

# Robot Application and Labor Force Employment: Substitution or Complementation?

## —An Empirical Analysis Based on the Data from 22 Economies

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The rise of robotics has brought great uncertainty to the labor market. Based on the sectoral data from 22 economies during 2008–2019, this paper explores the impact of robot application on employment. The results show that, on the whole, robot application will have complementary effects on labor force employment, and the grouped regression by economic development level and demographic characteristics supports this conclusion, while the effect of robot application on labor force employment is significantly different by industry. Further research shows that the degree of robot use is the key factor that determines the effect of robots on employment, and the complementary effect is dominant in economies with low degree of robot application, and the substitution effect is dominant in economies with high degree of robot application. In addition, obvious spillover effects are observed in robotic application. On the one hand, robot application will have a forward crowding-out effect and a reverse siphon effect, which drive the labor force moving from the primary industry to the secondary and tertiary industries. On the other hand, robot application will also have heterogeneous effects on the labor force employment of economies in the upstream and downstream position along the value chain through the transmission effect of the Global Value Chains (GVC). The conclusions of this paper provide some practical implications for the rational formulation of artificial intelligence plans in the context of “stabilizing employment”.

**Keywords:** robots, labor force employment, substitution effect, complementary effect

### 1. Introduction

According to the data published by the International Federation of Robotics (IFR),

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the number of industrial robots installed worldwide increased from 53,000 in 1993 to 383,000 in 2020, and the global stock of industrial robots grew from 557,000 in 1993 to 3,015,000 in 2020. In particular, from 2014 to 2020, the world's industrial robots experienced a surge in growth, with installation and stock increasing by an annual average rate of up to 9.6% and 12.7% respectively. The rise of industrial robots has provided solutions to the aging problem in some developed economies, and also directed the way for emerging economies such as China to improve production efficiency and upgrade their industrial structure. Therefore, governments around the world have been issuing policies with strong orientation to promote the research & development and widespread of the robot application. Take China as an example. In 2006, the State Council issued the *Outline for National Mid- and Long-term Science and Technology Development Plan (2006–2020)*; in 2013, the Ministry of Industry and Information Technology released the *Guiding Opinions on Promoting the Development of the Industrial Robot Industry*; in 2016, the State Council issued the *Development Plan for the Robot Industry (2016–2020)*. This series of measures has caused China's robot stock to grow at an average annual rate of 33.1% from 2006 to 2020, and surpassed Japan to become the world's leading country in 2016.

The application of robots has attracted widespread attention from Chinese and overseas scholars to study its relationship with economic development. Due to the fact that robots possess both the operational abilities of laborers in the narrow sense and the characteristics of primitive capital as a production tool, the robot factor included in the production function is set to have the dual attributes of capital and labor. This poses challenges to the applicability of classical production theory. In response, Zeira (1998) proposed the Task Model that incorporates intelligent robots into the production function. On this basis, some scholars further explored whether the application of robots affects total labor demand, employment structure and production efficiency (Graetz and Michaels, 2018). Specifically, consensus has been basically reached on the impact of robot application on production efficiency and employment structure, but no consistent conclusion has been drawn on the impact on labor demand. For example, Acemoglu and Restrepo (2018, 2019, 2020) argued that robots have both substitution and complementary effects on labor force, with the net effect determined by whichever is dominant, and further used data in the US to show that the substitution effect is more pronounced. In contrast, Gregory *et al.* (2018) and Graetz and Michaels (2018) found that although robot application reduces the job share of low-skilled workers, the total number of jobs does not decrease. As much as robotics is an important force driving a country's technological innovation and industrial structure upgrading, its impact on employment cannot be ignored. It is especially important to properly understand such impact in the context of the demographic changes and economic restructuring in China.

This paper uses multi-country and industry-specific data on the stock of robots

and labor force employment to conduct empirical research on the impact of robot application on employment from the perspective of economies, industries, and time sequence. Based on the Kuznets hypothesis, it explores the changing patterns of the impact. This paper is innovative in the following areas. Firstly, previous researches showed that the impact of robotics on employment exhibits linear characteristics, whether it is complementary or substitutive. This paper attempts to introduce the Kuznets hypothesis into the labor market and empirically demonstrates that the impact exhibits an inverted U-shaped structure featuring a shift from complementary to substitutive effects. This to some extent explains the reasons for the discrepancies in the conclusions of existing literatures. Secondly, this paper goes beyond the previous researches that only look at the unidirectional labor flow between the secondary and tertiary industries caused by robotics application to integrate all three industries into a unified analytical framework. It analyzes in depth the two-way labor flow among the three industries, offering new quantitative basis for labor reallocation theories. Thirdly, previous researches mainly focus on the domestic industrial chain transmission effects of robot application on employment, while lacking exploration on the international industrial chain transmission effects. Based on this research perspective, this paper finds that the application of robots in the upstream economies along the industrial chain significantly inhibits the growth of downstream employment, while the impact of robot application in the downstream economies on the upstream job market is not significant. This paper expands the perspective of subsequent research and provides references for formulating relevant trade policies.

## 2. Literature Review and Theoretical Hypotheses

### 2.1. Impact of Robot Application on Total Employment

Previous researches are not consistent in their conclusions regarding to the impact of robot application on total employment. Some scholars believed that the efficiency advantage of robots will benefit non-automated jobs, thereby creating greater demand for labor (Autor and Salomons, 2018). This viewpoint has been supported by empirical evidence. For example, Gregory *et al.* (2018) studied the EU data, finding that the application of robots caused 9.6 million old jobs to be replaced from 1999 to 2010, but 21 million new jobs emerged. Based on transnational data research, Autor and Salomons (2018) found that robot application will reduce the proportion of workers' labor value added in all industries, but in terms of employment alone, it can promote overall job growth through countervailing effects. Wei *et al.* (2020) reached similar conclusions based on data from China respectively.

