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Disruptive Displacement: The Impacts of Industrial Robots on the Energy Industry's International Division of Labor from a Technological Complexity View

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Abstract: In light of the growing economic uncertainties worldwide, the use of industrial robots has emerged as a significant opportunity for improving the production efficiency and the international division of labor in China's energy industry. This study employed a two-way fixed-effect model utilizing data from 31 Chinese provinces between 2011 and 2019 to investigate the impact of industrial robots on the energy industry's participation in the international division of labor. The results of the study indicated that the widespread application of industrial robots can boost the international division of labor status of China's energy sector. This conclusion remains robust even after addressing the potential endogeneity issues and conducting a range of sensitivity tests. Furthermore, our findings suggest that the regions that possess abundant energy resources or exhibit a lower carbon intensity are more likely to leverage the use of industrial robots to increase the technological sophistication and enhance their participation in the international division of labor. The application of industrial robots in the energy industry can enhance the international division of labor through two distinct channels: optimizing the factor structure and reducing the export costs. Our findings have important policy implications for ensuring energy security and improving the energy industry's participation in the international division of labor.

Keywords: industrial robot; international division of labor; export technology complexity

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1. Introduction

Since the 1970s, China has developed a processing model that leverages its advantages in the international division of labor, resulting in a significant expansion of trade. By 2013, China had become the world's largest goods trading nation, with its goods trade exceeding RMB 31 trillion by 2019. International trade has been a critical driver of China's economic development [1]. However, an undeniable fact is that the gap between China's energy supply and demand is expanding, and this poses a significant challenge to its economic development. China's external dependence on crude oil and natural gas reached 72% and 46%, respectively, in 2021. The slow progress in optimizing China's energy consumption and import structure and the increasing concentration of resources are exacerbating China's energy security problem [2]. Moreover, the global economic situation has had a profound impact on the global value chain of the division of labor system. In recent years, the global environment has become increasingly complex, and protectionism is on the rise. Global economic development has reached an important crossroads, and multilateralism faces greater uncertainty. The future of free trade mechanisms and the international division of labor is uncertain. Against this backdrop, China's need for effective energy security is facing greater challenges [3]. To respond to the challenges posed by the changing world economic environment, the 2021 National Work Conference on Development and Reform highlighted the need to strengthen the construction of energy production, supply, storage, and marketing systems to ensure energy security. Among these measures, enhancing high-quality energy trade, breaking the strong position of multinational companies in the international division of labor, promoting Chinese energy companies to deepen their involvement in the value chain [4], and improving their position in the international division of labor system have become urgent issues that need to be addressed.

According to recent research, technological advancements can significantly impact an individual's level of participation in the global value chains' division of labor. A firm's total factor productivity largely influences its position in the global production chain. Increasing the income from technology and improving the total factor productivity can improve China's unfavorable position in related industries in the global value chain. Moreover, enhancing the research and development (R&D) intensity and rationally applying technological achievements can also improve the industry's international division of labor position [5,6]. However, the implementation of protectionist policies in developed countries, where the protection of relevant technologies is prioritized, poses a challenge for upgrading the technology and international division of labor status in developing countries. China's changing national conditions, such as an aging population, rising labor costs, and the uncertainty surrounding foreign demand, also pose significant challenges for product upgrading. The development and progress of artificial intelligence technology in the 21st century have propelled the robust development of modern industrial robots, which have brought together various modern high technologies, significantly contributing to an enterprise's productivity [7]. This presents new opportunities and possibilities for overcoming China's current dilemma and improving the energy sector's international division of labor. This is especially crucial in the context of China's "carbon neutrality" efforts, which demand higher development standards for the energy industry to enhance its quality and efficiency. Therefore, it is of great practical significance to investigate the impact of industrial robots on the international division of labor in the energy industry.

The application of industrial robots has an impact on the structure of the workforce. Although scholarly research on the subject has yet to reach a fully consistent conclusion, it represents a departure from previous technological advances. Some scholars contend that the adoption of industrial robots will increase the demand for skilled workers while reducing the need for unskilled workers and simultaneously leading to an increase in the use of skilled personnel [8]. However, others disagree, arguing that industrial robots differ from other technological advances in that their impact may cover the workforce at different skill levels [5,6,9]. The manner in which the adoption of industrial robots affects the structure of the workforce is primarily influenced by the substitution effect and the productivity effect. The substitution effect refers to the way that industrial robots can occupy positions that would otherwise be held by human workers and perform the necessary tasks. The productivity effect refers to the fact that technological advances can increase productivity while driving the need for related jobs that are still in the technological stagnation stage. This increase in productivity reduces production costs and product prices, resulting in an increase in real income for the population and the related demand for consumer goods and services. Ultimately, this raises the labor demand for tasks that have not been replaced by related technological advances [6,10].

The economic impact of industrial robots is the second factor to consider. Extensive research conducted by national and international scholars demonstrated that industrial robots are a primary tool for enhancing productivity. A panel data study that examined the use of industrial robots concluded that their application led to a decrease in product prices and contributed to an increase in the total factor productivity [5]. In a study conducted by Chen et al. (2019) [11], it was found that the utilization of artificial intelligence resulted in a reduction in the labor demand during the production processes, an increase in the total factor productivity, an acceleration of the accumulation of capital, and a consequent increase in the return on capital. These factors positively impacted economic growth and served to mitigate the effects of aging on economic growth [11]. Another study conducted by Lin et al. (2020) [12] employed a dynamic general equilibrium model that combined AI and heterogeneous capital to examine their impact on economic growth. The results indicated that AI played a significant role in optimizing the capital structure, driving economic growth, and promoting an increase in the population's consumption level [13].

