The Impact of Industrial Robot Applications on Global Value Chains Division Position

Kaiqing Wang *

Business School, The Hong Kong University of Science and Technology, Hong Kong, China

* Corresponding Author Email: kaiqing_wang1901@163.com

Abstract. This paper surveys the GVC division position across forty-five countries and fourteen manufacturing sub-sectors during the period from 1999 to 2018 to illustrate the impact of applications of industrial robots on the GVC position. The study proves that an increasing level of utilization of industrial robots significantly improves the GVC division position in the manufacturing sector. By automating repetitive and precision tasks, robots enhance efficiency and productivity, therefore allowing deeper specialization in specific stages of the manufacturing process. This technological progress allows for a more connected global production network and hence better integration into GVC. The study also evaluates the spillover effects across value chains and the moderating impact of industrial agglomeration on smart manufacturing.The empirical results show that the application of industrial robots enhances productivity and encourages innovation in related sectors, thereby driving downstream industry growth and promoting industry specialization.Despite the improvement in GVC division positions, robots also contribute to making global value chains more diversified and resilient. Flexible and adaptive manufacturing systems can adapt to disruptions, such as pandemics and geopolitical tensions, ensuring continuity in production and increasing stability and competitiveness in smart manufacturing systems.

Keywords: Global Value Chains; GVC division position; Industrial robots; GVC resilience.

1. Introduction

The contemporary economic environment has been significantly facilitated by globalization and technological advancements, particularly in trade within global value chains (GVCs) focused on intermediary goods rather than final goods. This shift encourages countries to leverage their comparative advantages at specific stages of the manufacturing process, thereby promoting global industrial linkages through sequential manufacturing processes. According to the "2019 Global Value Chain Report," over two-thirds of international trade is now linked to activities within global value chains (GVCs), underscoring their pivotal role in shaping the global production network. Driven by advancements in automation technology, robots have been playing a crucial role in several national strategies, including the United States’ "Industrial Internet," Germany’s "Industry 4.0," and China’s "Made in China 2025" initiative. The application of industrial robots fosters economic growth in multiple dimensions and serves as a key driver in transitioning the global value chains from conventional to intelligent manufacturing paradigms. Against the background of evolving global value chains and the extensive deployment of industrial robots, this paper examines how robotic integration will fundamentally alter GVC positioning for the manufacturing industries of various countries.

This research intersects with two prominent strands in existing literature. Firstly, it aligns with three mainstream methods for measuring GVC division position. In 2010, Koopman et al. proposed a methodology for calculating the division position within GVCs at the country-industry level [1]. By examining the international supply and demand for intermediate merchandise in production, this approach elucidates a country’s position in the industry within the global production network. This method was further developed by Wang et al., who analyzed the disparity between GVC forward and backward participation degrees [2]. Building on the aforementioned foundations, Antras et al. Identified the components of upstreamness and downstreamness in an industry’s position within GVCs [3]. These indices, derived primarily from the Leontief input-output table, quantify the 'physical position' of an industry within GVCs. In addition to the value chain decomposition methods discussed, Wang et al. posited that the distance of an industry's value chain production is also a crucial indicator of its position within GVCs [4].

Apart from the calculation methods of GVC division positions, this study is also pertinent to the existing literature on the economic impacts of industrial robot applications. The economic impacts of implementing smart manufacturing, particularly through industrial robots, has garnered significant attention in recent studies by scholars [5]. As a capital-enhancing technology, robots not only provide immediate production efficiency but also contribute to sustained capital accumulation and technological advancement. This advancement, in turn, increases productivity in conventional tasks, leading to long-term productivity growth [6]. Moreover, the role of robots extends beyond productivity enhancement to influence the broader economic landscape, including changes in the factor endowment structure and the labor market. Acemoglu and Restrepo refine the Zeira's task model to examine the dual effects of artificial intelligence on labor. The substitution effect involves replacing human labor with machines, which tends to reduce labor demand, wages, and overall employment levels. Conversely, the productivity effect suggests that the application of robots will boost demand for skilled workers [7].

While significant academic effort has focused on the economic and labor market impacts of industrial robotics, less scrutiny has been directed towards their effects on GVC division position. Consequently, this paper aims to bridge this void by scrutinizing the impact of robotics on the GVC positioning of manufacturing sectors across diverse nations. Furthermore, this study investigates the implications of robotics on vertical integration and industry-wide spillovers. It also elucidates how robotic applications can prompt both diversification and specialization within a nation's industrial framework. Given the economic vulnerabilities highlighted by the COVID-19 pandemic, this research also examines how intelligent manufacturing technologies bolster GVC resilience.

