Industrial Robots, Global Value Chains, and Income Distribution

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Abstract

The phenomenon of "replacing human with robots" is a key example of the current technological revolution, with implications for income distribution among residents. Concurrently, integrating into global production networks has become a key strategy for nations' production activities. The objective of our study is to incorporate the utilisation of industrial robots into the theoretical framework of biased technological progress. It is salient to highlight that the utilisation of industrial robots exacerbates income disparities between capital and labour, as well as between skilled and unskilled employees. This study selects panel data for 45 nations from 2005 to 2019, and also lends support to our hypotheses outlined in the theoretical section. An investigation into the mechanisms reveals that the extensive adoption of industrial robots exacerbates the uneven distribution of income shares between capital and labour, as well as the disparities in job demand and wage levels among heterogeneous labour forces. The aforementioned mechanisms ultimately lead to the deterioration of income inequality among residents. Furthermore, this article reveals that active participation in the global value chains serves to mitigate the income gaps caused by robotics deployments. This study offers insights that can inform development of intelligent manufacturing and pursuit of common prosperity.

Keywords: industrial robots; global value chains; income inequality; skill bias

JEL Codes: E24, F62, O32

1 Introduction

Since the advent of the first computer in the United States in 1946, intelligent technologies have gradually permeated various aspects of human society. Over the past few decades, economists have sought to incorporate industrial robots as an emerging technology into production functions and examine their impact on economic development. Artificial intelligence is generally categorized into two types: Artificial Narrow Intelligence (ANI) and Artificial General Intelligence (AGI). ANI represents intelligent systems designed for particular tasks or specific areas. These systems primarily employ pattern recognition in order to automate and optimise specific tasks. In contrast, AGI refers to AI systems that demonstrate broad learning and reasoning abilities comparable to those observed in humans. AGI is characterized by autonomy and creativity, enabling it to think and solve problems independently. In comparison to the recent emergence of general artificial intelligence systems, the application of narrow artificial intelligence is more widespread and mature. Industrial robots are often regarded as a prototypical example of narrow AI, due to their exceptional task execution capabilities, high degree of automation, and precision. These characteristics make industrial robots a prominent focus in extant studies examining intelligent technology.

The impact of industrial robots on income distribution among residents has become a pivotal topic in evaluating the utility of artificial intelligence. Existing literature suggests that the introduction of industrial robots is linked to an increase in the proportion of capital income, accompanied by a decline in the proportion of labour income. In order to examine the impact of industrial robotics on economic growth, Zeira (1998) integrated industrial robotics into the production function and constructed a task model. He found that the pervasive adoption of automation resulted in a sustained increase in the rate of capital return. Benzell et al. (2015) further employed the two-stage overlapping generations (OLG) model to provide a theoretical explanation for the decline in the labour income share resulting from technological advancements. An empirical analysis of labour income shares across more than fifty countries over the past thirty-five years revealed that the deepening integration of automation generated a decline in the employee's remuneration in most countries (Karabarbounis & Neiman, 2014). Additionally, the empirical evidence indicated that the rate of capital return exhibited an opposite trend, with the capital income share in the gross national product increasing. Consequently, capitalists would amass greater wealth and the income disparity between capitalists and employees would widen (Berg et al., 2016).

The ongoing advancement of industrial robotics has prompted scholars to note that automation not only enhances the capital return rate but also exerts an influence on the employment structure and income wage gap. With regard to the impact on the employment structure, Acemoglu and Restrepo (2018) built upon Zeira's task model and developed a corresponding theoretical framework. Their research highlighted that industrial robots exerted both substitution effects and productivity effects on the labour market. The substitution effect reflects the decrease in labor demand when robots replace human labor. Given the limitations by current intelligent technology, industrial robots have a higher substitution effect on routine tasks compared to non-routine ones. This discrepancy results in greater unemployment among low-skilled workers. Conversely, utilizing robots for high-skilled tasks reduces production costs, boosts productivity, and creates new jobs, thereby increasing the demand for skilled labor in enterprises (Frey & Osborne, 2016). Graetz and Michaels (2018) carried out an empirical analysis using data on the deployment of robots across various industries in 17 countries from 1993 to 2007. Their research shows that the deployment of industrial robots led to unemployment for low-skilled workers and indirectly broadened the income disparity across heterogeneous labor groups. In terms of the impact on wage disparity, Hemous and Olsen (2022) hypothesized that unskilled labor is substitutable while high-skilled labor is complementary with automation technology. Their conclusion suggests that competition among low-skilled workers will intensify in the backdrop of automation, resulting in a decline in their remuneration. Dauth et al. (2017) analyzed industrial robot data from the German manufacturing sector and found that advances in automation resulted in a reduction in the average remuneration of medium-skilled and low-skilled workers.

Technological advancements have exerted a remarkable influence on economic growth and income distribution, while also accelerating the rise of international trade. During the past few decades, improvements in transportation facilitated the emergence of global production networks. Developed countries sought to relocate their outdated industries to developing nations, a process known as "deindustrialisation". This shift gave rise to the transfer of production processes across national borders, thereby fostering the formation of international value chains. The concept of the global value chains (GVC) was first articulated by Krugman (1995). This definition primarily examines the operation of global production networks from the standpoint of intermediate goods trade. The value chain theory disaggregates the industrial chain into relatively independent production segments. In this framework, each country engages in the production and trade of intermediate goods in a sequential manner, with the products ultimately reaching the demand side (Alfaro et al., 2019). The existing studies evaluating GVC metrics can be broadly classified into three categories. The first is the vertical specialization index, which was introduced by Hummels et al. (2001). This index is employed to ascertain the proportion of foreign content in a nation's total exports. A higher value on this index indicates a greater degree of integration and interdependence of a country's production activities within the GVC. The second approach developed by Koopman et al. (2010) examines the international supply and demand of intermediate products within the production process. This method assesses a country-industry's participation rate in the GVC and its specific position within the GVC. By using a value-added decomposition of gross exports, they constructed a quantitative index to help determine whether a particular sector in a country is positioned upstream or downstream in global production networks. As an enhancement to the aforementioned methodologies, Fally (2012) proposed a means of evaluating a country's position within the industrial chain utilizing the number of production stages. Moreover, Antràs et al. (2012) constructed indices of GVC upstreamness, which quantify the physical position of a specific industry within the international production network.

The extant literature on the impact of GVC on income inequality primarily concentrates on two domains. The first domain examines the influence of GVC participation on income inequality, while the second domain investigates the impact of GVC positioning on income distribution. Carpa and Martinez-Zarzoso (2022) demonstrated that offshoring could contribute to a reduction in income disparities. Their empirical analysis, which covered 39 countries over the period 1995–2016, revealed that offshoring exerted a considerable influence on reducing inequality in developing countries over the long term. Ndubuisi and Owusu (2022) investigated the impact of GVC participation and upstream specialisation on wage distribution. The results of their studies demonstrate that an in-depth involvement and upgrade within international value chains are in relation to higher wages and lower income inequality in developed countries. Exploiting the GVC forward and backward correlation degrees proposed by Koopman, Szymczak and Wolszczak-Derlacz (2022) studied the overall effects of GVC on the labor market. Their empirical evidence demonstrated that an improvement in a nation's position within the value chain held a beneficial impact on wages and labour demand. In light of the fact that the distribution of wage income represents merely a subset of the income distribution, Cai et al. (2023) incorporated both the labour share and the wage gap into their analyses. Their findings indicate that an enhancement in a country's position within the GVCs would serve to diminish domestic income inequality.

This article integrates the use of industrial robots with the concept of biased technological progress, aiming to derive the theoretical impacts of robotics on income disparities. We examine how these disparities manifest between capital and labor, and between high-skilled and low-skilled workers. Subsequently, the national income distribution data is matched with the industrial robot data, forming a panel dataset of 45 countries from 2005 to 2019 for empirical testing. Furthermore, we underscore the moderating influence of GVC embeddedness on the aforementioned effects. Based on our literature review, this article potentially offers three incremental innovations and contributions. Firstly, while existing literature on the influence of industrial robotics on income distribution is relatively abundant, it is deficient in comprehensive studies that simultaneously address disparities in factor income shares and the revenues of heterogeneous labour. Consequently, we present a more comprehensive supplement to this gap, addressing both theoretical modelling and empirical analyses. Secondly, existing studies that examine the mechanisms by which automation applications impact income disparities often overlook the importance of globalised production. This article addresses this issue by incorporating GVC participation and division position into the theoretical model, thereby exploring the modulations of GVC integration on income disparity in the backdrop of biased technological progress. This approach not only makes a modest contribution to the existing literature but also suggests policy pathways for governments to mitigate inequality and achieve inclusive growth. Thirdly, due to the difficulty of obtaining industrial robot data from developing countries, many studies rely on data from developed countries. In contrast, this article employs a more comprehensive and representative cross-national sample for empirical analysis, with the objective of providing a valuable contribution to the extant research.

The structure of this article is as follows: The second section presents the theoretical model and the hypotheses derived from it. The third section details the empirical model and the data utilized in the study. The fourth section discusses the empirical analysis, including the baseline regression and robustness tests. The fifth section explores the underlying mechanisms. The sixth section examines the moderating effects. Finally, the seventh section summarizes our findings.

2 Theoretical framework

In this section, we incorporate the impact of industrial robotics on income distribution into the CES (Constant Elasticity of Substitution) production function. The theoretical model elucidates the influence of industrial robot applications on income inequality, focusing on two primary aspects: the disparity in revenues between capital and labour, and the differences in income shares among heterogeneous labour forces. To further analyse the effect of GVC embedding on domestic labour demand and the relative bargaining power among factors, we adopt the assumption of an imperfectly competitive market in order to depict the moderating process of biased technological progress on income inequality in the context of global production.

