sustainability

Article

Industrial Robots and the Employment Quality of Migrant Workers in the Manufacturing Industry

Bo Chen [1] and Dong Tan [2,*]

[1] College of Science and Technology, Ningbo University, Ningbo 315212, China
[2] The School of Economics, Xiamen University, Xiamen 361005, China
* Correspondence: tandong568@163.com

Abstract: Machine and manufacturing migrant workers in the new era are side by side cooperation and interaction of the new labor force form. Based on the dynamic survey of China's floating population in 2011 and the data collected by the International Federation of Robotics, the Bartik instrument variable method is used to analyze the impact of industrial robots on the employment quality of the floating population in manufacturing industry at the city level. As the city scale expands, industrial robots have an inverted U-shaped effect on the employment quality of manufacturing migrant workers. Industrial robots have a positive U-shaped influence on the number of hours that migrant workers in manufacturing work, with an inflexion point of 1.3721 units per 10,000 workers. The influence of industrial robots on migrant workers' working conditions in the manufacturing sector was U-shaped, and 1.668 units per 10,000 workers marked the tipping point. Nevertheless, industrial robots have an inverse influence on the occupation stability of migrant workers in the manufacturing industry. Precisely, the installation density of industrial robots in the manufacturing industry has a detrimental impact on the occupational stability of migrant employees. Industrial robots are negatively associated with the working conditions of migrant workers employed in manufacturing. There were detrimental effects on the employment quality of manufacturing migrant workers in cities with higher and lower population densities. In the end, for every manufacturing farmer using an industrial robot, the likelihood of being miserable and almost happy went up by 2.64 percent and 5.59 percent, respectively, while the likelihood of being happy went down by 7.62 percent.

Keywords: employment quality; industrial robots; manufacturing; migrant worker

check for updates

Citation: Chen, B.; Tan, D. Industrial Robots and the Employment Quality of Migrant Workers in the Manufacturing Industry. *Sustainability* **2023**, *15*, 7998. https://doi.org/10.3390/su15107998

Academic Editor: Luigi Aldieri

Received: 1 May 2023
Accepted: 10 May 2023
Published: 14 May 2023

1. Introduction

Industry 4.0 describes the combination of traditional manufacturing technology and modern information technology, with CPS (cyber physical systems) at its core, that is transforming the manufacturing industry using intelligence and networks [1,2]. Industry 4.0 is also considered as the Fourth Industrial Revolution, which refers to an industrial revolution centered on artificial intelligence [2,3]. Every industrial revolution is aimed at liberating the labor force. During the First and Second Industrial Revolutions, machines largely replaced human physical labor. The core feature of the Third Industrial Revolution was information technology. Due to the development of computer technology, while liberating human physical labor, some mental labor was also liberated, and factories began to implement automatic assembly line production modes. The Fourth Industrial Revolution aims to simulate a human brain using computers. Digital information is the raw material [4]. An intelligent factory system carries out analysis, judgment, decision making, supply, design, manufacturing, sales, after-sales, and other processes in production to realize the rapid and high-quality supply of products [5,6]. Compared with the Third Industrial Revolution, due to the support of big data and the Internet of Things, factory machines are highly intelligent, and human mental labor will be liberated to the greatest extent, promoting changes in production modes [7–9]. The corresponding Industry 4.0 fields cover manufacturing, electronic technology and optics, chemical medicine, aerospace, etc. [9,10]. Robots play an important role as Industry 4.0-sustainable tools [11–14]. Mohd Javaid et al. studied the effect of robotics on enhancing the implementation of Industry 4.0 [13]; their results showed that robotic machines are widely used in industrial markets and could be useful for helping enterprises to decrease costs. Industry 4.0 technologies can also improve environmental sustainability, in which robots have been shown to play an important role [14].

The expansion of China's manufacturing sector is significantly influenced by the industrial robot industry. Several advantageous policies have recently been released to encourage the deployment of industrial robots. In 2016, the National Medium and Long-Term Scientific and Technological Development Plan (2006–2020) was released, and for the first time, intelligent robots were placed in the advanced manufacturing technology category [15]. Guidance on the Promotion and Development of the Robot Industry was published in 2013 with the goal of achieving a robot density of 100 units per 10,000 employees by the launch of "Made in China 2025" in 2020, which was three times the robot density in the manufacturing industry predicted for 2015. In order to expand into other industries, particularly the service sector, the Robotics Industry Development Plan (2016–2020) was introduced in 2016.

China's robot sector has seen rapid growth since 2010, owing to advancements in automation technologies and ongoing industrial robot innovation. China, which has been the world's top consumer of industrial robots for five years in a row and will account for 44% of the total global stock in 2020, first surpassed Japan in 2016 with the greatest operational stock of industrial robots (349,470 units) [16]. The number of industrial robots installed in China rose between 2010 and 2018 at an average annual pace of 33.82 percent, indicating a rapid growth phase (IFR). China's industrial robot density has surpassed the global average since 2018 and now stands at 14 units per 1000 workers (White Paper on the Development of China's Industrial Robot Industry in 2020), which is still less than some developed and developing nations such as Singapore, Korea, Germany, and Japan. The COVID-19 pandemic had a considerable impact on the world economy in 2020, although China's total need for industrial robots has not changed considerably [17]. The overall output of robots in industrial businesses above the national scale reached 206,851 units in the first three quarters of 2020, with a growth rate of 22.2% each year, according to statistics given by the NBS and IFR. According to the CCI (China Commerce Management Institute) forecast, the size of the industrial robot market in China will reach USD 100.7 billion by 2025 [18].

Using industrial robots has been shown to cause several issues in the labor market [19]. China has seen a drop in the growth of the working-age population and fast-growing labor expenses in recent years, which corresponds with the intense use of industrial robots [20]. Not only have automation and robotics technologies changed how contemporary manufacturing is carried out, they have also become deeply ingrained in practically every area of people's lives [21].

The manufacturing sector in China, which accounts for more than 80% of all industries, is the focus of this study. This sector employs a high number of manual employees who are particularly vulnerable to robot shocks because it is a labor-intensive sector [22]. In 2021, 273.95 million migrant workers, or around 30.63 percent of the working force, were present in China. Due to greater income, the industrial sector is where most workers concentrate, accounting for 27.30 percent of all migrant workers in 2020. The exchange rate of Yuan currency against the US dollar in 2020 was 6.8974. The average monthly income of migrant workers is 4096 yuan, which is not only lower than the income of urban private enterprise of 12,398 yuan, but also far lower than the income of urban non-private enterprise of 6949 yuan. Of all migrant workers, 13.40 percent belong to labor unions; 46.30 percent are employed for more than 56 h per week; 64.72 percent are employed under contracts; and 18.27 percent are employed as urban workers who are covered by medical insurance.

This research makes four contributions to the current body of literature. First, we add to the existing literature by providing evidence for the nonlinear impact of industrial robots on the quality of employment of manufacturing migrant workers. This study focuses primarily on urban scale, working distance, work conversion, individual characteristics, and the institutional environment. The data at the prefecture level, which were matched using the International Federation of Robotics and the China Migrants Dynamic Survey, are also being used for the first time. While there is a wealth of research that examines issues at a national, regional, and industry level, most studies ignore the fact that migrant workers in manufacturing are the primary group affected by industrial robots. Third, we create a comprehensive index system that combines subjective and objective techniques to ideally gauge the caliber of migrant workers in the manufacturing industry. We dig further into the link between industrial robots and the quality of employment of future manufacturing migrant workers from the standpoint of metropolitan scale and population density. This new research gives fresh insight into the true mechanism of this relationship.

2. Theoretical Analysis

2.1. Literature Review

The 1970s were a formative decade for the study of labor quality. The idea of employment quality has evolved and now encompasses four modes, including the "Quality of Work Life" (OLS) proposed by the Federal Productivity Council of the United States, "Decent Work" by the International Labor Organization (ILO), "Quality in Job" by the European Commission, and the multi-dimensional European job quality index. A number of studies have been conducted to examine the effects of work experience on personal life as part of the Quality of Work Life proposal made by the Federal Productivity Council. Theoretically, QWL has no definitive definition. ILO 's definition of "decent work" may be broken down into six categories, including "opportunities for work", "work in free circumstances", "productive work", "equity in work", "security at work", and "dignity at work". The four components of the European Employment Quality definitions—wage level, social security and representation rights, contract type, and training opportunities—are all included. Laeken indicators were added to the four core aspects of socioeconomic security, education and training, working conditions, and gender equality based on employment quality in the European Union to reflect current institutional and state policy disparities [23]. The multi-dimensional European job quality index, which takes into account pay, unconventional forms of employment, working hours and work-life balance, working conditions and job security, skills and career development, and collective interest representation, is currently more extensively utilized [24]. Although these studies focus on manufacturing migrant workers' employment quality, they infrequently combine subjective and objective indicators into a single rating method.

