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# Production automation and skill premium: a perspective of deepening the division of labor in enterprises

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This article describes the deepening of enterprise division of labor from three dimensions: vertical specialization level (VSI), global value chain (GVC) level and global value chain (GVC) position, and integrates production automation and deepening of enterprise division of labor within a framework to explore the impact of production automation on enterprise skill premium and the mechanism by which production automation affects skill premium by promoting deepening of enterprise division of labor. This article uses the matching data of the International Robotics Federation IFR data, Chinese industrial enterprise data, and Chinese customs data from 2001 to 2014 to conduct an empirical test. The result shows that the improvement of production automation level has expanded the skill premium of enterprises. The amplifying effect of production automation on the skill premium is stronger in firms with high levels of specialization and high levels and positions in global value chains. Improving production automation has expanded the skill premium in the context of deepening the division of labor in enterprises. The mechanism test shows that production automation can promote the deepening of enterprise division of labor, and there are chain and ripple effects of production automation on skill premium from the perspective of deepening multi-level division of labor. Heterogeneity testing shows that the chain and spillover effects have different strengths and weaknesses in the skill premium of general trading enterprises, enterprises in the Middle East, and non-state owned enterprises.

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## Introduction

The revolutionary advancements in IoT, big data, and AI are driving forces ushering industries into an era of rapid automation. This surge in automation not only boosts total factor productivity but also enhances the availability of sophisticated smart products, facilitating the shift from traditional to modern development models. By fostering innovative industries and business paradigms, these technologies pave the way for sustainable, high-quality growth. China has long prioritized the expansion of robotics and automation sectors, recognizing their transformative potential in shaping the future economy. Since 2006, the Chinese government has proposed that intelligent robots should be included in advanced manufacturing technologies in the frontier science and technology, and proposed that by 2025, China should become a global curator of robotics innovation, a high-end manufacturing agglomeration and a new high ground for integrated application, and the automation industry, such as robots, has gained a good momentum of development. According to IFR's statistics on robot stock data (see Fig. 1), the size of China's industrial robot market has been consistently growing over the past decade, with robot stock growing exponentially since 2016 and far exceeding that of developed countries such as the U.S., Germany, the U.K., Japan, and South Korea.

The proliferation of diverse robot types in manufacturing has spurred industrial automation and hastened the "machine replacing man" trend. The application of automation equipment such as robots, on the one hand, can directly replace some unskilled labor positions, such as welding, painting, palletizing, and other highly repetitive and relatively simple tasks (Frey and Osborne 2017); On the other hand, some emerging jobs have been created, such as robotic system operation, maintenance, operation, repair, and related engineering and technology development jobs, which require higher skills and expertise and will increase the demand for skilled labor (Autor 2015). Existing research generally agrees that automation applications displace primarily unskilled labor, while new jobs created tend to increase demand for skilled labor only due to the complexity of emerging technology applications. It's hardly surprising that the rise of automation—particularly robotics—could fuel a growing demand for highly skilled workers while diminishing opportunities for unskilled labor in production. This shift is likely to exacerbate wage disparities between these two groups. While China has seen some reduction in income inequality in recent years, it remains among the world's more unequal societies, with a Gini coefficient consistently above the critical threshold of 0.4. A key driver of this disparity is the widening pay gap between workers of varying skill levels.

At the same time, in the wave of production automation, profound changes have taken place in the form of production organization of enterprises. Whether multinational companies or domestic small and medium-sized enterprises, they gradually focus on their own advantages to develop core businesses, divest intermediate businesses or purchase intermediate products from outside, and the degree of specialization and division of labor among enterprises is constantly deepening (Shi and Li 2020). This leads us to think: Will production automation affect the skill wage gap (or skill premium)? Will production automation affect skill premiums by promoting deeper division of labor among enterprises? This study examines the impact of production automation on the skill premium within enterprises, adopting a division-of-labor perspective. Leveraging matched datasets—including the International Federation of Robotics (IFR) statistics from 2001 to 2014, Chinese industrial enterprise records, and Chinese customs data—the analysis incorporates both automation and labor specialization into a unified framework. The research evaluates not only the direct influence of automation on wage disparities between skilled and unskilled workers but also investigates how automation-driven shifts in labor division contribute to these disparities. To delve into the multifaceted impact of production automation on the skill premium within the framework of enterprise division of labor, this study aims to illustrate the intricacies of this division from three distinct angles: enterprise specialization division of labor, global value chain level and global value chain position. An enterprise's specialized division of labor is essentially a snapshot of how the company internally segments tasks and assigns responsibilities among departments or individuals within the production cycle.Through specialization, enterprises can achieve efficient collaboration and optimization of the production process. In the context of production automation, in order to further improve production efficiency, enterprises tend to use advanced automation equipment to replace unskilled labor. The nifty features of automated gear make it a stellar match for skilled workers, which in turn boosts the need for such expertise and creates a sweet spot for skilled labor. The level of GVCs and the location of GVCs paint a picture of how a company splits its labor forces from the outside looking in. GVCs signify how much of the global production web an economic player can tap into, and they're a key gauge of how that player engages in the global labor split to snag more resources, markets, and profits for its