2.1 Industrial robots and factor income shares

Building on Acemoglu's (2019) theory of biased technological progress, our model posits that the market comprises only two factors of production: capital and labour. At the present stage, we assume that the capital and labour factors are interchangeable and that each factor is internally homogeneous. This article further conceptualises advancements in industrial robotics in the short term as a form of capital-augmenting technological progress. Such developments typically result in significant improvements in capital productivity, while their indirect effects on labour productivity become apparent over a longer period of time. In light of the aforementioned assumptions, we put forth a reformulation of the traditional CES production function, which takes the following form:

$$Y = \left[\lambda Y_K^{\alpha} + (1-\lambda) Y_L^{\alpha}\right]^{\frac{1}{\alpha}} \tag{1}$$

In equation (1), Y represents total output, with Y_K and Y_L respectively denoting the contributions of capital and labour. The parameters λ and $(1-\lambda)$ represent the shares of capital and labour, where λ ranges between 0 and 1. Given the substitutability between capital and labour, the elasticity of substitution α also lies between 0 and 1. Assuming that the productivities of capital and labour are A_K and A_L respectively, and their inputs are K and L. The initial CES function can be further expressed as follows:

$$Y = [\lambda(A_K K)^\alpha + (1-\lambda)(A_L L)^\alpha]^{\frac{1}{\alpha}} \tag{2}$$

To better reflect real-market scenarios, we assume that the factor market is characterized by imperfect competition, implying the presence of monopolies. The market shares and bargaining power of different factor owners vary. In accordance with this supposition, competition between labor and capital is neither entirely free nor fair, resulting in a divergence between factor prices and their marginal costs (Raurich et al., 2012). This discrepancy ($P > MC$), referred to as the price markup, is frequently employed as a means of gauging the monopoly power and bargaining capacity within a given market for a specific product or factor (Berry et al., 2019). The incorporation of the factor price markup into the original production function allows for the expression of the capital-labour income share ratio in equation (2) as follows:

$$\frac{S_K}{S_L} = \frac{rK}{wL} = \frac{\phi_K MC_K K}{\phi_L MC_L L} = \frac{\phi_K}{\phi_L} \cdot \frac{\lambda}{1-\lambda} \cdot \left(\frac{A_K K}{A_L L}\right)^\alpha \tag{3}$$

In the formula above, w and r represent the prices of labour and capital respectively, while ϕ_K and ϕ_L denote the markups on the prices of these two factors. In the event of a technological shock from robotics, the productivity of capital will increase at a more rapid rate than that of labour. Consequently, the value of A_K/A_L will increase. To further delineate the impact of such biased technological progress on the differential in factor income shares, the partial derivatives of the above expression with respect to A_K/A_L are calculated as follows:

$$\frac{\partial \frac{S_K}{S_L}}{\partial \frac{A_K}{A_L}} = \frac{\phi_K \lambda \alpha}{\phi_L (1-\lambda)} \cdot \left(\frac{K}{L}\right)^\alpha \cdot \left(\frac{A_K}{A_L}\right)^{\alpha-1} > 0 \tag{4}$$

The results presented in equation (4) demonstrate that biased technological advancements contribute to an increase in the disparity in income shares between capital and labour. The advent of industrial robotics, which exemplifies capital-augmenting technological progress, is poised to supplant labour through heightened production efficiencies and reduced costs. This dynamic exacerbates the existing uneven distribution between capital and labour in the market, thereby perpetuating the expansion of the income gap between these two factors.

2.2 Impact of industrial robotics on heterogeneous labour

In accordance with the initial assumption that there are only two types of intermediate inputs, the previously considered homogeneous labour force is further divided into two categories. One category comprises unskilled labour engaged in routine tasks, while the other category encompasses skilled labour, which carries out irregular tasks without fixed patterns. The distribution parameters between skilled and unskilled workers are respectively represented by β and $1-\beta$. The elasticity of substitution between the two types of labour is denoted by γ. According to existing literature on the measurement of substitution elasticity between production factors, there is a predominant substitution effect between skilled and unskilled workers (Bils et al., 2024). Therefore, the initial equation (1) can be rewritten as follows:

$$Y_L = \left[\beta(A_S S)^{\gamma} + (1-\beta)(A_U U)^{\gamma}\right]^{\frac{1}{\gamma}} \tag{5}$$

Assuming an imperfectly competitive market, the markup shares for skilled and unskilled labour are denoted as ϕ_S and ϕ_U, respectively. By referencing the derivation process from equations (2) to (3), the income share disparity between heterogeneous labour groups can be expressed as follows:

$$\frac{S_S}{S_U} = \frac{\phi_S MC_S S}{\phi_U MC_U U} = \frac{\phi_S}{\phi_U} \cdot \frac{\beta}{1-\beta} \cdot \left(\frac{A_S S}{A_U U}\right)^{\gamma} \tag{6}$$

Industrial robotics technology is not only capital-augmenting but also exhibits skill-biased characteristics. Its application enhances the productivity of high-skilled labor compared to low-skilled labor (Acemoglu & Restrepo, 2020), which implies an increase in A_S/A_U. Furthermore, automation technology also presents opportunities for high-skilled workers while substituting for low-skilled labor (Frey & Osborne, 2016), thereby further widening the S/U ratio:

$$\frac{\partial \frac{S_S}{S_U}}{\partial \frac{A_S}{A_U}} = \frac{\phi_S \beta \gamma}{\phi_U (1-\beta)} \cdot \left(\frac{S}{U}\right)^{\gamma} \cdot \left(\frac{A_S}{A_U}\right)^{\gamma-1} > 0 \tag{7}$$

$$\frac{\partial \frac{S_S}{S_U}}{\partial \frac{S}{U}} = \frac{\phi_S \beta \gamma}{\phi_U (1-\beta)} \cdot \left(\frac{S}{U}\right)^{\gamma-1} \cdot \left(\frac{A_S}{A_U}\right)^{\gamma} > 0 \tag{8}$$

Equations (7) and (8) indicate that biased technological progress, which leads to differences in productivity and employment opportunities between heterogeneous labour groups, will result in a continual widening of the income share disparity between skilled and unskilled workers. As a skill-biased technology, industrial robotics has the effect of increasing employment opportunities and income for those in high-skilled occupations, while simultaneously worsening the situation for those in low-skilled occupations. Therefore, the automation advancements ultimately exacerbate the income gap between skilled and unskilled workers. In light of the impact of industrial robotics on income disparity between production factors, we put forward our first theoretical hypothesis:

Hypothesis 1: *The increase in the application of industrial robotics amplifies income distribution disparity.*

2.3 GVC as a moderator of robotics-driven income inequality

As globalization advances and the concept of GVC emerges, scholars have recognized that economic liberalisation and technological progress exert an influence on the bargaining power of both labour and capital (Stiller, 2023). The impact of GVC on income disparities in the context of industrial robotics primarily manifests through the modulation of the supply-demand dynamics of labor in domestic factor markets, thereby enhancing the bargaining position of employees. An increase in demand for labour typically results in a strengthening of the bargaining power of workers, which in turn leads to an increase in the proportion of labour income. The prevailing methodologies for evaluating GVC integration are largely concerned with the levels of participation and the relative positions (Gal & Witheridge, 2019). Hence, this article analyses GVC integration from these two perspectives. The price mark-up share typically reflects the firm's pricing power and competitive advantage during economic engagements. Therefore, in our analysis, we utilize the price mark-up share of factors to gauge their bargaining power. Given the assumption of imperfect competition in factor markets, both ϕ_K and ϕ_L are not equal to 1. If $\phi_K > \phi_L$, the bargaining power of labor relative to capital is lower, leading to an increase in capital's revenue compared to labor. Conversely, if the bargaining power of labor increases, the income share of capital diminishes. Assuming that GVC integration enhances employment opportunities, thereby improving the relative bargaining power and mark-up share of labor, the following implications can be deduced:

$$\frac{\partial(\phi_K/\phi_L)}{\partial GVC} < 0 \tag{9}$$

$$\frac{\partial(\phi_K/\phi_L)}{\partial GVCP} < 0 \tag{10}$$

GVC and $GVCP$ in the above equations represent the degree of participation and position within GVC, respectively. Based on equation (4), we further derive the impact of GVC integration on the income shares disparity under the context of industrial robot applications. By employing the implicit function differentiation rule, it becomes evident that:

$$\frac{\partial\left(\frac{\partial S_K/S_L}{\partial A_K/A_L}\right)}{\partial GVC} = \frac{\lambda\alpha}{1-\lambda}\left(\frac{K}{L}\right)^{\alpha}\left(\frac{A_K}{A_L}\right)^{\alpha-1}\cdot\frac{\partial(\phi_K/\phi_L)}{\partial GVC} < 0 \tag{11}$$

$$\frac{\partial\left(\frac{\partial S_K/S_L}{\partial A_K/A_L}\right)}{\partial GVCP} = \frac{\lambda\alpha}{1-\lambda}\left(\frac{K}{L}\right)^{\alpha}\left(\frac{A_K}{A_L}\right)^{\alpha-1}\cdot\frac{\partial(\phi_K/\phi_L)}{\partial GVCP} < 0 \tag{12}$$

The derivations indicate that deepening integration into GVC in the backdrop of robotics can partially mitigate the widening income disparities between labor and capital, by enhancing the relative bargaining power of labor. In light of these findings, this article proposes the second hypothesis:

Hypothesis 2: *In the context of widespread use of industrial robots, active integration into GVC and improvement of the GVC position can help alleviate the widening income disparities caused by biased technological innovation.*

3 Empirical model and data description

3.1 Empirical model

To examine the impact of industrial robot applications on income inequality, this article follows the theoretical model outlined above and constructs the baseline regression model as shown in Equation (13).

$$Gini_{it} = \beta_0 + \beta_1 robdens_{it} + X'_{it}\gamma + \theta_i + \lambda_t + \varepsilon_{it} \tag{13}$$

In the equation, the variable i represents a country or region, while t represents the year. The dependent variable $Gini_{it}$ denotes the Gini coefficient of country i in year t, which is used to measure the degree of income inequality. The key explanatory variable $robdens_{it}$ represents the industrial robot penetration in all industries of country i in year t, serving as an indicator of the application and promotion of industrial robots across countries. The variable X denotes other control variables that affect income distribution. θ_i and λ_t represent country fixed effects and year fixed effects, respectively. The inclusion of country fixed effects serves to control for the inherent macro-level characteristics of each country that are assumed to remain constant over time. Year fixed effects help control for time-varying trends of the dependent variable. ε_{it} represents the error term, capturing other random factors not included in the model. The objective of this article is to estimate the coefficient β_1. A significant positive value for β_1 would indicate that the utilisation of industrial robots exacerbates existing disparities in income distribution among residents. A significantly negative β_1 would indicate that the widespread use of industrial robots is conducive to the promotion of common prosperity. If the research hypothesis of this article is substantiated, β_1 will be found to be positive.