In recent years, industrial robotics have undergone increasing advancements and their applications have expanded to various fields, prompting more scholars to study the relationship between their use and international trade. Goldfarb and Trefler (2018) [14] were the first to explore the relationship between AI and international trade, revealing that factors such as economies of scale, knowledge creation, and the geographical location of knowledge diffusion may contribute to the impact of AI on international trade patterns. Since then, the adoption of industrial robotics has been shown to affect the status of neighboring countries in the international division of labor, as demonstrated by Artuc et al. (2020) [15] who found that a large-scale implementation of robots in the North can lead to increased imports in the South, resulting in both regions achieving a higher production and trade of intermediate and final goods. However, the expansion of production and trade of intermediate goods in the North may come at the expense of a smaller share for the South, potentially hindering the growth of the international division of labor in the region. Scholars have also noted that non-manufacturing industries have shown a greater interest in the use of industrial robots and related technologies [16]. The application of industrial robots and the digitization in the manufacturing industry has also led to an improvement in the international division of labor status of service industries and the quality of service trade development [17]. Empirical studies have further demonstrated that industrial robots have different technological levels in the services industry [10,18,19].

The research on industrial robots is continuously expanding, with scholars increasingly exploring their implications for international trade. Some scholars have even suggested that industrial robots could provide a vital opportunity for developing countries to overcome their challenges and achieve a competitive advantage. However, much of the current research on industrial robots and their impact on global value chains and the international division of labor has been concentrated on the manufacturing and services sectors. As such, there is a gap in the literature that examines the influence of industrial robots on the exports within the energy sector, creating an opportunity for this paper to contribute to the field.

Compared to the existing literature, this paper's potential contributions are threefold. (1) The research questions focus not only on the impact of industrial robots on labor and employment, but also on the actual influence of the robot applications on industry progress as artificial intelligence technology continues to advance. (2) The research content delves into the microscopic mechanisms behind the impact of industrial robots on the energy industry's participation in the international division of labor. This paper not only examines the effect of industrial robots on the energy industry's participation in the international division of labor but also analyzes the path of this impact in depth. (3) The research dataset was constructed by manually matching the industrial robot data, industrial enterprise database data, and customs database data, and providing a sample that can be used to study the technical complexity of the industrial robots affecting the energy exports. This paper confirms that industrial robots play a role in enhancing the technical complexity of energy product exports, and further verifies that they can optimize the factor allocation and reduce the export costs, providing a theoretical basis for leveraging industrial robots to enhance the international division of labor in China's energy industry. Drawing on existing research, this paper constructed a panel dataset using robot data from the International Robot Federation (IRF) website for China and other countries, as well as provincial-level data from databases, such as EPS. The dataset was used to investigate the impact of the industrial robot applications on China's international division of labor position in the energy industry and to examine the causal pathways of this impact. The plausibility of the results was tested for the period spanning from 2011 through 2019.

The following is the proposed sequencing of the paper. In Section 2, we will describe the theoretical mechanism analysis and hypotheses that underpin this study. In Section 3, we will explain the selection of the variables and the model construction adopted for this study. In Section 4, we will provide an empirical analysis of the theoretical framework developed in Section 2. Section 5 will provide further tests of the influence mechanism, while Section 6 will provide the conclusion and policy implications of this study.

2. Theoretical Analysis and Research Hypothesis

2.1. The Application of Industrial Robots Affects the Complexity of Export Technology

Robots are a highly sophisticated technology that have been increasingly adopted in various stages of corporate product development and production processing. As such, robots can exert a significant impact on the progress of various industries.

Product innovation is widely recognized as a critical driver of export complexity [20,21]. In the process of product development, innovation is often a trial and error process, requiring significant R&D efforts and experimentation, which can lead to increased marginal costs [22]. In contrast, robots offer a solution to the challenges of R&D by providing rapid and precise results, allowing for more reliable and efficient experimentation. This not only improves the quality of the product but also shortens the development cycle, enabling enterprises to introduce competitive products into the market quickly. By increasing the technical input during the export product development process, product innovation is an effective means to expand the product coverage and optimize the product quality [23], ultimately leading to an increase in the export technology complexity.

The deployment of industrial robots in the production and processing system holds the potential to transform the original production process and increase the production efficiency. One advantage of robots is their ability to assess product states quickly and accurately and autonomously perform the processing using hardware, such as light and sound sensing, and software, such as big data. As a result, the application of robots can improve the product quality of enterprises and enhance the technical complexity of exported products. However, the implementation of robots may also lead to the replacement of some labor. Robots can perform tasks in the production process that are impossible for human labor, resulting in a possible shift in the production process and an increase in labor productivity. The scale effect generated from the increased labor productivity enables industries to exploit their differentiation advantages and boost the technological complexity of their exports. Simultaneously, the enhancement of the labor productivity implies that enterprises can regulate their production costs, and effective cost management is a crucial means for enterprises to enhance their export complexity [24–26].

In summary, the utilization of robots in critical aspects of enterprise product development, production, and processing presents an opportunity to enhance the export complexity of the industry. Building upon this insight, we propose the following.

Hypothesis 1. *Industrial robot applications promote the upgradation of the technological complexity of exports in the energy industry.*

2.2. The Mechanism of Industrial Robots Affecting the Technical Complexity of Exports

More precisely, the integration of industrial robots advances the technological complexity of enterprise exports by the following two means.

