Available Online: 8 May 2026 DOI: 10.54254/2977-5701/2026.33350

Research on the impact of industrial robot application on the length of global value chains in manufacturing: a backward linkage perspective

Haiqiang Sun

Jiangxi University of Finance and Economics, Nanchang, China

1914879537@qq.com

Abstract. Against the backdrop of advances in artificial intelligence and digitalization, the impact of industrial robots on the global division of labor in manufacturing has become an important research topic. This study conducts an empirical analysis using data on industrial robots from the International Federation of Robotics (IFR) and panel data from 14 sub-sectors of China's manufacturing industry. The results show that the application of industrial robots significantly extends the length of global value chains in manufacturing. Further analysis indicates that industrial robots promote participation in global production networks within capital-intensive industries, while shortening the backward linkage length in labor-intensive industries. In addition, industrial robots influence global value chain length primarily through two channels: human capital upgrading and technological innovation.

Keywords: industrial robots, global value chain length, manufacturing industry

1. Introduction

At present, the division of labor along Global Value Chains (GVCs) has become the core paradigm of international specialization and a key vehicle for the circulation of the global economy. Countries participate in production networks based on their respective comparative advantages, thereby forming an interdependent and closely interconnected global production system. However, it is noteworthy that developing countries, constrained by relatively weak industrial foundations, have long relied on low-cost labor to embed themselves in the low-end segments of GVCs, such as processing and assembly. As a result, they remain in a disadvantaged position in international trade, characterized by low value added and weak bargaining power. For China, as a major global manufacturing country, promoting the transformation and upgrading of its manufacturing sector and enhancing its core industrial competitiveness are not only intrinsic requirements for achieving high-quality economic development, but also essential pathways to breaking out of low-end lock-in and to more deeply integrating into—and even leading—the global division of labor within GVCs.

With the rapid iteration of artificial intelligence technologies, industrial robots, as a core application carrier within the manufacturing sector, have been widely integrated into various stages of global value chains. Their fundamental value lies in advancing the automation of industrial production: on the one hand, they liberate labor from repetitive, arduous, and hazardous tasks; on the other hand, they create favorable conditions for labor to transition toward high-skill and high-value-added positions, thereby facilitating human capital upgrading. Meanwhile, the recent resurgence of trade protectionism and the intensification of de-globalization trends have prompted some developed countries to pursue reindustrialization strategies, aiming to reshore high-end manufacturing activities. This development poses significant challenges to China's manufacturing sector, which has long held the status of the "world's factory", and further underscores the urgency of industrial transformation and upgrading. In this context, China's 14th Five-Year Plan for the Development of the Robot Industry explicitly proposes expanding both the depth and breadth of industrial robot applications, providing an important policy opportunity for manufacturing upgrading. In practice, the deep integration of industrial robots spans the entire value chain—including research and development, production, and services—by optimizing production processes, improving efficiency, and reducing operational costs. This, in turn, promotes industrial restructuring, enhances the competitiveness of China's manufacturing sector within GVCs, and contributes to the continuous extension of global value chain length.

Against this backdrop, a review of the relevant literature reveals several key findings. First, most studies suggest that the digital economy can extend GVC length and contribute to chain stability [1], while some identify an inverted U-shaped relationship between digitalization and chain length [2]. Trade liberalization and regional economic integration tend to lengthen GVCs, whereas various trade restrictions shorten them [3]. Second, at the labor market level, robot adoption exerts a substitution effect on low-skilled jobs while simultaneously generating high-skilled employment opportunities and contributing to job polarization [4]. At the firm level, it enhances resilience, promotes servitization, and facilitates specialized division of labor [5]. At the macro level, it reduces the extent of outsourcing and generates fiscal benefits through related channels [6]. Finally, a strand of literature has examined the relationship between industrial robots and GVCs, generally confirming that robot adoption enhances China's degree of GVC embedding [7], strengthens industrial chain resilience, and drives upgrading toward higher value-added segments. The underlying mechanism primarily operates through the substitution of low-end labor, cost reduction, and efficiency gains, thereby improving firm competitiveness and deepening participation in global production networks [8].