2. Model and Data

This study utilizes three-dimensional data structured around "country-industry-year." The data on global value chains (GVCs) division status are sourced from OECD-Tiva and UIBE GVC database, while the stock of industrial robots originates from the IFR database. Other data related to country-specific features primarily come from the WDI database, whereas data associated with specific industry segments are mainly sourced from the UNIDO database (INSTAT, ISIC Revision 3.0). Given the differing scopes of these databases, we first conducts industry matching. Using the ISIC Revision 3.0 employed by the UIBE GVC database as a reference, the industries in the other two databases are filtered, merged, and then matched to identify common countries and years. Samples with significant data gaps are removed. Ultimately, the dataset comprises data from 45 countries across 14 manufacturing sub-sectors spanning from 1999 to 2018.

For measuring the GVC position, this paper first employs the intermediate value-added decomposition method proposed by Koopman et al. in the baseline regression [1]. This involves assessing a country's specialization in the global value chains by calculating the international differences in the supply and demand for intermediate products in the country's production process. In Equation (1), $\mathrm{GVCpos_{ijt}}$ denotes the GVC positioning of country i in sector j at time t. $\mathrm{IV_{ijt}}$ represents the indirect value-added exports, namely the trade value of intermediate goods exported to other nations. This metric assesses how much value-added is encompassed within the intermediate goods exported, which are processed domestically before being re-exported to a third country. $\mathrm{FV_{ijt}}$ Signifies the foreign value added included in the exports of final products, while $\mathrm{E_{ijt}}$ indicates the total trade value of exports. The specific data for computation is sourced from the OECD-Tiva database, which is widely utilized in research endeavors.

$$\mathrm{GVCpos_{ijt}}=\ln\left(\frac{IV_{ijt}}{E_{ijt}}+1\right)-\ln\left(\frac{FV_{ijt}}{E_{ijt}}+1\right) \tag{1}$$

$$\mathrm{GVCP_{ijt}}=\ln\left(GVCforward_{ijt}+1\right)-\ln\left(GVCbackward_{ijt}+1\right) \tag{2}$$

$$\mathrm{GVCL_{ijt}}=PLv_{ijt}/PLy_{ijt} \tag{3}$$

To more accurately assess the embeddedness of each country's manufacturing sector within Global Value Chains (GVCs), this article employs the two aforementioned indices to replace the dependent variable $\mathrm{GVCpos_{ijt}}$ in the benchmark regression. $\mathrm{GVCP_{ijt}}$ Proposed by Wang et al. is developed based on Koopman’s methodology [1, 2]. Wang et al. enhance the analysis of GVC positioning through a more intuitive measurement which provides a clearer understanding of the 'upstreamness' level of a specific industry within a country’s GVCs. Building on the Production Length concept, this research also utilizes the methodology developed by Zheng and Liu to build the third dependent variable $\mathrm{GVCL_{ijt}}$[8]. Specifically, this indicator is the ratio of the forward and backward-linkage GVC Production Length indexes. The calculation methods are outlined in Equation (2) - (3). From the construction process of these three aforementioned dependent indicators, it can be inferred that the higher the values of these variables, the higher the manufacturing industry of specific country is positioned within the global value chains.

In terms of core explanatory variable selection, we gauge the extent of industrial robot application in various countries' manufacturing sectors using industrial robot density. This index is derived by dividing the matched annual stock of industrial robots in each country's segmented industry by the employment figures in that industry within the respective country. The specific computation formula is as follows, where the subscripts carry the same meanings as described earlier:

$$robdens_{ijt}=robotstock_{ijt}/employee_{ijt} \tag{4}$$

Based on the core sample data above ,this paper establish the following benchmark regression model in order to further explore the impact of industrial robots on the GVC division status in the manufacturing sector. Beyond the variables and subscripts mentioned before, X_{it}denotes the control variables used in the baseline regression. θ_i γ_jAnd $\varphi_t$separately represent country, industry, and time fixed effects, while ε_{ijt} signifies the error term. This article mainly focus on the estimating coefficients β_1. If the regression results indicate that the coefficient of the explanatory variable is positive, it implies that automation application facilitates the upgrading of a country's division position in the GVC of manufacturing.