Optimizing the factor structure is a crucial pathway for industrial robots to upgrade the export technical complexity. According to the factor substitution theory, the capital–labor ratio is closely linked to the usage of capital and labor. Specifically, if the price of a production factor increases, technology will progress towards reducing the use of that factor and eventually replacing it, leading to biased technological progress [27]. Technological advancements, such as industrial robots, affect both capital (K) and labor (L), thereby changing the factor allocation structure of the firms. With the changing national conditions, more rational enterprises will further invest in capital to maximize profits. Industrial robots are primarily a result of capital deepening, capable of filling low- and medium-skilled labor positions and completing the corresponding work. By scaling up the usage of industrial robots and other technologies, enterprises can reduce the usage of labor (L) and increase capital investment (K), thereby enhancing the capital–labor ratio (K/L), accelerating capital deepening, and enabling the optimization and upgrading of the factor structure. Factor markets are also linked to industrial robots. The existing literature suggests that encouraging companies to engage in intelligent production and increasing the application of industrial robots is an effective approach to optimize the production costs when the price of capital decreases [28]. The application of industrial robots can alter the proportion of the factors invested in production and effectively manage the production costs of the industry, thereby fulfilling the need for the increased technological complexity of the exports in the energy sector.

Furthermore, the application of industrial robots plays a significant role in reducing the cost of exporting products, thereby enhancing the technical complexity of the industry's exports. On the one hand, robots facilitate the synergistic development of various aspects of international trade, including transportation, storage, packaging, loading, and unloading. This results in reduced expenses during transportation and distribution and meets the demand of the enterprises for low transportation costs. On the other hand, the practical application of robot technology, such as the sorting and handling of robots, allows for intelligent product storage, leading to a further decrease in the overall product storage costs in the industry. As a result, whether in logistics and transportation or intelligent storage, the widespread usage of robots has led to a reduction in the fixed costs of exports, enabling enterprises to invest more capital in research and development, enhance the technical content of their products, and improve the technical complexity of their exports. Therefore, based on these observations, we propose a second hypothesis for this study.

Hypothesis 2. *The optimization of the factor allocation and reduction in export costs through the application of industrial robots promotes an increase in the technical complexity of the exports.*

3. Empirical Study Design

3.1. Indicator Selection

3.1.1. Explained Variables

The explained variable in this paper is the technological complexity of the exports in China's energy industry ($Complx$). The concept of the export technological complexity was first proposed by Hausmann et al. (2007) [25]. Since then, various methods for measuring this variable have been proposed by scholars worldwide. Xu and Lu (2009) [29] modified the calculation method by utilizing provincial export data and GDP per capita when cross-country comparisons were not necessary. In this study, we calculated the export comparative advantage index of the different energy products in each province and used it as the weighted average to obtain the technological complexity of the exported energy products ($PRODY_n$).

$$PRODY_n = \sum_m \frac{\frac{X_{mn}}{X_m}}{\sum_m \frac{X_{mn}}{X_m}} Y_m \tag{1}$$

In this study, the subscripts m and n represent the provinces and products, respectively. X_{mn} represents the export value of product n in province m, while X_m represents the total export value of all the products in province m. Additionally, Y_m represents the GDP per capita of province m.

After calculating the technological complexity of the exported energy products, we then used the export weight of each province to derive the export technical complexity of each province ($EXPY_m$). This was calculated using the following formula.

$$EXPY_m = \sum_n \frac{X_{mn}}{X_m} PRODY_n \tag{2}$$

In this paper, we considered the requirements of the panel data regression and data availability and classified the energy sources into six categories, namely coal, coke or semicoke, crude oil, oil, natural gas, and electricity. This classification was based on the data obtained from the various sources, such as the China Energy Statistical Yearbook, Chinese customs data, and the EPS micro database, which provided the data related to the energy industry. Using this information, we calculated the technical complexity of the exports in the energy industry.

3.1.2. Core Explanatory Variables

In this paper, the level of industrial robot adoption was measured by the density of industrial robot use, which was represented by the core explanatory variable, the industrial robot penetration (*Robots*). Following the methods proposed by Acemoglu and Restrepo (2020) [5] and Wang and Dong (2020) [30], this paper used the industry-level robot penetration and the labor employment ratio of each firm to calculate the level of industrial robot adoption by each firm. The specific measurement formula is presented as follows.

$$Robots_{jit} = \frac{PWP_{jit=2011}}{ManuPWP_{t=2011}} \times \frac{MR_{it}^{CH}}{L_{i,t=2011}^{CH}} \tag{3}$$

Specifically, the variable $Robots_{jit}$ measures the penetration of industrial robots in industry i and enterprise j in year t. It was calculated as the product of three terms: (1) the ratio of the proportion of employees in the production department of enterprise j in industry i in the manufacturing industry in 2011 (base period) to the median proportion of employees in the production department of all the enterprises in the manufacturing industry in 2011 ($\frac{PWP_{jit=2011}}{ManuPWP_{t=2011}}$_($t$ = 2011)), (2) the stock of industrial robots belonging to the enterprise j in industry i in year t (MR_{it}^{CH}), and (3) the employment number of industry i in China in 2011 ($L_{i,t=2011}^{CH}$). Finally, the calculated industrial robot penetration of each listed enterprise was matched and summed with the provinces one by one to obtain the penetration of industrial robots at the provincial level.

3.1.3. Control Variables

To examine the impact of industrial robots on the technological complexity of the exports in the energy industry and to ensure the robustness and reliability of our econometric regression results, this paper controlled the other variables that might have affected the technological complexity of the energy exports (see Table 1), following the approach of Xu et al. (2022) [31].

Table 1. Variable definitions.