Some scholars, however, held that despite the countervailing effects, substitution effects are dominant in most cases (Acemoglu and Restrepo, 2018). They further proposed that new technologies not only affect workers' production efficiency in current tasks, but produce a "displacement effect" over the allocation of new tasks, resulting in a greater favor of capital in the allocation of task content and deepening the adverse influence over labor force (Acemoglu and Restrepo, 2019). Empirically, Acemoglu and Restrepo (2020) analyzed the data of the US, concluding that robotics has negative impact on employment, more so in states with a higher degree of robotics use. In addition, some scholars considered that, under the offset effect of substitution effect and complementary effect, the impact of robots on employment is not obvious. For instance, Arntz *et al.* (2016) researched transnational data and found that though robotics application reduces jobs for low-skilled labor force, its impact on overall employment is not significant.

In summary, robot application has a positive complementary effect and a negative substitution effect on employment. The working mechanism of complementary effect can be summarized into two aspects. First, the application of robots is conducive to improving production efficiency, stimulating the expansion of corporate scale, and bringing about greater labor demand (Autor and Dorn, 2013; Autor and Salomons, 2018). At the same time, the mechanism may produce a ripple effect in the entire supply chain and work in a wider scale (Wang and Dong, 2020). Second, the application of robots helps create new business formats, new models and new job demands (Wang *et al.*, 2020), and the newly generated demand often outnumbers the jobs replaced (Gregory *et al.*, 2018). The working mechanism of substitution effect can also be summarized into two aspects. First, robots enjoy comparative advantages in some jobs compared with labor force and therefore will replace this portion of labor force, leading to "technological unemployment" (Acemoglu and Restrepo, 2020). Second, robot application will intensify the Matthew Effect, in which case large enterprises, with scale and technical strength, compress the living space of small and medium-sized ones (SMEs), causing the labor force originally employed in SMEs to be "indirectly replaced." To sum up, it is difficult to accurately predict the employment effects of robotics with sheer theoretical analysis. Accordingly, this paper proposes the following competing hypotheses to be verified:

Hypothesis H1a: When complementary effects are dominant, robot application brings up the labor demand.

Hypothesis H1b: When substitutive effects are dominant, robot application brings down the labor demand.

It is worth noting that, the existing literatures based on transnational samples and developing country samples tend to conclude that complementary effects are dominant or the impact is not significant (Arntz *et al.*, 2016; Gregory *et al.*, 2018),

while those based on samples from countries such as the United States where robots were introduced early and used extensively are more likely to conclude that substitution effects are dominant (Acemoglu and Restrepo, 2018, 2019, 2020). This phenomenon is similar to the inverted U-shaped curve hypothesis about economic development and income gap in the course of industrialization proposed by Kuznets. If this hypothesis is introduced into the labor market, will the impact of robots on employment resemble the Kuznets curve for its connection with the development stage and degree? Given so, this paper puts forward the second research hypothesis:

Hypothesis H2: The impact of robotics on employment is not simply linear, but in an inverted U-shaped structure featuring the transition from complementation to substitution as robots are used to a higher degree.

## 2.2. Impact of Robot Application on Employment Spillover

Previous literatures examine the robot-induced employment spillover mainly in two dimensions. The first is the inter-industry spillover of labor. For instance, Autor and Dorn (2013) believed that automation technology will have a substitution effect on labor force in routine tasks, but the labor force is not squeezed out of the labor market because of the substitution, instead, they are pushed into services and other industries. Dauth *et al.* (2018) studied data in Germany and found that the substitution effect of robot application on manufacturing will countervail in the service industry, canceling out the substitution and complementary effects in general. Zhao *et al.* (2020) found based on China Labor-force Dynamics Survey data that robot application has not reduced the overall regional employment level, but accelerated the reallocation of labor between the secondary and tertiary industries. The second is the spillover of labor in the industrial chain. For example, Kong *et al.* (2020) studied the industry-specific data in China, finding that robot application is conducive to job growth in local downstream industries, but the impact on employment in upstream industries is not significant. Wang and Dong (2020) concluded based on data on Chinese listed companies that robot application has a negative impact on labor force employment in both upstream and downstream industries.

Essentially, the biased influence of robot application on work force engaged in routine tasks will twist the structure of the employment market and push labor force to transfer from production sectors to services (Autor and Dorn, 2013). However, according to the “push-pull” theory, population migration is susceptible to both pushing force from the origin and pulling force from the destination. When this theory is introduced into study on employment spillover, the impact of robot application on employment may include both inter-industry forward crowding-out effects and reverse siphon effects. As to the spillover effect of labor in the industrial chain, previous

researches mostly focus on the conduction effect of the impact in the domestic industrial chain, without paying close attention to whether the rise of robotics is coupled with the anti-globalization wave in recent years and the return of industries worldwide. In theory, the advantage of robotics in efficiency helps bring down the labor cost, weaken the motivation of upstream economies in the industrial chain for offshore outsourcing of labor-intensive industries, and hence pose adverse influence on employment in downstream economies. Based on such analysis, this paper proposes the following hypotheses:

Hypothesis H3a: The impact of robot application on employment includes both inter-industry forward crowding-out effects and reverse siphon effects.

Hypothesis H3b: The impact of robot application on employment is transmitted not only in the domestic industrial chain, but also in the international industrial chain.

### 3. Data, Models and Variables

#### 3.1. Data Sources

The empirical data in this paper mainly comes from the International Federation of Robotics (IFR),<sup>1</sup> the International Labor Organization (ILO),<sup>2</sup> the World Bank,<sup>3</sup> and the Research Institute for Global Value Chains of the University of International Business and Economics (UIBE GVC).<sup>4</sup> Specifically, the data on robot stock by industry comes from IFR, and this database counts the use of robots in about 75 economies. The industry-specific data on the number of employees, the average weekly working hours of the labor force, the gender ratio of industry practitioners and the proportion of highly skilled labor comes from the ILO. Industrial value added and competitive advantage data are sourced from the UIBE GVC. The dependency ratio data derives from the World Bank. In addition, because of the lack of some industry-specific data of China in the ILO and World Bank databases, it is sought from the *China Statistical Yearbooks* and the *China Labor Statistical Yearbooks* over the years.