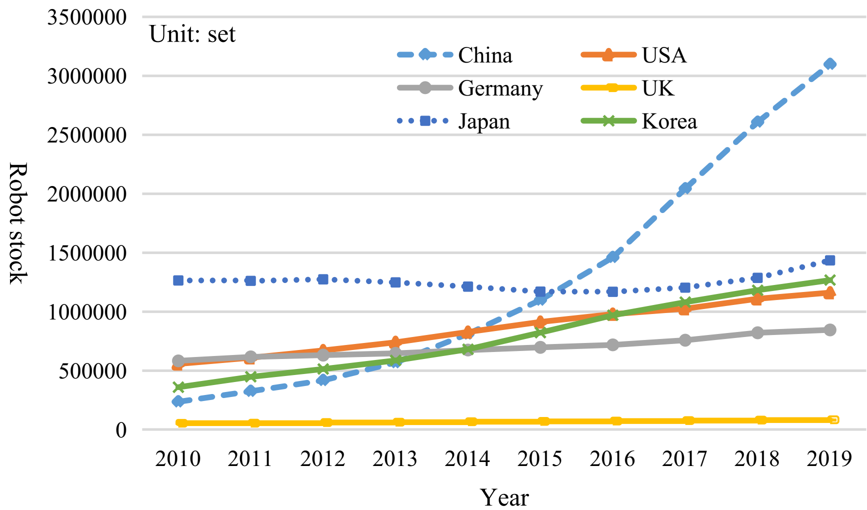


**Fig. 1** Inventory of robots in major countries from 2010 to 2019.

growth and innovation pursuits. The level of an enterprise's GVC emphasizes the extent to which the enterprise participates in value creation on a global scale, while the location of the GVC emphasizes the enterprise's position and role in the GVC. Existing studies point out that the higher the enterprise GVC level and the closer the GVC position is to the downstream, the more it tends to undertake high-skill-intensive production tasks and the more high-skill labor is needed to complete them (Antràs et al. 2012; Liu 2016), which leads to the expansion of the skill premium. This study offers valuable insights into how automation in production affects skill-based wage disparities within the framework of hierarchical corporate labor structures. Its findings not only deepen our comprehensive understanding of this economic phenomenon but also serve as a practical resource for refining income distribution policies—both in China and across the globe. The paper's implications extend beyond academic circles, presenting actionable intelligence for policymakers seeking to address modern labor market challenges.

## Literature review

Technological advancements' effects on employment remain a central issue for labor economists. Since the 1980s, the information technology revolution characterized by the widespread use of computers has led to a "double growth" phenomenon in employment and wages, which has also led to the rapid replacement of new and old jobs, as well as the employment demand and wage differentiation of labor with different skills (Chiacchio et al. 2018; Jung and Lim 2020).

The interplay between automation and various skill levels exhibits varying degrees of complementarity and substitution, showing high complementarity with advanced skills and substitution with basic skills. After the application of automation, the demand for low skilled labor has been relatively reduced, leading to the expansion of the wage gap for highly skilled labor. Autor et al (2003) highlights how advancements in information technology systematically displace low-skilled workers performing repetitive tasks while simultaneously driving up demand for highly skilled labor in non-routine roles. This dynamic, they argue, widens the earnings divide between these workforce segments. Expanding on this, Lankisch et al. (2017) incorporated automation capital into their analysis of skill-based capital accumulation, demonstrating that automation in the U.S. labor market depressed real wages for low-skilled workers while increasing the skill premium. Similarly, Bughin et al. (2018) observed that industrial automation disproportionately reduces opportunities for low-skilled labor, shifting demand toward highly skilled workers. Their findings reveal a stark decline in low-skilled labor's income share—from 33% to just 20%. These trends are not unique to Western economies; Wang et al. (2020) and Hu et al. (2021) corroborate these conclusions within China's labor market context. Their research identifies industrial robots as key drivers of the widening skill premium, operating through both productivity gains and job displacement effects.

Current research primarily explores the impact of automation on skill premiums by focusing on individual workforces, overlooking the effect of internal company labor structures. This paper aims to investigate whether the deepening of this internal division of labor, driven by production automation, further influences the skill premium. While previous studies haven't directly tackled the interplay between these three factors, they have examined the connection between automation and how companies organize their work. Closely related research investigates how the internet and AI are reshaping enterprise specialization. Some scholars are also keeping a close eye on the link between AI and this trend toward increasingly specialized businesses. Shi and Li (2020) reveals that the Internet has played a pivotal role in enhancing labor division within China's manufacturing sector. Similarly, Yuan et al. (2021) demonstrated that advanced digital technologies—particularly big data and AI—drive greater specialization among firms. Scholars have also explored how artificial intelligence influences labor division across global value chains. For instance, Liu and Pan (2020) analyzed manufacturing sector panel data from 38 countries (and regions) using WIOD input-output tables, concluding that AI strengthens a firm's integration and positioning in global value chains by lowering trade barriers and improving resource efficiency. Lv et al. (2020) found that artificial intelligence can achieve a leap in the value chain by replacing low-end labor in enterprises and improving enterprise productivity. Zhang and Li (2022) conducted empirical research using panel data from 2006–2015 at the municipal level, and found that artificial intelligence mainly improves the embedding degree of global value chains in cities through two ways: improving labor productivity and improving labor mismatch. Regarding the relationship between enterprise division of labor and skill premium, Shepherd (2013) believes that enterprises oriented by international division of labor require more highly skilled workers, and production integration will lead to higher wages for skilled workers than for unskilled workers, which increases the degree of wage inequality between the two types of workers. Hummels et al. (2014) found that companies that participate widely in international labor division through offshore outsourcing have a wage elasticity of about −0.022 for low skilled workers and 0.03 for high skilled workers, indicating that outsourcing tends to increase the skill premium within the company. Sheng and Hao (2021) based on China's micro enterprise data, empirical research has found that the participation of enterprises in international division of labor has an inverse U-shaped relationship with the skill wage gap, and changes in the skill structure and profit sharing mechanism caused by enterprises' participation in international division of labor have caused a U-shaped trend in the skill wage gap.

The existing research has explored the dynamics of automation and the skill premium, as well as how automation affects the division of labor within firms. This has offered valuable insights into how production automation impacts the skill premium, particularly by examining how it intensifies the division of labor. However, there are still some gaps in the analysis. Firstly, the existing literature does not integrate production automation, enterprise division of labor, and skill premium within a single framework, building a complete logical system, and systematically studying the formation mechanism of skill premium. Secondly, the existing literature lacks a microscopic mechanism to examine the impact of production automation on skill premiums from the perspective of enterprise division of labor. Finally, the existing literature lacks empirical evidence to study the interaction between production automation, enterprise division of labor, and skill premium. These are also the focus of this article.