	Variable Symbolic	Variable Name	Variable Definition
Explained variable	*Complx*	Export technology complexity	Technical content of export products
Core explanatory variable	*Robots*	Industrial robot penetration	Robot stock/employment
Control variable	*Develop*	Economic development level	Household consumption level index
	FDI	Foreign direct investment	Total registered foreign investment
	Patent	Technology innovation level	Patent application authorization number

Table 1. *Cont.*

	Variable Symbolic	Variable Name	Variable Definition
Control variable	*Labor*	Human capital	Average number of students in colleges and universities
	Index	Internet development	Internet broadband access port
	Fin	Financial development	Science and technology finance index

In this study, we examined the factors affecting the application of industrial robots by the enterprises. Specifically, the level of economic development, as measured by the level of residential consumption, played a crucial role in determining the ability of a region to utilize high technology. We used the level of residential consumption in each province to represent this variable [32].

Furthermore, foreign direct investment (FDI) can crowd the market when introducing technology, thereby affecting the technological sophistication of the exports in the energy industry [10,13,33]. To measure FDI, we used the total amount of foreign registered investment in each province.

The level of technological innovation, as represented by the number of patent applications granted in each province, can significantly impact the export complexity of a country's products, which in turn changes the export structure. Therefore, we used this variable to indicate the level of technological innovation [34].

Human capital is essential for providing labor to the production of enterprises. The quality of human capital affects the R&D capability of enterprises and determines the technical complexity of their products for export. In this study, we used the average number of students per 100,000 in higher education in each province to represent this variable [26].

Internet development strengthens inter-industry linkages and facilitates the division of labor in the industry. Moreover, it improves the efficiency of resource utilization and the flow of technology. To measure the internet development, we used the number of internet broadband access ports in each province [35].

Lastly, we examined the degree of financial development, which can help alleviate information asymmetry, improve the efficiency of fund utilization, and encourage the industry to enhance the sophistication of export technology. As an essential means of combining finance and innovation, technology finance reflects the goal of financial development. Therefore, we used the Technology Finance Index to represent this variable [36].

3.2. Basic Model Settings

In this paper, we constructed a basic econometric model by identifying the indicators to measure the consumption and industrial upgrading.

$$Complx_{it} = \alpha_0 + \alpha_1 Robots_{it} + \alpha_2 X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{4}$$

where subscripts i and t represent the provinces and years, respectively; $Complx_{it}$ represents the technical complexity of the energy export of province i in year t, which is the explained variable of this paper; $Robots_{it}$ represents the consumption scale and consumption structure of province i in year t, which is the core explanatory variable of this paper; X_{it} is the control variable; μ_i and γ_t represent the unobserved provinces and the time fixed effects, respectively; ε_{it} is a random disturbance term; and α is the main parameter. In Equation (4), the core estimation parameter is represented by α_1. A significantly positive value of α_1 indicates that the increased use of industrial robots promotes the improvement of the export technology complexity in China's energy industry. On the other hand, if the value of α_1 is not significant, the conclusion cannot be supported.

3.3. Data Source and Variable Description

This paper aims to investigate the impact of industrial robots on the technical complexity of China's energy industry exports using the panel data from 31 provinces in China over a period of 9 years, from 2011 to 2019. The data sources used in this study mainly included customs export data, statistical yearbooks, and the EPS database of each province. To avoid the influence of outliers and potential bias in the conclusions, a 1% tail reduction was applied to the collated data before and after conducting the further regression analysis on the processed data. The descriptive statistics of each variable are presented in Table 2.

Table 2. Descriptive statistics.

Var. Name	Obs.	Mean	SD	Min	Median	Max
$Complx$	279	16.657	90.456	−97.627	−1.704	1211.009
$Robots$	279	1401.858	2387.037	16.770	553.219	17,363.777
$Develop$	279	102.526	1.226	100.567	102.266	106.338
FDI	279	1662.923	2744.061	7.259	621.000	19,533.000
$Patent$	279	50,471.229	75,386.375	121.000	22,820.000	5.27×10^5
$Labor$	279	2557.991	802.073	1082.149	2383.000	5612.870
$Index$	279	202.348	91.647	16.220	212.360	410.280
Fin	279	806.145	724.299	7.600	600.329	4112.233

Note: "Obs." indicates observation; "Mean" indicates mean; "SD" indicates standard deviation; "Min" indicates minimum; "Median" indicates median; "Max" indicates maximum.

Table 2 shows that the technical complexity of the energy industry exports ($Complx$) ranged from −97.627 to 1211.009, indicating a significant variation in the level of the technical complexity across the different provinces. Similarly, the industrial robot penetration ($Robots$) varied widely, with a minimum value of 16.770 and a maximum value of 17,363.777, suggesting a significant disparity in the adoption of industrial robots across the different regions of China.

4. Results

The estimation methods for the short panels (N large T small) included three types of mixed regressions, fixed effects, and random effects models. To determine the appropriate regression model, the Hausman test was applied. The test results indicated that the χ^2 statistic was 27.15 with a p-value of 0.0001, which rejects the random effect at the 1% level. Thus, the fixed-effect model should be used.

4.1. Data Source and Variable Description

In this study, we initially analyzed the effect of industrial robots on the technical complexity of the energy exports by regressing Equation (1) using a two-way fixed-effect model that was controlled for the province and year effects.

The results of the baseline regression are presented in Table 3. Columns (1) and (2) display the results without the inclusion of the region-fixed and year-fixed effects, while columns (3) and (4) show the control for both the region and year-fixed effects. As demonstrated in Table 3, the estimated coefficient of the industrial robot penetration remained significantly positive at the 5% statistical level, regardless of the inclusion of the region and year-fixed effects. This finding aligned with our prior expectations and suggests that the use of industrial robots has a noteworthy positive impact on the technical complexity of the energy exports. Furthermore, the application of industrial robots can enhance the competitiveness of the export products within the energy industry and foster international improvements in the division of labor.

Table 3. Regression results of the two-way fixed-effect model.