3.2 Data description

The Gini coefficient is currently regarded as an appropriate metric for gauging income distribution inequality. Accordingly, this article utilizes the Gini indexes sourcing from the World Development Indicators (WDI) database as the dependent variable. In accordance with the methodology proposed by International Federation of Robotics, the penetration rate of industrial robots across different nations is calculated. This index is employed to quantify the extent of industrial robot application. The specific calculation method is delineated as follows.

$$robdens = \frac{\text{industrial\_robot\_stock}}{\text{employment}} \times 100 \tag{14}$$

$$employment = \text{labor force} \times (1 - \text{unemployment\_rate}) \tag{15}$$

The objective of this article is to aggregate the stock of industrial robots across various sectors within each country and ascertain each country's annual industrial robot stock. The research then obtained the density of industrial robot applications by dividing this aggregate by the total employment of each nation. In order to derive the core explanatory variable of this study, namely the industrial robot penetration rate, the relatively small magnitude of this metric is multiplied by 100. The sector-specific industrial robot stock data for each country has been sourced from the International Federation of Robotics (IFR). The International Federation of Robotics (IFR) dataset encompasses the stock and growth of robots from 1993 to 2019 across more than 100 countries. In accordance with ISO standards, the data is classified according to industry and application. Furthermore, data pertaining to the labour force and unemployment rates for each country are sourced from the World Development Indicators (WDI) database.

Furthermore, this study incorporates pertinent control variables to enhance the precision of the regression results. The selected control variables are classified into two categories: macroeconomic and demographic. The macroeconomic variables include GDP per capita (pgdp) calculated in current US dollars, the proportion of government fiscal expenditure to GDP (gov), the ratio of industrial and service sector value-added to GDP (indser), the urbanization rate (urban), and the degree of trade openness (open). The urbanization rate is measured by the proportion of urban population to the total national population, while trade openness is gauged by the ratio of a country's total trade volume to its GDP. In order to mitigate the impact of outliers on the overall trend, this study applies a logarithmic transformation to all macroeconomic variables. With regard to the demographic control variables, this study selects the annual population growth rate (popg) and the male-to-female labour force ratio (gender) in order to more accurately characterise the population trends and gender structure of the nations under consideration. The data required for control variables is mainly derived from the WDI database.

Based on the availability and completeness of data, we ultimately choose panel data from 45 countries from 2005 to 2019 for regression analysis. In consideration of indicators with minor data gaps, this article uses extrapolation methods to fill in the missing data. This method effectively fills in gaps for minor missing data at both the beginning and the end of consecutive years without distorting the overall trend of the variables across countries. Table 1 presents the symbols and descriptive statistics of the principal variables required for the empirical analysis conducted in this study.

Table 1: Descriptive statistics of key variables

Symbol	Variable	N	Mean	Std.	Min	Max
Gini	Gini index	675	35.8554	7.9953	21.3000	64.8000
robdens	Industrial robot penetration	675	0.1541	0.5692	0.0000	6.6034
lnpgdp	GDP per capita	675	9.6831	1.1063	6.5330	11.5416
lngov	Government expenditure	675	2.8312	0.2913	1.6984	3.3299
lnindser	Industry and services value added	675	4.3109	0.1043	3.9098	4.5143
lnurban	Urbanization	675	4.2330	0.2620	3.3062	4.5854
lnopen	Trade openness	675	4.3208	0.5277	3.0958	5.4774
popg	Population growth rate	675	0.6549	0.6988	-1.8537	2.8910
gender	Male-to-female labor force ratio	675	4.2701	0.2573	3.2950	4.5063

4 Empirical analysis

4.1 Baseline regression

The objective of this article is to examine the impact of industrial robot usage on income distribution across countries. The data for the various variables are substituted into equation (13), in which the Gini coefficient represents the dependent variable and the penetration of industrial robots serves as the core explanatory variable for regression analysis. The results are presented in Table 2. In column (1) of Table 2, only the core explanatory variable is controlled. In columns (2) and (3), macroeconomic and demographic control variables are gradually included in the regression model.

Table 2: Baseline regression

	Gini		
	(1)	(2)	(3)
robdens	0.1984**	0.4651***	0.4251***
	(2.3602)	(4.6298)	(4.0541)
lnpgdp		-2.5063***	-2.1961***
		(-4.2957)	(-3.5776)
lngov		-5.3869***	-5.2793***
		(-5.3083)	(-5.2135)
lnindser		-3.6749	-4.5768*
		(-1.4464)	(-1.7801)
lnurban		2.7224	1.6085
		(0.8470)	(0.4878)
lnopen		0.9064	0.9580
		(1.1424)	(1.2040)
popg			-0.4381**
			(-2.2283)
gender			0.8989
			(0.3786)
Constant	35.8248***	75.7054***	77.2318***
	(579.2617)	(4.3742)	(3.7179)
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	675	675	675
R^2	0.9647	0.9703	0.9705

Note: Values in parentheses are *t*-statistics, clustered by country and year. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. N and R^2 represent the sample size and goodness of fit.

To achieve more accurate statistical inference, these three columns control for both country and year fixed effects while also adopting clustered standard errors by country-year. As illustrated in Table 2, the coefficients of the core explanatory variable in all three columns are significantly positive at the 1% statistical level. This conclusion is in accordance with the theoretical hypotheses of our study, which suggests that an increase in the penetration of industrial robots intensifies income inequality among residents. In general, the advancement of robotics is expected to have a capital-enhancing and skill-biased effect, which may ultimately lead to greater income disparity between capital and labour, as well as between high-skilled and low-skilled employees. Consequently, the industrial robot deployment exacerbates income inequality within nations, thereby impeding the promotion of common prosperity.

4.2 Robustness analysis

4.2.1 Changing estimation methods

The baseline regression model may exhibit heteroskedasticity, autocorrelation, and contemporaneous correlation issues. To address these complications in a more effective and robust manner, we employ commonly-used methodologies, including Feasible Generalized Least Squares (FGLS), Panel-Corrected Standard Errors (PCSE), and the Standardized Cochrane-Orcutt Correction (SCC), to address the deficiencies present in the original panel data.

In general, the feasible generalized least squares (FGLS) method is more effective than ordinary least squares (OLS) regression in addressing Heteroskedasticity (Cheng et al., 2015). Nevertheless, this approach tends to result in an underestimation of the standard errors. To address this issue, we adopt Panel-Corrected Standard Errors (PCSE) for regression analysis. The reliability of PCSE has been demonstrated in the presence of Heteroskedasticity and contemporaneous correlation (Reed & Webb, 2010). Given that the application of PCSE estimation typically yields more accurate outcomes for long panels, this study further employs the asymptotically efficient non-parametric covariance matrix estimation method (SCC) in the robust check. The SSC method is particularly effective in dealing with Heteroskedasticity, autocorrelation, and cross-sectional correlation in short panels (Amengual et al., 2024). In light of the fact that the selected variables do not strictly conform to a normal distribution, we also adopt a Poisson test to examine the robustness of our baseline regression. Table 3 presents the results of the aforementioned regression analysis. As demonstrated in Table 3, the coefficients for industrial robot penetration (robdens) are positive at the 1% statistical level, which is consistent with the findings from the OLS regression. The results suggest that our hypothesis that the utilisation of industrial robots intensifies income inequality remains valid.

Table 3: Changing estimation methods

	Gini				
	(1) OLS	(2) FGLS	(3) PCSE	(4) SCC	(5) Poisson
robdens	0.4251***	0.4036***	0.4509***	0.4251***	0.0097***
	(4.0541)	(5.2648)	(3.2456)	(5.8042)	(3.3071)
lnpgdp	-2.1961***	-2.1172***	-1.8474***	-2.1961***	-0.0520*
	(-3.5776)	(-6.4512)	(-2.9239)	(-4.7430)	(-1.9264)
lngov	-5.2793***	-5.5074***	-3.3818***	-5.2793***	-0.1336**
	(-5.2135)	(-8.6019)	(-3.3966)	(-8.1143)	(-2.5168)
lnindser	-4.5768*	-4.1016**	-3.3789	-4.5768**	-0.1269
	(-1.7801)	(-2.3969)	(-1.4850)	(-2.2872)	(-1.5864)
lnurban	1.6085	0.8586	1.7690	1.6085	0.0442
	(0.4878)	(0.4506)	(0.4574)	(0.9907)	(0.2835)
lnopen	0.9580	0.0860	-0.3380	0.9580	0.0222
	(1.2040)	(0.1796)	(-0.4048)	(1.4845)	(0.6197)
popg	-0.4381**	-0.3818***	-0.3474*	-0.4381***	-0.0139
	(-2.2283)	(-2.7144)	(-1.8745)	(-3.3084)	(-1.4097)
gender	0.8989	3.1541**	1.5338	0.8989	0.0459
	(0.3786)	(2.1920)	(0.9389)	(0.9358)	(0.3099)
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
F	11.9919***			23837***	
Wald chi2		79720***	1695598***		95***
N	675	675	675	675	675

4.2.2 Changing dependent variable

In order to assess the state of income distribution, the Gini coefficient is the most commonly used metric. It provides an effective indication of the extent of income inequality. However, the Gini coefficient is not without limitations, including its inability to adequately reflect structural differences in income distribution. Moreover, the Gini coefficient is sensitive to alterations in the income shares of middle-income groups, but less responsive to fluctuations in the income levels of high- income and low-income groups. To more accurately gauge the shifts in revenues between high- and low-income groups, this study deploys the methodology put forth by Bilan et al. (2020) to calculate the Kuznets Index (Kuznets). This index is constructed using the ratio of income share held by the top and bottom 20% from the WDI database. Moreover, the aforementioned income Gini coefficient does not fully account for the degree of inequality in the distribution of social resources. In contrast, the wealth Gini coefficient offers a more comprehensive and multi-dimensional perspective on economic inequality (Islam & McGillivray, 2020). The wealth Gini coefficient considers all forms of wealth owned by households, thus enabling a more nuanced understanding of the uneven distribution of social opportunities.