Researchers often look at the elements that affect employment quality from three angles: at the macro level, at the workplace level, and from the perspective of the individual labor practitioners [25–27]. From a macro viewpoint, academics primarily examine how economic globalization, the privatization of emerging nations, and labor market features directly affect job quality [28,29]. One group of researchers primarily examined two elements of the effect of economic globalization on the quality of employment of people in different countries: decreasing living expenses and increasing labor market unpredictability [30]. Privatization in developing countries has resulted in wage declines and unemployment, and the loss of state control has significantly altered market labor relations; the emergence of the private sector includes those with permanent positions, high occupational safety, and higher salaries, and the welfare characteristics of the labor relations in the public sector are significantly reduced [31]. From the perspective of dual labor market segmentation, employment quality was found to be greater in the primary labor market and lower in the secondary labor market. The focus of academic studies at the level of employment characteristics is on the ownership attributes, industry attributes, and productivity level of firms. The excessive cyclicality of employee wages and working conditions is what causes instabilities in economic activity in the "informal sector" (private businesses, family businesses, etc.). Demographic features, labor productivity, and employment form are the key research subjects in terms of the personal characteristics of employees. The employment quality of family members will also affect the employment quality of individual workers. In addition, many studies have shown that the employment quality of male workers is generally better than that of female workers. Informal employment poses a number of challenges for both 'legitimate employers' and employees [32,33]. For example, 'tripartite employment' makes it difficult for employees to protect their rights while also making it challenging for 'legitimate employers' to monitor and evaluate their employees [34]. Scholars have mostly concentrated on the income characteristics of immigrants, the assimilation of immigrants' income, and the income disparity between immigrants and local labor when examining the employment quality of immigrants [35,36]. The strong indigenous impacts of human capital, age, skills, and other characteristics on migration income have been demonstrated in different studies on the factors determining migration income [37]. In addition, although non-employed immigrants' initial income levels are lower than employment-oriented immigrants', non-employed immigrants in the United States experience higher rates of income growth than employment-oriented immigrants [38,39]. In contrast, non-European immigrants in Sweden experience income disadvantages that vanish 15 to 20 years after migration [40]; that is, their pay levels do not catch up with those of local employees for the first 20 years after arriving in Sweden. In Los Angeles, China Xiangqian, Ireland, and elsewhere, others have examined the wage disparity between foreign-born workers and native-born workers. Their findings indicate that before 1980, there was an increase in the percentage of Latin American immigrants working in "Brown-collar" employment in Los Angeles. In Ireland, with the same human capital, migrants' income was shown to be about 18% lower than that of the local labor force, and the percentage of social welfare received was only half that of the local labor force. In Xiangqian, immigrants' average income lagged far behind that of the local labor force from 1981 to 1991, and the income gap has widened.

Numerous studies have examined how the effects of industrial robots on employment and salaries relate to industry-level variation, local labor market shocks, and corporate-level waves [41,42]. The effects of industrial robots on employment have drawn the attention of many scientific researchers. In one study, the three-stage least squares approach for simultaneous equations was used to explore the effect variables impacting the use of industrial robots, job growth and structure, and labor costs using panel data from 42 nations [43]. The findings showed that the widespread use of industrial robots directly results from rising unit labor costs and hourly pay levels. Additionally, as industrial robot usage increases, unit labor costs decrease and employment increases, particularly for low-skilled workers. A production function was established in another study to examine the interaction between industrial robots and the U.S. labor market [42]. For every extra industrial robot per 10,000 employees, the employment-to-population ratio fell by 1.8–3.4 percent, and worker income fell by 2.5–5.0 percent. Rather than contributing to a decline in overall employment, an increase in industrial robots has resulted in an increase in manufacturing jobs and a decrease in business service jobs [44]. Further studies have linked increased industrial robot use to reduced labor share in total income and higher labor productivity. With the instrumental variables of robots' competitive advantage in specific tasks, Graetz and Michaels analyzed panel data on the use of industrial robots within industries in seventeen countries from 1993 to 2007 [45]. Their findings showed that 0.36 percentage points raised labor productivity and improved overall factor productivity, reducing output prices. Acemoglu and Restrepo point out that robot technology will significantly affect labor remuneration and employment [46]. If one robot is added to every thousand workers, the employment ratio will decrease by 0.2%, and the wage will decrease by 0.42%. Data from the U.S. labor market shows that every 0.1 percent increase in robots creates 0.2 percent fewer jobs and 0.42 percent fewer wages. Wei Xihai et al. found that robots positively correlate with the employment of irregular immigrants [47]. However, for the less skilled workers in orthodox jobs, robots are more likely to replace orthodox jobs. The use of robots will significantly reduce the employment rate of the labor force, especially in industries that are easily replaced by machines. However, the effect varies widely across labor market structures and is more pronounced in regions with higher levels of education, weaker labor protections and higher levels of marketization [48]. Industrial robots still have the potential to boost labor employment. That is because using robots is likely to raise the return on capital in one industry, which will raise the return on capital in other industries, where more labor is needed to replace capital [49].

The impact of industrial robots on wages has also attracted the attention of many scholars. Dauth et al. empirically analyzed the application of industrial robots in the labor market in Germany and found that robots could improve labor efficiency but did not increase wages in the labor market [44]. In large-scale enterprises with low wage rates, high penetration of robots, and capital-intensive industries, the negative adjustment effect of robot application on minimum wage is more significant. There are two opposing views on the impact of robots on corporate compensation: to increase compensation through robots and to reduce compensation through robots [50,51]. Yan Xueling takes China's manufacturing industry from 2006 to 2017 as an example and uses statistical analysis methods to empirically analyze industrial robots' impact on manufacturing employment [52]. It is found that the application of industrial robots has a particular impact on employment in the manufacturing industry and has a significant negative impact on job opportunities. With every 1% increase, job opportunities will decrease by 4.6%. Overall, the effect on wages has been modest. Wang Jing studied the compensation effect of using industrial robots on the minimum wage distribution of labor income by combining theory and demonstration [53]. The empirical analysis shows that the increase in the minimum wage has a noticeable promoting effect on the growth of enterprise labor income. However, the promoting effect is gradually weakened with the increase in the penetration degree of robot technology, especially in the large-scale, low wage level, high penetration degree of industrial robot technology, and capital-intensive industries. Moreover, others start from the current situation of the Chinese manufacturing industry, with USA robots of the same industry in the United States as the instrumental variable; the research finds that in the manufacturing industry, the application of industrial robots still has a particular impact on our manufacturing industry. With every 1% increase in industrial robot devices, the manufacturing industry will decrease by 6.2%. This is an improvement over the baseline regression coefficient, but its effect on wages also fades over time [52].

In addition, although the employment percentage of low-skilled employees has declined, overall employment has not changed [54,55]. Using panel data of Spanish manufacturing enterprises from 1990 to 2016, Koch et al. applied difference-in-difference estimation combined with a propensity score reweighting to discuss the characteristics of the firms that had more motivation to apply for industrial robots and the difference between the adopting firms and non-adopting firms [56]. According to the first response, successful businesses tended to have higher labor and output productivity as well as a focus on specialized skill sets. In the latter case, output climbed by 20–25 percent over a four-year period, the labor cost ratio fell by 5–7 percentage points, and jobs expanded by a net 10% overall. China Employer-Employee Survey (CEES) data, collected at the industry and firm level of manufacturing enterprises, were used to make their proposal. The authors suggested that rising labor costs, government connection, and market factors play an even more important role in China's adoption of robots, and the more manual tasks enterprises have, the more likely it is that robots will be used. An insufficient number of middle-aged people skilled in manual production jobs (as a result of aging) increases the use of industrial robots, increases labor productivity, and decreases labor share. By using the inverse probability of treatment weighting (IPTW) and propensity score matching (PSM) difference-in-differences methods, Tang et al. came to the conclusion that industrial robots favor hiring highly skilled and highly educated workers and contribute to the development of a skill-biased employment structure (DID) [57].

A flexible neoclassical labor market model created by Cortes et al. demonstrates how regular occupations employees must take on non-routine manual tasks or become unemployed as a result of automation technology; the model includes endogenous occupation, participation decisions, and the heterogeneity of workers. Faber et al. showed that US robots have had a significant negative influence on employment in Mexico, with less educated male machine operators suffering more adverse effects than female machine operators [58]. Robotization increases labor costs in manufacturing businesses indefinitely; however, it also increases productivity and performance in industrial firms, especially in SMEs and big enterprises [59]. Our work is most closely related to the research by Sachs and Kotlikoff [60], who found that adopting robots not only lowers families' overall income levels and their capacity to save, but also limits their ability to invest in skills and physical capital, ultimately lowering the quality of life for each generation's members [61]. Additionally, it has a detrimental long-term effect on the living conditions of multigenerational families.

As can be seen, the current research primarily focuses on the impact of human capital, social capital, and individual characteristics on the employment quality of migrant workers in the manufacturing industry; it does not examine the impact of industrial robots and related sub-indices on the employment quality of migrant workers in the manufacturing industry, including income, working hours, occupation stability, and workfare.