	(1)	(2)	(3)	(4)
	Complx	*Complx*	*Complx*	*Complx*
Robots	0.00449 *** (0.00109)	0.00820 *** (0.00246)	0.00399 ** (0.00145)	0.00615 * (0.00292)
Develop		3.524 (2.005)		−1.157 (4.742)
FDI		−0.00689 ** (0.00222)		−0.00863 *** (0.00250)
Patent		0.000546 *** (0.000111)		0.000740 *** (0.000176)
Labor		0.0175 ** (0.00622)		−0.0330 * (0.0131)
Index		0.0701 (0.0376)		1.017 ** (0.322)
Fin		−0.0433 *** (0.00950)		−0.0401 ** (0.0121)
_cons		−399.7 (208.6)		170.5 (501.7)
Id effect	No	No	Yes	Yes
Year effect	No	No	Yes	Yes
N	279	279	279	279
R^2			0.080	0.254

Note: The numbers in the brackets are standard errors; ***, **, and * indicate a statistical significance at the 1%, 5%, and 10% levels, respectively. "No" means that the effect was not controlled; "Yes" means that the effect was controlled.

Column (4) of the regression results in Table 3 demonstrated that a 1% increase in the robot penetration led to a 0.162% increase in the technical complexity of the energy industry exports, assuming the other control variables remained constant. This finding confirmed Hypothesis 1 and underscored the crucial role that industrial robots play in promoting the international division of labor within the energy industry. Notably, among the control variables, the coefficients for the level of technological innovation and the degree of internet development were significantly positive at the 1% level, indicating that these factors facilitated the improvement of the technical complexity of the energy exports, which was in line with the previous research. Conversely, FDI was significantly negative at the 1% level, potentially due to the market competition and inadequate technology spillover from foreign capital. Labor was also significantly negative at the 10% level, implying that merely increasing the quantity of labor in China's energy sector is insufficient to meet the demands of the technological sophistication, highlighting the need for quality talent. Additionally, the coefficient of the degree of financial development was significantly negative, potentially due to a mismatch of financial resources in China's energy industry, which hindered the overall level of the international division of labor.

4.2. Endogenetic Treatment

4.2.1. Lagging the Core Explanatory Variables by One Period

Since the introduction and use of industrial robots in production processes may involve a lag effect, companies may not immediately achieve the desired technological upgrade when implementing them. Instead, they might gradually achieve it in subsequent periods. To account for this possibility, this section introduces the robot penetration index with a lag of one period into the model to test the impact of the industrial robot penetration on the technological sophistication of the exports. The results in column (1) of Table 4 demonstrated that the robot penetration at the one-period lag remained significantly positive at the 1% level, further supporting the robustness of Hypothesis 1.

Table 4. Endogenous treatment.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	Complx	***Robots***	***Complx***	***Robots***	***Complx***
L.Robots	0.00831 * (0.00342)				
Robots_US		0.591 *** (4.771)			
Robots			0.037 ** (2.433)		
Robots_JP				−0.262 *** (−3.751)	
Robots					0.043 ** (2.509)
rk LM test		0.000		0.000	
rk F test		264.35		255.38	
Control variables	YES	YES	YES	YES	YES
Id effect	YES	YES	YES	YES	YES
Year effect	YES	YES	YES	YES	YES
Observations		279	279	279	279
R-squared		0.872	0.140	0.868	0.106

Note: The numbers in the brackets are standard errors; ***, **, and * indicate a statistical significance at the 1%, 5%, and 10% levels, respectively. "No" means that the effect was not controlled; "Yes" means that the effect was controlled.

4.2.2. Two-Stage Least Squares (2SLS) for the Tool Variable Estimation

Endogeneity problems may arise when regressing the industrial robot penetration in each province on the technological complexity of the exports in the energy sector, as an increased level in the international division of labor in energy could affect the industrial robot penetration. Firstly, a region's higher level in the energy division of labor could result from its strong research capability and better layout of high-tech industries, which would make it easier and less costly to receive and use industrial robots in the region. This could lead to a reverse causality between the explanatory variables and the core explanatory variables. Secondly, different companies may develop their robot use programs according to their actual situation and the requirements of their development direction, based on their current division of labor status. To address this endogeneity issue, we measured the industrial robot use as an instrumental variable, as suggested by Acemoglu and Restrepo (2020). They found that the competition among large manufacturing countries is intense, and the technologies and equipment used in the competition are similar. Therefore, the industrial robot use can be used as a valid instrumental variable when studying the impact of the industrial robot use on the employment in the United States.

To mitigate the potential endogeneity problems affecting the findings of this paper, this section followed the approach of Yan et al. (2021) [37] and Wang and Dong (2020) [30] by incorporating the stock of industrial robots from the United States and Japan in Equation (3) instead of relying solely on the Chinese industrial robot stock. Additionally, the newly computed industrial robot penetration at the provincial level in China was employed as an instrumental variable, and the two-stage least squares (2SLS) was used for the instrumental variable estimation. The data on the stock of industrial robots in the United States and Japan were sourced from the IFR. By employing this methodology, this paper can better address the potential endogeneity concerns and provide more robust and reliable results.

The regression results are presented in Table 4, where columns (2) and (4) present the results of the one-stage regression, and columns (3) and (5) show the results of the regression using the penetration degrees calculated as the instrumental variables from the industrial robot stock in the United States ($Robots\_US$) and Japan ($Robots\_JP$), respectively. To address the endogeneity issue, this paper used the newly calculated industrial robot penetration at the provincial level in China as an instrumental variable and employed the two-stage least squares estimation. The results in Table 4 showed that the application of industrial robots was significantly positive with the export technological complexity, which was consistent with the previous benchmark regressions, indicating that the application of industrial robots still had an impact on the export technological complexity after the endogeneity was addressed. It is worth mentioning that in this result, the influence of the instrumental variables on the export technical complexity was greater than that of the Chinese industrial robot penetration. This may be attributed to the earlier industrialization and stronger technological strength of the United States and Japan. The use of industrial robots enables different industries to cooperate with each other, improving the efficiency of the industrial robot use. The rk F-statistic was 264.35 and 255.38 with $Robots\_US$ and $Robots\_JP$ as instrumental variables, respectively, which were greater than the critical values, indicating that no weak instrumental variable problem was present. The p-values for both the rk LM tests were 0, rejecting the original hypothesis, and there was no under-identification problem.