Given the statistical starting years and missing data in the main databases, this paper selects 2008–2019 as the research sample. To ensure the completeness of data for each industry during the sample period and avoid regression errors caused by missing industries or missing statistical data, 22 sample economies with complete statistical data available for the same industry categories were selected. It should be noted that

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<sup>1</sup> <https://ifr.org/worldrobotics>

<sup>2</sup> <https://www.ilo.org/shinyapps/bulkexplorer12/>

<sup>3</sup> <https://data.worldbank.org.cn/indicator>

<sup>4</sup> <https://v2.fangcloud.com/share/a26979974d538c7e5aeb24b55a?lang=en>

the IFR and ILO industry classification standards are not fully consistent. Based on the IFR industry classification, this paper aggregates some industries in the ILO and arrives at seven industry categories, namely agriculture, forestry, animal husbandry and fishery, manufacturing, production and supply of electricity, gas and water, quarrying and mining, education and research & development, construction, and other services. The analysis sample in the economy-industry-year three dimensions is eventually made available with 1,848 valid observed value in total.

### 3.2. Model

This paper uses data in the three dimensions of economy, industry and year to explore the impact of robot application on labor force employment, and constructs the following model:

$$\ln lab_{ijt} = \beta_0 + \beta_1 \ln rob_{ijt} + Zcontrol_{ijt} + u_i + v_j + r_t + \varepsilon_{ijt} \quad (1)$$

Wherein,  $i$  means economy,  $j$  industry, and  $t$  year. Explained variable  $\ln lab_{ijt}$  refers to logarithm of the number of employees, core explanatory variable  $\ln rob_{ijt}$  is logarithm of robot stock, and  $control_{ijt}$  refer to controlled variables, including characteristic variables of industry and of economy.  $u_i$ ,  $v_j$  and  $r_t$  respectively represent economy, industry and year fixed-effect, and  $\varepsilon_{ijt}$  is random error term.

### 3.3. Setting of Variables

#### 3.3.1. Explained Variables

The number of employees ( $\ln lab$ ). The year-end number of employees of the seven industry categories in the sample countries in 2008–2019 is taken as the explained variable, and its logarithm is used.

#### 3.3.2. Core Explanatory Variables

Robot application ( $\ln rob$ ). The year-end robot stock of the seven industry categories in the sample countries in 2008–2019 is taken as the core explanatory variable, and its logarithm is used. Direct use of this indicator for regression of the number of employees is likely to cause errors for endogeneity reasons. To avoid endogeneity problems as a result of missing variables and reciprocal causation, this paper selects instrumental variables according to similarity in industrial structure by the logic that

industrial structure partially reflects a country's internal and external demand at a particular development stage and largely determines its favor of new technologies and equipment. Robotics strategies adopted by the countries similar in industrial structure are therefore correlated. Besides, robot application in other countries won't produce direct influence on the country, meeting the exogeneity requirement.

To select the instrumental variables, this paper first respectively calculates the industrial structure rationalization index of the 59 main economies in the IFR database year by year in 2008–2015,<sup>1</sup> then uses the Pearson correlation coefficient to match the 59 economies by industrial structure similarity to get the economies most similar to the 22 sample economies in industrial structure, and takes their industry-specific robot stock as an instrumental variable that is marked IV1. Similarly, the industrial structure supererogation index is adopted for matching and construction of another instrumental variable IV2. By following the principle of selecting the optimal, this paper selects the most proper instrumental variable in the model estimation for regression. The measurement formulas of industrial structure rationalization and supererogation are as follows:

$$TL = \sum_1^n (y_i / y) \times \ln(y_i / l_i / y / l) \quad (2)$$

$$TS = y_3 / y_2 \quad (3)$$

Wherein,  $TL$  is Theil index of industrial structure rationalization,  $y_i$  is the value-added of the industry  $i$ ,  $y$  is the total value-added of primary, secondary and tertiary industries,  $l_i$  is the the number of employees in the industry  $i$ , and  $l$  is the total number of employees in the three industries. Given the data availability, this paper calculates  $TL$  with the data of the three industries.  $TS$  means industrial structure supererogation index;  $y_3$  and  $y_2$  respectively mean valued-added of the tertiary and secondary industry.

### 3.3.3. Control Variables

Five controlled variables are set as follows. The first is the average weekly working hours ( $\ln weekwork$ ). It's necessary to control the actual working hours in regression because of its close connection with demand for labor force. The second is the gender ratio ( $\ln gender$ ) and the proportion of highly skilled labor ( $hskills$ ). Gender structure

<sup>1</sup> Limited by the data availability, this paper uses 2008–2015 data to replace 2008–2019 data, and tests with the industrial structure supererogation index to verify rationality of the replacement. Results show that the industrial structure of the sample economies differs only mildly between 2008–2015 and 2008–2019.



representing physical strength and skill structure representing abilities are important metrics of the employment structure (Chen and Hou, 2021) and should necessarily be considered as controlled variables. Specifically, highly skilled labor refers to labor with skill3 and skill4 as categorized by ILO for labor skills. The third is industry size ( $\ln iva$ ). Industry size has major influence on an industry's demand for labor and is expressed with the logarithm of industrial value-added after deflation of purchase power. The fourth is industrial competitive advantage ( $rca$ ). Industries with competitive advantages can better absorb labor force and promote job growth. The variable is expressed with the ratio between the share of the industry's export in the country's total export and the share of the industry's export globally in global total export. The fifth is dependency ratio ( $dependency$ ). It is closely related to ability in labor force supply and has important impact on the quantity and quality of employment (Cai, 2020). The variable is expressed with the ratio between non-working-age population and working-age population.