## Variable measurement and data source

**Model building**. In order to measure the impact of production automation on skill premiums, this article constructs the following model:

$$SP_{ft} = \alpha + \beta_0 PR_{it} + \beta_1 X + \mu_t + \nu_f + \varepsilon_{ift} \tag{1}$$

Where, subscript $i$ represents industry, $f$ represents enterprise, and $t$ represents year. $\mathrm{SP}_{ft}$ represents the skill premium of enterprise $f$ in year $t$, $\mathrm{PR}_{it}$ represents the production automation degree in the $t$ year of industry $i$, which is the core explanatory variable of this paper. $\beta_0$ is the coefficient of key concern, and the indicator measure of production automation degree will be detailed in the following. $X$ represents a series of control variables, $\mu_t$ represents the fixed effect of the year, $v_f$ denotes firm fixed effects, $\varepsilon_{ift}$ is a random disturbance term.

### Measurement of main variables

*Skill premium*. The dependent variable is the skill premium—the wage disparity between skilled and unskilled workers in a firm. Since the China Industrial Enterprise Database only provided relevant indicators for calculating skill premiums in 2004, this article refers to the methods of Sheng and Hao (2021) to calculate skill premiums, as follows:

$$SP_{ft} = \frac{\left[\ln(\overline{wage_{ft}}/wage^{\eta}_{ft})\right]}{\partial_{ft}} = \frac{\ln(\overline{wage_{ft}}) - \ln(wage^{\eta}_{ft})}{\partial_{ft}} \quad (2)$$

Wherein, $\overline{wage_{ft}}$ refers to the average wage of the enterprise, which is calculated by dividing the sum of the "enterprise payroll payable" and "enterprise welfare payable" indicators in the employment enterprise database by the "total employees at the end of the year". Superscript $\eta$ means unskilled labor. $\partial_{ft}$ represents the proportion of skilled labor and it is calculated by dividing the number of workers with college degree or above by the total number of employees at the end of the year. The industrial and enterprise database only provided the number of employees with different degrees in 2004, and the proportion of skilled labor in other years was based on the idea of Chen et al. (2017). Given that we want to keep as many of the 2004 non-incumbent businesses in the sample as possible, we're going to operate under the assumption that a company's proportion of skilled labor in year t mirrors that of the province it's located in. With that assumption in hand, we can get down to brass tacks and calculate the figures.

*Production automation*. The core explanatory variable of this article is the degree of enterprise production automation. Referring to the practice of Acemoglu and Restrepo (2020), this article uses the inventory of robots per million employed people to construct industry-level production automation indicators. The specific formula is: $\mathrm{PR}_{it} = \mathrm{MR}_{it}/L_{i,2000}$, $\mathrm{MR}_{it}$ represents the industrial robot stock in the th year of the industry, $L_{i,2000}$ indicates the total number of employees in the $i$ industry in 2000, $\mathrm{PR}_{it}$ indicates the degree of production automation of the $i$ industry in year $t$, reflecting the distribution density of automation in a certain industry.

*Vertical specialization level of firms*. When examining corporate organizational structures, vertical integration and specialization exist as opposing forces—like two ends of a seesaw. The more a company embraces vertical integration, the less specialized it becomes in its core operations. Conversely, when businesses focus on specialization, they typically reduce their vertical integration, concentrating instead on excelling within their particular niche. These approaches represent fundamentally different strategic orientations in business management. Therefore for the measurement of the variable of firms' vertical specialization level, this paper refers to Yuan et al. (2021) and Liu et al. (2017), and takes the vertical integration of firms as an inverse indicator of firms' vertical specialization level. The vertical integration of enterprises is measured using the modified Value Added to Sales (VAS) method. The specific measurement formula is as follows:

$$VAS_{adj} = \frac{\text{Value added} - \text{Net profit} + \text{Net assets} \times \text{Average Net Return}}{\text{Sales volume} - \text{Net profit} + \text{Net assets} \times \text{Average Net Return}} \times 100\% \quad (3)$$

The added value is calculated by deducting the cost of sales from total revenue. A company's primary income reflects its sales revenue, while its main business costs account for the expenses tied to those sales. Net profit is derived by subtracting income tax from gross profit. Similarly, net assets are determined by subtracting total liabilities from total assets. The average return on net assets (RONA) represents the mean performance across various industries over time, with each industry's RONA being the quotient of net profit divided by net assets. The reverse indicator of $\mathrm{VAS_{adj}}$ is the degree of specialization of the enterprise, namely, $\mathrm{VSI} = 1 - \mathrm{VAS_{adj}}$. The higher the value of VSI, the higher the degree of specialization of the enterprise. To ensure the effectiveness of the measurement, samples other than $0 \le \mathrm{VSI} \le 1$ are eliminated.

*Global value chain levels of enterprises*. Pursuant to prior literature research and employing the methodology outlined by Lv et al. (2020), the equation for assessing the extent of a company's global value chain is presented as:

$$GVC\_lv = \frac{V_{AF}}{X} = \frac{\{M^P_A + X^O[M^O_{Am}/(D + X^O)]\} + 0.05\{M^T - M^P_A - [M^O_{Am}/(D + X^O)]\}}{X} \quad (4)$$

Among them, $GVC\_lv$ indicates the level of global value chains at the firm level, $V_{AF}$ represents the actual foreign added value of the enterprise, and $X, M, D$ represents export, import, and domestic sales, respectively. The superscript $P, O$ indicates processing trade and general trade, respectively. The subscript m represents intermediate goods under the BEC classification. The specific method is to first convert the customs HS-8 digit product code to HS-6 digit, and then convert it to intermediate goods under the BEC classification according to the Classification by Economic Category provided by the United Nations Statistics Division, excluding consumer goods and capital goods. According to the time interval studied in this article, during the specific conversion process, the conversion table of HS96 was used in 2001, the conversion table of HS02 was used in 2002–2006, and the conversion table of HS02 was used in 2007 The HS07 conversion table was used in 2011, and the HS12 conversion table was used in 2012–2014. $M^T$ represents the intermediate investment of the enterprise. $M^P_A$ represents the actual processing trade import volume of the enterprise, and $M^O_{Am}$ represents the actual general trade intermediate input import volume. For detailed calculation process, refer to Lv et al. (2015). The coefficient of 0.05 represents 5% of the intermediate input value of the enterprise as foreign added value.