4.3. Robustness Test

4.3.1. Add Control Variable

The technological complexity of the energy exports was influenced by multiple factors, including the infrastructure and firm factors. Therefore, the control-related factors may overlook other important factors and lead to non-robust estimation results. To account for this, we included additional control variables to control for the effects of the other factors. Specifically, we examined the level of infrastructure improvement (inf) by using road area per capita (square meters) as an indicator. The influence of the firm factor was examined by selecting the share of employees of state-owned enterprises in the energy sector as a variable ($property$).

Table 5 presents the estimation results after adding the two control variables mentioned above in Column (1). The results show that the regression coefficient of the industrial robot penetration remained significantly positive even after accounting for the influence of the other factors on the technological complexity of the exports in the energy sector at different levels. This suggests that the influence of the industrial robot penetration on the technological complexity of the energy exports was not affected by the other factors, and that the previous estimation results were robust.

Table 5. Robustness test.

	(1)	**(2)**
	Complx	***Complx***
Robots	0.00603 * (0.00296)	0.00000471 * (0.00000223)
Develop	−1.470 (4.814)	−0.000934 (0.00358)
FDI	−0.00877 *** (0.00252)	−0.00000660 *** (0.00000191)

Table 5. *Cont.*

	(1)	(2)
	Complx	***Complx***
Patent	0.000735 *** (0.000178)	0.000000565 *** (0.000000134)
Labor	−0.0292 * (0.0137)	−0.0000252 * (0.0000100)
Index	1.000 ** (0.327)	0.000776 ** (0.000246)
Fin	−0.0402 ** (0.0122)	−0.0000307 ** (0.00000924)
Inf	−1.227 (1.262)	0.210 (0.379)
Property	3.108 (21.18)	
_cons	210.3 (511.9)	
Id effect	YES	YES
Year effect	YES	YES
N	279	279
R^2	0.257	0.254

Note: The numbers in the brackets are standard errors; ***, **, and * indicate a statistical significance at the 1%, 5%, and 10% levels, respectively. "No" means that the effect was not controlled; "Yes" means that the effect was controlled.

4.3.2. Replace Dependent Variable

Equation (1) suggests that as the world per capita income increases, the technical complexity of the exported products tends to increase, while the characteristics of the products generally remain stable over time. To ensure the intertemporal stability of the product characteristics, a standard technical complexity index for the exported products was introduced [30]. The formula for the standard technical complexity index is as follows.

$$PRODY_n = \frac{PRODY_n - PRODY_{min}}{PRODY_{max} - PRODY_{min}} \tag{5}$$

The intertemporal stability of the product characteristics was ensured by introducing the standard technical complexity index of the exported products, as shown in Equation (5). Here, $PRODY_{min}$ and $PRODY_{max}$ represent the minimum and maximum product technical complexity of all the export products, respectively, and $PRODY_n$ represents the technical complexity of the export product standards. The estimated results in column (2) of Table 5 did not differ significantly from the benchmark results, indicating that the inclusion of the standard technical complexity index did not affect the robustness of the previous estimation results.

4.4. Heterogeneity Test

4.4.1. Distinguish Energy Output

The regional differences in the energy production and the industrial robot application may lead to varying impacts from the use of industrial robots on the technical complexity of the energy exports. In order to account for this, we adopted a group regression approach to analyze the samples of the regions that were rich and not rich in energy production. The results, presented in columns (1) and (2) of Table 6, show that the use of industrial robots in regions with abundant energy production significantly increased the technical complexity of the energy exports, while the effect of industrial robots in regions with a more backward energy production was not significant. This difference could be attributed to the fact that the regions with a low energy production may not be able to use industrial robots on a large scale due to the region's actual situation, and thus, are unable to achieve a scale effect. Additionally, the regions with an abundant energy production were more likely to have access to targeted financial and technical support, leading to higher levels of industrial robot adoption. As a result, the factor structure optimization and export cost reduction from the application of industrial robots were more pronounced in the energy production-rich regions, which was conducive to the improvement of the technical complexity of the energy industry exports in these regions.

Table 6. Heterogeneity test.

	(1)	(2)	(3)	(4)
	Complx	*Complx*	*Complx*	*Complx*
Robots	0.0220 *** (0.00316)	0.000949 (0.00943)	0.00149 (0.00303)	0.0180 ** (0.00617)
Develop	−15.48 * (6.940)	−2.413 (5.487)	−0.944 (1.200)	−7.477 (12.75)
FDI	−0.0139 *** (0.00346)	−0.000968 (0.00624)	−0.0190 *** (0.00221)	−0.0141 * (0.00589)
Patent	0.0000990 (0.000214)	0.000364 (0.000348)	−0.000134 (0.000191)	0.000378 (0.000309)
Labor	0.0128 (0.0186)	−0.0293 (0.0164)	0.00318 (0.00435)	−0.0651 * (0.0313)
Index	−0.0261 (0.441)	1.063 * (0.412)	0.157 (0.102)	2.426 ** (0.850)
Fin	−0.0402 ** (0.0151)	0.0273 (0.0251)	0.0150 * (0.00649)	−0.0570 * (0.0269)
_cons	0.0220 *** (0.00316)	0.000949 (0.00943)	96.72 (128.2)	876.4 (1355.6)
Id effect	YES	YES	YES	YES
Year effect	YES	YES	YES	YES
N	126	153	90	189
R^2	0.477	0.265	0.729	0.281

Note: The numbers in the brackets are standard errors; ***, ** and * indicate a statistical significance at the 1%, 5%, and 10% levels, respectively. "No" means that the effect was not controlled; "Yes" means that the effect was controlled.

