skills at the provincial level. However, because the survey cannot cover the data of all sample provinces, it can only calculate the data of 16 provinces in 2009 and before, and the data of 4 provinces in 2009-15 and the first "industry average wage representation method". Compare and verify. The results show that the results of the micro-integration of the skills wage gap are similar to those of the macro proxy indicators. Finally, this paper expresses the income gap between high-skilled labor and low-skilled labor as the ratio of the average wage in information transmission, software and information technology services to the average wage in manufacturing.

4.2. Explanatory Variables

The core explanatory variable of this paper is the usage of industrial robots. In view of the fact that the use of robots in China mainly relies on imports (Li Lei & Xu Dace, 2020), and the statistics of China Customs provide data such as the annual import volume of industrial robots in each province, this paper uses the import data of industrial robots as a proxy variable for the stock of industrial robots. According to customs statistics, there are 10 industrial robot products corresponding to HS2002 eight-digit codes, including multi-functional industrial robots (84795010), unlisted industrial robots (84795050), resistance welding robots (85152120), fully automatic or semi-automatic resistance straight seam Pipe welding machines (85152191), fully automatic or semi-automatic resistance welding machines and apparatus, not listed (85152199), electric arc (including plasma arc) welding robots for metal working (85153120), automatic or semi-automatic electric arc for metal working (85153120) Including plasma arc) spiral pipe welding machines (85153191), fully automatic or semi-automatic electric arc (including plasma arc) welding machines and apparatus for metal working (85153199), laser welding robots (85158010) and unlisted welding machines and The device is used for electrical machines and devices for thermal spray metal or cermet (85158090). In this paper, the annual import volume of industrial robots in each province is used as a substitute variable for the annual robot usage in each province.

This paper sets the moderating variable—the skill structure of labor supply. The skill structure of labor supply is represented by the proportion of the population with a college degree or above in the population aged 16 and above. In the provincial labor market, the skill structure of labor supply is an indicator that reflects the state of labor supply, which will directly affect the changes in the skill-based wage gap, as well as the effect of the use of industrial robots on the skill-based wage gap.

According to the specific experience of relevant research, this paper sets the following control variables. 1) Export. This paper uses the ratio of exports to GDP to measure the importance of exports to economic development. Exports will change the elasticity of substitution between labor and other factors, and affect labor employment and wages (Sheng Bin and Niu Rui, 2009). Exports also have an impact on the demand for and wages of low-skilled labor, thereby affecting the skills wage gap. 2) Foreign direct investment. This paper uses the ratio of foreign direct investment (converted to RMB denominated) to GDP to measure the impact of foreign direct investment on the economy. According to previous research, foreign direct investment in China is mostly concentrated in the low-end links of high-end industries, which is expected to have an impact on the labor wage and skill-based wage gap. 3) GDP per capita. Since the explanatory variables and other control variables in this paper are measured by nominal values, the nominal GDP per capita data is used here, and the data comes from the statistical yearbooks of various provinces in China. GDP per capita reflects the level of regional economic development and can have an impact on the demand for skilled labor and skill-based wage gaps. 4) Proportion of state-owned economy. This paper uses the ratio of the total sales output of state-owned enterprises above designated size to GDP to measure the status of the state-owned economy in the economy. The impact of the share of the state-owned economy on the skills premium is uncertain. Some studies have shown that the larger the capital of the state-owned economy, the greater the demand for high-skilled labor (Shen Guangjun et al., 2020). Studies have also shown that if the state-owned economy accounts for a high proportion, the degree of marketization will be low, which is not conducive to the allocation of human resources and the increase of wages. Therefore, the role of the state-owned economy on the skills wage gap remains to be tested. 5) Fixed asset investment. This paper uses the proportion of fixed asset investment to GDP to measure. New equipment and new facilities can reflect the speed of technological progress and the degree of innovation development, which may generate demand for skilled labor, thereby affecting the skill-based wage gap. 6) Industrial structure. The upgrading of the industrial structure includes the advanced and rationalized industrial structure. There are many indicators to measure the industrial structure, such as the proportion of the output value of the tertiary industry to the regional GDP, the ratio of the output value of the tertiary industry to the secondary industry, and the rationalization of the industrial structure, index, etc. This paper focuses on the advanced industrial structure, that is, the evolution of the industrial structure from the primary and secondary industries to the tertiary industry. Therefore, the ratio of the output value of the tertiary industry to the output value of the secondary industry is used as an indicator to measure the "industrial structure", and the Take the natural logarithm. The data comes from the "China Urban Statistical Yearbook" of the corresponding year and the provincial statistical yearbooks, etc., and some missing values are filled by interpolation. 7) Population aging. At present, the indicators for measuring population aging are relatively uniform. There are two methods for measuring population aging: one is to use the proportion of the elderly population, that is, the proportion of the population over 65 years old to the total population; the other is to use the old-age dependency ratio, which is It is expressed as the proportion of the population aged 65 and over to the working population aged 15 to 64. This paper uses the old-age dependency ratio indicator to measure, and the data comes from the statistical yearbooks of various provinces.