*Embedded location of enterprise global value chain*. To figure out where a company sits within the global value chain, the first step is to pinpoint the location index of the global value chain at the industry level. Then, you've got to work out the proportion of each product type based on the specific industry of the company's exports. Finally, you wrap it all up by calculating a weighted sum. When it comes to gauging how far upstream an industry is in the value chain, we're leaning on the method laid out by Antràs et al. (2012), using the following formula:

$$\begin{aligned} GVC\_u_{it} = {} & 1 \times \frac{F_i}{Y_i} + 2 \times \frac{\sum_{j=1}^{N} d_{ij} F_i}{Y_i} + 3 \times \frac{\sum_{j=1}^{N}\sum_{k=1}^{N} d_{ik} d_{kj} F_j}{Y_i} \\ & + 4 \times \frac{\sum_{j=1}^{N}\sum_{k=1}^{N}\sum_{l=1}^{N} d_{il} d_{lk} d_{kj} F_j}{Y_i} + \cdots \end{aligned} \quad (5)$$

Where the subscripts $i$ and $j$ represent specific industries, $N$ represents the total number of industries, $F_i$ represents the final use portion of the output of the $i$ industry, $Y_i$ represents the total output of the $i$ industry, $d_{ij}$ is the input demand coefficient, representing the intermediate input in the output of the $i$ industry needed to produce a unit of final consumer goods in the $j$ industry in a closed economy, $d_{ij} \geq 0$. The numbers 1, 2, 3, and 4 for each item in Eq. (5) indicate the number of production steps. The larger the number, the longer the number of production steps, and the farther away this production link in the value chain is from the final consumer product. The upstream degree of the industry level value chain, $GVC\_u_{it}$, represents the sum of infinite items, $GVC\_u_{it} \geq 1$. The larger the upstream degree index of the industry value chain, the higher the relative position of the industry in the production chain, the higher the embedded position of the value chain, and the closer to the upstream; On the contrary, the closer to the downstream production link, the lower the embedded position of the value chain.

The enterprise value chain location index is weighted based on the industry value chain location index, and the formula is:

$$GVC\_ui_{ft} = \sum_{i}^{N} \frac{X_{fit}}{X_{ft}} GVC\_u_{it} \tag{6}$$

Where, $GVC\_ui_{ft}$ represents the value chain upstream index of enterprise $f$ in year $t$, $X_{fit}$ represents the total export volume of enterprise $f$ in industry $i$ in year $t$, $X_{ft}$ represents the total export volume of enterprise $f$ in year $t$, and $GVC\_u_{it}$ represents the global value chain upstream index of an industry in year $t$. During the specific calculation of the enterprise value chain location index, a key point is how to match the products exported by the enterprise to the industry to which it belongs. For this purpose, this article refers to the method of Tang and Zhang (2018), matching each category of segmented products to the ISIC classification standard based on the HS goods tax code of the enterprise's exported products, and then sorting them out again with the industry in this article to maintain the consistency of industry classification before and after writing.

*Control variables*. Drawing from the current body of research, this article takes steps to control for confounding variables that could influence skill premiums, aiming to mitigate endogeneity issues stemming from omitted variable bias. To be precise: The age of the company (lnage) is calculated by finding the difference between the company's founding year and the current year, adding one, and then taking the natural log. The company's debt-to-asset ratio (lndebt) is determined by dividing total liabilities by total assets, and then logging the result. Company size (lnscale) is gauged by the logged value of the firm's industrial sales. The proportion of state-owned equity (pguozi) is expressed as the ratio of state-owned capital to the company's total paid-in capital. Similarly, the proportion of foreign investment (pwaizi) is the ratio of foreign capital to paid-in capital. Finally, the logged value of per-employee wages (lnsalary) is derived by dividing total wages by the number of employees and then taking the logarithm of that quotient. Enterprise total factor productivity (tfp), the common methods used by academics to calculate the total factor productivity of industrial enterprises include the least squares method (OLS method), Olley and Pakes (1996) (referred to as the OP method) Levinsohn and Petrin (2003) (referred to as the LP method), etc. Unlike ordinary least squares (OLS), both the Olley-Pakes (OP) and Levinsohn-Petrin (LP) methods employ semi-parametric estimation, which can mitigate endogeneity issues to some degree. In contrast to OLS, OP and LP offer a partial fix for endogeneity, simultaneity bias, and selection bias through their use of semiparametric estimation techniques. However, the OP method's reliance on fixed asset investment data—often missing from industrial enterprise databases—can lead to a substantial loss of samples during estimation. The LP method uses the intermediate input variable to replace the fixed asset investment amount, which can reduce the loss of sample size. Beyond intermediate inputs, the Levinsohn-Petrin (LP) methodology requires several key variables to estimate a firm's total factor productivity. These include the company's output, measured as industrial value added; its labor force, represented by year-end employee headcounts; and capital stock, quantified through the net book value of fixed assets. These components serve as fundamental building blocks in the LP approach to productivity analysis.