2.2. Hypothesis

Income, work hours, occupational stability, and workfare are some sub-indices of employment quality impacted by industrial robots for migrant workers employed in manufacturing. First, industrial robots have increased total factor productivity and labor productivity, in addition to lowering production costs. The demand for low-skilled migrant workers to undertake procedural and repetitive jobs in the manufacturing industry has decreased as a result of the increased labor productivity of upstream and downstream industries brought about by industrial robots [45]. Additionally, the productivity of these businesses has grown by 20%; however, the use of industrial robots results in a 20% reduction in the pay of production workers, such as welders and assemblers. The overall salary of businesses has grown by 8% as a result of the change in labor demand toward skilled personnel, such as qualified technicians, engineers, and researchers. Here, a dynamic model of a business is constructed that accounts for the observed size premium in enterprises choosing to apply robots, the S-shape of robot dissemination across time, and these distilled forms of reactions to robot applications [41]. According to transitional dynamics arguments based on Acemoglu and Restrepo's model [62], the negative displacement effect of robotization can indeed be reversed when a certain threshold is exceeded. This is because the negative substitution effect can initially outweigh the positive productivity and composition effects. This suggests that there is a U-shaped association between employment and industrial robots [63]. As a result, it eventually boosts both the demand for and pay of migrant workers in the industrial sector. Additionally, the influence of industrial robots on employment stability exhibits features of an inverted U, which is the reverse of the U-shaped effect on migrant workers' employment in the manufacturing sector.

Second, there is a significant U-shaped relationship between the total number of hours worked and the density of industrial robots. Through the rise in total factor productivity, industrial robots have reduced the number of hours that migrant employees in manufacturing must put in [64]. When compared to medium- and high-skilled migrant employees, robots have mostly decreased the percentage of hours worked by low-skilled migrant workers [45]. The majority of the migrant workforce in China's labor-intensive industrial sector is made up of unskilled laborers. As a result of industrial robots, migrant employees in manufacturing have less work to carry out. Industrial robots, a type of skill-biased technological advancement, need to provide some proof of the rule of declining marginal returns, a key economic tenet. When the marginal utility of industrial robots is equal to zero, their numbers will stop increasing. The manufacturing companies will keep undervaluing migrant labor in order to maximize their profits. The impact of industrial robots on the number of hours worked by migrant employees in industry is thus U-shaped.

Thirdly, the life cycle theory states that there are three stages to the need for workfare in migrant workers: the emergence of knowledge of workfare in the early stage, the search for enhanced workfare in the middle stage, and the absence of partial workfare in the late stage. The implementation of the minimum wage system in 2003 raised fixed expenses for businesses while also serving to safeguard the rights and interests of migratory employees. The Social Insurance Law of 2010 mandated that businesses pay for three different forms of insurance and a housing fund for migratory employees, increasing the variable expenses of businesses. Thirdly, according to the life cycle theory, there are three periods in which migrant workers require workfare: the early stage sees a rise in knowledge about workfare, the middle stage is characterized by the quest for improved workfare, and the late stage features the absence of partial workfare. The introduction of the minimum wage system in 2003 increased employers' fixed costs while also defending the rights and interests of migrant workers. The Social Insurance Law of 2010 increased businesses' variable costs by requiring them to pay for three distinct types of insurance and a housing fund for migrant workers.

H1. *During the initial stages of the application of industrial robots in the manufacturing industry, migrant workers' income, work hours, and workfare are reduced, which reduces their employment quality. When the application of industrial robots exceeds a saturation point, it enhances migrant workers' income, work hours, and workfare, which contributes to the employment quality of the migrant workers. Industrial robots have an inverse influence on the occupation stability of migrant workers in the manufacturing industry.*

Most scholars' research on the employment quality of industrial robots and mi-grant workers in manufacturing industry are single-trend studies. Specifically, some scholars believe that industrial robots have a negative relationship with the income of manufacturing farmers [65,66]. Some scholars argue that there is no correlation [67,68]. Some scholars believe that industrial robots can improve the employment quality of migrant workers in manufacturing industries [68,69]. Urban growth lowers the cost of shared labor, intermediate investments, and transportation. Additionally, due to spatial agglomeration, knowledge can spread more quickly, making it easier for employees and their employers or other corporations to collaborate on studies [70]. This also gives employees more opportunities to quickly gain valuable experience that will improve their human capital [71]. In addition, the higher productivity, better access to healthcare, higher standards of living, and higher wages associated with big cities draw more groups of qualified people than small cities do, contributing significantly to the pay premium impact of urban size [72]. However, as cities grow, overcrowding causes traffic jams, urban pollution, and skyrocketing housing costs, negating the beneficial effects of worker productivity and pay levels [73]. The proportional magnitudes of these positive and negative effects determine the total effect. Overly large cities are detrimental to economic growth and worker productivity because of the inverted U form of urban scale [74]. The adoption of industrial robots results in a change in industrial composition, which is hypothesized to produce an inverted U-shaped relationship with urban employment and real income per worker [75]. On the basis of the study above, we suggest Hypothesis 2:

H2. *As city scale expands, industrial robots have an inverted U-shaped effect on the employment quality of manufacturing migrant workers.*

3. Method and Data

3.1. Model and Estimations

To examine the influence of industrial robots on employment quality of manufacturing migrant workers, the regression model was constructed as follows:

$$quality_{ci} = \alpha_0 + \alpha_1 zzrobot_c + \alpha_2 zzrobotsq_c + \alpha_3 Z_i + \alpha_4 Z_c + \delta_c + \varepsilon_{ci} \quad (1)$$

where i represents a single migrant worker, c represents the city, and $quality_{ci}$ denotes the level of employment for migrant workers in manufacturing at that location with reference to the square of the installation density of industrial robots in the manufacturing business; α_1 is the semi-elasticity coefficient, which shows how the employment quality of migrant workers in manufacturing varies for every incremental industrial robot installation density unit; and Z_i is a vector of control variables describing demographic, mobility, unit, and urban characteristics. Gender, age, marital status, education level, skill training, and mode of employment acquisition were among the demographic characteristic factors. Mobility time and mobility range are two examples of the mobility characteristic variables. The job characteristic variables included unit ownership and occupation level. The variables describing a city's characteristics included its level of economic development, degree of global openness, and extent of reliance on foreign capital. According to the literature [76], per capita GDP, the percentage of imports in GDP, the percentage of exports in GDP, and the percentage of foreign direct investment in GDP [76] were used as city-level variables.

3.2. Variable Measurement

A combination of subjective and objective methods was used to construct an employment quality index system for manufacturing migrant workers, including wage level, job characteristics, labor rights protection, workfare, and subjective sensation. The system is based on the multi-dimensional employment quality index used by Leschke and Watt [24] and is armed with the data collected by the China Migrants Dynamic Survey in 2011 [77]. In this study, we employed job satisfaction as a subjective indicator and salary level, work hours, occupation stability, and workfare as objective variables. Due to the irregular and overtime labor of migrant workers, the number of hours worked per week was equal to the number of days worked per week times the number of hours worked each day. The labor agreement was equivalent to one if it had regular intervals, a timeframe to do one-time activities, or a probationary period. If there was no contract, the labor agreement was equal to zero with at least one of the following: a housing provident fund, a pension fund, medical insurance, industrial injury insurance, unemployment insurance, and maternity insurance. If the individual was working and living locally while experiencing less, the same, or greater happiness than in their hometown, their level of well-being was coded as one, two, or three, respectively.

First, the construction of standardized sub-indicators is as follows:

$$x_{ij}^{sta} = \frac{x_{ij} - min_j}{max_j - min_j}, j = 1, \cdots, 5 \quad (2)$$

where x denotes the standardized sub-indicators; i denotes individual migrant workers; j denotes the five dimensions of the employment quality of manufacturing migrant workers; $j = 1, \ldots, 5$ denotes migrant workers' income, work hours, occupation stability, workfare, and job well-being, respectively; max_j denotes the maximum value of the indicator j; and min_j denotes the maximum value of the indicator j. The number of hours worked per week was negatively correlated with the employment quality of manufacturing migrant workers. Therefore, we constructed an inverse index of the hours worked per week, which corresponded to one minus the standardized value of the hours worked per week.

Second, we determined the sub-indicator weights. According to the procedures of the European Commission and the European Foundation, the equal-weighted average approach was used to calculate the employment quality of migrant workers in manufacturing, which was then multiplied by 100. Basic descriptive statistics for migrant workers employed in manufacturing are provided in Table 1, including employment quality, pay, hours worked, workfare, occupation stability, and well-being. The sample means and standard deviations for each indicator and sub-indicator are provided in columns 3–4.

$$Q_i = \sum_{j=1}^{5} \frac{x_{ij}^{sta}}{5} \times 100 \quad (3)$$

Table 1. Descriptive statistics for the employment quality of manufacturing migrant workers.

Variables	Measure	Mean	Standard Deviation
Employment quality index of manufacturing migrant workers	Scores 1–100	56.236	11.254
Subjective indicators			
Wage level	Last month income (CNY)	367.840	131.262
Work hours	Weekly work hours	52.362	9.214
Workfare	Possession of old-age, medical, unemployment, injury, or birth insurance and housing funds = 1; other = 0	0.036	0.206
Occupation stability	Labor contract signing rate (yes = 1; no = 0)	0.886	0.617
Objective indicators			
Job well-being	Unhappiness = 1; almost = 2; happiness = 3	2.638	0.446

Notes: Wage level and weekly work hours were calculated according to the original data for last month income and daily work hours multiplied by weekly working days after a bilateral contraction tail.