4.4.2. Differentiate Carbon Emission Intensity

Due to the vastness of China and the significant differences in the economic development and environmental conditions across its provinces, the use of industrial robots may have varying effects on the technical complexity of the energy sector exports across the different regions. In light of this, we referred to Shi and Liu (2022) [38] for a regional division based on the carbon emission intensity of each province [39]. Specifically, the Class I region, which comprises ten provinces, including Ningxia, Inner Mongolia, Xinjiang, Guizhou, Shanxi, Hebei, Qinghai, Gansu, Jilin, and Liaoning, is characterized by a high carbon intensity. On the other hand, the Class II region, which includes 21 provinces such as Heilongjiang, Shaanxi, Anhui, Yunnan, Guangxi, Shandong, Henan, Tianjin, Hubei, Jiangxi, Chongqing, Hunan, Hainan, Sichuan, Jiangsu, Fujian, Zhejiang, Guangdong, Shanghai, Tibet, and Beijing, has a relatively lower carbon intensity level.

Following the regional division results, we conducted additional grouping tests to explore the issue of regional heterogeneity in the impact of industrial robots on the technical complexity of the energy exports. Table 6 presents the regression results of the industrial robots' impact on the technical complexity of the energy exports in the Class I and Class II regions. Columns (3) and (4) of Table 6 indicate that the regression coefficient of the industrial robots' application on the technical complexity of the exports was significantly positive in the Class II regions with a low to medium carbon intensity. This suggests that the application of industrial robots significantly enhanced the level of the international division of labor in energy in the Class II regions and increasing the level of the industrial robot application can effectively improve the technical complexity of the energy exports in the region. The reason for this may be that, compared to the Class I regions, the Class II regions have a more reasonable industrial structure, a relatively higher level of production technology, a more reasonable distribution of high-tech and modern service industries, and a more efficient and reasonable application of industrial robots. It is worth noting that the impact of industrial robots on the technical complexity of the exports in the Class I regions was not significant. This may be due to the higher carbon intensity and less advanced industrial structure of these regions, resulting in a less efficient and less effective application of industrial robots in these regions.

5. Mechanism Inspection

The empirical findings of this study demonstrated that the adoption of industrial robots contributed to an increase in the technical complexity of the exports, and this relationship was robust. The second part of the theoretical mechanism analysis posited that the use of robots could have a "cost-saving effect" on a firm's export sophistication. Specifically, our results indicated that the use of robots could impact a firm's variable costs by enhancing its productivity or affecting its fixed production costs by reducing overhead expenses, ultimately influencing the firm's export technological complexity. Therefore, this study examined the mechanism from both the efficiency and cost perspectives.

To test the theoretical Hypothesis 2, we introduced the following model.

$$Element_{it} = \alpha_0 + \alpha_1 Robots_{it} + \alpha_2 X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (6)$$

$$Fixcost_{it} = \alpha_0 + \alpha_1 Robots_{it} + \alpha_2 X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (7)$$

where $Element_{it}$ represents the element structure, $Fixcost_{it}$ represents the export cost, and the other control variables are consistent with the benchmark regression above.

5.1. Element Structure

According to the economic literature, the factor structure of an industry reflects its endowment status and comparative advantage in production. In particular, if an industry has a significant share of capital in its factor structure, then it must improve the quality of its products and increase its exports based on its endowment advantage in order to achieve an international division of labor status. This proposition is supported by the previous research [23,40]. Therefore, it is crucial for industries to recognize their factor endowments and leverage them effectively in order to compete successfully in the global market.

The adoption of industrial robots can be viewed as an increase in capital inputs, which may be more prevalent in industries with a higher share of capital relative to those with a higher share of labor. This can obscure the impact of the robots on quality improvement through a greater share of the capital inputs. However, the factor structure of an industry depends not only on the total amount of capital inputs but also on the relative proportions of the capital and labor inputs. Thus, the changes in the labor inputs are equally important. Although robots affect the factor structure through the capital factor, the impact on labor should not be overlooked.

The application of industrial robots affects the complexity of the export technology for two main reasons. First, in terms of the capital factor, as the scale and variety of robot applications expand and the level of robot use in the production process of enterprises continues to increase, capital-intensive production tasks become more complex. This factor-biasing pattern leads enterprises to favor the use of capital to produce high-quality products, which ultimately results in an increase in the technological complexity [23,40]. Second, in terms of the labor factors, the "substitution" and "creation" theories determine the impact of the robots on labor. The “substitution theory” posits that robots are designed for specific production needs and can perform relatively fixed tasks, so an increase in the number of robots will inevitably displace human labor and result in the “man-for-machine” phenomenon. In contrast, the “creation theory” suggests that the application of robots can expand the scale of production and increase consumer demand, leading to an expansion of production and an increase in the demand for labor. Additionally, a large-scale application of robots requires the support of related skills, which can create new job opportunities.

Therefore, the application of industrial robots can alter the structural elements of an industry and affect the technological complexity of enterprises. This paper defines the factor structure (*Element*) as the ratio of fixed assets to the number of employees employed, drawing from Yuan et al. (2022) [41].