Table 4: Changing dependent variable

	Kuznets			Wealth Gini		
	(1)	(2)	(3)	(4)	(5)	(6)
robdens	0.1473***	0.3145***	0.3124***	0.0708	0.4641***	0.4076***
	(3.8157)	(7.0542)	(6.7420)	(0.9746)	(3.7063)	(3.2719)
lnpgdp		-1.8810***	-1.9841***		-1.8353**	-1.8762**
		(-5.7838)	(-5.6850)		(-2.2410)	(-2.3461)
lngov		-2.2854***	-2.2666***		-5.0668***	-4.8626***
		(-5.0904)	(-5.0087)		(-4.0669)	(-3.9465)
lnindser		-0.9475	-1.1482		7.4105**	5.5261*
		(-0.7671)	(-0.9010)		(2.4714)	(1.8505)
lnurban		3.8189**	3.3964**		12.6234***	9.5968**
		(2.4355)	(2.1129)		(2.7721)	(2.0500)
lnopen		0.0699	-0.0301		1.7642**	1.4258*
		(0.1547)	(-0.0656)		(2.2041)	(1.7817)
popg			-0.1040			-0.9416***
			(-1.0774)			(-3.2563)
gender			-1.8385*			-6.2836***
			(-1.7787)			(-3.1244)
Constant	7.2465***	19.5223**	31.4722***	75.2628***	14.3145	63.9872**
	(235.9760)	(2.3893)	(3.3047)	(975.9788)	(0.6057)	(2.4299)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	675	675	675	675	675	675
R^2	0.9719	0.9770	0.9772	0.9787	0.9805	0.9810

Accordingly,this article further collects the wealth Gini coefficients (Wealth Gini) from the World In-equality Database (WID) to replace the dependent variable in the baseline regression.Table 4 presents the results of the analysis, with the first three columns employing the Kuznets Ratio as the dependent variable and the latter three columns utilising the Wealth Gini coefficient. All six columns include fixed effects for both country and year. Columns (1) and (4) incorporate solely the core explanatory variable, columns (2) and (5) include macroeconomic control variables, and columns (3) and (6) incorporate control variables pertaining to population structure. In columns (3) and (6), the coefficient for the core explanatory variable is significantly positive, passing the 1% statistical significance level. This result suggests that an increase in industrial robot penetration exacerbates income distribution inequality among countries, in alignment with the findings of the baseline regression.

4.2.3 Changing core explanation variable

In the baseline regression, this study employs the stock number of industrial robots per one hundred employees as a gauge for a nation's level of automation development. However, the density of industrial robot stock in a country may be influenced by various factors, including the level of industrialisation and the economic foundations. As a result, it is not an entirely robust indicator of the dynamic changes in domestic industrial robot investment. Furthermore, this study adopts the annual installations of industrial robots from the International Federation of Robotics (IFR) for the period between 2005 and 2019. Following the same processing as that applied to the industrial robot stock density (robdens), the industrial robot increment density (robindens) is obtained and subsequently adopted as the core explanatory variable for robustness testing. Moreover, the import value of industrial robots can be considered a reasonable reflection of a country's demand for such devices (Artuc et al., 2023). Consequently, this study has selected the import value of industrial robots from the United Nations Comtrade database as a substitute for industrial robot penetration. In the HS2002 coding system, industrial robots are primarily categorised under the following seven six-digit codes: 842489 (spraying robots), 842890 (handling robots), 847950 (multi-purpose robots and robot end effectors), 848640 (automated material handling robots specifically for IC factories), 851521 (resistance robots for automobile production lines and other resistance welding robots), 851531 (arc, including plasma arc welding robots) and 851580 (laser welding robots for automobile production lines and other welding robots). The import trade values of the aforementioned seven categories of robots can be aggregated and subjected to the same processing as that applied to the industrial robot stock density, thereby deriving a proxy variable for a country's industrial robot import value (robvalue). This variable is also deployed as the primary explanatory variable in the regression analysis that follows.

Table 5: Changing core explanation variable

	Gini					
	(1)	(2)	(3)	(4)	(5)	(6)
robindens	0.1445**	0.2880***	0.2620***			
	(1.9833)	(3.3718)	(3.0321)			
robvalue				0.3911**	0.5837***	0.5491***
				(2.1820)	(3.4027)	(3.2230)
lnpgdp		-2.4868***	-2.1716***		-2.5661***	-2.2399***
		(-4.2655)	(-3.5414)		(-4.4420)	(-3.6958)
lngov		-5.3034***	-5.2002***		-5.0585***	-4.9811***
		(-5.2585)	(-5.1702)		(-5.0512)	(-4.9885)
lnindser		-3.7453	-4.6642*		-3.7110	-4.5614*
		(-1.4735)	(-1.8140)		(-1.4547)	(-1.7718)
lnurban		2.4764	1.3532		1.0489	0.1423
		(0.7749)	(0.4131)		(0.3428)	(0.0453)
lnopen		0.8900	0.9436		0.8448	0.9158
		(1.1186)	(1.1825)		(1.0540)	(1.1422)
popg			-0.4492**			-0.4165**
			(-2.2814)			(-2.0976)
gender			0.9060			1.2122
			(0.3818)			(0.5262)
Constant	35.8256***	76.7081***	78.2781***	35.6259***	82.5902***	81.5259***
	(582.9595)	(4.4336)	(3.7723)	(308.1510)	(4.8871)	(3.9790)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	675	675	675	675	675	675
R^2	0.9647	0.9702	0.9704	0.9648	0.9704	0.9706

In Table 5, the core explanatory variable in the first three columns is robot installation density (robindens). Following the gradual addition of control variables, the coefficients of the core explanatory variable are found to be statistically significant at the 1% level. The core explanatory variable in the latter three columns is the import value of industrial robots (robvalue). In these columns, the coefficients of the core explanatory variable remain significantly positive at the 5% statistical level or above. These findings suggest that the conclusion that industrial robot utilisation contributes to an exacerbation of income disparities remains valid, given the alterations of the explanation variable. Therefore, the robustness of the baseline regression results is further confirmed.

4.2.4 Instrumental variable method

While the robustness tests above lend support to the conclusions of the baseline regression, the results may still exhibit unidentified endogeneity issues. The sources of endogeneity can be attributed to several factors. Firstly, the omission of important variables may result in a bias. Secondly, the estimated model may suffer from bilateral causality. Specifically, it is possible that a larger income gap may not be the result of greater robot adoption, but rather a cause of it. Thirdly, there is the potential for selection bias, which encompasses both sample selection bias and self-selection bias. The adoption of a two-way fixed-effects model with panel data and robust standard errors is only capable of addressing endogeneity issues that arise from time-invariant omitted variables. However, this method is not capable of resolving other sources of endogeneity. To alleviate the issues of reverse causality and sample selection bias, this study employs instrumental variables in a two-stage least squares (2SLS) estimation. In line with the approach set out by Acemoglu and Restrepo (2020), we deploy minusrob as the instrumental variable. This index calculates the average stock density of industrial robots in all sample countries except the home country (country i). In addition, following the methodology outlined by DeStefano and Timmis (2024), the Bartik variable is constructed using the shift-share method to ensure robustness. The specific construction of the Bartik is presented as follows:

$$\text{Bartik} = \text{robdens}_{i,2005} \times \Delta G\text{robdens}_t \tag{16}$$

In the equation above, $\text{robdens}_{i,2005}$ represents the industrial robot penetration rate in country i in 2005. This variable is closely associated with the core explanatory variable (robdens). The rate of change in global robot penetration ($\Delta G\text{robdens}_t$) represents the growth rate of global industrial robot penetration in year t, with the data from the home country i excluded. After appropriate control for country and year fixed effects, this parameter exhibits good exogeneity. Consequently, the Bartik instrument variable, derived from the initial robot penetration rate in the home country and the annual growth rate of global industrial robot penetration, effectively addresses endogeneity issues arising from reverse causality, omitted variables, and other factors (Jaeger et al., 2018). The results of the two-stage least squares estimation for the aforementioned two instrumental variables are presented below:

Table 6 presents the regression results derived from the two-stage least squares (2SLS) estimation. Columns (1) and (2) employ minusrob as the instrumental variable. Columns (3) and (4) utilize the Bartik instrumental variable (Bartik), constructed via the shift-share method. The first-stage regressions presented in Columns (1) and (3) demonstrate that the coefficients of both instrumental variables are statistically significant at the 1% level. These outcomes suggest a strong correlation between the instrumental variables and the industrial robot penetration rate (robdens) across nations, thereby satisfying the relevance condition. In the second-stage regressions displayed in Columns (2) and (4), the coefficients of the estimated core explanatory variable utilising instrumental variables are markedly positive, aligning with the findings of our baseline regression analysis. The conclusion indicates that, following the alleviation of endogeneity concerns through instrumental variable methods, the deployment of industrial robots continues to exacerbate income inequality among residents. In addition to utilising instrumental variables in the

Table 6: Instrumental variable

	robdens	Gini	robdens	Gini
	(1)	(2)	(3)	(4)
robdens		0.4085***		1.0417***
		(4.1239)		(4.1075)
minusrob	-1.5636***			
	(-147.4391)			
Bartik			0.0171***	
			(9.2570)	
lnpgdp	0.0101	-2.1908***	0.2689***	-2.1529***
	(1.2758)	(-3.7637)	(6.1388)	(-3.4834)
lngov	0.0008	-5.2698***	-0.0160	-5.9985***
	(0.0537)	(-5.4765)	(-0.2897)	(-5.7386)
lnindser	0.0222	-4.5900*	0.9852***	-3.5629
	(0.6471)	(-1.8805)	(4.5493)	(-1.4100)
lnurban	-0.1112*	1.5691	-0.1722	2.4542
	(-1.8279)	(0.5013)	(-0.8231)	(0.7881)
lnopen	0.0482***	0.9600	0.0082	1.4682*
	(4.1883)	(1.2718)	(0.1168)	(1.8334)
popg	0.0056**	-0.4396**	-0.0139	-0.2902
	(2.0195)	(-2.3559)	(-0.7955)	(-1.6107)
gender	0.0225	0.9023	-0.2607*	0.9887
	(1.1247)	(0.4004)	(-1.6481)	(0.4059)
Constant	0.9080***	83.9654***	-4.6159**	73.7985***
	(2.8363)	(4.2632)	(-2.5314)	(3.6764)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
LM statistics	10.5374**		9.6922**	
F statistics	21872		86	
N	675	675	630	630

least squares regression analysis, the article also performs validity tests for the instruments. The LM statistics for both instrumental variables exceed the 1% significance level, thereby rejecting the null hypothesis of under-identification. Furthermore, the F-statistics for both instrumental variables are considerably above the 10 threshold, thus rejecting the hypothesis of a weak instrument. These findings serve to reinforce the rationale behind the selection of the instrumental variables.