Two distinct patterns can be seen in Table 1. First, the manufacturing migrant workers' average employment quality index (49.92) was 2.16 percentage points lower than the non-agricultural migrant workers' average index (52.08), indicating a greater opportunity for development. The average salary of migrant workers in the manufacturing sector was CNY 337.75, with a high standard deviation translating to a wide range of earnings. The average weekly number of work hours of migrant workers in the manufacturing sector was 56.62 h, which was 28.73 percent more than the permissible work week of 44 h. This suggests that migrant employees frequently work over the legal limit in this sector. The average workfare for migrant employees in manufacturing is 6.90 percent, which indicates that their working conditions are subpar. The Labor Contract Law provides legal protection for the majority of manufacturing migrant employees, with an average of 72.40 percent of labor contracts being signed by these workers. Second, migrant workers in manufacturing reported an average job satisfaction rating of 2.35 out of 3, where China was the country with the highest score. The equation for the installation density of industrial robots in China can be written as:

$$zzrobot_{2011}^{CA} = \frac{zzrobotos_{2011}^{CA}}{ML_{2011}^{CA}} \tag{4}$$

where the manufacturing industry runs over all the classification manufacturing industry in the IFR data. Here, $zzrobot_{2011}^{CA}$ stands for the 2011 installation density of industrial robots in China's manufacturing industry, $zzrobotos_{2011}^{CA}$ denotes the 2011 operational stock of industrial robots in China's manufacturing industry, and ML_{2011}^{CA} denotes the 2011 employment of urban units in China's manufacturing industry.

We constructed an equation for the installation density of industrial robots at the region-level $zzrobot_{c,2011}^{CA}$, which can be written as

$$zzrobot_{c,2011}^{CA} = \frac{CL_{c,2011}^{CA}}{TL_{c,2011}^{CA}} * \frac{zzrobot_{2011}^{CA}}{L_{2011}^{CA}} \tag{5}$$

where $zzrobot_{c}^{CA}$ represents for the 2011 installation density for city c, $zzrobot_{2011}^{CA}$ denotes the 2011 operational stock of industrial robots in China's manufacturing industry, and L_{2011}^{CA} denotes total employment in the urban industry in 2011. The main measure of the share of employment depends on two variables, where CL_{c}^{CA} denotes the employment in urban units in 2011 in city c and TL_{c}^{CA} denotes the total employment in urban units in 2011 in city c.

The Bartik instrumental variable approach is frequently used to examine tax income, immigration status, and employment [78–80]. Studies on the influence of robots on the US labor market are closely connected to this research and have used the shift-share technique described above for analysis [42,81,82]. Thus, using the installation density in the US as our explanatory variable, we calculated the installation density of industrial robots in China's manufacturing sector. There were three primary reasons for this: First, China has aggressively established supporting policies connected to the robotics sector to encourage businesses to replace manpower with industrial robots in order to quickly achieve industrial transformation and upgrading, which worsens the competitive dynamics between China and the U.S. Second, there is a constant growth trend in the adoption of industrial robots between China and the United States, the largest economies in the world, which supports the relationship between the two variables. Third, a highly developed and fiercely competitive labor market in the US may best represent the effects of external industrial robot technology on the Chinese labor market and ensure the exogeneity criterion is satisfied [83].

We constructed an equation for the installation density of industrial robots in China at the city level using the installation density of industrial robots in the US:

$$zzrobot^{CA}_{c,2011} = \frac{CL^{CA}_{c,2011}}{TL^{CA}_{2011}} \times zzrobot^{US}_{2011} \tag{6}$$

where $zzrobot^{CA}_{c,2011}$ denotes the installation density of industrial robots in China's manufacturing industry in 2011 and $zzrobot^{US}_{2011}$ denotes the installation density of industrial robots in the US manufacturing industry in 2011. The main measure of the share of employment depends on two variables, where $CL^{CA}_{c,2011}$ denotes employment in urban units in city c in 2011 and $TL^{CA}_{c,2011}$ denotes employment in urban units in China's manufacturing industry in 2011 [42].

We established a link between the use of industrial robots and the standard of employment for migrant workers in the manufacturing sector. To solve the endogenous problem, we used a parsimonious model that utilized the installation density of industrial robots in China's manufacturing sector to offset the installation density of industrial robots in the US manufacturing sector. The direct causal effects of the density of industrial robots installed in the United States on the employment quality of China's manufacturing migrant workers are mirrored by the estimation coefficient of the parsimonious model, which can explain the partial causal effects of the two variables in China. As a consequence, it can be said that exogenous industrial robot technology shock has an effect on the employment quality of migrant workers in China's manufacturing industry, which is why we must pay more attention to the regression findings of the simplified model, as shown in Equation (7).

$$quality_{ci} = \alpha_0 + \alpha_1 zzrobot^{CA}_{c,2011} + \alpha_2 zzrobotsq^{CA}_{c,2011} + \alpha_3 Z_i + \alpha_4 Z_c + \delta_c + \varepsilon_{ci} \tag{7}$$

3.3. Data Sources

In order to combine industry-level data from the International Federation of Robotics with individual-level employment features, statistics were obtained from the 2011 *China Labor Statistical Yearbook*. The 30 provinces (autonomous regions and municipalities), which contain 285 prefecture-level cities, were the focus of our regression research, with the exclusion of Tibet and the Xinjiang Production and Construction Corps. Using microdata from the 2011 China Migrants Dynamic Survey for each prefecture-level city, we calculated the employment quality of migrant workers in manufacturing. This employment characteristic was composed of compensation, working conditions, the frequency of signing contracts, workfare, and well-being. In July 2011, the National Health Commission carried out a survey that collected data on fundamental demographics, mobility scope and trend, employment and social security, income and expenditure data, residence, fundamental public health services, the management of marriage and family planning services, child mobility and educational opportunities, and psychological culture. We used the CMDS 2011 data for many different things. First, the sample size is impressively representative of all regions in China—close to 200,000 residences yearly. Second, incorporating both objective and subjective data allowed for a more complete evaluation of the employment quality of migrant workers in manufacturing than just subjective or objective indicators.

The sample included migrants from urban–rural areas, urban areas, and rural areas. The five questionnaire questions "hukou status", "mobility status", "unit ownership status", "employment status", and "social insurance status" were used to differentiate these groups. We only focused on rural–urban migrants with rural registration who had been moving for at least six months and whose employment status was employee. In addition, we excluded data where unit owners were land contractors, workers were housewives, students were in kindergarten, and social security status was ambiguous. Additionally, the variables that had missing values were also disregarded. We received samples from respondents between the ages of 16 and 55, since males and females retire at 55 and 60, respectively. There were 27,130 samples altogether.

We also took a few control factors into account. Age, gender, marriage, education level (illiterate, primary school, junior middle, senior school, or college and above) dummy variables, and government skill training were the individual attribute variables. The individual work factors included unit ownership (state-owned enterprise vs. non-state-owned enterprise) virtual variables and occupation (regular personnel, management people, and technician personnel) dummy variables. Per-capita GDP, Chinese imports, exports, and foreign domestic investment were among the city-level indicators found in the *China Urban Statistical Yearbook* and the *China Urban Construction Statistical Yearbook*. Working distance has a U-shaped influence on the employment quality of migrant workers in manufacturing, according to prior research (e.g., Li and Yuan, 2017), and government-sponsored jobs help create positions with greater employment quality. We used dummy factors for mobility time, working distance (city to county = 1; province to province = 2; across province = 3), and work acquisition channel (self-seeking, being introduced by family and friends, or being introduced by the government sector).

4. Results and Discussion

4.1. Descriptive Statistics of Variables

Table 2 showed descriptive statistics of variables, variables include independent variable, dependent variables, exogenous variables, work characteristic variables and city characteristic variable. For the independent variables, the mean employment quality of manufacturing migrant workers was 47.625. Industrial robots per 10,000 employees in manufacturing industry in China is 0.114, the average of industrial robots per 10,000 employees in manufacturing industry in US is 1.694, and the standard deviation of industrial robots per 10,000 employees in manufacturing industry in China is larger than mean, which indicates that the data show a large variation.

Table 2. Descriptive statistics of variables.

Variables	Measure	Mean	Standard Deviation
Independent variable			
Employment quality of manufacturing migrant workers		47.625	12.628
Dependent variable			
Industrial robots per 10,000 employees in manufacturing industry in China	units	0.114	0.186
Exogenous variable			
Industrial robots per 10,000 employees in manufacturing industry in US	units	1.694	1.436
Demographic variable			
Age	year	33.224	7.112
Gender	male = 1; female = 0;	0.685	0.526

Table 2. *Cont.*

Variables	Measure	Mean	Standard Deviation
Marriage	married = 1; unmarried, widowed or divorced = 0	0.826	0.536
Education			
Illiterate	Yes = 1; No = 0	0.008	0.166
Primary school	Yes = 1; No = 0	0.139	0.248
Junior middle school	Yes = 1; No = 0	0.779	0.562
Senior school	Yes = 1; No = 0	0.223	0.486
College and above	Yes = 1; No = 0	0.079	0.239
Government skill training	Yes = 1; No = 0	0.556	0.568
Work acquisition channel			
self-seeking	Yes = 1; No = 0		
Introduction by relatives and friends	Yes = 1; No = 0	0.689	0.654
Government sector introduction	Yes = 1; No = 0	0.025	0.136
Mobility characteristic variable			
Mobility time	year	5.776	3.827
Working distance	city across county = 1 province across city = 2 across province = 3	2.264	0.779
Work characteristic variable			
Occupation level			
Ordinary personnel	Yes = 1; No = 0		
Management personnel	Yes = 1; No = 0	0.033	0.364
Technician personnel	Yes = 1; No = 0	0.186	0.448
Unit ownership			
State-owned enterprise	Yes = 1; No = 0	0.089	0.284
Non-state-owned enterprise	Yes = 1; No = 0		
City characteristic variable			
Per capital gross domestic product	$	1.911	0.084
Proportion of import in gross domestic product	%	0.487	0.428
Proportion of export in gross domestic product	%	0.379	0.326
Proportion of foreign domestic investment in gross domestic product	%	0.046	0.021

4.2. Baseline Results

A model for the installation density of industrial robots in China's manufacturing sector built using data from US industrial robots may ease the endogeneity challenges of significant factors since the results of the baseline model and the parsimonious model were largely comparable. The major findings, which demonstrated the U-shaped influence of industrial robots on the employment quality of migrant workers in manufacturing, were analyzed using the parsimonious model.