**Data source**. The data feeding into the realm of production automation, concerning robotic variables, originates from the esteemed International Federation of Robotics (IFR). This entity meticulously tracks the global robot population, categorizing it by sector, nation, and the calendar year. The figures stem from a comprehensive yearly questionnaire distributed to manufacturers, encompassing data from 50 countries spanning from 1993 to 2014. This vast dataset captures about 90% of the industrial robot landscape. It breaks down into six distinct sectors: agri-fishery, mining, manufacturing, utilities, construction, and educational/research/development services. Within the manufacturing sector, data encompasses 13 distinct subfields. These range from the processing and production of food and beverages, textiles and garments, to the crafting of wood and furniture. The sector also touches on paper and printing, the creation of chemical raw materials and products, and the pharmaceutical industry. It includes the production of rubber and plastics, non-metallic minerals, and metal products. Additionally, it covers the manufacturing of general and specialized equipment, vehicles, railway, ship, aerospace, and other transport equipment. The industry extends to electrical machinery and equipment, as well as computers, communications, and a host of other electronic devices. Firstly, the robot data of China from 2001 to 2014 is extracted from the IFR database. Due to the difference between the industry classification in the IFR data and the industry classification used in the Chinese industrial enterprise database, the method of Yan (2020) is used for industry matching. The key distinction lies in how this study categorizes industries: it groups mining, utilities (electricity, gas, and water supply), and transportation equipment manufacturing—including automotive, railway, marine, and aerospace sectors—under a single classification. Additionally, metal processing and smelting operations are consolidated within the metal products sector. The industry-specific robotics data employed in this analysis has been compiled accordingly.

Furthermore, the study integrates information sourced from both the China Industrial Enterprise Database and the China Customs Database, spanning the years 2001 to 2014. The specific processing steps for the data are as follows: (1) Due to the absence of the key indicator for calculating the technical premium of "employee compensation payable" in the 2008–2010 industrial enterprise database, the 2008–2010 data are deleted; (2) Clean up the industrial enterprise database by referring to the method of Nie et al. (2012), and delete samples with abnormal indicators and missing key variables; (3) Consolidate industrial enterprise and customs databases. Referring to the idea of Yu (2015), first use the company name and year to match the two databases. For samples with missing company names that do not match, further use the last 7 digits of the company's postal code and phone number that exist in both databases to match the year again, to obtain enterprise level industry and customs matching data; (4) Next, merge the matched enterprise level data with the adjusted industry classification IFR data by year and industry to obtain the unbalanced panel data required for this study. Furthermore, with the shift in China's industry nomenclature during the data collection timeframe, the category for manufacturing transportation equipment was done away with post-2012, getting split into

**Table 1 Descriptive statistics of main variables.**

| Variable | Obs | Mean | Std.dev. | Min | Max |
|---|---|---|---|---|---|
| SP | 344,669 | 1.074 | 0.088 | 1 | 4.891 |
| PR | 344,669 | 0.181 | 0.541 | 0 | 6.58 |
| VSI | 344,669 | 0.186 | 0.126 | 0 | 0.997 |
| GVC_lv | 344,669 | 0.319 | 0.318 | 0 | 1 |
| GVC_ui | 344,669 | 2.501 | 1.063 | 0 | 9.887 |
| lnage | 344,669 | 2.003 | 0.763 | 0 | 4.605 |
| lndebt | 344,669 | −0.782 | 0.733 | −11.691 | 2.895 |
| lnscale | 344,669 | 11.124 | 1.396 | 3.466 | 19.284 |
| pguozi | 344,669 | 0.028 | 0.144 | 0 | 1 |
| pwaizi | 344,669 | 0.3 | 0.428 | 0 | 1 |
| lnsalary | 344,669 | 2.909 | 0.825 | −4.323 | 12.473 |
| tfp | 344,445 | 4.301 | 1.225 | −5.156 | 10.627 |

specialized sectors like auto manufacturing, rail, marine, aviation, and others. As a result, the stats for transportation equipment manufacturing between 2012 and 2014 were culled from aggregated figures, and those aggregate numbers were adopted consistently in the empirical analysis. All the data on control variables were sourced from the China Industrial Enterprise Database.

In the present analysis, we leveraged various sources for our data. The educational attainment of employees across different regions, instrumental in gauging skill premiums within firms for years aside from 2004, was sourced from the China Labor Statistics Yearbook. The employment figures for China's manufacturing sector, categorized by industry, were culled from the China Industrial Statistical Yearbook. Similarly, data for the mining and the electricity, gas, and water production and supply sectors were obtained from the China Statistical Yearbook. For the U.S. manufacturing sector, employment statistics were provided by NBER-CES, while data for non-manufacturing industries were sourced from the BEA's U.S. Bureau of Economic Analysis. The upstream degree of the industry value chain's measurement was obtained from China's 2002 input-output table. Table 1 presents the descriptive statistics for the primary variables.

## Empirical analysis results

**Benchmark regression**. In order to combat the impact of heteroskedasticity and autocorrelation on estimations, the regressions presented here are industry-clustered. Table 2's columns (1), (2), and (3) delve into the baseline regression that explores the effects of production automation on wage premiums for skills. Column (1) showcases the regression's outcome without any control variables or fixed effects included. The estimated coefficient stands at 0.0226, a figure that's positively significant at the 1% confidence level. This translates to a 0.0226-unit increase in skill wage premiums per unit of automation. When control variables are introduced in column (2), the coefficient for production automation drops to 0.0105, yet it remains positively significant at the 1% level. Column (3), which incorporates both control variables and fixed effects, retains the same positive coefficient, suggesting that enhancing an enterprise's level of production automation will, in turn, boost its skill wage premium.

**Endogenous test**. Direct use of enterprise production automation to analyze its impact on skill premiums may lead to endogenous issues, such as production automation affecting the labor skill premium of enterprises. Conversely, the higher the skill premium, it means that the wages of skilled workers in enterprises are much higher than those of unskilled workers, which will further stimulate skilled workers to actively update their skills and increase