4.2.5 PSM-DID

To address the issue of endogeneity in regression analysis, this article further employs the Propensity Score Matching Difference in Differences (PSM-DID) method to ascertain whether the results remain robust after the effect of self-selection has been mitigated. As Laschi et al. (2016) observed, following a few pioneering works from 2009 to 2012, a series of breakthroughs were achieved in the field of soft robotics. These technological breakthroughs enable industrial robots to adapt to diverse work environments and task requirements, thereby enhancing their versatility and adaptability. The malleability of these robots allows them to perform a variety of tasks, effectively replacing multiple traditional hard robots. As a result, the extensive deployment of soft robots can lead to a reduction in the costs associated with the acquisition and maintenance of traditional robots, as well as a decline in the demand for labour. The statistical data also indicates a prompt increase in the utilisation of industrial robots in developing countries since 2012, with a majority proportion accounted for by flexible industrial robots (Hägele et al., 2016). Therefore, the advancements in soft robotics in 2012 provide an excellent natural experiment, which allows for the examination of the aforementioned issue in a controlled setting. In order to facilitate the partitioning of the treatment and control groups, this study designates regions where the penetration rate of industrial robots exceeds 0.02 as the treatment group, while regions below 0.02 are categorised as the control group. The specific regression model is defined as follows:

$$\mathrm{Gini}_{it} = \beta_0 + \beta_1 \mathrm{treated}_i \times \mathrm{time}_t + \beta_2 \mathrm{treated}_i + \beta_3 \mathrm{time}_t + X'_{it}\gamma + \theta_i + \lambda_t + \varepsilon_{it} \tag{17}$$

In equation (17), the treated value for the treatment group is set to 1, while the control group is assigned a value of 0. The time variable is designated a value of 0 prior to the occurrence of the shock, and a value of 1 subsequent to 2012. The variable X represents control variables that are consistent with the baseline regression. The symbols θ_i and

λ_t denote country and year fixed effects, while ε_{it} represents the error term. In the implementation of PSM-DID, propensity score matching is the critical factor in addressing sample self-selection bias. This procedure allows us to conclude that the treatment and control groups are operating under the same standards, thereby verifying the robustness of the baseline regression.

Table 7: PSM-DID

	Gini		
	(1)	(2)	(3)
time×treated	1.1566***	0.6707**	0.6491**
	(4.5552)	(2.5370)	(2.4927)
time	-2.4438***	-1.3138***	-1.5896***
	(-5.6388)	(-2.6495)	(-2.8436)
treated	-1.7173***	-1.5378***	-1.6033***
	(-5.4886)	(-4.4223)	(-4.5931)
lnpgdp		-2.0223***	-1.5962***
		(-3.5487)	(-2.6924)
lngov		-5.4103***	-5.3426***
		(-5.3271)	(-5.2939)
lnindser		-1.0291	-1.8845
		(-0.3922)	(-0.7190)
lnurban		6.1172*	5.3772
		(1.8952)	(1.6302)
lnopen		1.1325	1.2659
		(1.4693)	(1.6409)
popg			-0.4626**
			(-2.4580)
gender			2.1804
			(0.9160)
Constant	37.7527***	45.5401**	38.6920*
	(121.0188)	(2.5306)	(1.7843)
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	674	674	674
R^2	0.9669	0.9713	0.9716

To select appropriate matching covariates, the study uses variables extracted from the Penn World Table (PWT) database, including population (lnpop), exchange rate (xr), average working hours (lnhour), capital stock (lncap), and number of employees (lnemp).

In addition, we adopt an annual matching approach to improve the precision of the matching and to better control for confounding factors that vary over time. The results of the PSM-DID test are obtained as shown in Table 7. In all three columns of Table 7, the coefficients of the interaction term, the treatment dummy variable and the time dummy variable are significantly positive at the 5% statistical level. This finding suggests that even after partially accounting for sample selection bias, the conclusion that the use of industrial robots exacerbates income inequality remains robust.

5 Mechanism analysis

Theoretical models and empirical tests have previously indicated that the increased use of industrial robots has contributed to the widening of income disparities among residents. The theoretical framework presented in the second section of this article suggests that the uneven distribution of labour and capital benefits, shifts in job positions among diverse labour forces, and wage disparities resulting from the application of industrial robots are potential mechanisms contributing to the continuous widening of income gaps among residents. To further validate this hypothesis, this article constructs a mechanism testing model as follows:

$$KL_{it} = \beta_0 + \beta_1 robdens_{it} + X'_{it}\gamma + \theta_i + \lambda_t + \varepsilon_{it} \tag{18}$$

$$SUemp_{it} = \beta_0 + \beta_1 robdens_{it} + X'_{it}\gamma + \theta_i + \lambda_t + \varepsilon_{it} \tag{19}$$

$$SUincome_{it} = \beta_0 + \beta_1 robdens_{it} + X'_{it}\gamma + \theta_i + \lambda_t + \varepsilon_{it} \tag{20}$$

In comparison to the conventional factor income share, the average rate of return per component can better identify issues of income distribution inequality. Consequently, this article employs the factor rate of return as a proxy for the factor income share. The specific calculation methods for capital and labour factor return rates are presented in equations

(19) and (20). The labour compensation is defined as the product of the proportion of total labour income over output and the GDP via income approach. The quantity of labour factors is equivalent to the number of employed individuals. In accordance with Basu's (2019) theoretical model, the calculation of GDP utilising the income approach necessitates the aggregation of incomes across all factors of production. Furthermore, price markup shares in imperfectly competitive markets are incorporated into both capital income (such as rent, interest, and profits) and labour income (wages). Therefore, the methodology employed in calculating the capital compensation is justified to some extent. The data on GDP by income approach, the ratio of labour compensation, employment figures, and capital stock are all derived from the PWT database.

The employment gap ($SUemp$) and wage gap ($SUincome$) between skilled and unskilled workers are considered as metrics for measuring job mobility and wage disparity among heterogeneous labor forces, respectively. The data for both metrics are sourced from the International Labour Organization's database (ILOSTAT), which classifies the labor force into high, medium, and low categories according to the International Standard Classification of Occupations (ISCO-08). Accordingly, regressions were performed using the three aforementioned metrics as dependent variables, with the results presented in Table 8. The dependent variables in columns (1) to (3) are the ratio of capital and labor income shares (KL), the employment gap ($SUemp$) and the income gap ($SUincome$) between skilled and unskilled workers.

$$\text{labor income share} = \frac{\text{labor compensation}}{\text{employees}} \tag{21}$$

$$\text{capital income share} = \frac{\text{GDP} - \text{labor compensation}}{\text{capital stock}} \tag{22}$$

As demonstrated in Table 8, the coefficient of the core explanatory variable is markedly positive in all three columns, exceeding the 5% statistical significance threshold. This suggests that the utilisation of industrial robots exerts a positive influence on the three mechanism variables, thereby substantiating the theoretical hypotheses posited in this study. Consistent with our theory, the advancement of industrial robotics significantly improves the capital production efficiency. Nevertheless, the enhancement in labour productivity is comparatively gradual, leading to an increasingly uneven distribution of capital and labor within the market. Furthermore, the advancement of industrial robot technology has a skill-biased characteristic, creating employment opportunities and wage increases for skilled workers while worsening the situations of unskilled workers in job markets. Generally, high-skilled labor is defined as professionals with higher education and less susceptible to replacement by industrial robots. In contrast, low-skilled labor refers to junior workers engaged in routine tasks, typically with lower education. The tasks they perform are relatively straightforward and follow a set sequence of steps, which makes them more vulnerable to the advent of robots.

Table 8: Mechanism analysis

	KL (1)	SUincome (2)	SUemp (3)
robdens	0.9653***	0.3526***	0.0041**
Control vars		Yes	
Country FE		Yes	
Year FE		Yes	
N	674	629	644
R^2	0.9637	0.9612	0.9722

6 The moderating effects of GVC integration

6.1 The moderating effect of GVC participation

Based on the theoretical derivation presented earlier, this article posits that a country's level of GVC embedding exerts a moderating effect on income inequality within the context of automation development. At present, the assessment of GVC integration can be classified into two principal categories. The first method evaluates a country's involvement in GVCs, while the second measures its position within the GVC framework. Accordingly, this article employs the prevailing methodologies to calculate the indicators of GVC participation and position.

The degree of a country's participation in GVC can be gauged by two predominant indicators. The first indicator is the Vertical Specialization Index which measures the degree of involvement by calculating the foreign value-added ratio (FVAR) in a country's export products (Upward et al., 2013). The second method evaluates a country's GVC participation by aggregating the international supply and demand levels of intermediate products used in the country's production process. This approach was proposed by Koopman et al. (2010) and has been extensively applied in GVC-related research. The specific calculation methods for these two indicators and the moderation effect models constructed based on them are as follows:

$$FVAR_{ir} = \frac{FV_{ir}}{E_{ir}} \tag{23}$$

$$par_{ir} = \frac{IV_{ir}}{E_{ir}} + \frac{FV_{ir}}{E_{ir}} \tag{24}$$

$$Gini_{it} = \beta_0 + \beta_1 robdens_{it} + \beta_2 robdens_{it} \times FVAR_{it} + \beta_3 FVAR_{it} + X'_{it}\gamma + \theta_i + \lambda_t + \varepsilon_{it} \tag{25}$$

$$Gini_{it} = \beta_0 + \beta_1 robdens_{it} + \beta_2 robdens_{it} \times par_{it} + \beta_3 par_{it} + X'_{it}\gamma + \theta_i + \lambda_t + \varepsilon_{it} \tag{26}$$

In the aforementioned equations (21) and (22), the variable i represents a specific country, while r denotes the industry. As this study is primarily concerned with the overall trade level of a country, the indicator values have been aggregated across all industries in order to obtain the national-level indicator. In accordance with the methodology proposed by Koopman et al. (2010), IV represents the domestic indirect export value-added for country i. This term denotes the domestic value-added embodied in intermediate products used by an importing country for the production of goods ultimately consumed in a third country. The term FV denotes the foreign value-added embedded within exported goods. E represents the total export value of country i. The data are sourced from the OECD-TIVA database, which is regarded as an authoritative source for input-output analyses.