Table 3 presents our baseline results for the employment quality of manufacturing migrant workers. Column 1 presents our basic linear regression specification, which only includes a linear term for the number of industrial robots. We estimated a strong negative correlation between industrial robots and the employment quality of manufacturing migrant workers with a coefficient of −5.3718 (standard error = 2.0415). Column 2 provides ordinary least squares (OLS) estimates, in which we controlled for a quadratic term. The coefficient of the linear term for industrial robots was significantly negative and the coefficient of the quadratic term was significantly positive. Therefore, industrial robots exhibit a U-shaped impact with a turning point at 0.226 units per 10,000 workers. Column 3 shows our basic linear regression specification of the parsimonious model. We found a strong negative correlation between industrial robots and the employment quality of manufacturing migrant workers with a coefficient of −0.6005 (standard error = 0.2283). Column 4 provides the parsimonious model, controlling for the industrial robot quadratic term. As expected from the fact that our measure of industrial robots had a U-shaped impact on the employment quality of manufacturing migrant workers, the linear term and quadratic term were −3.2510 (standard error = 0.9957) and 0.8051 (standard error = 0.2942), respectively.

Table 3. Impact of industrial robots on the employment equality of manufacturing migrant workers.

Variables	Employment Quality of Manufacturing Migrant Workers			
	(1)	(2)	(3)	(4)
	Basic Linear Regression	OLS	Parsimonious Model	Parsimonious Model
Industrial robots per 10,000 workers	−6.4268 *** (1.8426)	−27.1136 *** (7.3628)		
Square of industrial robots per 10,000 workers in China		61.2684 *** (20.2293)		
Industrial robots per 10,000 workers in China			−0.8856 *** (0.1768)	−5.1326 *** (0.8136)
Square of industrial robots per 10,000 workers in US				0.9362 *** (0.3218)
Observations	14,738	14,738	14,738	14,738
City FE	Yes	Yes	No	No
Control	Yes	Yes	Yes	Yes
U-test of square term		0.418 ***		2.546 ***

Notes: Robust standard errors are in parentheses. The coefficients with *** are significant at the 10% confidence level, respectively.

The longer periods of mobility that migrant workers have, the higher their employment quality. This is likely because migrant workers are able to accumulate richer human capital, social capital, and work experience with time, which is conducive to high-quality employment.

Education level—notably college and above, which is more than twice as high as junior high school—had a positive effect on the employment quality of migrant manufacturing workers. Due to the favorable spillover impact of higher education, numbers of primary school-educated migrant workers in manufacturing have mostly remained steady.

As a consequence of the lower costs of trial and error and increased possibility of landing better positions, migrant workers in manufacturing are more likely to find higher-quality employment when they do so through friends and family as opposed to searching on their own. On the other hand, the positions offered by the government only provide a minimal level of job security for migrant employees with a limited educational and occupational background, which does not improve the employment status of migrant workers in the manufacturing sector. State-owned companies contribute to improving the quality of industrial employment held by migrant workers.

4.3. Robustness

Next, we test the robustness of our employment quality model using a range of different estimation models and alternative control variables. For brevity, we will focus on the reduced model. Table 4 shows the results of the application of the generalized method of moments (GMM) to ensure the validity of our findings in the presence of heteroskedasticity, which are similar to our baseline results in Table 2, column 4. In addition, our baseline results were shown to be robust when we applied the limited information maximum likelihood (LIML) method to overcome the problem of weak instrumental variables.

Table 5 further shows that our parsimonious results were not appreciably different with the replacement of hourly wage with monthly wage as the control variable. Column 2 shows that our results were robust if we dropped weekly work hours values less than 20 h in order to remove observations with extremely short working time and inadequate employment observations. Column 3 goes one step further to reconstruct the employment quality index of manufacturing migrant workers and change the definition of well-being, which consists of injury insurance, unemployment insurance, and maternity insurance, together with a housing fund. Reassuringly, the results were also comparable to our baseline results.

Table 4. Robustness test of the impact of industrial robots on employment equality of migrant workers in manufacturing: Change the estimation method.

Variables	Employment Quality of Manufacturing Migrant Workers	
	(1)	(2)
	GMM	LIML
Industrial robots per 10,000 workers	−4.3628 *** (0.9826)	−3.5846 *** (0.9369)
Square of industrial robots per 10,000 workers	0.8468 *** (0.3326)	0.8718 *** (0.3364)
Control	Yes	Yes
City FE	Yes	Yes
Observations	14,738	14,738
R square	0.2218	0.1786
Hansen J/Log likelihood	—	—
Wald chi2	—	—
U-test of square term	2.3462 ***	2.3462 ***

The coefficients with *** are significant at the 10% confidence level, respectively.

Table 5. Robustness test of the influence of industrial robots on employment equality of migrant workers in manufacturing: Change control variables.

Variables	Employment Quality of Manufacturing Migrant Workers		
	Employment Quality I	Employment Quality II	Employment Quality III
	Parsimonious Model	Parsimonious Model	Parsimonious Model
	(1)	(2)	(3)
Industrial robots per 10,000 workers	−2.9126 *** (0.7648)	−3.8162 *** (1.2364)	−3.3628 *** (1.0692)
Square of industrial robots per 10,000 workers	0.7128 ** (0.3124)	0.8516 *** (0.1964)	1.0126 *** (0.3628)
Control	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Observations	14,738	14,738	14,738
R square	0.0754	0.1326	0.1841
U-test of square term	2.3264 **	2.0311 ***	1.6726 ***

The coefficients with *** and ** are significant at the 10% and 5% confidence level, respectively.

Table 6 showed the robustness test of the effect of industrial robots on employment equality of migrant workers in manufacturing: changing independent variables. The installation of industrial robots reflects the annual increment in industrial robots and is a flow indicator, while the installation density of industrial robot reflects the annual industrial robots per 10,000 workers and is a stock indicator. The estimates in column 1 are similar to our baseline results. Secondly, as the installation density of industrial robots in the Czech Republic is closer to the installation density of industrial robots in China, we re-estimated the effect of industrial robots using the installation density of industrial robot installations in the Czech Republic multiplied by the share of employment in Chinese prefecture-level cities [42]. Theoretically, limited resources determine the competition between China and other countries, reflected in the expansion of industrial robot applications in China and the reduction in industrial robot applications in other countries, which satisfies the correlation condition. Moreover, the variation in the employment quality of manufacturing migrant workers in China is only affected by the installation density of industrial robots in China and is not related to the installation density of industrial robots in the Czech Republic, which meets the requirement of exogeneity. Our results are also comparable to our baseline results when we turn to the installation density of industrial robots in secondary industries, which account for more than 80% of all industries. Further, our results are robust when we consider the installation density in all industries.

Table 6. Robustness test of the effect of industrial robots on employment equality of migrant workers in manufacturing: changing independent variables.

Variables	Employment Quality of Manufacturing Migrant Workers			
	Basic Linear Regression	OLS	Parsimonious Model	Parsimonious Model
	(1)	(2)	(3)	(4)
Industrial robots per 10,000 workers	−1.5361 *** (0.6328)	—	—	—
Square of industrial robots per 10,000 workers	0.3314 *** (0.0854)	—	—	—
Czech industrial robots per 10,000 workers	—	−2.8321 *** (0.8416)	—	—
Square of Czech industrial robots per 10,000 workers	—	0.3614 *** (0.1462)	—	—
Industrial robots per 10,000 workers in secondary industry	—	—	−5.1026 *** (0.9936)	—
Square of industrial robots per 10,000 workers in secondary industry	—	—	0.9316 *** (0.3321)	—
Industrial robots per 10,000 workers in all industries	—	—	—	−3.0239 *** (0.8514)
Square of industrial robots per 10,000 workers in all industries	—	—	—	0.9537 *** (0.3814)
Control	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations	14,738	14,738	14,738	14,738
R square	0.1726	0.1362	0.1514	0.1837
U-test of square term	4.1126 ***	4.2618 ***	2.5132 ***	2.2817 ***

The coefficients with *** are significant at the 10% confidence level, respectively.

Table 7 presents the outlier-robust specifications of the parsimonious model. The cities with the highest installation density of industrial robots in the manufacturing industry may lead to upward estimates and the cities with the lowest installation density may lead to downward estimates. Consequently, all three specifications result in very approximate estimates of the effects of industrial robots in manufacturing industry similar to our baseline estimates from column 4 in Table 3.