On the basis of the previous analysis, **Table 1** lists all the variables and data sources needed in this empirical study.

The descriptive statistics in **Table 2** show that the data of each variable is in line with common sense, and there are large differences in the data between provinces, which provides a good data basis for empirical analysis. In addition,

Table 1. Variable definition and description.

	Variable	Definition	Index	Data Description
Explained variable	*w*	Skill-based wage gap	$\frac{wh_{it}}{wl_{it}}$	China Labor Statistics Yearbook China Provincial Statistical Yearbook World Input-Output Database (WIOD) China Urban Household Survey Data (UHS)
Core explanatory variables	*R*	Number of industrial robots	Import volume of industrial robots	China Commodity Trade Database with data support from China Customs, National Bureau of Statistics, China Provincial Statistical Yearbook
Moderator	*SLS*	Labor supply skill-based structure	The proportion of the population with a college degree or above in the population aged 16 and above	China Labor Statistics Yearbook China Population and Employment Statistical Yearbook
Control variable	*exp*	Export	The ratio of exports to GDP	China Provincial Statistical Yearbook
	fdi	Foreign direct investment	The ratio of total foreign investment to GDP	China Provincial Statistical Yearbook
	pgdp	GDP per capita	GDP to total population ratio	China Provincial Statistical Yearbook
	lnst	Industrial structure	The ratio of the output value of the tertiary industry to the output value of the secondary industry	China Provincial Statistical Yearbook
	old	Population structure (aging situation)	The proportion of the population aged 65 and over in the working population aged 15 to 64	China Provincial Statistical Yearbook
	mon	Proportion of state-owned economy	The ratio of gross output value of SOEs above designated size to GDP	China Provincial Statistical Yearbook
	gdk	Fixed asset investment	Ratio of fixed asset investment to GDP	China Provincial Statistical Yearbook

Table 2. Descriptive statistics for variables.

Variable Name	Variable Symbol	Observation	Mean	Variance	Min	Max
Skill-based wage gap	*w*	300	1.643	0.457	0.673	2.852
Number of industrial robots	*R*	300	1495.517	2626.740	0.262	21,196.970
Skill-based structure of Labor supply	*SHL*	300	0.116	0.066	0.034	0.444
Export	*exp*	300	0.166	0.188	0.015	0.898
Foreign direct investment	*fdi*	300	0.397	0.540	0.047	5.708
GDP per capita	*pgdp*	300	3.123	1.898	0.593	10.359
Industrial structure	*lnst*	300	0.856	20.823	0.261	2.635
Population structure (aging situation)	*old*	300	0.134	5.281	0.072	0.162
Proportion of state-owned economy	*mon*	300	0.384	0.183	0.101	0.834
Fixed asset investment	*gdk*	300	0.675	0.209	0.253	1.328

the logarithm is taken for the variable "industrial robot usage" with a large mean, and taking logarithm does not affect the direction and significance of the coefficient, but the interpretation method should be adjusted.

By the way, the data range in this article is from 2005 to 2016, and the reasons why the data has not been updated to the latest are as follows: First, the issue of data availability. The data of China's customs import and export data and the data of the world input-output database used in this article are updated slowly. It is difficult to obtain and organize the latest data at the provincial level. Second, from 2005 to 2016, the operational stock of industrial robots in China increased at an average annual rate of 38%, indicating that this stage can be used as a good research object.