Table 1. Descriptive Statistics

| Variables    | Meaning                            | Sample Size | Mean    | Standard Deviation | Minimum | Maximum |
|--------------|------------------------------------|-------------|---------|--------------------|---------|---------|
| $\ln lab$    | Logarithm of number of employees   | 1848        | 6.6217  | 2.2839             | 1.1499  | 12.6090 |
| $\ln rob$    | Logarithm of robot stock           | 1848        | 4.3108  | 3.1971             | 0       | 13.3481 |
| $weekwork$   | Average weekly working hours       | 1848        | 39.9502 | 4.1059             | 27.3345 | 56.3769 |
| $gender$     | Gender ratio                       | 1848        | 4.5517  | 6.2079             | 0.3221  | 65.6667 |
| $\ln iva$    | Industry size                      | 1848        | 10.5838 | 2.0838             | 5.1766  | 16.6516 |
| $rca$        | Industrial competitive advantage   | 1848        | 0.9858  | 0.7643             | 0.0090  | 5.6739  |
| $dependency$ | Dependency ratio                   | 264         | 0.5005  | 0.0685             | 0.3604  | 0.6847  |
| $hskills$    | Proportion of highly skilled labor | 264         | 0.3802  | 0.0882             | 0.0660  | 0.5435  |

## 4. Empirical Analysis

### 4.1. Population Regression and Analysis

Table 2 reports the empirical results of how robot application affects total employment. Except for column (1), robot application has positive impact on

labor force employment, which passes the 5% significance test. The comparison among columns (1)–(3) indicates that the estimated coefficient of including the core explanatory variable alone into the model is positive but not significant, while as industry characteristic variables and economy characteristic variables are successively included into the model, the regression coefficient value and significance of robot application are gradually increased. Given the possible endogeneity with the core explanatory variable, column (4) adopts 2SLS for estimation. The result shows that the impact of robot application on employment remains significantly positive and the estimated coefficient is substantially higher than that in column (3), indicating that the instrumental variable method can effectively address the estimation errors caused by missing variables and reciprocal causation. The comprehensive analysis of columns (3)–(4) suggests that in general, the impact of robot application on labor force employment is dominated by complementation.

Table 2. Overall Impact of Robot Application on Employment

| Variables             | (1)                   | (2)                    | (3)                    | (4)                    |
|-----------------------|-----------------------|------------------------|------------------------|------------------------|
| <i>ln rob</i>         | 0.0177<br>(0.0147)    | 0.0444***<br>(0.0154)  | 0.0445***<br>(0.0150)  | 0.5071***<br>(0.1196)  |
| <i>ln weekwork</i>    |                       | −2.6786***<br>(0.2253) | −2.6729***<br>(0.2266) | −3.7755***<br>(0.3845) |
| <i>ln gender</i>      |                       | −0.1428**<br>(0.0599)  | −0.1405**<br>(0.0600)  | −0.2096***<br>(0.0514) |
| <i>ln iva</i>         |                       | 0.1695***<br>(0.0339)  | 0.1707***<br>(0.0338)  | 0.0755*<br>(0.0459)    |
| <i>rca</i>            |                       | 0.0946***<br>(0.0180)  | 0.0945***<br>(0.0180)  | 0.1220***<br>(0.0220)  |
| <i>dependency</i>     |                       |                        | −0.8724<br>(0.7533)    | 0.5671<br>(1.1436)     |
| <i>hskills</i>        |                       |                        | −0.2394<br>(0.8463)    | −4.8973***<br>(1.6938) |
| <i>cons</i>           | 6.5454***<br>(0.0675) | 14.5481***<br>(0.9831) | 15.0388***<br>(1.0701) | 18.5619***<br>(1.6248) |
| Economy fixed effect  | Yes                   | Yes                    | Yes                    | Yes                    |
| Industry fixed effect | Yes                   | Yes                    | Yes                    | Yes                    |
| Year fixed effect     | Yes                   | Yes                    | Yes                    | Yes                    |
| First-stage F value   | —                     | —                      | —                      | 28.6090                |
| Sample size           | 1848                  | 1848                   | 1848                   | 1848                   |
| Adj.R <sup>2</sup>    | 0.9531                | 0.9657                 | 0.9657                 | 0.9288                 |

Note: \*, \*\* and \*\*\* indicate the significance level of 10%, 5% and 1% respectively, and in the parentheses is robust standard error. The same below. Column (4) adopts the instrumental variable IV1 for regression.

The benchmark regression of the controlled variables and the 2SLS regression yield results are just as expected. Take column (4) for example. The estimated coefficient of the average weekly working hours ( $\ln weekwork$ ) of the labor force is significantly negative, indicating that under constant total workload, the longer average weekly working hours, the weaker demand for labor force. The estimated coefficient of gender ratio ( $\ln gender$ ) is significantly negative, indicating that an excessively high proportion of male employees is unfavorable to overall job growth, which coincides with the reality that increasingly more women are flooding into the labor market. The estimated coefficient of the proportion of highly skilled talents ( $hskills$ ) is negative and passes the 5% significance test for two possible reasons. First, highly skilled talents yield higher productivity, while higher productivity of individual laborers drives down the corporate demand for labor force. Second, economies with a higher proportion of highly skilled talents are more likely to offshore outsourcing of non-core industries, mostly labor-intensive. Therefore, a higher proportion of highly skilled talents is possibly not helpful for overall job growth.

#### 4.2. Heterogeneity Regression and Analysis for Different Industries

To explore industry heterogeneity, Table 3 reports the regression results by industry.<sup>1</sup> Specifically, Panel A and Panel B respectively introduce the benchmark regression and 2SLS regression. Given the mild discrepancies between their estimation results, to avoid possible endogeneity problems, Panel B is analyzed below as an example.<sup>2</sup> As shown in the table, the introduction of robotics into agriculture, forestry, animal husbandry and fishery, manufacturing, construction, and other services can all significantly boost employment, while the introduction into production and supply of electricity, gas and water and quarrying and mining can both significantly restrain employment. As to education and research & development, the impact of robot application on employment is not significant.