$$GVCpos_{ijt}=\beta_0+\beta_1 robdens_{ijt}+\vartheta \mathrm{X_{it}}+\theta_i+\gamma_j+\varphi_t+\varepsilon_{ijt} \tag{5}$$

Table 1. Descriptive Statistics.

variable	N	mean	sd	min	p50	max
robdens	12600	0.0321	0.2521	0	0.0006	12.3955
GVCpos	12574	0.6309	0.1062	0	0.6263	1
GVCP	12594	-0.0099	0.1816	-0.6127	-0.0293	3.133
GVCL	12594	1.0326	0.2978	0.4257	0.9806	2.4522
ln*pgdp*	12600	9.6479	1.175	5.8942	9.9331	11.5416
gov	12600	17.6823	4.518	5.4652	18.4768	27.935
ind	12600	27.4023	6.4668	0	26.6369	48.5485
open	12600	90.1326	59.8835	18.349	71.4205	437.3267
ln*rd*	12586	7.5597	1.1328	1.1959	7.946	9.1376
hci	12600	3.0259	0.4857	1.6012	3.1044	4.1545

In the selection of control variables, given the absence of segmented industry data, this paper has opted for certain segmented nation variables strongly correlated with the dependent variable to enhance the precision of the regression results. Sourced from the World Development Indicators (WDI) database, these variables specifically include the logarithm of GDP per capita in current US dollars (lnpgdp), the ratio of government fiscal expenditure to gross domestic product (gov), the proportion of industrial output to gross national product (ind), trade openness (open), the logarithm of research and development expenditure (lnrd), and the human capital index (hci). Due to the presence of minor data gaps, we adopt a common practice in academia, utilizing interpolation to fill in missing data. This method effectively complements minor gaps in data across consecutive years without disrupting the overall trend of variables in each country, hence representing a reasonable approach. The statistical description of the aforementioned primary variables is outlined as shown in Table 1.

3. Benchmark Analysis

In accordance with the design of the econometric model outlined above, we investigate the direct impact of industrial robot usage on the positioning within Global Value Chains (GVCs) through the baseline regression. By incorporating high-dimensional fixed effects, the empirical analysis controls for unobserved heterogeneity across regions, industries and over time, while the use of heteroscedasticity-robust standard errors addresses potential issues of non-constant variance in the error terms. This comprehensive approach can rigorously examine the relationship between industrial robot usage and GVC positioning. As depicted in Table 2, the coefficients of the core explanatory variables in the baseline regression maintain statistical significance at the 10% confidence level after sequentially introducing three dependent variables. This consistent finding suggests that higher industrial robot penetration in countries is associated with an upward shift in its division position within Global Value Chains (GVCs).Through Pearson correlation coefficient tests, the results have determined that there is no significant multi-collinearity among the variables.

Table 2. Benchmark Regression.

VARIABLES	(1) *GVCpos*	(2) *GVCP*	(3) *GVCL*
robdens	0.0061***	0.0050*	0.0525***
	(3.74)	(1.76)	(6.01)
ln*pgdp*	-0.0114***	-0.0229***	-0.0066
	(-3.07)	(-3.37)	(-0.53)
gov	0.0020***	-0.0045***	0.0002
	(2.62)	(-3.63)	(0.09)
ind	-0.0021***	0.0015*	0.0002
	(-4.30)	(1.94)	(0.13)
open	0.0004***	0.0002	-0.0001
	(7.24)	(1.60)	(-0.47)
ln*rd*	0.0049*	0.0070	-0.0029
	(1.88)	(1.38)	(-0.32)
hci	0.0042	-0.0206**	-0.0333**
	(0.94)	(-2.34)	(-2.03)
Constant	0.6727***	0.2454***	1.2173***
	(14.70)	(3.23)	(7.49)
Observations	12,560	12,580	12,580
R-squared	0.5187	0.4452	0.2182

Note: Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1.

While each approach has its advantages in providing an in-depth understanding and quantification of a country's or sector's position within global value chains (GVCs), Koopman's approaches are generally considered superior. These methods are highly valued for their comprehensiveness, intuitiveness, and practical applicability in analyzing GVC positions. On the other hand, the empirical results above show that the regression coefficients of control variables related to GVCpos, align closely with expected outcomes. This consistency further underscores the robustness and reliability of Koopman's approach in empirical research. Therefore, for the upcoming study, this paper has selected GVCpos as the dependent variable for regression analysis.