In summary, while the existing literature has explored the determinants of GVC length, the economic effects of industrial robots, and the relationship between the two, there remains a relative paucity of research that systematically analyzes how industrial robot adoption affects the length of manufacturing GVCs from the perspective of backward linkages. To address this gap, this paper investigates the impact of industrial robot application on the length of global value chains in manufacturing, thereby enriching both the theoretical and empirical evidence in this field.

2. Theoretical analysis and research hypotheses

2.1. Technological innovation effect

As a core general-purpose technology of the new round of industrial revolution, industrial robots exhibit significant technological spillover effects and can effectively drive overall technological progress in the manufacturing sector. At the firm level, the application of industrial robots empowers innovation through a "learning effect". During the process of introducing robots and advancing production automation, firms rely on complementary technological systems, collaborative R&D, and outsourced service partnerships to acquire frontier production knowledge and track market trends. This process continuously enhances their capacity for technology absorption, assimilation, and re-innovation, thereby strengthening endogenous innovation capabilities, improving product quality, and reinforcing core competitiveness in international markets. At the industry level, intelligent transformation establishes a strong reverse-pressure mechanism that facilitates comprehensive technological upgrading in manufacturing. Once industrial robots are introduced as a new production factor, firms are compelled to undertake systematic adjustments across multiple dimensions—including R&D design, production process optimization, organizational management innovation, and supporting infrastructure upgrading—in order to adapt to intelligent production modes. At the same time, such transformation induces coordinated upgrading along the upstream and downstream segments of the industrial chain, prompting component suppliers and technical service providers to enhance their supporting capabilities. This process forms a virtuous cycle of "robot application—technological upgrading—industrial chain improvement", further amplifying the technological spillover effects of industrial robots and injecting sustained momentum into high-quality manufacturing development. Consequently, by stimulating technological innovation and promoting technological progress, industrial robot adoption increases the roundaboutness and specialization of production processes, thereby extending the length of global value chains.

Based on this, the following hypothesis is proposed: H1: Industrial robot application promotes the extension of global value chain length in manufacturing by fostering technological innovation.

2.2. Human capital effect

Industrial robots are, in essence, a skill-biased general-purpose technology. Their widespread application can significantly optimize the structure of human capital and provide momentum for value chain upgrading. In the production process, industrial robots can substitute for routine labor in performing high-intensity, high-risk, and repetitive tasks, thereby reducing labor costs and workplace risks. The labor thus released is reallocated toward higher-skilled positions, leading to an optimized human capital structure. This enables firms to focus more on technological R&D, process improvement, and product upgrading, thereby enhancing value added and deepening participation in global value chains. At the industry level, robot adoption improves resource allocation efficiency and accelerates the digital and intelligent transformation of manufacturing, further increasing production roundaboutness and the overall length of value chains. Meanwhile, the growing demand for complementary services—such as robot operation and maintenance, system integration, and technical services—encourages the workforce to strengthen professional training and continuously update knowledge, thereby promoting overall human capital development. Higher-quality human capital, in turn, supports more complex production specialization, more refined intermediate input coordination, and the expansion of longer value chains.

Accordingly, the following hypothesis is proposed: H2: Industrial robot application promotes the extension of global value chain length in manufacturing by enhancing human capital.

3. Model specification and data description

3.1. Baseline model specification

Building on the existing literature, this paper further examines the impact of industrial robot application on the position of manufacturing industries within global value chains. Based on the preceding analysis and following the approach of Bin Liu and Tong Pan [9], the baseline model is specified as follows (Equation (1)):

$$Ply_{it} = \beta_0 + \beta_1 Robot_{it} + \delta X_{it} + \sigma_i + \mu_t + \varepsilon_{it} \tag{1}$$

where i denotes manufacturing sub-sectors and t denotes years. As discussed earlier, the dependent variable is proxied by Ply_{it}, representing the length of the global value chain for industry i in year t, defined from the perspective of backward linkages. The key explanatory variable, $Robot_{it}$, measures the number of newly installed industrial robots in industry i in year t. X_{it} is a vector of control variables, including industry scale ($Sales$), capital accumulation ($Netasset$), R&D expenditure (Rde), and foreign direct investment (Fdi). In addition, σ_i represents industry fixed effects, μ_t represents year fixed effects, β_0, β_1, and δ are the estimated coefficients, and ε_{it} is the error term.