5. Empirical Analysis

5.1. Main Regression Results

First of all, combined with theoretical analysis, the ordinary least squares regression method is used for stepwise regression, and control variables are added one by one to ensure that while R^2 continues to increase, the coefficients of existing variables do not change systematically. Then, the fixed-effect regression model was used to test the theoretical hypothesis, controlling for the time fixed effect, and clustering at the provincial level. The fixed-effects model was chosen because after the Hausman test on the panel data, the p-value was 0.0000, which strongly rejected the null hypothesis, indicating that we should choose to use the fixed-effects model.

The regression results of the panel fixed effects model are shown in Table 3. It can be seen that the R^2 of the model is greater than 50%, indicating that the model fits the sample well and the model setting is correct. The effect of the use of industrial robots on the skills wage gap is consistently positive. Column (5) in

Table 3. Impact of Industrial robot use on skill-based wage gap (fixed effects regression results).

Variable Name	Variable	(1)	(2)	(3)	(4)	(5)
Number of industrial robots	*lnR*	0.073 (0.145)	0.067 (0.162)	0.082 (0.154)	0.118* (0.151)	0.121* (0.156)
Skill-based structure of Labor supply	*SHL*				0.354 (0.456)	0.287 (0.452)
Foreign direct investment	*fdi*		0.075** (0.013)	0.086** (0.023)	0.078** (0.023)	0.081** (0.019)
GDP per capita	*pgdp*		−0.067 (0.127)	−0.158 (0.130)	−0.147 (0.137)	−0.012 (0.125)
Proportion of state-owned economy	*mon*		−0.388 (0.450)	−0.492 (0.448)	−0.692 (0.409)	−0.631 (0.409)
Fixed asset investment	*lngdk*					0.020 (0.147)
Population structure (aging situation)	*old*			−0.230 (0.295)	−0.081* (0.323)	−0.004* (0.287)
Industrial structure	*lnst*			1.968 (1.455)	1.318 (1.329)	1.007 (1.299)
Constant term	*-cons*	1.066*** (0.483)	1.387*** (0.418)	1.306*** (0.472)	1.254*** (0.510)	2.061*** (0.42)
R^2	R^2	0.506	0.531	0.543	0.483	0.505
Adjusted R^2	$adj.R^2$	0.489	0.508	0.516	0.448	0.470
Observations	*N*	300	300	300	300	300

Note: *represents $p < 0.10$, **represents $p < 0.05$, and ***represents $p < 0.01$; all regression coefficients are clustered at the provincial level, and time fixed effects are controlled.

Table 3 shows the regression results after all control variables are included. It is known that the use of industrial robots has a significant positive effect on the skill-based wage gap. The use of industrial robots significantly increases the skills wage gap, and for every 1% increase in the use of industrial robots, the skills wage gap will expand by 0.121 units, a result that is significant at the 5% significance level, thus validating Hypothesis 1, That is, the use of industrial robots will exacerbate the wage gap between high-skilled and low-skilled labor. Under certain conditions of the skill structure of labor supply and other variables, the application of intelligent technology will significantly increase the skill premium.

5.2. Robustness Check and Endogeneity Problem

Since any economic development phenomenon is continuous and affected by historical factors, in theory, the skill-based wage gap will also be affected by the previous skill-based wage gap. Therefore, it is considered to include the skills wage gap with a lag period into the regression equation, and examine the skill-based wage gap in the skill-based wage gap. In the presence of a lag, is the role of the use of industrial robots robust in widening the skills wage gap? In this case, there is a strong correlation between the explained variables and the lagged explained variables, and the dynamic panel fixed-effects model (GMM method) should be used for regression and analysis. In addition, the use of industrial robots may be affected by the skill-based wage gap and there is a reverse causal relationship, resulting in an endogeneity problem. Therefore, the use of industrial robots with a lag period of one period is selected as an instrumental variable. The selection of this instrumental variable satisfies the correlation and exogenous requirements, because the current skill-based wage gap cannot affect the usage of industrial robots in the lag period.