Table 9: Moderating effect of GVC participation

	Gini					
	(1)	(2)	(3)	(4)	(5)	(6)
robdens	0.3625***	0.5541***	0.5130***	0.3638***	0.6486***	0.5939***
	(4.4939)	(5.8891)	(5.0829)	(3.9243)	(6.0979)	(5.2795)
robdens×FAVR	-7.6291***	-5.1174**	-4.7882**			
	(-3.6398)	(-2.3929)	(-2.1793)			
FVAR	16.1776***	-2.9748	-1.4510			
	(4.1003)	(-0.4909)	(-0.2372)			
robdens×par				-5.7192***	-4.3605***	-3.9243**
				(-3.4712)	(-2.6671)	(-2.3262)
par				10.1402***	-0.6737	-0.6569
				(4.6586)	(-0.1710)	(-0.1653)
lnpgdp		-2.4939***	-2.2326***		-2.5124***	-2.2296***
		(-4.2274)	(-3.6182)		(-4.2286)	(-3.5778)
lngov		-5.2710***	-5.1900***		-5.2882***	-5.1992***
		(-5.2215)	(-5.1440)		(-4.9943)	(-4.9227)
lnindser		-3.1734	-4.0847		-3.2808	-4.1424
		(-1.2344)	(-1.5660)		(-1.2875)	(-1.6025)
lnurban		2.7234	1.7063		2.6638	1.6380
		(0.8434)	(0.5154)		(0.8240)	(0.4931)
lnopen		1.2943	1.1814		1.1056	1.1417
		(1.2319)	(1.1301)		(0.9086)	(0.9422)
popg			-0.4003**			-0.4043**
			(-2.0714)			(-2.0615)
gender			0.7363			0.7802
			(0.3073)			(0.3288)
Constant	33.1790***	71.9020***	74.7378***	32.4548***	73.3816***	75.2251***
	(51.1735)	(4.0830)	(3.5978)	(44.8743)	(4.2220)	(3.6429)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	674	674	674	674	674	674
R^2	0.9656	0.9705	0.9706	0.9661	0.9705	0.9706

Following the calculation of the foreign value-added ratio (FVAR) and the international supply-demand level of intermediate products during the production process (par) for each country, these metrics are subsequently integrated into equations (23) and (24) for regression analysis, as illustrated in Table 9. The initial three columns of Table 4 incorporate the FVAR as a moderating variable, whereas the subsequent three columns utilise the par levels as the moderating variables. Across these six columns, the coefficient of the core explanatory variable (*robdens*) is found to be significantly positive at the 1% statistical level, while the coefficients of the interaction terms are found to be significantly negative at a minimum of the 5% statistical level.

6.2 The moderating effect of GVC division position

In addition to GVC participation levels, a country's income distribution is influenced by its location within GVC. Two countries with identical GVC participation levels may have different levels of GVC position. To offer a more detailed understanding of a nation's GVC integration characteristics, this article introduces the concept of a country's division position within the GVC for further analysis.

The extant literature employs two principal methods for gauging a country's position within the GVC. The initial method is aligned with the GVC participation rate (par), as proposed by Koopman et al. (2010). This index evaluates a country's position within the GVC by assessing the discrepancies between international supply and demand for intermediate products throughout the production process. A higher value indicates that a country is positioned further upstream in the GVC, primarily exporting intermediate products that require additional processing to other countries. In general, countries with a high GVC status are either rich in resources or possess strong capabilities in innovation. Conversely, a lower index value indicates that the country is located further downstream in the GVC, primarily acting as a hub for absorbing foreign intermediate products and assembling them. The specific calculation method for the index pos is as follows, with the meanings of each variable aligned with Equation (21):

$$pos_{ir} = \ln\left(\frac{IV_{ir}}{E_{ir}} + 1\right) - \ln\left(\frac{FV_{ir}}{E_{ir}} + 1\right) \tag{27}$$

In constructing indices of GVC upstreamness and downstreamness, the second method of assessing a country's embeddedness in GVC is based on the physical distance between the production and consumption ends of the industry. Fally (2012) notes that if a larger share of production flows from sector A to sector B, then sector A is considered to be more upstream in the value chain relative to sector B. Antras et al. (2012) define the degree of GVC upstreamness based on the infinite series of industrial sector outputs, and further demonstrate that their method for assessing GVC embeddedness is equivalent to Fally's approach. Accordingly, we develop a simplified method derived from Antras et al. (2012)'s upstream measurement model to calculate GVC upstreamness indices (up) for all industries in forty-five sample countries over fifteen years. The specific calculation formula is as follows:

$$up_{ir} = (I - D)^{-1} Y / Y_{ir} = (I - \Delta)^{-1} 1 \tag{28}$$

The subscripts i and r in equation (28) represent the specific country and industry, respectively. I is an $n \times n$ unit matrix, D denotes the $n \times n$ direct consumption coefficient matrix, and Y is the column matrix of total output. $(I - \Delta)^{-1}$ represents the full demand coefficient matrix (the Leontief inverse matrix), while 1 denotes a column vector where all elements are equal to one. By definition, a country's GVC upstreamness (up) is always greater than one. A higher coefficient of upstreamness indicates that the country's production is more oriented towards the earlier stages of production. This article utilizes the World Input-Output Tables (WIOTs) compiled by the OECD to calculate the full demand coefficient matrices and upstreamness levels for all industries in different countries. Furthermore, using the two above-mentioned methods to measure the GVC division position, the model is constructed with interaction terms of moderating variables as follows:

$$Gini_{it} = \beta_0 + \beta_1 robdens_{it} + \beta_2 robdens_{it} \times pos_{it} + \beta_3 pos_{it} + X'_{it}\gamma + \theta_i + \lambda_t + \varepsilon_{it} \tag{29}$$

$$Gini_{it} = \beta_0 + \beta_1 robdens_{it} + \beta_2 robdens_{it} \times up_{it} + \beta_3 up_{it} + X'_{it}\gamma + \theta_i + \lambda_t + \varepsilon_{it} \tag{30}$$

Table 10: Moderating effect of GVC division position

	Gini					
	(1)	(2)	(3)	(4)	(5)	(6)
robdens	0.4752***	0.5950***	0.5616***	0.5749***	0.8510***	0.7901***
	(5.7999)	(6.2466)	(5.6457)	(3.3313)	(4.8897)	(4.3602)
robdens×pos	-4.1409***	-2.9072***	-2.8518**			
	(-4.0282)	(-2.6497)	(-2.5419)			
pos	9.9762***	-0.5321	0.9659			
	(4.6055)	(-0.1753)	(0.3075)			
robdens×up				-1.8154**	-1.8090**	-1.7053**
				(-2.3257)	(-2.4981)	(-2.2579)
up				0.2105	-0.6202	-0.3492
				(0.1968)	(-0.6770)	(-0.3719)
lnpgdp		-2.5258***	-2.1779***		-2.5440***	-2.2531***
		(-4.1559)	(-3.3319)		(-4.3743)	(-3.6810)
lngov		-5.2879***	-5.2332***		-5.2405***	-5.1655***
		(-5.2847)	(-5.2329)		(-5.1625)	(-5.0906)
lnindser		-3.2587	-4.1826		-3.2629	-4.0827
		(-1.2723)	(-1.6130)		(-1.2711)	(-1.5700)
lnurban		2.7858	1.4961		2.9220	1.8703
		(0.8373)	(0.4343)		(0.9033)	(0.5644)
lnopen		1.0645	0.9596		1.0496	1.0779
		(1.2326)	(1.1083)		(1.2982)	(1.3337)
popg			-0.4220**			-0.4020**
			(-2.0961)			(-2.0619)
gender			0.9394			0.7310
			(0.3935)			(0.3059)
Constant	35.3415***	72.9012***	75.4699***	35.3461***	73.7194***	75.1226***
	(296.7945)	(4.1460)	(3.6186)	(15.4027)	(4.1352)	(3.5181)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	674	674	674	674	674	674
R^2	0.9656	0.9704	0.9706	0.9649	0.9705	0.9706

The results of these regressions are presented in Table 10. The first three columns of

Table 10 utilize pos as the moderating variable, while the subsequent columns use the up as the moderating variable. Columns (1) and (4) do not include any control variables. In contrast, columns (2) and (5) incorporate macroeconomic control variables, and columns (3) and (6) further include demographic control variables. Across these six columns, the coefficients on the core explanatory variable (robdens) are significantly positive at the 1% statistical level. Additionally, the interaction term between industrial robot density and the moderating variables is significantly negative. These empirical analyses suggest that improving a country's integration within global production networks can lessen the effects of industrial robot adoption on income disparities.

7 Heterogeneous analysis

Countries at different stages of development may exhibit variations in the manner in which GVC integration affects income inequality in the context of industrial robot deployment. Accordingly, this study classifies 45 sample countries into distinct groups based on five variables and employs grouped regressions to investigate the differential impact of the moderating factors.

7.1 Technology intensity

Given the disparate effects of industrial robot technology on income disparities across different technology departments (Guo & Su, 2023), increasing the proportion of technologically intensive industries within a nation may positively influence the wealth distribution. This article utilizes the share of medium- technology and high-technology sectors' output in total industrial value added (MHT) from the World Development Indicators (WDI) database to measure a country's level of technological intensity. A country is classified as technologically intensive if its technological intensity exceeds the annual median technological intensity (MMHT) of all countries during the sample period; otherwise, it is classified as non-technologically intensive. In conducting the grouped regressions, this article employs the GVC participation index (par) and the division position index (pos) constructed by Koopman et al. (2010) to measure a country's embedding degree and location within the GVC. Given the differences in distribution and variance between the two sample groups after grouping, we utilize a bootstrap-based Fisher test to compare the coefficients of interaction terms in the regressions.

In columns (1) and (2) of Table 11, we undertake an analysis of the differential performances of GVC participation between non-technology-intensive and technology-intensive regions. By observing the coefficients, it can be found that the interaction coefficients of core explanatory variables and regulating variables in columns (1) is not significant, while the interaction coefficients of core explanatory variables and regulating variables in columns (2) is statistically significant at 5%. It reveals that an increase in the degree of GVC embedding can serve to mitigate the income inequalities caused by industrial robots, particularly in technology-intensive areas. Furthermore, the interaction coefficients of core explanatory variables and regulating variables in columns (3) is not significant, while the interaction coefficients of core explanatory variables and regulating variables in columns (4) is statistically significant at 5%, which demonstrate that the moderating influence of GVC position promotion is predominantly evident in technology-intensive regions. The moderating impact of GVCs on income disparities in the context of automation development is more pronounced in technology-intensive countries. This phenomenon is also supported by existing theoretical literature. Hummels et al. (2014) observed that the changes in the relative prices of labour before and after a country joins the global production network are inversely related to the original labour abundance in that country. It is typical for capital accumulation to be more substantial in technology-intensive areas than in non-technology-intensive ones. Consequently, as technology-intensive countries engage in globalised production, the relative price of labour rises more rapidly, thereby enhancing the moderating effect on income disparities.