5.2. Reducing Export Costs

Although the introduction of robots can initially increase costs and exacerbate the financing constraints for firms, the advantages of the low-variable costs associated with their usage gradually emerge over time. Specifically, industrial robots can replace low-skilled labor and reduce wage expenses for firms, while also squeezing the market space for low-skilled labor, which indirectly reduces the average wage level and production costs. These benefits are especially significant for export-oriented firms, where the demand for low-skilled labor, such as handling and warehousing, is urgent. Consequently, the application of industrial robots can lower export costs and free up capital for technology research and development, which in turn upgrades the enterprise’s export products.

However, when measuring export costs, there may be deviations between the actual costs and the book records of enterprises, as the standards for measuring various cost items incurred during the export process are not always uniform. To address this, this study followed Fu and Lu (2021) [42] and used a proxy variable for the fixed production costs (*Fixcost*) as the sum of the financial, administrative, and selling costs.

In Table 7, columns (1) and (2) examine the impact of the robot usage on the factor structure and fixed costs, respectively. The coefficient of the core explanatory variable was significantly positive in column (1), indicating that the application of industrial robots optimized the enterprise factor structure, promoted capital deepening, and adjusted the labor structure. Meanwhile, the regression coefficient in column (2) was also significantly positive, suggesting that the use of industrial robots could optimize the export costs. Therefore, it can be inferred that the main mechanisms driving the use of robots in industry to improve the technical complexity of the exports are the factor structure optimization and fixed cost reduction, which confirms Hypothesis 2.

Table 7. Test results of the action mechanism.

	(1)	**(2)**
	Element	***Fixcost***
Robots	0.0148 ** (0.00593)	0.0117 *** (0.00394)
Develop	3.037 (9.638)	−5.034 (6.395)
FDI	0.00507 (0.00509)	0.00247 (0.00338)
Patent	−0.000946 *** (0.000358)	−0.000186 (0.000237)

Table 7. *Cont.*

	(1)	(2)
	Element	***Fixcost***
Labor	−0.0245 (0.0267)	0.0273 (0.0177)
Index	2.895 *** (0.655)	−0.367 (0.435)
Fin	−0.0954 *** (0.0246)	−0.0788 *** (0.0163)
_cons	−162.0 (1019.6)	757.5 (676.4)
Id	YES	YES
Year	YES	YES
N	279	279
R^2	0.567	0.238

Note: The numbers in the brackets are standard errors; ***, ** indicate a statistical significance at the 1%, 5% levels, respectively. "No" means that the effect was not controlled; "Yes" means that the effect was controlled.

6. Conclusions and Policy Implications

The utilization of industrial robots undoubtedly plays a significant role in enhancing the Chinese energy industry's level of participation in the international division of labor. This paper examined the empirical impact of industrial robots on the level of participation and the underlying mechanisms from the perspective of their technological complexity. To accomplish this objective, we employed the data on the robots from various countries provided by the IFR and several databases such as the EPS. Our research findings indicated that industrial robotics enhances the level of participation in the international division of labor in China's energy industry. We further observed a regional heterogeneity whereby the impact of industrial robotics on the export technology complexity was more pronounced in the regions with an abundant energy production and a low carbon emission intensity. Moreover, the promotion effect was most significant for the regions with an abundant energy production. Lastly, the application of industrial robotics improved the technical complexity of the exports by optimizing the factor structure and reducing the export costs. In light of the widespread adoption of robotics, this paper established a theoretical link between the robotics application and the energy industry's participation level in the international division of labor. Furthermore, we provided evidence based on the perspective of the export technology complexity, which offered valuable policy insights to enhance the Chinese energy industry's high-quality development and enable Chinese energy enterprises to realize their status in the international division of labor system.

Based on the findings of this study, the following recommendations are proposed.

Firstly, in order to enhance the participation of the energy industry in the international division of labor, the cost of applying industrial robotics technology needs to be reduced to enable its large-scale application in the sector. Although industrial robots have been widely used in the energy industry, their high price and lack of scale have impeded their deep integration with the sector. Therefore, it is essential to further reduce the cost of applying industrial robot technology and promote its integration with the energy industry to meet the need for large-scale production operations. This can be achieved by optimizing and upgrading the entire production process, from R&D to design, processing, and sales, and by enhancing the use of emerging technologies in economically underdeveloped regions to transform the traditional energy industry into an intelligent and digitized system, thereby improving the competitiveness of the energy products in the global market.

Secondly, more effective and transparent theoretical policies should be formulated to improve the international division of labor in the energy industry. To ensure the long-term stability of an enterprise's investment in the research and development of related technologies, subsidies for the purchase of industrial robots and other related technologies should be increased to reduce the financial pressure on the enterprises during the preliminary research and development stage. Additionally, education in the disciplines related to industrial robots should be deepened, and more highly skilled talents should be cultivated to match the intelligent development of the enterprises. Finally, the government can play a leading role in coordinating and advocating for the commercial platform of industrial robotics, improving the transparency of information for both R&D and the use of robots. Additionally, the government can encourage financial institutions to invest in SMEs to reduce the mismatch of funds, thereby enabling more SMEs to enhance their R&D and innovation capabilities through advanced technologies, such as industrial robots, and to achieve a higher level of participation in the international division of labor for Chinese energy enterprises.

It is important to note that the energy data used in this study were mainly derived from the customs and industrial enterprise databases, and the export technical complexity of the energy industry was measured by dividing the energy into six categories. However, due to the limitation of a statistical caliber, the current measurement of the export technical complexity of the regional energy industries was limited. To address this limitation, future research should focus on narrowing the statistical caliber and accessing the data related to the robots of non-listed enterprises, thus enabling data matching between the number of industrial robots and energy enterprises, resulting in a more detailed analysis.

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