Table 7. Robustness test of the influence of industrial robots on employment equality of migrant workers in manufacturing: Changing the sample interval.

Variables	Employment Quality of Manufacturing Migrant Workers		
	(1)	(2)	(3)
	Parsimonious Model	Parsimonious Model	Parsimonious Model
Industrial robots per 10,000 workers	−5.1248 *** (0.8746)	−3.5426 *** (0.8317)	−4.2618 *** (0.9124)
Square of industrial robots per 10,000 workers	0.8526 *** (0.3314)	0.8456 *** (0.3618)	0.8424 *** (0.3126)
Control	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Observations	13,284	12,147	13,117
R square	0.1426	0.1238	0.1614
U-test of square term	2.0319 ***	2.3624 ***	2.1634 ***

Notes: Robust standard errors are in parentheses. The coefficients marked with *** is significant at the 10% confidence level. Column 1 excludes 0.1 percent of the sample; column 2 excludes 0.2 percent of the sample; column 3 excludes 0.3 percent of the sample.

4.4. Different Indicators

We used an OLS model to estimate the effect of industrial robots on the wage and work hours of manufacturing migrant workers, as they are interval variables. We also used a probit model to estimate the effect of industrial robots on the employment stability and workfare of manufacturing migrant workers, as they are binary variables. We used an ordered probit model to examine the effect of industrial robots on the well-being of manufacturing migrant workers, as it is a multi-categorical variable.

Table 8 shows numerous sub-indicator measurements of the employment quality of manufacturing migrant workers. The income of migrant manufacturing employees was found to be significantly positively impacted by industrial robots, with an inflection point of 1.547 robots per 10,000 workers. As the installation density of industrial robots surpasses 1.547 units per 10,000 employees, the income of migrant workers in the manufacturing sector is lowered by 58.54 percent or increases by 41.46 percent in the other direction.

Table 8. The regression results of the influence of industrial robots on different indicators.

Variables	Income	Working Time	Occupational Stability	Workfare
	(1)	(2)	Probit	Probit
	OLS	OLS	(3)	(4)
Industrial robots per 10,000 workers	−0.5264 *	−17.2628 *	−0.1356 *	−0.9314 ***
	(0.2341)	(7.3316)	(0.1139)	(0.2243)
Square of industrial robots per 10,000 workers	0.7124 *	53.1646 ***	—	2.5914 ***
	(0.6639)	(25.2287)		(0.5814)
Observations	14,738	14,738	14,738	14,738
R square	0.2716	0.1849		
Pseudo R^2			0.2128	0.0587
Wald chi-squared			1876.24 ***	347.38 ***
U-test of square term	0.2341 **	0.2238 **		0.2094 ***
Industrial robots per 10,000 workers in US	−0.0517 *	−1.7456 *	−0.0336 *	−0.0741 ***
	(0.0448)	(0.8429)	(0.0134)	(0.0339)
Square of industrial robots per 10,000 workers in US	0.0316 *	0.8426 ***	—	0.0361 ***
	(0.0077)	(0.3517)		(0.0029)
Observations	14,738	14,738	14,738	14,738
R square	0.3716	0.1628		
Pseudo R^2			0.2314	0.0776
Wald chi-squared			1738.26 ***	284.39 ***
U-test of square term	1.547 **	1.372 **		1.668 ***
Control	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes

The coefficients marked with ***, ** and * are significant at the 10%, 5% and 1% confidence level.

One reason for this might be that while industrial robots first replaced low-skilled migrant labor because of their similar drawbacks, the employment of high-skill migrant workers was established because humans and machines operate best together. The supply of migrant workers is greater than the demand in the manufacturing sector because substitution effects outweigh promotion benefits, which has a detrimental effect on migrant workers' wages in this sector. The promotion impact outweighs the substitution effect in the second stage, increasing the pay of migrant employees in the manufacturing sector.

With an inflection point of 1.372 units per 10,000 workers, industrial robots were found to have a positive U-shaped influence on the number of hours that migrant workers in manufacturing work. After reaching 1.170 units per 10,000 employees, the number of hours that migrant workers work decreases by 41.49 percent and increases by 58.51 percent in the opposite direction.

According to the marginal effects, the installation density of industrial robots in the manufacturing industry has a detrimental impact on the occupational stability of migrant employees. For every unit increase, the likelihood that a migrant worker will sign a labor contract drops by 13.56 percent. The influence of industrial robots on migrant workers' working conditions in the manufacturing sector was found to be U-shaped, and 1.559 units per 10,000 workers marked the tipping point. When 1.668 units per 10,000 employees is exceeded, the likelihood of owning migrant workers' wages in the manufacturing sector decreases by 55.89 percent, while on the other hand, it increases by 44.11 percent.

The use of industrial robots is negatively associated with the working conditions of migrant workers employed in manufacturing. For every additional industrial robot, the likelihood of misery and almost happiness rises by 2.64 and 5.59 percent, respectively, while the likelihood of happiness falls by 7.62 percent. This is consistent with the notion that migrant workers are concerned about robots taking jobs away from them. Table 9 showed the impact of industrial robots on job welfare indicators in different countries.

Table 9. The impact of industrial robots on job welfare indicators in different countries.

Variables	**Industrial Robots per 10,000 Workers in China**	**Industrial Robots per 10,000 Workers in US**
	(1)	**(2)**
Less happiness	0.2317 *** (0.0368)	0.0264 *** (0.0126)
Almost	0.4726 *** (0.0426)	0.0559 *** (0.0134)
More happiness	−0.6729 *** (0.0864)	−0.0762 *** (0.0145)
Control	Yes	Yes
City FE	Yes	Yes
Observations	14,738	14,738
Pseudo R square	0.1564	0.0786
Wald chi-square	754.23 ***	645.16 ***

The coefficients marked with *** is significant at the 10% confidence level.

4.5. Urban Scale

In comparison to urban scale, population density has reduced error, making it a better indicator of the concentration of economic activity. The job quality of migrant workers in the manufacturing sector was examined through urban scale in Table 10. For simplicity, we will concentrate on the same specifications as in column 4 of Table 2. With the exception of industrial robots in medium population size cities, where it had a positive effect, we detected detrimental effects of industrial robots on the employment quality of manufacturing migrant workers in cities with higher and lower population densities.

Table 10. Heterogeneous estimates of the effect of industrial robots on the employment quality of manufacturing migrant workers across population density.

Variables	**Entire Sample**	**Higher Population Density**	**Medium Population Density**	**Lower Population Density**
	(1)	**(2)**	**(3)**	**(4)**
Industrial robots per 10,000 workers in US	−4.3264 ***	−2.1532 **	3.6482 ***	−6.3728 ***
Square of industrial robots per 10,000 workers in US	(0.8426)	(0.7914)	(0.9536)	(1.6284)
Observations	0.8765 *** (0.2238)	—	—	—
Control	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations				
R square	0.1729	0.2364	0.1010	0.0982
U-test of square term	2.364 ***	—	—	—

The coefficients marked with *** and ** were significant at the 10% and 5% confidence level.

5. Conclusions

Robots play a pivotal part in improving the sustainable development of enterprises, among other aspects. Based on the data collected in the China Migrants Dynamic Survey in 2011 and the International Federation of Robotics, this paper uses the Bartik instrument variable method to analyze the influence of industrial robots on the employment quality of migrant workers in the manufacturing industry at the city level. The conclusions are as follows:

1. As the city scale expands, industrial robots have an inverted U-shaped effect on the employment quality of manufacturing migrant workers. Specifically, the income of migrant manufacturing employees was found to be significantly positively impacted by industrial robots, with an inflexion point of 1.547 robots per 10,000 workers. Industrial robots have a positive U-shaped influence on the number of hours that migrant workers in manufacturing work, with an inflexion point of 1.3721 units per 10,000 workers. The influence of industrial robots on migrant workers' working conditions in the manufacturing sector was U-shaped, and 1.668 units per 10,000 workers marked the tipping point.
2. Industrial robots have an inverse influence on the occupation stability of migrant workers in the manufacturing industry. Precisely, the installation density of industrial robots in the manufacturing industry has a detrimental impact on the occupational stability of migrant employees. Industrial robots are negatively associated with the working conditions of migrant workers employed in manufacturing. There were detrimental effects on the employment quality of manufacturing migrant workers in cities with higher and lower population densities.
3. For every manufacturing farmer using an industrial robot, the likelihood of being miserable and almost happy went up by 2.64 percent and 5.59 percent, respectively, while the likelihood of being happy went down by 7.62 percent.