4. Extended Analysis

To deepen the understanding of the complex effects of robotics on global production networks, this study expands the in-depth analysis to explore the vertical spillovers and resilience enhancements in global value chains (GVCs) induced by automation. Furthermore, this paper investigates the moderating role of industrial agglomeration on these dynamics within the benchmark regression framework. This approach allows the research to capture not only the direct impacts of automation but also its broader implications across interconnected industrial sectors

4.1. Vertical Spillover Effects

In the transformation of the manufacturing sector, there is a growing integration of production, sales, and service activities within the industrial value chain. This interconnectedness implies that the adoption of smart technologies in one segment can trigger 'ripple effects' throughout related industries. To analyze these dynamics, this paper utilize the forward and backward linkage indices from the UIBE GVC database to assess the vertical spillover effects of automation within the manufacturing sector [9]. The GVC forward linkage refers to the value-added export of a specific industry through all sectors of a country, either directly or indirectly, signifying the downstream transmission effect. Conversely, the GVC backward linkage of an industry denotes the added value from all domestic industries encompassed in the total export of a particular sector, representing the upstream transmission effect. The specific construction methods of upstreamand downstreamare given in Equation(6)-(7).The coefficient β_{up} in the regression equation (8) reflects the backward linkage effects of industrial robot density on the manufacturing industry, termed as upstream spillover effects. The coefficient β_{down}reflects the forward linkage effects of automation, termed as the downstream spillover effects.

$$\mathrm{upstream_{ijt}}=\mathrm{backwards_{ijt}} \times \mathrm{robdens_{ijt}} \tag{6}$$

$$\mathrm{downstream_{ijt}}=\mathrm{forwards_{ijt}} \times \mathrm{robdens_{ijt}} \tag{7}$$

$$\mathrm{GVCpos_{ijt}}=\beta_0 + \beta_1 \mathrm{robdens_{ijt}}+\beta_{up}\mathrm{upstream_{ijt}}+\vartheta X_{it}+\theta_i+\gamma_j+\varphi_t+\varepsilon_{ijt} \tag{8}$$

$$\mathrm{GVCpos_{ijt}}=\beta_0 + \beta_1 \mathrm{robdens_{ijt}}+\beta_{down}\mathrm{downstream_{ijt}}+\vartheta X_{it}+\theta_i+\gamma_j+\varphi_t+\varepsilon_{ijt} \tag{9}$$

The estimated results in Table 3 indicate that the coefficients of upstream and downstream transmission are statistically insignificant and positively significant, respectively. This suggests that the installation of robots in a country's manufacturing industry does not have a significant impact on the GVC position of its upstream industries. However, there is a significant positive effect on the GVC position in the downstream industries. To further interpret the generation of forward spillover effects, it is posited that downstream industries are more likely to benefit from the production and consumption stages facilitated by robotic applications. Firstly, the deployment of industrial robots significantly impacts the production processes in downstream industries by enhancing productivity, reducing costs, and improving product quality. This allows these industries to quickly realize economic benefits and gain competitive advantages. Additionally, downstream industries are typically closer to markets and consumers, making them more responsive to market demands. The adaptability afforded by industrial robots enables customized production, which meets rapidly changing market demands and thus enhances the positioning of downstream industries in the Global Value Chains (GVCs).

Table 3. Vertical Spillover Effects.

VARIABLES	(1) *GVCpos*	(2) *GVCpos*	(3) *GVCpos*	(4) *GVCpos*
upstream	0.0097	-0.0147		
	(0.23)	(-0.35)		
downstream			0.1051***	0.0842**
			(3.02)	(2.47)
robdens	0.0058	0.0086	-0.0195**	-0.0146*
	(1.00)	(1.46)	(-2.31)	(-1.76)
Constant	0.0233***	0.0774	0.0233***	0.0759
	(29.68)	(1.56)	(30.84)	(1.54)
Control Variables	No	Yes	No	Yes
Observations	12,594	12,580	12,594	12,580
R-squared	0.4302	0.4341	0.4304	0.4342