The regression results of the dynamic panel model considering the endogeneity problem are shown in **Table 4**. The one-step difference GMM estimation results are similar to the system GMM estimation results, and the two-step difference GMM estimation results are mainly used to test whether the preconditions of the dynamic panel model are satisfied. In the estimation results of the dynamic panel fixed-effect model (two-step differential GMM) in column (2) of **Table 4**, the $AR(2)\_P$ value and the $Sargen\_P$ value are both greater than 0.1. It can be seen that there is no second-order serial correlation. There is no over-identification problem, indicating that the model setting is reasonable. The estimated results of the system GMM in column (3) of **Table 4** show that when the skill structure of labor supply is at the sample mean, every 1% increase in the use of industrial robots will increase the skill-based wage gap by 0.325 units. As a robustness test, the one-step difference GMM estimation results show that when the skill structure of labor supply is at the sample mean, for every 1% increase in the use of industrial robots, the skill-based wage gap will expand by 0.342 units. This shows that the effect of the use of industrial robots on the skill-based wage gap is still significantly positive, and the use of industrial robots will increase the wage gap between high-skilled labor and low-skilled labor, which is consistent with the previous benchmark regression results, Hypothesis established.

Take a comprehensive look at the regression results in columns (1) and (3) of **Table 4**, and analyze the regression coefficients of the control variables. The increase in the proportion of exports will help narrow the skill-based wage gap, which is consistent with the current situation in my country. In the past, when the economy was developed by relying on demographic dividends, China's exports accounted for a relatively high proportion of GDP, and exports were mainly concentrated in low-end manufacturing links that could give full play to China's comparative advantages of labor. Such an export model increases employment opportunities for low-skilled labor to a certain extent, and raises the income level of low-skilled labor, thus reducing the skill-based wage gap. Foreign direct investment generally widens the skill-based wage gap, and this result is also in line with the results of relevant literature research and in line with theoretical expectations. Because foreign-funded enterprises tend to hire high-skilled labor,

Table 4. Impact of Industrial Robot Use on Skill-based Wage Gap(Solve endogenous problems).

Variable Name	Variable Symbol	Skill-based Wage Gap *w*		
		(1) One-step differential GMM	(2) Two-step differential woGMM	(3) System GMM
Skill-based Wage Gap first-order lag term	L1.*w*	0.399*** (0.139)	0.441*** (0.156)	0.823*** (0.068)wo
Number of industrial robots	*lnR*	0.342*** (0.468)	0.280*** (0.566)	0.325*** (0.041)
Skill-based structure of Labor supply	*SHL*	2.334* (1.350)	1.675 (1.287)	−0.372 (1.186)
Export	*exp*	−0.677 (0.450)	0.247 (1.201)	-0.151 (0.127)
Foreign direct investment	*fdi*	−0.004 (0.043)	0.005 (0.039)	0.017 (0.021)
Fixed asset investment	*lngdk*	−0.217 (0.170)	−0.288 (0.177)	−0.134 (0.072)
Proportion of state-owned economy	*mon*	−0.063 (0.452)	0.026 (0.268)	0.111 (0.061)
Industrial structure	*lnst*	−1.063 (1.539)	2.636 (5.829)	−0.120 (0.205)
Population structure (aging situation)	*old*	−0.367 (0.339)	−0.136 (0.729)	−0.421 (0.035)
Observations	*N*	240	240	240
Individual, year fixed effects		control	control	control
$Prob > chi^2$		0.000	0.000	0.000
$AR(1)\_P$		0.000	0.000	0.000
$AR(2)\_P$		0.250	0.454	0.391
$Sargan\_P$		0.113	0.113	0.119
Hansen		-	0.998	-

Note: In the differential GMM estimation, the estimated coefficients of the one-step method are used to explain the economic relationship, and the results of the two-step method are mainly used to test over-identification and second-order serial correlation. *represents $p < 0.10$, **represents $p < 0.05$, ***represents $p < 0.01$.

this will help increase the employment and income of high-skilled labor. An increase in the proportion of fixed asset investment will have a negative effect on the skills wage gap. According to the research of other literatures, infrastructure construction can solve the employment of low-skilled labor more, and has the effect of narrowing the skill-based wage gap. This provides inspiration for stable employment, and in the future, the employment problem of low-skilled labor can be alleviated by promoting the construction of new infrastructure. In terms of population structure, the deepening of the aging degree will narrow the skill-based wage gap. Regions with serious aging problems will have more job opportunities due to labor shortages. Changes in skill requirements for some jobs will not completely affect low-skilled labor substitution effect. There is uncertainty about the impact of the share of the state-owned economy on the skills premium.