3.2. Variable definitions

3.2.1. Core explanatory variable

For the measurement of industrial Robot Application (Robot), this paper uses the "country–industry–time" panel data on industrial robots published annually by the International Federation of Robotics (IFR), which includes both robot stock and new installations. Due to limitations in data availability at the annual level, and following the methodology of Gang Peng et al. [10], the number of newly installed industrial robots is adopted as the primary proxy for the level of robot application. Given the presence of zero values in the installation data, the variable is constructed by taking the logarithm after adding one to the original values.

3.2.2. Dependent variable

Global value chain length (Ply): This study employs the indicator of backward average production length within global value chains to examine the impact of industrial robot application on the backward linkage length in manufacturing.

3.2.3. Control variables

The control variables include Industry Scale (Sales), Capital Accumulation (Netasset), R&D expenditure (Rde), and Foreign direct investment (Fdi).

3.3. Data sources and description

This study draws on data from the UIBE-GVC database, the International Federation of Robotics (IFR), and various statistical yearbooks. Industry classifications and time dimensions across these datasets are harmonized to construct a consistent panel. The final sample consists of data from 14 manufacturing sub-sectors in China over the period 2007–2018. The definitions, measurements, and types of the variables are summarized in Table 1.

Table 1. Variable definitions, measurement methods, and types

Variable Symbol	Variable Definition	Measurement Method	Variable Type
Ply	Global value chain length	Backward average total production length	Dependent variable
Robot	Industrial robot application	Log of new industrial robot installations	Core explanatory variable
Sales	Industry scale	Log of industry sales output	Control variable
Netasset	Capital stock	Log of net fixed assets	
Fdi	Foreign direct investment	Log of FDI inflows	
Rde	R&D expenditure	Log of internal R&D expenditure	

Table 1. Continued

Eri	Technological innovation	Log of effective invention patents	Mediating variable
Rdp	Human capital	Log of full-time equivalent R&D personnel	

4. Empirical analysis

4.1. Descriptive statistics

Prior to conducting regression analysis, it is necessary to clarify the basic characteristics and distribution patterns of the sample data. To this end, descriptive statistics are reported for all variables in order to capture their key features. Table 2 presents the descriptive statistical results.

Table 2. Descriptive statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Ply	168	6.512	0.394	5.481	7.340
Robot	168	5.541	2.720	0	10.78
Sales	168	10.59	0.897	8.525	12.07
Netasset	168	9.009	0.990	6.460	10.72
Fdi	168	8.906	0.954	7.208	10.75
Rde	168	14.57	1.519	9.642	17.04

As shown in Table 2, the sample consists of 168 observations. The Global value chain length (Ply) ranges from 5.481 to 7.340, with a mean of 6.512 and a standard deviation of 0.394, indicating that the variation in value chain length across manufacturing sub-sectors is relatively modest overall. In contrast, the number of newly installed industrial robots exhibits greater dispersion, with a minimum value of 0, a maximum value of 10.78, a mean of 5.541, and a standard deviation of 2.720. This suggests that there are substantial differences in the degree of industrial robot adoption across manufacturing industries in China during the period 2007–2018.

4.2. Baseline regression analysis

Following the preceding analysis, this study employs a fixed effects model for estimation and adopts a stepwise regression approach for empirical testing. Columns (1)–(5) of Table 3 report the baseline regression results. Column (1) presents the results without control variables, while Columns (2)–(5) sequentially Incorporate capital stock (Netasset), Foreign direct investment (Fdi), R&D expenditure (Rde), and Industry Scale (Sales).

Table 3. Baseline regression results

	(1)	(2)	(3)	(4)	(5)
Variables	Ply	Ply	Ply	Ply	Ply
Robot	0.051***	0.054***	0.053***	0.045***	0.045***
	(6.27)	(5.04)	(5.06)	(3.56)	(3.97)

Table 3. Continued

Netasset		-0.012	0.003	-0.192***	-0.351***
		(-0.47)	(0.08)	(-3.83)	(-4.15)
Fdi			-0.018	-0.446***	-0.470***
			(-0.58)	(-5.04)	(-5.63)
Rde				0.426***	0.383***
				(5.33)	(4.62)
Sales					0.285*
					(1.95)
Constant	6.455***	6.550***	6.577***	6.196***	5.497***
	(53.96)	(29.32)	(28.56)	(22.71)	(12.62)
Observations	168	168	168	168	168
R-squared	0.265	0.265	0.266	0.406	0.429