The impact of robot application on labor force employment across industries is not consistent for the possible reason that endowment characteristics of industries give them different capacity to accommodate robotics. For instance, the employment effect of robotics may appear heterogenous for different levels of industry concentration. In highly concentrated industries such as production and supply of electricity, gas and

<sup>1</sup> Given that the impact of robotics on employment is possibly lagged, this paper attempts to introduce one period lagged core explanatory variable into the regression model. The result shows not significant lagged effects in most industries (agriculture, forestry, animal husbandry and fishery, construction, production and supply of electricity, gas and water, education and research & development, and other services), and the lagging is therefore no longer taken into consideration.

<sup>2</sup> To avoid weak instruments as much as possible, agriculture, forestry, animal husbandry and fishery, education and research & development, and construction in Panel B adopt the instrumental variable IV1, whereas other industries use IV2 for regression.

water and quarrying and mining, robots are more likely to replace human labor because the industries are able to bear the cost of using a large number of robotics equipment. In industries with less concentrated markets such as agriculture, forestry, animal husbandry and fishery and manufacturing, robotics-induced efficiency advantage for enterprises, not so much different in their market positions, is more likely to stimulate expansion in enterprise size and therefore generate stronger demand for non-automated jobs (Wang and Dong, 2020). In addition, the effects of robot application are mainly manifested during production, mostly by liberating workers from physical labor, while those in education and research & development are mainly engaged in brainwork, making possible that robots will not have a significant impact on employment in the industry.

Table 3. Impact of Robot Application on Employment by Industry

| Variables                     | Agriculture, forestry, animal husbandry and fishery | Manufacturing         | Production and supply of electricity, gas and water | Quarrying and mining  | Education and research & development | Construction          | Other services      |
|-------------------------------|-----------------------------------------------------|-----------------------|-----------------------------------------------------|-----------------------|--------------------------------------|-----------------------|---------------------|
| Panel A: Benchmark Regression |                                                     |                       |                                                     |                       |                                      |                       |                     |
| $\ln rob$                     | 0.0002<br>(0.0090)                                  | 0.0485***<br>(0.0092) | -0.0225***<br>(0.0081)                              | -0.0406**<br>(0.0160) | -0.0095*<br>(0.0055)                 | 0.0474***<br>(0.0155) | 0.0004<br>(0.0021)  |
| Sample size                   | 264                                                 | 264                   | 264                                                 | 264                   | 264                                  | 264                   | 264                 |
| Adj.R <sup>2</sup>            | 0.9988                                              | 0.9993                | 0.9967                                              | 0.9948                | 0.9992                               | 0.9969                | 0.9997              |
| Panel B: IV 2SLS              |                                                     |                       |                                                     |                       |                                      |                       |                     |
| $\ln rob$                     | 0.0575**<br>(0.0250)                                | 0.0786**<br>(0.0364)  | -0.0473**<br>(0.0212)                               | -0.2652*<br>(0.1586)  | 0.0012<br>(0.0335)                   | 0.0531*<br>(0.0395)   | 0.0330*<br>(0.0185) |
| First-stage F value           | 29.7820                                             | 13.4130               | 36.4180                                             | 3.6060                | 4.7190                               | 15.8460               | 7.5530              |
| Sample size                   | 264                                                 | 264                   | 264                                                 | 264                   | 264                                  | 264                   | 264                 |
| Adj.R <sup>2</sup>            | 0.9988                                              | 0.9993                | 0.9971                                              | 0.9903                | 0.9993                               | 0.9974                | 0.9996              |

Note: Quarrying and mining, education and research & development, and other services didn't pass the weak instruments test. The method of limited information maximum likelihood (LIML) is used for re-evaluation, yielding results not significantly different from 2SLS, which indicates that the influence of weak instrumental variables is not profound. All the regressions in the table have the controlled variables, and fixed effects of economy, industry and year in control. The same below.

### 4.3. Heterogeneity Regression and Analysis for Different Economies

#### 4.3.1. Heterogeneity in Economic Characteristics

This paper explores the economy heterogeneity in robotics' impact on employment in the three dimension of unemployment rate, per capita GDP, and proportion of highly skilled talents. By referring to Wang and Dong (2020), it categorizes the 22 sample economies into two groups for grouped regression with the median of their mean unemployment rate in 2008–2019 as threshold. The same method is applied to per capita GDP and proportion of highly skilled talents for grouping (the same grouping method is used in Table 5). The data on unemployment rate and per capita GDP is from the World Bank database.

Table 4. Heterogeneity in Economic Characteristics

| Variables                     | Unemployment rate     |                      | Per capita GDP        |                       | Proportion of highly skilled talents |                       |
|-------------------------------|-----------------------|----------------------|-----------------------|-----------------------|--------------------------------------|-----------------------|
|                               | Low                   | High                 | Low                   | High                  | Low                                  | High                  |
| Panel A: Benchmark Regression |                       |                      |                       |                       |                                      |                       |
| $\ln rob$                     | 0.0444**<br>(0.0185)  | 0.0268**<br>(0.0129) | 0.0549**<br>(0.0217)  | 0.0543***<br>(0.0160) | -0.0286<br>(0.0186)                  | 0.0677***<br>(0.0151) |
| Sample size                   | 924                   | 924                  | 924                   | 924                   | 924                                  | 924                   |
| Adj.R <sup>2</sup>            | 0.9640                | 0.9732               | 0.9669                | 0.9785                | 0.9766                               | 0.9751                |
| Panel B: IV 2SLS              |                       |                      |                       |                       |                                      |                       |
| $\ln rob$                     | 0.2267***<br>(0.1150) | 0.2324*<br>(0.1310)  | 0.3785***<br>(0.0977) | 0.1737***<br>(0.0608) | 0.1630***<br>(0.0625)                | 0.2565***<br>(0.0628) |
| First-stage F value           | 39.8340               | 11.6820              | 21.4010               | 18.5830               | 26.8260                              | 23.5240               |
| Sample size                   | 924                   | 924                  | 924                   | 924                   | 924                                  | 924                   |
| Adj.R <sup>2</sup>            | 0.9587                | 0.9685               | 0.9548                | 0.9764                | 0.9735                               | 0.9704                |

Panel B in Table 4 introduces the 2SLS regression.<sup>1</sup> According to the results, robot application has significantly positive impact on labor force employment in different groups, suggesting that in economies with different unemployment rates, economic development levels and talent structures, the complementary effect of robot application at the current stage prevails.