5.3. Mechanism Analysis

Substitution Effect

The use of industrial robots may affect the skill-based wage gap by affecting the skill structure of employment, especially the use of industrial robots tends to increase the employment of high-skilled labor and reduce the employment of low-skilled labor. The employment skills structure is set as an intermediary variable, and the employment skills structure is reflected by the proportion of employed persons with a college degree or below. The data source is the China Labor Statistics Yearbook. Next, the use of industrial robots is used as the key explanatory variable, and the employment skill structure is used as the explained variable, and the relevant variables are controlled for regression analysis.

The regression results of the fixed effect model in column (1) in **Table 5** show that the use of industrial robots has a significant positive impact on the employment skill structure of the labor market. The employment skills structure represented by the ratio of the number of low-skilled labor force increased by 0.295 percentage points. Considering that the use of industrial robots may be affected by the structure of employment skills, the use of industrial robots with

Table 5. Impact of industrial robot use on employability skills structure.

Variable Name	Variable Symbol	Employability Skills Structure *lnSS*			
		(1) Fixed Effects	(2) System GMM	(3) One-step differential GMM	(4) Fixed Effects
Number of industrial robots	*lnR*	0.295* (0.179)	0.118** (0.049)	0.770*** (0.219)	−0.005 (0.014)
Employability Skills Structure first-order lag term	L1.*lnSS*		0.788*** (0.035)	0.393*** (0.080)	
Skill-based structure of Labor supply	*lnSHL*				1.075*** (0.012)
Constant term	*_cons*	−2.295*** (0.479)	−0.765*** (0.175)		0.210*** (0.043)
Year fixed effects and control variables		c	control	control	control
Adjusted R^2	$adj.R^2$	0.8121			0.9977
Observations	*N*	240	180	210	240

Note: *represents $p < 0.10$, **represents $p < 0.05$, and ***represents $p < 0.01$; all regression coefficients are clustered at the provincial level, and time fixed effects are controlled.

one lag period is used as an instrumental variable for regression, and the time lag term of the explained variable is included. The results of the dynamic panel model are still robust and significant, as shown in column (2) of **Table 5**. The use of industrial robots has significantly improved the employability skills structure. But this effect can come from multiple sources. First, the application of intelligent technology in the industry has increased the demand for high-skilled labor; second, intelligence has reduced the demand for low-skilled labor; third, the supply of high-skilled labor has increased. Therefore, adding a variable representing the supply of high-skilled labor to the regression, it can be seen from the results of column (4) in **Table 5** that after adding the variable of supply of high-skilled labor, the estimated adjusted R^2 within the group rose to 0.9977, which greatly improves the fitting degree of the model to the data. The increase in the supply of high-skilled labor will significantly improve the employment skills structure, but at the same time, the impact of the use of industrial robots on the employment skills structure becomes less significant. This shows that the employment skills structure, that is, the employment volume of high- and low-skilled labor, is mainly affected by the skill structure of labor supply, but the use of industrial robots does have a certain "substitution effect" for low-skilled labor.

Demand Effect

We examine the impact of the use of industrial robots on the demand for high- and low-skilled labor separately.

First, to study the impact of the use of industrial robots on the demand for high-skilled labor. By combing past literature research, it can be seen that the use of industrial robots will affect the skill-based wage gap by increasing the demand for high-skilled labor. For the quantification of labor demand, referring to the research of Sun Zao and Hou Yulin (2019), labor demand can be expressed by relative wage growth rate. Therefore, this paper uses the relative growth rate of high-skilled labor wages as the explained variable to investigate whether the use of industrial robots affects the skill-wage gap through the demand for high-skilled labor. This paper uses the average wage growth rate of the information transmission, software and information technology service industries minus the average wage growth rate of urban employees to represent the relative growth rate of high-skilled labor wages. There may be room for improvement in this approach with macro data proxies. Since direct data on the number of highly skilled labor in the information transmission, software and information technology service industries in various provinces across the country are not available, this paper calculates by multiplying the number of highly skilled labor in various industries across the country by the relative labor productivity of other service industries including the information industry in the tertiary industry., the relative labor productivity is obtained by dividing the percentage of the added value of an industry in each province in the total output value of the industry in the country by the percentage of employment in the industry in each province in the total employment in the industry in the country. This estimation method ignores the demand for labor due to technological progress in the industry. However, it can be used to estimate the number of skilled labors by province and industry and use it as a control variable.