4.2. The moderating effects of industrial agglomeration

Industrial agglomeration can generally be categorized into two types: specialization and diversification. Specialization involves clustering similar enterprises within a region, which reduces search costs and enhances the efficiency of matching labor within the same industry, known as the 'labor pool effect'. In contrast, diversification involves the aggregation of complementary enterprises, which contributes to the structural stability of the factor market and mitigates the adverse effects of uncertainty risk. Regarding knowledge dissemination, industrial agglomeration fosters a 'knowledge spillover effect'. Specialization facilitates mutual learning among enterprises within the same industry, enhancing industry-specific expertise. Diversification, on the other hand, promotes cross-industry integration and innovation. To investigate the moderating effects of industrial agglomeration on the enhancement effects of robot application on the GVC division position, this paper incorporate interaction terms into the benchmark model. The level of specialization is measure using 'location entropy', while the level of diversification is represented by the reciprocal of the Herfindahl index. The computational methods for these indices are detailed below:

$$special_{ijt}=\frac{Y_{ijt}/Y_{it}}{Y_{jt}/Y_t} \tag{10}$$

$$diverse_{ijt}=\frac{1-\sum_{j\prime\neq j}\frac{Y_{ij\prime t}}{Y_{it}-Y_{ijt}}}{1-\sum_{j\prime\neq j}\frac{Y_{j\prime t}}{Y_t-Y_{jt}}} \tag{11}$$

In the aforementioned formulas, Y represents the output of manufacturing industry, with subscripts denoting the same as above. $special_{ijt}$ Denotes the specialization agglomeration level of industry j in country i during t period, while$diverse_{ijt}$signifies the corresponding level of diversification. The regression results, as shown in Table 4, reveal distinct impacts of different types of industrial agglomeration on GVC positioning through the application of robots. Specifically, the interaction term for the level of specialization shows a significantly positive coefficient. On the other hand, the coefficients for the diversification level indicate no significant adjustment effect beyond the baseline regression. The possible reason for these results may be that the application of robotics has a greater pull on specialized industries due to its ability to meet high customization and precision requirements. Specialized industries, such as high-end electronic equipment manufacturing and precision instrument production, often require strict production standards and complex processes. The high-precision operation and precise control capabilities of robots significantly improve production efficiency and product quality, thus enhancing the competitiveness of enterprises. Additionally, although the investment cost of robotics is high, the long-term benefits and technological leadership can often balance these investments in specialized industries. Therefore, these fields are more willing to accept and apply advanced technologies like robotics. In contrast, diversified industries may face a wide range of products and more frequent changes in market demand, making them relatively less dependent on high degrees of customization and precision. As a result, there is less demand for robotics applications in these industries.

Table 4. Industrial Agglomeration Effects.

VARIABLES	(1) *GVCpos*	(2) *GVCpos*	(3) *GVCpos*	(4) *GVCpos*
special×robdens	0.0128***	0.0114**		
	(2.60)	(2.17)		
special	0.0054***	0.0057***		
	(3.29)	(3.35)		
diverse×robdens			0.0025	0.0047
			(0.27)	(0.45)
diverse			-0.0002	-0.0001
			(-1.30)	(-0.76)
robdens	-0.0030	-0.0048**	-0.0014	-0.0041
	(-1.54)	(-2.47)	(-0.43)	(-1.06)
Constant	0.0174***	0.0808***	0.0233***	0.0870***
	(10.11)	(2.85)	(54.32)	(3.06)
Control Variable	No	Yes	No	Yes
Observations	12,517	12,503	12,517	12,503
R-squared	0.8349	0.8387	0.8346	0.8384

4.3. Resilience changes in GVC

The resilience of the global value chain refers to the ability of various participants in the global value chain to adapt and resist external impacts and changes. In the context of globalization, the formation and development of the global value chain have made countries and enterprises interdependent, while also bringing more risks and challenges. Enhancing the resilience of the global value chain means that enterprises participating in global production can react and adjust more flexibly and quickly in the face of various uncertainties and risks, maintaining the stability and sustainability of the supply chain. The application of industrial robots, in terms of improving production efficiency, reducing risks, promoting innovation, and diversifying geographical layouts, provides strong support for enhancing the resilience of the global value chain. Enterprises leveraging automation technology to participate in global production network have accelerated the transformation of the global value chain organizational structure from a "snake shape" to a "spider shape." This shift in organizational form reduces the excessive dependency of enterprises on the intermediate goods they need, ensuring that the global value chain can continue to operate normally even when disrupted by external impacts [10].