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The stepwise regression results indicate that as the goodness of fit improves with the inclusion of additional control variables, the estimated coefficient of industrial robot application remains consistently positive and statistically significant, suggesting a robust promoting effect. Specifically, in Column (1), where no control variables are included, the coefficient of Robot is positive and significant at the 1% level, indicating that an increase in industrial robot adoption contributes to the extension of manufacturing global value chain length. From Columns (2) to (5), as control variables are progressively introduced, the coefficient of Robot remains positive and statistically significant, confirming a stable positive relationship between industrial robot application and backward linkage length. In the full model reported in Column (5), the coefficient of Robot is 0.045 and remains significant at the 1% level. This implies that a 1% increase in the level of industrial robot application leads to a 0.045% extension in the length of the manufacturing global value chain. Overall, the results demonstrate that industrial robot adoption exerts a significant positive effect on the backward linkage length of manufacturing global value chains.

4.3. Robustness tests

4.3.1. Replacing the core explanatory variable

Robustness testing is conducted to assess the stability of the model's explanatory power. In this study, robustness is examined by replacing the core explanatory variable and by applying lagged specifications.

Table 4. Replacement of core explanatory variable

	(1)	(2)
Variables	Ply	Ply
Stock	0.055***	0.052***
	(7.59)	(4.77)
Netasset		-0.375***

Table 4. Continued

		(-4.53)
Fdi		-0.445***
		(-5.42)
Rde		0.376***
		(4.63)
Sales		0.285*
		(1.97)
Constant	6.430***	5.549***
	(53.50)	(12.74)
Observations	168	168
R-squared	0.284	0.445

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Specifically, the baseline regression is re-estimated by replacing the original measure of industrial robot application—i.e., the logarithm of newly installed industrial robots—with the logarithm of industrial Robot Stock (Stock), while keeping all control variables and model specifications consistent with Equation (1). The results are reported in Table 4. The regression results show that the estimated coefficient of the substituted variable (Stock) is consistent in sign with the baseline results and remains statistically significant at the 1% level. This indicates that whether industrial robot application is measured from a short-term incremental perspective (new installations) or a long-term stock perspective, its effect on enhancing the position of China's manufacturing sector in global value chains remains significantly positive. This provides strong evidence for the robustness of the main findings.

4.3.2. One-period lag regression

Considering the potential bidirectional causality between industrial robot application and the position of manufacturing industries in global value chains, endogeneity concerns may arise. On the one hand, the adoption of industrial robots can enhance production efficiency and product quality, thereby promoting upgrading within global value chains. On the other hand, firms positioned at higher segments of global value chains typically possess stronger capital capacity and technological demand, making them more inclined to adopt industrial robots to consolidate their competitive advantage. To mitigate this endogeneity bias, this study employs the one-period lag of industrial robot variables (both new installations and stock) as the core explanatory variables for re-estimation.

The results are presented in Table 5. The results indicate that, after introducing one-period lagged variables, both the lagged industrial robot installations and stock remain positively and significantly associated with the length of manufacturing global value chains at the 1% significance level. This suggests that industrial robot adoption continues to promote the extension of value chain length and deeper participation in global production networks, thereby further confirming the robustness of the study's conclusions.

Table 5. One-period lag regression results

	(1)	(2)	(3)	(4)
Variables	Ply	Ply	Ply	Ply
Robot	-0.090**	0.031**		
	(-2.27)	(2.42)		
Stock			-0.147***	0.036***
			(-2.79)	(2.96)
Sales	-1.718	0.919***	-0.973	0.885***
	(-1.63)	(8.07)	(-0.85)	(7.71)
Netasset	1.171	-0.608***	0.905	-0.606***
	(1.42)	(-7.07)	(1.14)	(-7.12)
Fdi	0.332	-0.255***	0.016	-0.254***
	(1.02)	(-2.97)	(0.04)	(-2.98)
Rde	0.069	0.013	0.040	0.030
	(0.35)	(0.17)	(0.24)	(0.41)
Constant	9.994***	4.682***	7.999**	4.716***
	(3.23)	(13.05)	(2.41)	(13.33)
Observations	48	120	48	120
R-squared	0.715	0.657	0.754	0.664

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.4. Heterogeneity analysis

Considering that manufacturing industries with different factor intensities exhibit substantial differences in production modes, technological requirements, and capital inputs, the impact of industrial robot adoption on their positions within global value chains may be heterogeneous. To account for this, and following the classification approach of Liangxiong Huang [11], this study divides the 14 manufacturing sub-sectors into two categories: labor-intensive and capital-intensive industries. Subsample regressions are then conducted to examine the heterogeneous effects of industrial robot application.