**Table 2 Benchmark regression and endogenous test of the impact of production automation on skill premium.**

| Variable | Benchmark regression | | | Endogenous test | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| PR | 0.0226*** (0.0004) | 0.0105*** (0.0005) | 0.0024*** (0.0005) | 0.0054*** (0.0009) | 11.1952*** (1.8560) | 0.0025*** (0.0024) |
| L.SP | | | | | | 0.0262*** (0.0060) |
| lnage | | 0.0065*** (0.0003) | 0.0018*** (0.0003) | 0.0032*** (0.0003) | 0.0053* (0.0181) | 0.0057* (0.0043) |
| lndebt | | −0.0010*** (0.0003) | −0.0002 (0.0003) | 0.0000 (0.0003) | 0.0198 (0.0197) | 0.0116* (0.0068) |
| lnscale | | −0.0082*** (0.0003) | −0.0029*** (0.0002) | −0.0046*** (0.0003) | −0.0858*** (0.0216) | −0.0024 (0.0050) |
| pguozi | | 0.0123*** (0.0016) | 0.0133*** (0.0015) | 0.0103*** (0.0016) | 0.4108*** (0.1227) | 0.0341 (0.0381) |
| pwaizi | | 0.0102*** (0.0006) | 0.0109*** (0.0006) | 0.0117*** (0.0006) | 0.2080*** (0.0525) | 0.0606*** (0.0089) |
| lnsalary | | 0.0156*** (0.0004) | 0.0205*** (0.0005) | 0.0181*** (0.0005) | 0.1329*** (0.0386) | 0.0108 (0.0071) |
| tfp | | 0.0171*** (0.0003) | 0.0028*** (0.0003) | 0.0033*** (0.0003) | 0.0161 (0.0180) | 0.0055 (0.0071) |
| _cons | 1.0704*** (0.0003) | 1.0273*** (0.0023) | 1.0044*** (0.0154) | 1.0044*** (0.0153) | 0.7550*** (0.3141) | 1.0157*** (0.0029) |
| Kleibergen-Paap rk LM statistic | | | | 263.080[0.000] | 28.077[0.000] | |
| Kleibergen-Paap rk Wald *F* statistic | | | | 190.558[16.38] | 27.552[16.38] | |
| AR (1) | | | | | | [0.000] |
| AR (2) | | | | | | [0.226] |
| Sargan test | | | | | | [0.284] |
| Fixed year | No | No | Yes | Yes | Yes | Yes |
| Fixed firm | No | No | Yes | Yes | Yes | Yes |
| Obs | 344,669 | 344,669 | 344,669 | 344,669 | 344,669 | 136,874 |
| $R^2$ | 0.25 | 0.095 | 0.277 | 0.15 | 0.176 | |

* and *** denote significant at the 10% and 1% levels, respectively, numbers in () are robust standard errors for industry-level clustering, numbers in [] are p values, and AR(1), AR(2), and Sargan report p values corresponding to the statistic. Same below.

the use of automation equipment to improve work efficiency. This suggests a potential bidirectional link between automation in production and the skill premium, which could skew research findings if not properly addressed. To mitigate this issue, employing suitable instrumental variables for analysis is essential.

In examining the academic literature on production automation, it's clear that a range of key approaches for choosing instrumental variables are highlighted. Graetz and Michaels (2018) delve into the realm of robotics adoption across 17 nations globally from 1993 to 2017, deploying two instrumental variables in their analysis. The first variable they employ is an industry-specific "replaceability" metric, a figure that stems from comparing 1980 with 2012 U.S. job statistics. This index assesses the necessity of robotic arm usage in the said industry back in 1980. However, due to the fact that the article's research object is a sample of developed countries, which is essentially structurally different from the use of manufacturing production automation in China, and the lack of data on the relevant industries in China, these two instrumental variables do not apply to the situation in China. In their study of the impact of robot use on industry employment in the U.S., Acemoglu and Restrepo (2020) suggest that due to the competition in manufacturing among large countries that can lead to convergence in technology and equipment, it is reasonable to select the robot installations in Germany, Japan, and South Korea as the instrumental variable.

The instrumental variables selected for this study are grounded in the real-world context of China's manufacturing sector. Covering the period from 2001 to 2014, this timeframe captures a phase of remarkable growth in China's manufacturing competitiveness alongside escalating trade tensions with the United States. Given this backdrop, U.S. industrial robotics data serves as an appropriate instrument. This approach makes sense for three key reasons: first, the competitive dynamics between Chinese and American manufacturers create interdependence in automation investments; second, American advancements in production automation directly influence China's adoption of related technologies; and crucially, the skill premium for Chinese workers remains largely unaffected by automation trends in the U.S. market. Therefore, the instrumental variables constructed in this paper can basically satisfy relevance and exclusivity, and to a certain extent, they are reasonable. Production automation in the U.S. is constructed in the same way as in China, and employment is benchmarked against U.S. employment by industry in 2000. The findings presented in Column (4) of Table 2 reveal the two-stage least squares (2SLS) estimates for the instrumental variables analysis. These results demonstrate a statistically significant positive relationship between production automation and labor skill premiums, providing robust evidence that automation adoption widens the skill-based wage gap within firms. This empirical validation strengthens the case for automation's role in reshaping workforce compensation structures. Compared with the OLS estimation in column (3), the coefficient of production automation is estimated in the same direction, and the value of the coefficient is significantly increased, which indicates that the effect of production automation on skill premium is underestimated due to endogeneity problem. The Kleibergen-Paap rk LM test statistic strongly rejects the null hypothesis of under-identification at the 1% significance level, confirming that the instrumental variables are well-specified. Furthermore, the Kleibergen-Paap rk Wald F statistic comfortably exceeds the Stock-Yogo weak identification threshold at the 10% level, effectively ruling out concerns about weak instruments. These results collectively demonstrate that the chosen instrumental variables are both relevant and robust for the analysis.

We recognize that the choice of U.S. industrial robotics data to construct the instrumental variables is not perfect, as industries in the U.S. and China may be subject to similar macroeconomic shocks. To ensure the robustness of the results, we refer to the idea of Yao et al. (2023) and use the industry average wage as an instrumental variable. The rising industry wage level accelerates the promotion and application of automation in China, suggesting that the average industry wage is highly positively correlated with production automation; at the same time, the average industry wage level does not directly affect the skill premium of firms, is not correlated with the original residual term, and satisfies the exclusivity requirement of the instrumental variable. The estimates presented in column (5) of Table 2 are in line with our main findings, further solidifying the robustness of our instrumental variables approach and lending additional credence to the reliability of our benchmark results.