<sup>1</sup> To avoid weak instruments, this paper adopts the instrumental variable IV2 for the unemployment rate regression and the double instrumental variables IV1 and IV2 for the regression of per capita GDP and proportion of highly skilled talents.

#### 4.3.2. Heterogeneity in Population Characteristics

This paper analyzes the heterogeneity of robotics' impact on employment in the context of different population characteristics from the two perspectives of gender ratio of employees and social dependency ratio. Given that social dependency ratio incorporates child and elderly dependency ratios with varying influence over labor force employment (Qi and Liu, 2020), dependency ratio is deconstructed into child dependency ratio and elderly dependency ratio for grouped regression. Panel B in Table 5 reports the 2SLS regression results.<sup>1</sup> According to the grouped regression result of gender ratio, robot application significantly promotes the job growth in economies with high gender ratios, but produces insignificant impact on economies with low gender ratios. This may be because females are more often engaged in interpersonal communications and other less replaceable unconventional tasks, reflecting the greater positive impact of robot application on female employment. Based on the grouped regression results of child dependency ratio, robotics' impact is significantly positive on the group with a lower child dependency ratio and negative on the group with a higher child dependency ratio. As for the possible reason, since robot application has a greater positive impact on female employment and female tends to bear the responsibility of rearing children, higher child dependency ratios tie down women from jobs and reduce the complementary effect on employment. According to the grouped regression result of elderly dependency ratio, for labor force employment in different groups, impact of robot application is both significantly positive.

Table 5. Heterogeneity in Population Characteristics

| Variables                     | Gender ratio         |                       | Child dependency ratio |                        | Elderly dependency ratio |                       |
|-------------------------------|----------------------|-----------------------|------------------------|------------------------|--------------------------|-----------------------|
|                               | Low                  | High                  | Low                    | High                   | Low                      | High                  |
| Panel A: Benchmark Regression |                      |                       |                        |                        |                          |                       |
| $\ln rob$                     | 0.0172<br>(0.0109)   | 0.0534***<br>(0.0187) | 0.1095***<br>(0.0188)  | -0.0383***<br>(0.0144) | 0.0436**<br>(0.0202)     | 0.0790***<br>(0.0186) |
| Sample size                   | 924                  | 924                   | 924                    | 924                    | 924                      | 924                   |
| Adj.R <sup>2</sup>            | 0.9793               | 0.9652                | 0.9643                 | 0.9800                 | 0.9646                   | 0.9774                |
| Panel B: IV 2SLS              |                      |                       |                        |                        |                          |                       |
| $\ln rob$                     | 0.3662**<br>(0.1664) | 0.1891<br>(0.1559)    | 0.1737***<br>(0.0537)  | 0.1572<br>(0.1115)     | 0.6556***<br>(0.1787)    | 0.6253***<br>(0.1922) |
| First-stage F value           | 11.4750              | 10.1660               | 29.2280                | 6.8460                 | 21.2880                  | 10.1280               |
| Sample size                   | 924                  | 924                   | 924                    | 924                    | 924                      | 924                   |
| Adj.R <sup>2</sup>            | 0.9609               | 0.9633                | 0.9645                 | 0.9762                 | 0.9176                   | 0.9146                |

<sup>1</sup> To avoid weak instruments, this paper adopts the instrumental variable IV1 for the regression of gender ratio and elderly dependency ratio and the double instrumental variables IV1 and IV2 for the regression of child dependency ratio.

## 5. Further Research

### 5.1. Robot Penetration Analysis

Scholars conclude differently as to the impact of robotics on employment. Based on analysis of the heterogeneity conclusions of the existing literatures, this paper believes such impact in a multi-country framework may not be linear, as stated by Acemoglu and Restrepo (2020), but in an inverted U-shaped structure featuring a shift from complementary to substitutive effects. Given so, this paper tries to validate the assumption in the three ways of introducing the perspective of time sequence, grouping by level of robot use,<sup>1</sup> and including into the model quadratic term of the level of robot use.

First, from the perspective of time sequence, the progress of time will drive a transformation of robots' usage from low to high. After 2014, the global installation of robots experienced an explosive growth. This paper takes the year of 2014 as the dividing point and conducts grouped regression for the period 2008–2013 and 2014–2019, respectively. If the regression coefficients of the two groups are both positive and the coefficient value and significance of the former are higher than the later, it indicates that as time progresses, the level of robot use across the countries continues to increase and its complementary effect on employment weakens. Second, in the case of grouping by the level of robot use, different economies differ evidently in such level in the same period of time. Accordingly, this paper divides the sample economies into “low level of robot use” and “high level of robot use” for grouped regression. If the coefficient of the former is significantly positive while that of the latter is significantly negative, it further suggests the level of robot use may be the driver for the shift from complementary to substitutive effects. Third, the level of robot use and its quadratic term are included into the model. If the coefficient of linear term is significantly positive and that of quadratic term significantly negative, it can be verified that the impact of robotics on employment is not linear, but in an inverted U-shaped structure featuring a shift from complementary to substitutive effects.