Table 6. Industry heterogeneity test

	(1)	(2)	(3)	(4)
Variables	Labor-intensive Ply	Capital-intensive Ply	Labor-intensive Ply	Capital-intensive Ply
Robot	-0.090**	0.031**		
	(-2.27)	(2.42)		
Stock			-0.147***	0.036***
			(-2.79)	(2.96)
Sales	-1.718	0.919***	-0.973	0.885***
	(-1.63)	(8.07)	(-0.85)	(7.71)
Netasset	1.171	-0.608***	0.905	-0.606***

Table 6. Continued

	(1.42)	(-7.07)	(1.14)	(-7.12)
Fdi	0.332	-0.255***	0.016	-0.254***
	(1.02)	(-2.97)	(0.04)	(-2.98)
Rde	0.069	0.013	0.040	0.030
	(0.35)	(0.17)	(0.24)	(0.41)
Constant	9.994***	4.682***	7.999**	4.716***
	(3.23)	(13.05)	(2.41)	(13.33)
Observations	48	120	48	120
R-squared	0.715	0.657	0.754	0.664

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The grouped regression results in Table 6 reveal significant heterogeneity in the effects of industrial robot application across industries with different factor intensities. Specifically, industrial robot adoption has a significantly positive effect on the global value chain length of capital-intensive industries, passing the 1% significance test. In contrast, for labor-intensive industries, robot application is associated with a reduction in value chain length. From a mechanistic perspective, capital-intensive industries typically possess stronger R&D capabilities and higher levels of resource endowment, which provide solid support for technological advancement. The adoption of industrial robots in such industries enhances product design, optimizes production processes, and facilitates the development of new materials, thereby generating positive effects on value chain extension. Conversely, in labor-intensive industries, where production relies more heavily on low-cost labor, robot substitution may compress certain production linkages, leading to a shortening of backward value chain length.

4.5. Mechanism analysis

To further clarify the transmission mechanisms through which industrial robot application affects the length of global value chains in China's manufacturing sector, this study conducts mediation effect tests based on the theoretical analysis presented earlier. As discussed, industrial robots may influence value chain length through two primary channels: technological innovation and human capital upgrading. To test these mechanisms, the following mediation models are constructed (Equations (2)-(5)):

$$Eri_{it} = \beta_0 + \beta_1 Robot_{it} + \delta X_{it} + + \varepsilon_{it} \tag{2}$$

$$Ply_{it} = \beta_0 + \beta_1 Robot_{it} + \beta_2 Eri_{it} + \delta X_{it} + + \varepsilon_{it} \tag{3}$$

$$Rdp_{it} = \beta_0 + \beta_1 Robot_{it} + \delta X_{it} + + \varepsilon_{it} \tag{4}$$

$$Ply_{it} = \beta_0 + \beta_1 Robot_{it} + \beta_2 Rdp_{it} + \delta X_{it} + + \varepsilon_{it} \tag{5}$$

Table 7. Mechanism test results

	(1)	(2)	(3)	(4)
Variables	Eri	Ply	Rdp	Ply
Robot	0.087***	0.033***	0.019**	0.050***
	(4.69)	(2.67)	(2.27)	(4.38)
Eri		0.146***		0.230**
		(3.68)		(2.17)
Netasset	-0.511***	-0.276***	0.273***	0.222
	(-3.05)	(-3.39)	(3.33)	(1.54)
Fdi	0.512**	-0.545***	-0.301***	-0.281***
	(2.45)	(-6.50)	(-4.83)	(-3.26)
Rde	0.687***	0.283***	0.367***	-0.555***
	(3.53)	(3.99)	(4.43)	(-5.62)
Sales	0.321	0.238*	0.696***	0.222**
	(1.47)	(1.76)	(9.22)	(2.39)
Constant	-6.552***	6.452***	-1.841***	5.921***
	(-8.57)	(12.32)	(-5.56)	(12.50)
Observations	168	168	168	168
R-squared	0.913	0.470	0.967	0.449