From the regression results in Table 6, it can be seen that the use of industrial robots increases the relative growth rate of high-skilled labor wages, and this effect is significantly positive at the 10% level after considering endogeneity. This shows that the use of industrial robots has a role in promoting the relative growth rate of high-skilled labor wages to a certain extent, that is, the use of industrial robots will increase the market demand for high-skilled labor. The increase in labor productivity in the information transmission software and information technology service industries will significantly increase the relative growth rate of wages in the information transmission software and information technology service industries.

Similarly, we can study the impact of the use of industrial robots on the demand for low-skilled labor. The relative growth rate of low-skilled labor wages is used as the explained variable, and the macro-proxy method is also used to represent the relative growth rate of low-skilled labor wages by subtracting the average wage growth rate of urban workers from the average wage growth rate in manufacturing. The results of Table 7 show that the use of industrial robots has a negative effect on the relative wage growth rate of low-skilled labor. The increased use of industrial robots causes wage growth in manufacturing to be lower than the

Table 6. The impact of Industrial Robot Use on the demand for high-skilled labor.

Variable Name	Variable Symbol	Relative growth rate of high-skilled labor wages *High_urbanwage*		
		(1) Fixed Effects	(2) System GMM	(3) One-step differential GMM
First-order lag terms of relative wage growth rates in information transmission software and information technology services	L1.*High_urbanwage*		−0.070* (0.063)	−0.137* (0.085)
Number of industrial robots	*lnR*	0.123* (0.063)	0.021 (0.015)	0.464 (0.511)
Labor productivity growth rate in the information transmission software and information technology services	*High_lpd*	0.238*** (0.057)	0.256*** (0.067)	0.214*** (0.042)
Constant term	*_cons*	−0.295 (0.179)		
Year fixed effects and control variables		control	control	control
Adjusted R^2	$adj.R^2$	0.285		
Observations	*N*	240	180	210

Note: *represents $p < 0.10$, **represents $p < 0.05$, and ***represents $p < 0.01$; all regression coefficients are clustered at the provincial level, and time fixed effects are controlled.

Table 7. The impact of Industrial Robot Use on the demand for low-skilled labor.

Variable Name	Variable Symbol	Relative growth rate of low -skilled labor wages *Low_urbanwage*		
		(1) Fixed Effects	(2) System GMM	(3) One-step differential GMM
The first-order lag term of relative wage growth in manufacturing	L1.*Low_urbanwage*		−0.125** (0.057)	−0.067 (0.042)
Number of industrial robots	*lnR*	−0.008 (0.014)	0.044 (0.123)	0.008 (0.006)
Manufacturing labor productivity growth rate	*Low_lpd*	−0.197*** (0.041)	−0.249*** (0.052)	−0.212*** (0.037)
Constant term	*_cons*	−0.475 (0.289)		
Year fixed effects and control variables		control	control	control
Adjusted R^2	$adj.R^2$	0.510		
Observations	*N*	240	180	210

Note: *represents $p < 0.10$, **represents $p < 0.05$, and ***represents $p < 0.01$; all regression coefficients are clustered at the provincial level, and time fixed effects are controlled.

relative wage growth rate for urban workers, but the effect is not significant. According to the conclusions of other literature studies, the reason may be that the scope of intelligent application is not large enough and lacks sufficient influence, or the intelligent development represented by the application of industrial robots may create new employment opportunities, and these new jobs may be crowded. The replacement of low-skilled labor has been fully accommodated, so that the wages of low-skilled labor have not declined significantly. In addition, the regression results also show that the increase in manufacturing labor productivity will significantly reduce the relative growth rate of manufacturing wages, which proves from the side that the increase in manufacturing productivity does not increase the wage growth rate of workers, but reduces the manufacturing labor force. The wage growth rate shows that there is a situation where machines are replacing labor, and overall productivity has increased substantially, but the wage growth rate of low-skilled labor has declined. Under such circumstances, the sustainable development path of the low-skilled labor force can only be to fully upgrade their own skills.