Due to the multidimensional nature of the resilience of the global value chain, this paper first characterizes the resilience of the global value chain from the aspects of stability and security. Drawing upon the specific measurement approach proposed by Yang et al, this research calculate the volatility of the forward length of GVC to assess its stability. Where the average forward value chain length of all industries ($\overline{PLv_t}$) is defined as the systemic risk, pl_{ijt}represents the GVC forward length of industry j in country i in year t, excluding systemic risk. T is the observation window period. This study adopt a moving window period and sets the window period to 3 years. Vol_pl_{ijt}Measures the corresponding GVC stability, with a higher value indicating greater fluctuation in the GVC.

$$pl_{ijt}=PLv_{ijt}-\overline{PLv_t} \tag{12}$$

$$Vol\_pl_{ijt} = \left[\frac{1}{T-1}\sum_{t=1}^{T}\left(pl_{ijT}-\frac{1}{T}\sum_{t=1}^{T}pl_{ijT}\right)^2\right]^{1/2} \tag{13}$$

The security of GVC focuses on equal opportunities for industries to participate in GVC division position and the diversification of such division. First, industries can embed themselves into the global value chain without marginalization by leveraging comparative advantages. Second, industries can achieve diversification in value chain division through the embedding of comparative advantages. Therefore, the disparity in the forward length of the global value chain is employed to measure GVC security, with the calculation formula as Equation (14).Where gap_pl_{ijt}represents the GVC length disparity, while $\max(\mathrm{PLv_{jt}})$represents the highest value attained by the GVC forward length for industry j in year t. A smaller gap between the global value chain lengths of industries indicates greater integration into various segments of GVC and, consequently, improved security of the global value chain.

$$gap\_pl_{ijt}=\max(\mathrm{PLv_{jt}})-\mathrm{PLv_{ijt}} \tag{14}$$

The impact of smart manufacturing on the resilience of the Global Value Chains (GVCs) is presented in Table 5. The results show that the application of industrial robots can enhance the stability of the GVCs and reduce disparities in the lengths of industry GVCs. This means that automation development helps to alleviate spatial constraints in globalized production. Additionally, the application of robotics contributes to technological spillovers within the industrial chain, fostering diversified development within the GVC and enhancing its security.

Table 5. The resilience changes in GVC.

	(1)	(2)	(3)	(4)
VARIABLES	*vol pl*	*vol_pl*	*gap_pl*	*gap_pl*
robdens	-0.0049**	-0.0049**	-0.0785**	-0.0781**
	(-1.97)	(-1.98)	(-2.35)	(-2.36)
Constant	0.0185***	-0.0054	2.7443***	2.4099***
	(57.94)	(-0.27)	(1,193.55)	(16.10)
Control Variables	No	Yes	No	Yes
Observations	11,962	11,948	12,594	12,580
R-squared	0.1315	0.1334	0.9363	0.9364

5. Conclusion

This study investigates how industrial robot applications affect GVC division positioning. The empirical results indicate that higher utilization of industrial robots notably improves GVC division positioning within the manufacturing sector. Further analysis reveals that adopting industrial robots not only enhances GVC division positioning but also generates horizontal and vertical spillover effects across value chains.

Regarding vertical spillover effects, this paper finds that industrial robots exert a positive downstream transmission effect. This indicates that automation technology directly accelerates the development and transformation of downstream industries by boosting production efficiency, lowering costs, and enhancing product quality and flexibility. Conversely, although upstream industries also benefit from advances in robotics, these effects tend to be more indirect and gradual. The study also highlights the moderating influence of industrial agglomeration. Findings indicate that, in comparison to diversification, industry specialization significantly enhances GVC positioning amidst automation. This is possibly due to the fact that industrial robots are often tailored for specific tasks such as welding, assembly, spraying, and inspection. They greatly enhance the precision of these specialized processes, thereby significantly boosting production capacity and quality in these sectors.

These technologies of automation are, therefore, instrumental in diversifying and increasing the resilience of global value chains. That is to say, along with technology that accommodates real-time monitoring and optimization, this is going to bring about a much more flexible and adaptive manufacturing system. Such smart manufacturing systems can be reconfigured at speed in the event of a global pandemic or other such disruptions, ensuring continuity of production and reducing negative impacts. This adaptability, aside from strengthening value chain stability, also underpins continuous improvement and the drive for innovation in ensuring competitiveness in the global marketplace.

In addition to the aforementioned effects, this paper also examines the influence of industrial robots on GVC resilience. Utilizing indices for GVC stability and security, the findings demonstrate that the adoption of automation significantly strengthens GVC resilience. The efficiency and precision of industrial robots in production establish an interconnected automated production system, enhance production transparency across nations, and mitigate disparities in production capacity among countries.

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