To measure the level of robot use, this paper refers to the method of “robot penetration” proposed by Wang and Dong (2020) and uses the following formula:

$$PR_{ijt} = rob_{ijt} / lab_{ij,t=2008} \quad (4)$$

Wherein,  $PR_{ijt}$  means robot penetration,  $rob_{ijt}$  robot stock, and  $lab_{ij,t=2008}$  the number of employees. To simplify the calculation, this paper leaves out industrial factors in the grouping by level of robot use and uses the Formula (4) alone to calculate the economy-level robot penetration. The median of the mean robot penetration of the

<sup>1</sup> This paper use “robot application” and “robot use” interchangeably, unless otherwise specified.

economies in the sample period is then taken as threshold to divide the 22 economies into two groups for grouped regression.

Table 6. Robot Penetration and Year Heterogeneity

| Variables                     | Period                |                       |                       | Penetration           |                       |                      |
|-------------------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|----------------------|
|                               | 2008–2019             | 2008–2013             | 2014–2019             | Full sample           | Low                   | High                 |
| Panel A: Benchmark Regression |                       |                       |                       |                       |                       |                      |
| $\ln rob$                     | 0.0445***<br>(0.0150) | 0.0373**<br>(0.0188)  | 0.0739***<br>(0.0259) | 0.0445***<br>(0.0150) | 0.0903***<br>(0.0144) | 0.0267<br>(0.0180)   |
| Sample size                   | 1848                  | 924                   | 924                   | 1848                  | 924                   | 924                  |
| Adj.R <sup>2</sup>            | 0.9657                | 0.9647                | 0.9667                | 0.9657                | 0.9656                | 0.9726               |
| Panel B: IV 2SLS              |                       |                       |                       |                       |                       |                      |
| $\ln rob$                     | 0.4394***<br>(0.0898) | 0.3271***<br>(0.0832) | 0.3032**<br>(0.1202)  | 0.5071***<br>(0.1196) | 0.9217***<br>(0.2265) | −0.2327*<br>(0.1244) |
| First-stage F value           | 22.1010               | 15.8110               | 13.1010               | 28.6090               | 20.8590               | 13.0920              |
| Sample size                   | 1848                  | 924                   | 924                   | 1848                  | 924                   | 924                  |
| Adj.R <sup>2</sup>            | 0.9390                | 0.9480                | 0.9623                | 0.9288                | 0.8512                | 0.9626               |

Panel B in Table 6 reports the 2SLS estimation results.<sup>1</sup> From the perspective of grouping by period, there exists a complementary effect between robot application and employment. In the grouped regression of “2008–2013” and “2014–2019”, the regression coefficients of robot application are both significantly positive, but the coefficient value and significance of the latter are decreased compared with the former. The consistence between the empirical results and the expectations suggests as the level of robot use increases, the complementary effect weakens, but the effect remains dominant at the current stage since the level of robot use in most economies hasn’t reached the critical value. In the sense of grouping by robot penetration, the group with low penetration shows a significant complementary effect between robot application and employment; in the group with high penetration, the substitutive effect dominates, further verifying that higher level of robot use helps drive the shift from complementary to substitutive effects.

## 5.2. Industry Spillover Analysis

To comprehensively understand the impact of robot application on the entire labor market, this paper includes all the industries covering robot application into a unified analysis framework. Meanwhile, to simplify the model, it digs into the labor force

<sup>1</sup> To avoid weak instrumental variables, in Panel B of Table 7, this paper adopts the double instrumental variables IV1 and IV2 for the grouped regression by period and the instrumental variable IV1 for the grouped regression by penetration.



reallocation mechanism driven by robotics from the perspective of three industries. Specifically, it first consolidates the data on the seven industry categories involved in the sample into three industries. Then, while exploring the impact of robot application in the secondary and tertiary industries on employment in the primary industry, to remove interference from the robots in the primary industry on the estimated results, it includes the primary-industry robot application into controlled variables. Lastly, the same method is applied to discuss the impact of robot application in the primary and tertiary industries on employment in the secondary industry as well as the impact of robot application in the primary and secondary industries on employment in the tertiary industry.

Table 7. Spillover Effects in the Three Industries

| Variables                      | Primary industry<br>$\ln rob_1$ | Secondary industry<br>$\ln rob_2$ | Tertiary industry<br>$\ln rob_3$ |
|--------------------------------|---------------------------------|-----------------------------------|----------------------------------|
|                                | (1)                             | (2)                               | (3)                              |
| Primary industry $\ln rob_1$   | 0.0248**<br>(0.0119)            | 0.0303***<br>(0.0094)             | 0.0130***<br>(0.0037)            |
| Secondary industry $\ln rob_2$ | -0.0393**<br>(0.0175)           | 0.0256**<br>(0.0128)              | 0.0273***<br>(0.0044)            |
| Tertiary industry $\ln rob_3$  | 0.0097<br>(0.0140)              | -0.0083<br>(0.0080)               | 0.0108***<br>(0.0034)            |
| Controlled variables           | Yes                             | Yes                               | Yes                              |
| Economy fixed effect           | Yes                             | Yes                               | Yes                              |
| Year fixed effect              | Yes                             | Yes                               | Yes                              |
| Sample size                    | 264                             | 264                               | 264                              |
| Adj.R <sup>2</sup>             | 0.9988                          | 0.9989                            | 0.9998                           |

Table 7 explains the pertinent estimated results. Estimated results of the variables along the main diagonal are significantly positive in mutual verification with the aforesaid regression results of industry heterogeneity. To be specific, column (1) lists the impact of robot application in the secondary and tertiary industries on employment in the primary industry. The result shows the application in the secondary industry will produce a siphon effect to curb the labor flow into the primary industry, while the application in the tertiary industry has an impact on the primary-industry employment that is not significant. Column (2) reports the impact of robot application in the primary and tertiary industries on employment in the secondary industry. According to the result, introduction of robots into the primary industry will generate a crowding-out effect to boost employment in the secondary industry, while the introduction into the tertiary industry also produces a certain degree of siphon effect on the secondary-industry employment. Column (3) shows the impact of robot application in the primary and secondary industries on employment in the tertiary industry. The result indicates that robots introduced into the primary and secondary industries will form a crowding-out

effect to promote the shift of labor force towards the tertiary industry. In general, the inter-industry spillover effect of robot application is manifested as the layer-by-layer crowding-out effect from the primary industry to the tertiary industry and the layer-by-layer siphon effect the other way around.