Table 11: Heterogeneity Analysis of Technology Intensity

	Gini			
	(1)	(2)	(3)	(4)
	MHT ≤ MMHT	MHT >MMHT	MHT ≤ MMHT	MHT >MMHT
robdens	4.0588	0.3718***	8.9870	0.4015***
	(0.4283)	(2.7194)	(0.7941)	(3.4730)
robdens×par	25.1619	-4.3943***		
	(0.4967)	(-2.6835)		
par	-10.9056	7.9060**		
	(-1.1182)	(1.9893)		
robdens×pos			-52.1690	-2.7847**
			(-0.8551)	(-2.3082)
pos			-6.3281	5.0691
			(-0.7877)	(0.9382)
lnpgdp	-0.9543	-3.5269***	-1.1996	-2.9675***
	(-1.1598)	(-3.5598)	(-1.3130)	(-2.6411)
lngov	-5.1902***	-4.6201***	-5.3397***	-5.3508***
	(-3.4611)	(-3.0643)	(-3.5747)	(-3.5233)
lnindser	-2.5093	1.6982	-3.2601	1.3224
	(-0.7080)	(0.3545)	(-0.9054)	(0.2823)
lnurban	8.4214	-4.8211	6.2115	-6.4797
	(1.5740)	(-1.0816)	(1.0729)	(-1.3201)
lnopen	3.5677**	-3.0687**	1.2167	-1.7132
	(2.0975)	(-1.9979)	(0.9736)	(-1.1400)
popg	-1.1142***	0.2961	-1.0301***	0.1924
	(-3.2682)	(1.3926)	(-2.9934)	(0.8654)
gender	6.1309**	-9.9511**	6.3984**	-10.8155**
	(2.0663)	(-2.2627)	(2.1302)	(-2.3352)
Constant	0.7771	149.1678***	21.5610	154.4986***
	(0.0253)	(5.1307)	(0.7326)	(5.1737)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	331	339	331	339
R^2	0.9720	0.9653	0.9712	0.9649

7.2 Human capital index

As evidenced by existing studies, the advent of industrial robots has a disparate impact on the income levels of those in high-skilled and low-skilled occupations (Acemoglu & Restrepo, 2019). Our mechanism analysis has also corroborated this conclusion. Therefore, enhancing the human capital levels could potentially serve to reduce the income disparities. In this article, we employ the Human Capital Index (HCI) from the World Development Indicators (WDI) database to illustrate the discrepancies within the labour force. Countries with an HCI above the annual median during the sample period are classified as high human capital countries. Conversely, those below are considered low human capital countries. This classification permits a comparative analysis of how human capital distinctions influence the economic impacts caused by robotics, with a view to offering insights that could mitigate the exacerbation of income inequality caused by technological advancement.

In Table 12, the first two columns examines the moderating effects of countries' GVC integration levels and how these effects vary between countries with heterogeneous human capital. The latter two columns explore variations in the GVC positions between the same groups. The interaction coefficients of core explanatory variables and regulating variables in columns (1) and (3) are not significant, while the interaction coefficients of core explanatory variables and regulating variables in columns (2) and (4) are at least statistically significant at 10%., indicating that the effects of GVC integration and position are predominantly evident in high human capital countries. As a nation's overall level of human capital increases, the mitigating impact of GVC participation and division status on income inequality under the background of industrial robot development is enhanced. In comparison to those with lower levels of skill, those with higher levels of skill and advanced education benefit to a greater extent from automation and global trade. These results suggest that improving a country's educational level can facilitate its workforce better adapt to the displacement and creation effects resulting from the application of industrial robots. Consequently, this adjustment could further alleviate income inequality among residents.

Table 12: Heterogeneity analysis of HCI

	Gini			
	(1)	(2)	(3)	(4)
	HCI ≤ $MHCI$	HCI >MHCI	HCI ≤ $MHCI$	HCI >MHCI
robdens	-0.4625	0.7045***	-1.1789	0.6611***
	(-0.1438)	(6.1862)	(-0.3827)	(6.3035)
robdens×par	0.1718	-2.7300*		
	(0.0116)	(-1.6580)		
par	-1.4711	-6.2151		
	(-0.2253)	(-1.5725)		
robdens×pos			5.9318	-2.6890**
			(0.3361)	(-2.4471)
pos			-1.6140	0.3163
			(-0.2776)	(0.0928)
lnpgdp	-1.4662	-2.6642***	-1.5263	-2.7572***
	(-1.4804)	(-3.0864)	(-1.5853)	(-2.8719)
lngov	-6.4516***	-4.6086***	-6.2414***	-4.4442***
	(-3.4659)	(-4.9489)	(-3.3608)	(-4.5842)
lnindser	-10.0869***	6.4656*	-10.2656***	6.9794*
	(-2.7848)	(1.6685)	(-2.9707)	(1.7629)
lnurban	-0.3932	19.1121***	-0.1872	18.5605***
	(-0.0807)	(2.9723)	(-0.0389)	(2.7790)
lnopen	3.4240*	-0.2966	3.3144**	-1.4061
	(1.7423)	(-0.2476)	(2.3538)	(-1.4044)
popg	-0.3921	-0.2163	-0.3623	-0.2561
	(-1.3626)	(-0.8588)	(-1.2685)	(-0.9565)
gender	4.8602	-1.8164	4.7721	-1.6509
	(1.5989)	(-0.7266)	(1.5817)	(-0.6309)
Constant	79.6178***	-23.8971	80.0034***	-21.2095
	(3.2697)	(-0.5568)	(3.2444)	(-0.4874)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	326	348	326	348
R^2	0.9583	0.9847	0.9583	0.9846

7.3 Government governance capacity

Although the analysis above suggests that increasing participation in GVCs and the division of labor is an effective way to mitigate the deterioration of income disparity among residents, it is clear that the phenomenon of wealth disparity triggered by smart development needs to be regulated by further redistributive policies. Since the governance capacity of a government has a significant impact on the implementation of its redistributive policies, this article selects the arithmetic mean of six assessment indicators in the Worldwide Governance Indicators (WGI) database to represent the comprehensive governance capacity of a government for the subsequent test. The reference indicators provided by the WGI database are government effectiveness, government stability, government quality, the rule of law, transparency, and civic participation, which comprehensively consider all aspects of government governance and provide a relatively comprehensive assessment. In terms of sample group delineation, this article uses the median of the average level of governance (MWgi) of governments in each country over a fifteen-year period as the criterion. A country is classified as high governance if the average level of government governance over the sample period is greater than or equal to the median. Conversely, it is classified as a low governance country.

The first two columns of Table 13 mainly examine the differential performance of the degree of GVC embeddedness across countries in low and high governance level countries. The last two columns of Table 13 mainly examine the differential performance of the GVC embeddedness position across countries. The interaction coefficients of core explanatory variables and regulating variables in columns (1) and (3) are not significant, while the interaction coefficients of core explanatory variables and regulating variables in columns (2) and (4) are statistically significant at 5%, which indicates that the degree of GVC embeddedness and division position can mitigate the moderating effect of the widening income distribution gap caused by industrial robots, which is mainly reflected in high governance level countries. The negative moderating effect of increased GVC embeddedness and location on income inequality is more pronounced when a country scores higher on government governance. This implies that the economic growth brought about by the embeddedness of GVCs and the application of industrial robots requires rational redistribution and resource integration by the government and relevant institutions in order to realize a distribution pattern that takes into account both equity and efficiency.

Table 13: Heterogeneity analysis of government governance capacity

	Gini			
	(1)	(2)	(3)	(4)
	WGI ≤ $MWGI$	WGI >MWGI	WGI ≤ $MWGI$	WGI >MWGI
robdens	3.6143	0.2189*	10.3745	0.2201*
	(1.1325)	(1.8044)	(1.5839)	(1.8770)
robdens×par	-30.7774	-4.4948**		
	(-0.9299)	(-2.2806)		
par	-4.8853	0.6751		
	(-0.5890)	(0.2044)		
robdens×pos			-73.1865	-3.2940**
			(-1.4741)	(-2.4097)
pos			-12.7145*	4.0259
			(-1.6705)	(0.8530)
lnpgdp	-2.7680***	-2.2521**	-2.9337***	-2.0707**
	(-3.1358)	(-2.3493)	(-2.9522)	(-2.1314)
lngov	-9.3990***	-3.2399***	-9.1675***	-3.3448***
	(-4.5397)	(-3.0049)	(-4.3976)	(-3.0720)
lnindser	-7.7047*	-2.8292	-8.3609*	-3.4355
	(-1.7860)	(-0.7339)	(-1.9672)	(-0.8865)
lnurban	6.7429	-18.1768**	6.9811	-18.0415**
	(1.4547)	(-2.2654)	(1.3937)	(-2.2292)
lnopen	2.3027	-0.4632	2.3546**	-0.7126
	(1.2382)	(-0.3256)	(2.0240)	(-0.5568)
popg	-0.7117**	-0.2293	-0.6438*	-0.2740
	(-2.0670)	(-1.0239)	(-1.8665)	(-1.2108)
gender	-2.7267	8.8593**	-3.1795	9.3272**
	(-0.9368)	(2.3612)	(-1.0477)	(2.4839)
Constant	99.3020***	119.1675***	102.5095***	118.8146***
	(3.0832)	(2.6453)	(3.2517)	(2.6169)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	297	377	297	377
R^2	0.9680	0.9562	0.9682	0.9562

7.4 Economic freedom

An increase in a country's economic freedom can effectively promote trade liberalization and lead to economic growth, which in turn increases the funds available for promoting industrial robotics applications and further improves the level of industrial robotics adoption (Lawson et al., 2024). At the same time, countries with higher economic freedom usually have more flexible labor markets, can adapt to technological change more effectively, and invest more in training low-skilled labor, which can reduce the risk of unemployment due to technological substitution, thus mitigating the negative impact of industrial robotics applications that exacerbate income inequality (Chen et al., 2021). Therefore, this article selects the economic freedom index provided by the Heritage Foundation to measure a country's economic freedom, and tests whether the effect of increasing the participation in global value chains and the status of division of labor, which can alleviate the worsening of income disparity among residents, has a differential performance in countries with different degrees of economic freedom. The economic freedom indicator provided by the Heritage Foundation covers the overall scores of more than 170 countries and regions since 1995 in nine areas, including freedom of commerce, freedom of trade, fiscal freedom, government size, monetary freedom, freedom of investment, financial freedom, intellectual property rights, and corruption, which is a good measure of a country's degree of economic freedom. In terms of sample group division, this article uses the median of the average economic freedom (MEF) of each country over a fifteen-year period as a criterion. If a country's economic freedom is greater than or equal to the median during the sample period it is classified as a high economic freedom country. Conversely, it is classified as a low economic freedom country.