6. Conclusion

The empirical results show the following main conclusions: First, the use of industrial robots has a significant positive effect on the expansion of the skill-based wage gap. The use of industrial robots will exacerbate the wage gap between the high-skilled and low-skilled labor in the market. Under certain conditions of the skill structure of labor supply and other variables, the application of intelligent technology will significantly increase the skill premium.

Second, the use of industrial robots will change the skill structure of employment, reducing the proportion of low-skilled workers. Low-skilled labor is more vulnerable to substitution effects than high-skilled labor. Third, the use of industrial robots will increase the demand for high-skilled labor to a certain extent, without a significant impact on the demand for low-skilled labor.

This paper makes a comprehensive analysis of the impact of the use of industrial robots on the skill-based wage gap, which is conducive to grasping the impact of intelligent transformation on the wage gap between high-skilled labor and low-skilled labor as a whole, and helps us deeply understand the wave of artificial intelligence revolution. It also provides guidance on how to adjust income distribution under technological shocks. The research conclusion of this paper shows that the intelligent development represented by the use of industrial robots is indeed more beneficial to high-skilled workers, has a certain impact on low-skilled workers, and may exacerbate income inequality. Faced with this situation, we should objectively recognize such a historical fact: from the first industrial revolution to the second industrial revolution to the third scientific and technological revolution currently underway, all major scientific and technological innovations have promoted rapid economic development. At the same time, it will also have an impact on the existing wealth distribution pattern, and this impact will even bring about social unrest in local areas (Yang Fei & Fan Cong, 2020). However, looking at some developed countries that have experienced shocks, they can always resolve crises and ease conflicts through institutional reforms, and ultimately control technical risks within a reasonable range and achieve coordinated development. The income distribution effect of technological changes will inevitably be affected by policy factors, and the Chinese government should also formulate corresponding policies in the context of intelligent technological changes in light of its own national conditions. Reasonable policy measures can make the process of technological change in our country more inclusive and enable all people to better share the fruits of technological change.

The empirical results of the adjustment variables in this paper show that improving the "skill structure of labor supply" can effectively reverse the widening gap in skill wages caused by intelligent development. The key is to match the level of intelligent development with the skill structure of labor supply. Therefore, while vigorously promoting the artificial intelligence revolution, we should also pay attention to improving the technical level of the labor force, and pay attention to the synchronization and coordination between the two. First, from the perspective of the positive effect of the use of industrial robots on the labor force, promote the transformation of industrial intelligence and automation, promote the development of employment-expanding intelligence, and give full play to the demand effect of industrial robot applications. Second, improve the structure of labor skills, increase the proportion of high-skilled laborers, improve the level of human capital in society, and strengthen the education and training of laborers.

Redistributive policies are adjustments to the consequences of primary distribution. In the face of the skills wage gap that may be exacerbated by intelligence, existing research proposes redistributive policies from the perspective of taxation and social security.

First, the robot tax. Existing literature examines whether and how robots should be taxed from multiple perspectives. The research results of Abbott and Bogenschneider (2018) indicated that the replacement of human labor by machines reduces the tax burden of enterprises. In order to make up for tax losses, an "automation tax" should be levied on enterprises, which not only maintains the relationship between humans and machines in the labor market Equal status, taxes can also be used to train workers and guarantee a minimum income for low-skilled labor. Guerreiro et al. (2017) argue that imposing a robot tax will bring about production distortion, efficiency loss and welfare loss. At the practical level, the collection of robot tax will also face the problem that the taxation category is difficult to define and the taxation standard is difficult to unify. In short, taxing robots is still an open issue at present.

Second, the universal basic income policy. Aiming at the problem that the progress of intelligent technology may bring about mass unemployment and reduce the welfare of workers, the universal basic income policy (UBI) can be used as an ultimate welfare distribution scheme to deal with technical unemployment. Universal basic income policy refers to the government's unconditional provision of a minimum income for each citizen. Its advantages lie in low administrative costs and high execution efficiency, and it can avoid the "welfare trap". To a certain extent, the distortion of the labor market and the economy by the current welfare program can be alleviated. However, this method is currently only applicable to developed countries such as Canada, Finland, and the Netherlands. The high financial requirements are currently not in line with China's national conditions. However, it is also possible to consider implementing this policy in some regions during special periods as a smooth transition plan to deal with the short-term impact of technological progress on the labor market.

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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