Author Contributions: Conceptualization, B.C.; methodology, D.T.; software, B.C. and D.T.; validation, D.T.; formal analysis, B.C. and D.T.; investigation, B.C.; resources, D.T.; data curation, B.C.; writing—original draft preparation, B.C. and D.T.; writing—review and editing, B.C. and D.T.; visualization, B.C.; supervision, B.C.; project administration, D.T.; funding acquisition, D.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by The National Social Science Fund of China, grant number 20CJY065, and General project of philosophy and social sciences of Jiangsu Province, grant number 2020SJA0259.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Ferreira, W.D.; Armellini, F.; de Santa-Eulalia, L.A.; Thomasset-Laperriere, V. A framework for identifying and analysing industry 4.0 scenarios. *J. Manuf. Syst.* **2022**, *65*, 192–207. [CrossRef]
2. Pawlyszyn, I.; Fertsch, M.; Stachowiak, A.; Pawlowski, G.; Oleskow-Szlapka, J. The Model of Diffusion of Knowledge on Industry 4.0 in Marshallian Clusters. *Sustainability* **2020**, *12*, 3815. [CrossRef]
3. Gajdzik, B.; Grabowska, S.; Saniuk, S. A Theoretical Framework for Industry 4.0 and Its Implementation with Selected Practical Schedules. *Energies* **2021**, *14*, 940. [CrossRef]
4. Jayashree, S.; Reza, M.N.H.; Malarvizhi, C.A.N.; Gunasekaran, A.; Rauf, M.A. Testing an adoption model for Industry 4.0 and sustainability: A Malaysian scenario. *Sustain. Prod. Consum.* **2022**, *31*, 313–330. [CrossRef]
5. Muller, J.M. Business model innovation in small- and medium-sized enterprises Strategies for industry 4.0 providers and users. *J. Manuf. Technol. Manag.* **2019**, *30*, 1127–1142. [CrossRef]
6. Erboz, G.; Huseyinoglu, I.O.Y.; Szegedi, Z. The partial mediating role of supply chain integration between Industry 4.0 and supply chain performance. *Supply Chain Manag. Int. J.* **2022**, *27*, 538–559. [CrossRef]

7. Liebrecht, C.; Kandler, M.; Lang, M.; Schaumann, S.; Stricker, N.; Wuest, T.; Lanza, G. Decision support for the implementation of Industry 4.0 methods: Toolbox, Assessment and Implementation Sequences for Industry 4.0. *J. Manuf. Syst.* **2021**, *58*, 412–430. [CrossRef]
8. Durmaz, N.; Budak, A. Analysing key barriers to Industry 4.0 for sustainable supply chain management. *J. Intell. Fuzzy Syst.* **2022**, *43*, 6663–6682. [CrossRef]
9. Tay, S.I.; Alipal, J.; Lee, T.C. Industry 4.0: Current practice and challenges in Malaysian manufacturing firms. *Technol. Soc.* **2021**, *67*, 101749. [CrossRef]
10. Laffi, M.; Boschma, R. Does a local knowledge base in Industry 3.0 foster diversification in Industry 4.0 technologies? Evidence from European regions. *Pap. Reg. Sci.* **2022**, *101*, 5–35. [CrossRef]
11. Strong, R.; Wynn, J.T.; Lindner, J.R.; Palmer, K. Evaluating Brazilian Agriculturalists' IoT Smart Agriculture Adoption Barriers: Understanding Stakeholder Salience Prior to Launching an Innovation. *Sensors* **2022**, *22*, 6833. [CrossRef] [PubMed]
12. Tsaramirsis, G.; Kantaros, A.; Al-Darraji, I.; Piromalis, D.; Apostolopoulos, C.; Pavlopoulou, A.; Alrammal, M.; Ismail, Z.; Buhari, S.M.; Stojmenovic, M.; et al. A Modern Approach towards an Industry 4.0 Model: From Driving Technologies to Management. *J. Sens.* **2022**, *2022*, 5023011. [CrossRef]
13. Mj, A.; Ah, A.; Rps, B.; Rs, C. Substantial capabilities of robotics in enhancing industry 4.0 implementation. *Cogn. Robot.* **2021**, *1*, 58–75.
14. Javaid, M.; Haleem, A.; Singh, R.P.; Suman, R.; Gonzalez, E.S. Understanding the adoption of Industry 4.0 technologies in improving environmental sustainability. *Sustain. Oper. Comput.* **2022**, *3*, 203–217. [CrossRef]
15. Hines, A. Getting Ready for a Post-Work Future. *Foresight Sti Gov.* **2019**, *13*, 19–30. [CrossRef]
16. Cheng, H.; Jia, R.; Li, D.; Li, H. The Rise of Robots in China. *IRPN Phys. Cap.* **2019**, *33*, 71–88. [CrossRef]
17. Umar, M.; Xu, Y.; Mirza, S.S. The impact of COVID-19 on Gig economy. *Econ. Res. Ekon. Istraz.* **2021**, *34*, 2284–2296. [CrossRef]
18. Zhang, L.H.; Gan, T.; Fan, J.C. Do industrial robots affect the labour market? Evidence from China. *Econ. Transit. Inst. Chang.* **2023**, *12*, 23–35. [CrossRef]
19. Fu, X.Q.; Bao, Q.; Xie, H.J.; Fu, X.L. Diffusion of industrial robotics and inclusive growth: Labour market evidence from cross country data. *J. Bus. Res.* **2021**, *122*, 670–684.
20. Acemoglu, D.; Restrepo, P. Demographics and Automation. *Rev. Econ. Stud.* **2021**, *89*, 1–44. [CrossRef]
21. Haapanala, H.; Marx, I.; Parolin, Z. Robots and unions: The moderating effect of organized labour on technological unemployment. *Econ. Ind. Democr.* **2022**, *15080*, 1–34. [CrossRef]
22. Brandl, B.; Strohmer, S.; Traxler, F. Foreign direct investment, labour relations and sector effects: US investment outflows to Europe. *Int. J. Hum. Resour. Manag.* **2013**, *24*, 3281–3304. [CrossRef]
23. Davoine, L.; Erhel, C.; Guergoat-Larivière, M. Monitoring quality in work: European employment strategy indicators and beyond. *Int. Labour Rev.* **2008**, *147*, 163–198. [CrossRef]
24. Leschke, J.; Watt, A. Challenges in Constructing a Multi-dimensional European Job Quality Index. *Soc. Indic. Res.* **2014**, *118*, 1–31. [CrossRef]
25. Wang, Q.; Shao, J.H. Research on the Influence of Economic Development Quality on Regional Employment Quality: Evidence from the Provincial Panel Data in China. *Sustainability* **2022**, *14*, 10760. [CrossRef]
26. Van Aerden, K.; Puig-Barrachina, V.; Bosmans, K.; Vanroelen, C. How does employment quality relate to health and job satisfaction in Europe? A typological approach. *Soc. Sci. Med.* **2016**, *158*, 132–140. [CrossRef]
27. Pocock, B.; Charlesworth, S. Multilevel Work-Family Interventions: Creating Good-Quality Employment over the Life Course. *Work Occup.* **2017**, *44*, 23–46. [CrossRef]
28. Vishnevskaya, N.T.; Zudina, A.A. Unemployment Benefits and Labour Market In OECD and Russia. *Mirovaya Ekon. Mezhdunarodnye Otnos.* **2019**, *63*, 32–41. [CrossRef]
29. Chen, W.H.; Mehdi, T. Assessing Job Quality in Canada: A Multidimensional Approach. *Can. Public Policy-Anal. Polit.* **2019**, *45*, 173–191. [CrossRef]
30. Uwajumogu, N.R.; Nwokoye, E.S.; Ojike, R.O.; Okere, K.I.; Ugwu, J.N.; Ogbuagu, A.R. Globalization and the proportion of women in vulnerable employment in sub-Saharan Africa: The role of economic, social, and political conditions. *Afr. Dev. Rev.* **2022**, *34*, 356–369. [CrossRef]
31. Putnick, D.L.; Bornstein, M.H. Is child labor a barrier to school enrollment in low- and middle-income countries? *Int. J. Educ. Dev.* **2015**, *41*, 112–120. [CrossRef] [PubMed]
32. Coomer, N.M.; Wessels, W.J. The Effect of the Minimum Wage on Covered Teenage Employment. *J. Labor Res.* **2013**, *34*, 253–280. [CrossRef]
33. Van Hoyweghen, K.; Van den Broeck, G.; Maertens, M. Employment Dynamics and Linkages in the Rural Economy: Insights from Senegal. *J. Agric. Econ.* **2020**, *71*, 904–928. [CrossRef]
34. Edlinger, G. Employer brand management as boundary-work: A grounded theory analysis of employer brand managers' narrative accounts. *Hum. Resour. Manag. J.* **2015**, *25*, 443–457. [CrossRef]
35. Fong, E.; Guo, H. Mainland Immigrants in Hong Kong: Social mobility over Twenty years. *J. Asian Public Policy* **2019**, *12*, 160–173. [CrossRef]
36. Epstein, G.S.; Hillman, A.L. Unemployed immigrants and voter sentiment in the welfare state. *J. Public Econ.* **2003**, *87*, 1641–1655. [CrossRef]