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The regression results in Table 7 provide empirical evidence for the mediating roles of technological innovation (Eri) and human capital (Rdp). First, for the technological innovation channel, the results in Columns (1) and (2) indicate that industrial robot application significantly promotes technological innovation through spillover effects, which in turn contributes to the extension of backward value chain length. This provides empirical support for Hypothesis H1.

Second, for the human capital channel, the results in Columns (3) and (4) show that industrial robot adoption significantly enhances human capital levels, which subsequently facilitates the extension of backward linkage length. This finding confirms Hypothesis H2.

5. Conclusion and policy implication

This study reviews the relevant literature and conducts an empirical analysis of the impact of industrial robot application on the length of global value chains in manufacturing, using industrial robot data from the International Federation of Robotics (IFR) and the UIBE-GVC database over the period 2007–2018. The results, supported by robustness and heterogeneity tests, indicate that industrial robot adoption significantly extends the length of manufacturing global value chains and facilitates China's deeper participation in the global division of labor. Moreover, this promoting effect is more pronounced in capital-intensive industries. Further mechanism analysis reveals that technological innovation and human capital accumulation constitute the two primary channels through which industrial robots contribute to value chain extension. Based on these findings, several policy implications are proposed. First, efforts should be sustained to advance the "Made in China 2025" strategy, with a focus on promoting the deep integration of industrial robots into the manufacturing sector. Second, greater emphasis should be placed on cultivating skilled talent capable of supporting intelligent manufacturing, while drawing on international experience to refine development strategies. Third, policy support should be strengthened for fundamental and industrial research related to robotics and automation technologies. Finally, the integration of industrial robots with high-tech manufacturing industries should be accelerated to optimize industrial structure and enhance the overall competitiveness of China's manufacturing sector within global value chains.

References

[1] Sun, W., & Gan, Q. (2024). Digital technology and value chain length: Extension or shortening? *Commercial Research,* (1), 1–11.

[2] Huang, X., Peng, J., & Zhao, Y. (2022). Trade liberalization, global value chains, and resource allocation efficiency. *Journal of Southeast University (Philosophy and Social Sciences), 24*(2), 48–60, 147.

[3] Zhao, X., & He, Z. (2022). Digital service trade barriers and value chain length. *Journal of Zhongnan University of Economics and Law*, (3), 139–150.

[4] He, X., & Liu, K. (2023). Robots, task content, and employment polarization: Evidence from Chinese industrial enterprises. *The Journal of Quantitative & Technical Economics, 40*(4), 52–71.

[5] Hou, D., Xiong, J., & Du, S. (2024). Intelligent manufacturing and firm resilience: Evidence from industrial robots. *Journal of Zhongnan University of Economics and Law*, (4), 120–134.

[6] Li, J., & Wu, Z. (2024). Tax dividends of robot adoption: A perspective of new-quality productive forces. *Management World, 40*(6), 1–15, 30, 16–19.

[7] He, Q., Gao, X., & Huang, J. (2024). Industrial robot application and the enhancement of industrial and supply chain resilience in manufacturing: Evidence from global value chain embedding of Chinese firms. *Journal of International Trade*, (2), 71–89.

[8] Lü, Y., & Li, M. (2020). Trade facilitation and global value chain embedding. *Journal of Beijing Technology and Business University (Social Sciences), 35*(5), 46–57.

[9] Liu, B., & Pan, T. (2020). The impact of artificial intelligence on the division of labor in manufacturing value chains. *The Journal of Quantitative & Technical Economics, 37*(10), 24–44.

[10] Peng, G., Lin, X., & Zhai, M. (2021). Intelligent manufacturing and position in global value chains: Mechanism analysis and empirical test. *Journal of Statistics, 2*(1), 26–35.

[11] Huang, L., Lin, Z., & Wang, X. (2023). Industrial robot application and global value chain restructuring: From the perspective of export product bargaining power. *China Industrial Economics,* (2), 74–92.