To tackle the issue of endogeneity, this study employs a dynamic panel model. Specifically, we use the two-step system GMM, incorporating a one-period lag of the skill premium to create this dynamic setup. This allows us to further confirm the impact of production automation on firms' skill premium. Looking at column (6) of Table 2, the $p$ values from the AR(1) and AR(2) tests suggest that the model's residuals aren't serially correlated, indicating a well-specified dynamic panel model. Furthermore, Sargan's test reveals no evidence of over-identification, implying that our choice of instrumental variables is on the mark. The results presented in columns (4)–(6) of Table 2 consistently demonstrate that production automation significantly widens the firm skill premium, even after addressing endogeneity, thus bolstering the robustness of our baseline regression findings.

According to the mean value of the deepening degree of division of labor among multi-level enterprises, the entire sample is divided into groups with low degree of division of labor among enterprises and high degree of division of labor among enterprises. The regression results are shown in Table 3. It can be seen that under the multi-level division of labor in enterprises, production automation significantly increases the skill premium. In firms with a high degree of specialization and a high level and

**Table 3 The effect of production automation on the skill premium in firms with different levels of division of labor.**

| Variable | VSI | | GVC level | | GVC position | |
|---|---|---|---|---|---|---|
| | Low | High | Low | High | Low | High |
| PR | 0.0026*** (0.0007) | 0.0031*** (0.0010) | 0.0015** (0.0007) | 0.0034*** (0.0010) | 0.0027*** (0.0007) | 0.0049*** (0.0013) |
| Control variable | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed year | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed firm | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs | 208,100 | 136,569 | 211,837 | 132,832 | 170,799 | 173,870 |
| $R^2$ | 0.363 | 0.437 | 0.354 | 0.433 | 0.394 | 0.362 |

** and *** denote significant at the 5% and 1% levels, respectively.

**Table 4 Robustness test.**

| Variable | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| PR | | | 0.0014*** (0.0012) | | 0.0026*** (0.0006) |
| treat*period | 0.0048** (0.0007) | | | | |
| Robot import amount | | 0.0029* (0.0003) | | | |
| Robot installation density | | | | 0.0009*** (0.0012) | |
| Control variable | Yes | Yes | Yes | Yes | Yes |
| Fixed year | Yes | Yes | Yes | Yes | Yes |
| Fixed firm | Yes | Yes | Yes | Yes | Yes |
| Obs | 278,364 | 9596 | 236,873 | 344,669 | 333,523 |
| $R^2$ | 0.251 | 0.384 | 0.316 | 0.277 | 0.282 |

*,** and *** denote significant at the 10%, 5%, and 1% levels, respectively.

position in global value chains, production automation has a stronger role in expanding the skill premium, indicating that increasing production automation will expand the skill premium in the context of deepening the division of labor in enterprises.

**Robustness test**. Table 4 reports the robustness test results for five scenarios.

*PSM-DID*. A multi-period double difference model (DID) is used to examine the impact of production automation on skill premiums, and the core explanatory variable, production automation, is replaced by a binary dummy variable that determines whether a company imports robots. According to the HS-8 digit tax code of products in the customs database, a total of 7253 enterprises that imported industrial robots were retrieved. After matching the last 7 digits of the enterprise name, zip code, and phone number with the industrial enterprise database, a total of 3701 enterprises remained, accounting for 51.03% of the total number of imported robot enterprises. If an enterprise imported robots in a certain year, assign a value of 1 to the enterprise in the current year and subsequent years, otherwise assign a value of 0. After the above processing, a total of 11025 observed values from imported robot enterprises are included in the entire sample. After comparison, the relevant data of imported robot enterprises selected in this article are highly comparable to other studies using the same dataset, such as Chen and Yao (2022).

In this paper, enterprises that have imported robots are used as processing groups, and a series of control variables mentioned above are used as matching variables. To minimize any potential bias from how our sample was selected and to get a more accurate picture, we first employed a one-to-one nearest neighbor matching technique based on propensity scores. The results of this matching suggest that, on average, adopting robots leads to a 0.002 bump in the skill premium, a result that's statistically significant at the 1% level. Essentially, this implies that companies that have brought in industrial robots see a 0.002 higher labor skill premium compared to those that haven't. Building on this, we then used a multi-period difference-in-differences model to dig deeper into how importing robots affects these skill premiums. The model we used is as follows:

$$SP_{ft} = \alpha + \phi treat_f{*}period_{ft} + \beta_1 X + \mu_t + \nu_f + \varepsilon_{ift} \qquad (7)$$

Where, $treat_f$ is a processing group virtual variable, with the value of 1 for enterprises that have imported industrial robots and 0 for enterprises that have not imported industrial robots; $period_{ft}$ is a dummy variable for the processing period. For enterprises that have imported industrial robots in the current year and subsequent years, the value is 1, and for previous years, the value is 0. For enterprises that have not imported robots, the value is 0 in each year; $treat_f{*}period_{ft}$ represents a virtual variable of processing effects; The meaning of other variables is the same as that of model (1). The estimated results are shown in column (1) of Table 4. The coefficient $\phi$ of $treat_f{*}period_{ft}$ is 0.0048, which is significantly positive at the level of 5%, indicating that the skill premium of enterprises that have imported industrial robots will significantly increase. That is, improving production automation will significantly increase the skill premium of enterprises. This conclusion is consistent with the benchmark regression results.

*Replacing production automation with the total amount spent by the enterprise on importing industrial robots*. By applying Chen and Yao's (2022) approach, the central explanatory factor has been swapped for the total expenditure incurred by companies on the import of industrial robots. The findings can be observed in column (2) of Table 4, where the estimated coefficient exhibits a statistically significant positive relationship at a 10% confidence interval. When juxtaposed against the baseline regression outcome presented in column (3) of Table 2, the trends align. While the coefficient's magnitude grows, its significance diminishes, yet the essence of the result remains unaltered, suggesting that the initial regression result is indeed robust.