37. Gabszewicz, J.; Tarola, O.; Zanaj, S. Migration, wages and income taxes. *Int. Tax Public Financ.* **2016**, *23*, 434–453. [CrossRef]
38. Khoronzhevych, M.; Fadyl, J. How congruent is person-centred practice with labour activation policy? Person-centred approach to vocational interventions on immigrant jobseekers in Norway. *Eur. J. Soc. Work* **2022**, *25*, 577–591. [CrossRef]
39. Lens, D. Does Self-Employment Contribute to Immigrants' Economic Integration? Examining Patterns of Self-Employment Exit in Belgium. *Int. Migr. Rev.* **2023**, *57*, 217–264. [CrossRef]
40. Baumann, M.; Chau, K.; Kabuth, B.; Chau, N. Association Between Health-Related Quality of Life and Being an Immigrant Among Adolescents, and the Role of Socioeconomic and Health-Related Difficulties. *Int. J. Environ. Res. Public Health* **2014**, *11*, 1694–1714. [CrossRef]
41. Humlum, A. *Robot Adoption and Labor Market Dynamics*; Rockwool Foundation Research Unit: Berlin, Germany, 2019.
42. Acemoglu, D.; Restrepo, P. Robots and Jobs: Evidence from US Labor Markets. *J. Political Econ.* **2020**, *128*, 2188–2244. [CrossRef]
43. Jung, J.H.; Lim, D.-G. Industrial robots, employment growth, and labor cost: A simultaneous equation analysis. *Technol. Forecast. Soc. Chang.* **2020**, *159*, 120202. [CrossRef]
44. Dauth, W.; Findeisen, S.; Südekum, J.; Woessner, N. *German Robots—The Impact of Industrial Robots on Workers*; CEPR Discussion Papers; CEPR: London, UK, 2017.
45. Graetz, G.; Michaels, G. Robots at Work. *Rev. Econ. Stat.* **2018**, *100*, 753–768. [CrossRef]
46. Raviola, A.; Guida, R.; Bertolino, A.; Martin, A.; Mauro, S.; Sorli, M. A comprehensive multibody model of a collaborative robot to support model-based Health Management. *Robotics* **2023**, *12*, 71. [CrossRef]
47. Wei, H.; Zhang, P.K. How Robots Reshape the Urban Labor Market: From a Perspective of Migrants' Job Tasks. *Econ. Perspect.* **2020**, *10*, 92–109.
48. Kong, G.W.; Liu, S.S. Robots and Labor Employment—An Empirical Investigation Based on Heterogeneity of Industries and Regions. *China Ind. Econ.* **2020**, *389*, 80–98.
49. Yang, G.; Hou, Y. The Usage of Industry Robots, Technology Upgrade and Economic Growth. *China Ind. Econ.* **2020**, *391*, 138–156.
50. Caselli, F.; Manning, A. Robot arithmetic: New technology and wages. *Am. Econ. Rev. Insights* **2019**, *1*, 1–12. [CrossRef]
51. Acemoglu, D.; Autor, D. Skills, Tasks and technologies: Implications for employment and earnings. *Handb. Labor Econ.* **2011**, *4*, 1043–1171.
52. Yan, X.L.; Zhu, B.K. Employment under Robot Impact: Evidence from China Manufacturing. *Stat. Res.* **2020**, *37*, 74–87.
53. Wang, J.; Wang, Y.J. Minimum Wage, Robot Application and Labor Income Share: Evidence from Listed Companies. *J. Financ. Econ.* **2022**, *48*, 106–120.
54. Dumagan, J.C.; Balk, B.M. Dissecting aggregate output and labour productivity change: A postscript on the role of relative prices. *J. Product. Anal.* **2016**, *45*, 117–119. [CrossRef]
55. Strelecek, F.; Zdenek, R.; Lososova, J. Influence of farm milk prices in the EU 25 on profitability and production volume indicators. *Agric. Econ. Zemed. Ekon.* **2007**, *53*, 545–557.
56. Koch, M.; Manuylov, I.; Smolka, M. Robots and Firms. *Econ. J.* **2021**, *131*, 2553–2584. [CrossRef]
57. Tang, H.X.; Zhang, X.Z.; Yan, W.U.; Zheng-Chu, H.E. The Comprehensive Development and Interactive Development of China's Manufacturing Industry's Development Quality and International Competitiveness. *China Soft Sci.* **2019**, *2019*, 128–142.
58. Faber, M. Robots and reshoring: Evidence from Mexican labor markets. *J. Int. Econ.* **2020**, *127*, 103384. [CrossRef]
59. Ballestar, M.T.; Díaz-Chao, Á.; Sainz, J.; Torrent-Sellens, J. Impact of robotics on manufacturing: A longitudinal machine learning perspective. *Technol. Forecast. Soc. Chang.* **2021**, *162*, 120348. [CrossRef]
60. Sachs, J.D.; Kotlikoff, L.J. *Smart Machines and Long-Term Misery*; NBER Working Paper; National Bureau of Economic Research: Cambridge, MA, USA, 2012.
61. Foote, A.; Grosz, M.; Stevens, A. Locate Your Nearest Exit: Mass Layoffs and Local Labor Market Response. *ILR Rev.* **2019**, *72*, 101–126. [CrossRef]
62. Acemoglu, D.; Restrepo, P. Competing with Robots: Firm-Level Evidence from France. *Eur. Econ. Microecon. Ind. Organ. E J.* **2020**, *110*, 383–388.
63. Sequeira, T.N.; Garrido, S.; Santos, M. Robots are not always bad for employment and wages. *Int. Econ.* **2021**, *167*, 108–119. [CrossRef]
64. Autor, D.; Salomons, A. *Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share*; National Bureau of Economic Research: Cambridge, MA, USA, 2018.
65. Cao, J.; Zhou, Y.L. Research progress on the impact of artificial intelligence on economy. *Econ. Perspect.* **2018**, *683*, 103–115.
66. Ferraro, S.; Cantini, A.; Leoni, L.; De Carlo, F. Sustainable Logistics 4.0: A Study on Selecting the Best Technology for Internal Material Handling. *Sustainability* **2023**, *15*, 7067. [CrossRef]
67. Benzell, S.G.; Kotlikoff, L.J.; LaGarda, G.; Sachs, J.D. *Robots Are Us: Some Economics of Human Replacemen*; NBER Working Paper; National Bureau of Economic Research: Cambridge, MA, USA, 2015.
68. Kim, Y. Examining the Impact of Frontline Service Robots Service Competence on Hotel Frontline Employees from a Collaboration Perspective. *Sustainability* **2023**, *15*, 7563. [CrossRef]
69. Autor, D.H.; Levy, F.; Mumane, R.J. The Skill Content of Recent Technological Change: An Empirical Exploration. *Q. J. Econ.* **2003**, *118*, 1279–1333. [CrossRef]
70. Gill, I.S.; Kharas, H. An East Asian Renaissance: Ideas for Economic Growth. *Asin-Pac. Econ. Lit.* **2007**, *2*, 1–386.
71. Roca, J.D.L.; Puga, D. Learning by Working in Big Cities. *Rev. Econ. Stud.* **2016**, *84*, 106–142. [CrossRef]

72. Combes, P.P.; Duranton, G.; Gobillon, L.; Puga, D.; Roux, S. The Productivity Advantages of Large Cities: Distinguishing Agglomeration from Firm Selection. *Econometrica* **2012**, *80*, 2543–2594. [CrossRef]
73. Rosenthal, S.S.; Strange, W.C. Evidence on the nature and sources of agglomeration economies. *Handb. Reg. Urban Econ.* **2004**, *4*, 2119–2171.
74. Black, D.; Henderson, V. A Theory of Urban Growth. *J. Political Econ.* **1999**, *107*, 252–284. [CrossRef]
75. Au, C.C.; Henderson, J.V. Are Chinese Cities Too Small. *Rev. Econ. Stud.* **2006**, *73*, 549–576. [CrossRef]
76. Liu, J.; Chang, H.; Forrest, J.Y.L.; Yang, B. Influence of artificial intelligence on technological innovation: Evidence from the panel data of china's manufacturing sectors. *Technol. Forecast. Soc. Chang.* **2020**, *158*, 120142. [CrossRef]
77. Erhel, C.; Guergoat-Larivière, M.; Leschke, J.; Watt, A. *Trends in Job Quality during the Great Recession: A Comparative Approach for the EU/Tendances de la Qualité de l'emploi Pendant la Crise: Une Approche Européenne Comparative*; Working Papers; HEL: Geneva, Switzerland, 2014.
78. Charles, K.K.; Hurst, E.; Notowidigdo, M.J. Housing Booms, Manufacturing Decline and Labour Market Outcomes. *Econ. J.* **2018**, *129*, 209–248. [CrossRef]
79. Beaudry, P.; Green, D.A.; Sand, B.M. In Search of Labor Demand. *Am. Econ. Rev.* **2018**, *108*, 2714–2757. [CrossRef]
80. Fajgelbaum, P.D.; Morales, E.; Suárez Serrato, J.C.; Zidar, O. State Taxes and Spatial Misallocation. *Rev. Econ. Stud.* **2018**, *86*, 333–376. [CrossRef]
81. Bartik, T.J.; W.E. Upjohn Institute for Employment Research. Who Benefits from State and Local Economic Development Policies? In *Economic Geography*; W.E. Upjohn Institute for Employment Research: Kalamazoo, MI, USA, 1991.
82. Goldsmith-Pinkham, P.; Sorkin, I.; Swift, H. Bartik Instruments: What, When, Why, and How. *Am. Econ. Rev.* **2020**, *110*, 2586–2624. [CrossRef]
83. Rajan, R.G.; Zingales, L. *Financial Dependence and Growth*; SPGMI: Compustat Fundamentals; National Bureau of Economic Research: Cambridge, MA, USA, 1996.