### 5.3. Transmission Effect of the GVC Position

Robot application affects not only the reallocation of labor force across industries, but also labor force employment across upstream and downstream economies along the global value chain (GVC). To identify whether the introduction of robots into GVC upstream economies produces any impact on downstream employment and whether it works the other way around, this paper constructs the following models:

$$\ln lab_{ijt} = \beta_0 + \beta_1 \ln rob_{i-3,jt} + \beta_2 \ln rob_{ijt} + \beta_3 control_{ijt} + u_i + v_j + r_t + \varepsilon_{ijt} \quad (5)$$

$$\ln lab_{ijt} = \alpha_0 + \alpha_1 \ln rob_{i+3,jt} + \alpha_2 \ln rob_{ijt} + \alpha_3 control_{ijt} + u_i + v_j + r_t + \varepsilon_{ijt} \quad (6)$$

Wherein,  $i-3$  means the economy three positions behind the GVC position of economy  $i$ , and  $i+3$  the economy three positions ahead of the GVC position of economy  $i$ ; other variables and letters have the same meaning as in the previous context. This paper uses data disclosed in the World Input-Output Database (WIOD 2016) and the method proposed by Koopman *et al.* (2012) to measure the GVC position index of the economies in 2014, which is used to represent the average GVC position index of the economies in 2008–2019.

Table 8 Spillover Effects of the GVC Position

| Variables             | Upstream-to-downstream conduction effect |                       | Downstream-to-upstream conduction effect |                      |
|-----------------------|------------------------------------------|-----------------------|------------------------------------------|----------------------|
|                       | (1)                                      | (2)                   | (3)                                      | (4)                  |
| $\ln rob_{i-3}$       |                                          |                       | -0.0094<br>(0.0110)                      | -0.0065<br>(0.0111)  |
| $\ln rob_{i+3}$       | -0.0280**<br>(0.0121)                    | -0.0249**<br>(0.0120) |                                          |                      |
| $\ln rob$             |                                          | 0.0460***<br>(0.0159) |                                          | 0.0384**<br>(0.0157) |
| Controlled variable   | Yes                                      | Yes                   | Yes                                      | Yes                  |
| Economy fixed effect  | Yes                                      | Yes                   | Yes                                      | Yes                  |
| Industry fixed effect | Yes                                      | Yes                   | Yes                                      | Yes                  |
| Year fixed effect     | Yes                                      | Yes                   | Yes                                      | Yes                  |
| Sample size           | 1596                                     | 1596                  | 1596                                     | 1596                 |
| Adj.R <sup>2</sup>    | 0.9629                                   | 0.9633                | 0.9643                                   | 0.9646               |

Table 8 summarizes the estimation results of transmission effects along the industrial chain. Columns (2) and (4) include local robot application ( $\ln rob$ ) into the regression model as a controlled variable. Before and after the inclusion, in the regression of the upstream-to-downstream transmission effect and the downstream-to-upstream transmission effect, the regression coefficient value and significance of the core explanatory variable haven't changed fundamentally, verifying that the regression results are robust and reliable. Specifically, the regression coefficient of  $\ln rob_{t+3}$  in column (2) is significantly negative, indicating the introduction of industrial robots into upstream economies in the GVC inhibits the downstream job growth. A possible reason is that robot application eases the pressure of labor cost for upstream economies that therefore are less motivated for offshore outsourcing of industries, which goes against the job growth in downstream economies. The  $\ln rob_{t-3}$  regression coefficient in column (4) is negative but not significant, suggesting the indistinct impact of industrial robots introduced into GVC downstream economies on upstream employment.

## 6. Conclusions and Suggestions

This paper uses the industry-specific data on robots in the economies disclosed by the IFR and the labor force employment data published by the ILO to examine the impact of robot application on labor force from the perspectives of industry and time sequence. The results show that in general, the use of robots has a significant complementary effect on labor force employment, but there are significant differences across industries. Additionally, endowment of economies affects the magnitude of the complementary effect but does not change its direction. Further research finds that the level of robot use plays a key role in labor force employment, with complementary effects dominating in economies with low robot application and substitution effects dominating in economies with high robot application. Finally, from an industry spillover perspective, the study finds that robotics application has promoted the reallocation of labor resources across the three industries and increased the employment share of the tertiary industry to some extent. The analysis of GVC position reveals that robot application in upstream economies significantly suppresses employment growth in downstream economies, while robot application in downstream economies has no significant impact on employment in upstream economies.

On such basis, this paper proposes two policy recommendations as follows.

First, launching tailored robot development strategies as per local conditions. The heterogeneity of the impact of robot application on employment, in terms of both economic entities and industries, exists among different provinces in China. Therefore, local governments need to introduce region-specific and coordinated robot

development strategies based on the local stage of industry development and the level of robot utilization. Additionally, the introduction of robots in upstream economies of GVC may have adverse effects on downstream job markets. Therefore, policymakers need to closely follow the robot-related policies in GVC upstream countries and regions and promptly develop coordinated development strategies with stakeholder countries to promote mutual benefit and win-win results.

Second, promoting the construction of a professional talent training system. To avoid the large-scale “technological unemployment” after reaching the critical point of the inverted U-shaped curve, governments need to take proactive measures and ramp up precautions. On the one hand, it’s important to vigorously promote labor skill training, guide the structure of labor market to align with robot technology, and translate the labor quantity dividend into human capital dividend. On the other hand, the improvement of the social welfare system and the unemployment insurance system need be accelerated, and hierarchical and diverse unemployment insurance schemes for different employee groups be proposed to ensure basic living standards for the unemployed while providing services for their reemployment.

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