Table 14: Heterogeneity analysis of economic freedom

	Gini			
	(1)	(2)	(3)	(4)
	EF ≤ MEF	EF >MEF	EF ≤ MEF	EF >MEF
robdens	-5.6531	0.5169***	3.1846	0.4707***
	(-0.7499)	(4.5430)	(0.3064)	(4.4886)
robdens×par	-19.2167	-5.2870***		
	(-0.5995)	(-3.4707)		
par	1.0824	2.2209		
	(0.1385)	(0.5363)		
robdens×pos			-71.2946	-3.0861***
			(-1.4095)	(-2.6761)
pos			-7.2918	0.3946
			(-0.8757)	(0.0908)
lnpgdp	-1.0267	-3.3729***	-0.8349	-3.3147***
	(-1.1355)	(-3.0599)	(-0.9264)	(-3.0115)
lngov	-6.0431***	-4.5186***	-5.8834***	-4.9034***
	(-4.7892)	(-3.1237)	(-4.6181)	(-3.5356)
lnindser	-7.5425*	-1.1752	-7.2755*	-1.3006
	(-1.9440)	(-0.2903)	(-1.8516)	(-0.3105)
lnurban	2.3573	-16.8472**	0.9400	-17.2391**
	(0.4765)	(-2.1127)	(0.1940)	(-2.0927)
lnopen	-0.4110	1.3990	0.0854	1.8845
	(-0.2276)	(0.8324)	(0.0661)	(1.4248)
popg	-1.4913***	0.0668	-1.4641***	0.0361
	(-3.7136)	(0.3028)	(-3.6716)	(0.1586)
gender	3.8478	4.5685	3.8083	4.4029
	(1.1687)	(1.2714)	(1.1758)	(1.1709)
Constant	73.6357**	132.7523***	74.6115**	134.9414***
	(2.2359)	(2.9567)	(2.3033)	(2.9527)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	306	364	306	364
R2	0.9745	0.9723	0.9746	0.9721

The first two columns of Table 14 mainly examine the differential performance of the degree of GVC embeddedness across countries in low and high economic freedom countries. The last two columns of Table 14 mainly examine the differential performance of the embedded position of GVCs across countries. The interaction coefficients of core explanatory variables and regulating variables in columns (1) and (3) are not significant, while the interaction coefficients of core explanatory variables and regulating variables in columns (2) and (4) are statistically significant at 1%, which indicates that the degree of GVC embeddedness and embeddedness position can mitigate the moderating effect of the widening income distribution gap caused by industrial robots, which is mainly reflected in high economic freedom countries. When a country has a higher degree of economic freedom, it can not only promote the widespread application of industrial robots, but also reduce the inequality of income distribution of residents through a more flexible labor market, a better education system, and higher training investment. Therefore, a government should also take into account the promotion of economic freedom in its own country while transforming intelligently.

7.5 Policy interventions

In order to seize the development opportunities brought by industrial robot technology, the world's major economies have taken industrial robots as the forefront and focus of the competition in the science and technology industry, paid unprecedented attention to the application and development of industrial robots, and stepped up planning and layout. Considering that the sample observation period of this paper is from 2005 to 2019, this paper constructs a dummy variable Policy2019 in order to investigate the role of policy intervention. If the governments of various countries introduce relevant industrial robot policies for the first time in 2019 or before, Policy2019 is assigned a value of 1. Policy2019 is assigned a value of 0 if governments have introduced policies for the first time after 2019.

The first two columns of Table 15 mainly investigate the differential performance of the regulatory effectiveness of the degree of global value chain embeddedness in countries with and without policy intervention. The last two columns of Table 15 mainly investigate the differential performance of the regulatory effectiveness of countries' GVC embeddedness. By observing the coefficients, it can be found that the interaction coefficients of core explanatory variables and regulating variables in columns (1) and (3) are not significant, while the interaction coefficients of core explanatory variables and regulating variables in columns (2) and (4) are at least statistically significant at 5%.

Table 15: Heterogeneity analysis of policy interventions

	Gini			
	(1)	(2)	(3)	(4)
	Policy2019=0	Policy2019=1	Policy2019=0	Policy2019=1
robdens	33.5299***	0.6111***	17.8864	0.5552***
	(2.8235)	(4.8792)	(1.5569)	(5.3213)
robdens×par	-29.7005	-4.6098***		
	(-0.6065)	(-2.7905)		
par	-24.0821**	3.2027		
	(-2.4668)	(0.8275)		
robdens×pos			-11.6345	-2.5597**
			(-0.2037)	(-2.4676)
pos			-3.7822	-2.1991
			(-0.4643)	(-0.5969)
lnpgdp	-3.3588***	-1.3510*	-3.3210***	-1.3565
	(-3.9090)	(-1.7749)	(-3.4792)	(-1.6222)
lngov	-1.5632	-6.6284***	-2.4007	-6.8694***
	(-0.8467)	(-5.9495)	(-1.1628)	(-6.1190)
lnindser	-5.3626	-2.9669	-5.3696	-1.8706
	(-1.4001)	(-0.7507)	(-1.3007)	(-0.4616)
lnurban	11.8551**	-5.9456	10.1506	-6.0574
	(1.9721)	(-1.5936)	(1.5170)	(-1.6257)
lnopen	8.4665***	-0.1011	4.0836***	0.7044
	(3.4736)	(-0.0826)	(2.6838)	(0.7795)
popg	-0.3642	0.0189	-0.5525**	0.0149
	(-1.3716)	(0.0824)	(-1.9994)	(0.0620)
gender	3.3713	-6.2413**	5.8363*	-6.4077**
	(1.0385)	(-2.4841)	(1.9583)	(-2.3393)
Constant	2.5818	130.5465***	13.2491	125.4654***
	(0.0790)	(5.1161)	(0.4237)	(5.0174)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	270	405	270	405
R^2	0.9732	0.9721	0.9720	0.9720

This shows that the degree and location of global value chain embedding can mitigate the moderating effect of the widening income distribution gap caused by industrial robots, mainly in countries with policy intervention, that is, in the year 2019 and before the government issued the first relevant policies to promote the development of industrial robots. When a national government introduces relevant policies to promote the development of industrial robots, there will inevitably be more funds and resources poured into the promotion of industrial robots, so as to improve the application level of industrial robots in the country. The application of industrial robots can reduce the cost and improve the quality, improve the total factor productivity and resource allocation efficiency, which will promote the deepening of the embeddisation degree and the improvement of the embeddisation position of countries' participation in the global value chain, so as to effectively mitigate the negative impact of the widening income distribution gap caused by the application of industrial robots (Huang et al., 2024).

8 Conclusion

The increasing development and deployment of industrial robots are reshaping national labor markets and significantly influencing income distribution, thereby exacerbating income disparities among residents. This study incorporates the application of industrial robots into the framework of biased technological progress theory. We posit that industrial robotics amplifies income inequality both between capital and labor and among heterogeneous labor groups. Using a panel dataset covering 45 countries from 2005 to 2019, we empirically examine the relationship between industrial robot adoption and income inequality. The findings demonstrate that the widespread use of robots exacerbates income disparities among residents. Mechanism analysis reveals that the pervasive deployment of robots widens the income gap between capital and labor while simultaneously creating additional employment opportunities and higher wages for skilled workers relative to unskilled workers. These outcomes align with our theoretical hypothesis that automation exhibits characteristics of capital-augmenting and skill-biased technological progress. Moreover, our analysis highlights the moderating role of global value chain (GVC) integration. Specifically, active participation in globalized production networks and improvements in a country's GVC position can mitigate the income inequality effects associated with the adoption of industrial robots.

In light of the aforementioned results, it is evident that a comprehensive policy framework is a crucial to address these challenges. Firstly, reforms in education and skills development are crucial to equip the labour force with complemantory skills to robots. Governments should prioritise investment in vocational training and upskilling programmes, especially for low-skilled workers, while fostering partnerships between educational institutions and industry to align training curricula with labour market needs. In addition, tertiary education systems should be restructured to emphasise the acquisition of skills relevant to automation-driven economies. Mechanisms for lifelong learning must also be put in place to enable continuous upskilling throughout workers' careers, ensuring that the workforce remains adaptable to future technological disruption. Secondly, addressing income inequality requires the implementation of robust income redistribution mechanisms and social security reforms. Governments should strengthen progressive tax systems with the revenues used for social welfare programmes and worker retraining initiatives. The establishment of comprehensive unemployment insurance and temporary income support for displaced workers can provide a safety net during transition periods. In parallel, incentives should be introduced for companies to adopt collaborative robots (cobots), which enhance human-robot cooperation rather than fully replacing human labour, thereby preserving jobs and promoting equitable technology adoption. Thirdly, it is crucial to actively integrate into global value chains while concurrently pursuing economic structural upgrading in order to mitigate the adverse effects of industrial robot adoption on inequality. To better leverage the moderating effects of global production, governments can further strengthen regional economic integration and cross-border cooperation. By participating in regional trade agreements and improving cross-border infrastructure, governments can more effectively facilitate the integration of local firms into global value chain production. Meanwhile, it would be prudent for governments to encourage firms to transition from low-value-added activities, such as basic assembly, to high-value-added stages, such as research and design. In order to facilitate this transformation, it is recommended that traditional policy tools, such as tax incentives and export subsidies, be complemented by targeted industrial policies specific to the robotics sector.

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