*Replace the sample interval*. Due to the relatively complete indicators and higher data quality in the industrial enterprise database from 2001 to 2007, this article uses the samples from 2001 to 2007 to retest the conclusions based on excluding the samples from 2008 to 2010. The regression analysis presented in column (3) of Table 4 demonstrates findings that align with the initial benchmark results. Both the direction and statistical significance of the production automation coefficients remain consistent, reinforcing the robustness of our conclusions.

*The proxy variable for production automation is expressed as the installation density of industrial robots*. Column (4) displays the regression outcomes, with no alterations to the coefficients' direction or significance, affirming the robustness of the baseline regression findings.

*Beyond the auto sector, which isn't included in the tally, we're talking about sectors like railroads, marine vessels, aviation, and the production of other transport gadgets*. According to the stats from IFR, industrial robots are being utilized at a much higher rate in the automotive field compared to other business realms. Is the impact of production automation on skill premiums caused by large-scale use in the automotive industry? To test whether the impact of production automation on skill premiums is universally significant, Therefore, the automobile industry and other transportation equipment manufacturing industries were excluded[1]. The regression analysis presented in column (5) of Table 4 reveals

**Table 5 Mechanism tests.**

| Variable | (1) VSI | (2) GVC_lv | (3) GVC_ui |
|---|---|---|---|
| PR | 0.0095*** (0.0007) | 0.0489*** (0.0017) | 0.0648*** (0.0075) |
| Control variable | Yes | Yes | Yes |
| Fixed year | Yes | Yes | Yes |
| Fixed firm | Yes | Yes | Yes |
| Obs | 344,669 | 344,669 | 344,669 |
| $R^2$ | 0.308 | 0.217 | 0.229 |

*** denote significant at the 1% levels.

compelling findings. The coefficient for production automation demonstrates a statistically significant positive relationship at the 1% confidence level. This suggests that even outside the automobile and transportation equipment manufacturing sectors, automation continues to drive up skill premiums. These results further validate the robustness of our baseline regression model.

**Mechanism test**. Benchmark regressions and a series of robustness tests confirm that production automation significantly amplifies the skill premium. Does production automation then affect the skill premium by influencing the division of labor in firms and hence the skill premium? In this regard, to mitigate the endogeneity of the division of labor in firms, we refer to Zhang (2020) to conduct mechanism tests. In the first step, we empirically test the impact of production automation on the division of labor in firms; in the second step, we theoretically demonstrate the impact of the division of labor in firms on the skill premium by combining relevant literature. First, to empirically test the impact of production automation on the division of labor in enterprises, this paper constructs the following model:

$$M = \alpha + \beta_{01}PR_{it} + \beta_1 X + \mu_t + \nu_f + \varepsilon_{ift} \tag{8}$$

In Eq. (8), $\beta_{01}$ represents the coefficient of production automation when the enterprise division of labor deepening M is taken as the explained variable, and the meaning of other variables is consistent with Eq. (1). If the $\beta_{01}$ coefficient in Eq. (8) is positive, it indicates that production automation will promote the deepening of enterprise division of labor. The significance of Eq. (8) is that the impact of production automation on skill premiums from this perspective is effective only when there is a significant impact of production automation on enterprise division of labor.

The findings presented in Table 5 reveal a strong positive correlation between production automation and the specialization of labor within firms. All three proxy variables measuring enterprise division of labor demonstrate statistically significant coefficients at the 1% confidence level, clearly suggesting that automation technology plays a crucial role in driving more sophisticated workplace specialization. This is because the application of enterprise production automation can effectively improve the production efficiency of enterprises through reducing the error rate in production, reducing labor costs, and improving the degree of coordination between various elements, thereby expanding the production scale. Expanding the production scale is a boon for businesses to nab top-tier value chain components, which, in return, spurs the intensification of labor specialization and fortifies their standing in the global division of labor (Dai et al. 2017). In addition, industrial robots replace low-skilled labor in firms, and in the process the average quality of the labor force increases, thus contributing to firms' division of labor deepening and international division of labor status. According to the existing literature, firms' division of labor deepening expands the skill premium in three main ways. First, as firms deepen the division of labor, they have access to a wider variety of better-quality and lower-priced intermediate products in both domestic and international markets, which improves the cost markup. The higher the firm's cost markup, the larger the profit margin (Yu and Zhi 2016). OECD (2013) notes that firms' participation in the international division of labor will change the structure of China's skilled labor force, while Jiang and Milberg (2013) argue that this structural change will have a significant impact on workers' wages and bargaining power. Skilled labor has strong bargaining power in the profit distribution chain by virtue of its scarcity, and thus the skill premium for firms expands (Anwar and Sun 2012). Second, by engaging in both domestic and global specialization, companies steadily enhance their expertise through hands-on experience and the diffusion of technological know-how. As innovation increasingly favors advanced skills, the demand for highly trained workers grows, driving up their wages relative to less skilled labor. Third, the increase in the level of enterprise specialization, the level of GVC and the GVC position is conducive to taking on more skill-intensive production tasks, increasing the demand for skilled labor and thus the skill wage premium. It is worth noting that the deepening of the division of labor in firms may cause knock-on and spillover effects, i.e., the deepening of the division of labor may, in turn, require the introduction of more robots and thus affect the skill premium. This is because a high degree of division of labor will enable enterprises to continuously improve their specialized production capacity, and the complex production process will be further divided into repeatable production segments, which creates the conditions for the large-scale introduction of machines and equipment, accelerating the speed of enterprises to replace manual labor with machines, thus affecting the demand for skilled labor and further expanding the skill premium. The analysis reveals that production automation affects the skill premium by altering enterprise labor division.

**Linkage and spillover effects of production automation and enterprise division of labor on skill premiums**. Production automation and enterprise division of labor are mutually causal, and deepening the division of labor will in turn require the introduction of more automation equipment and thus affect the skill premium. In order to identify the linkage and spillover effects of production automation and enterprise division of labor on the skill premium, the following model is constructed:

$$SP_{ft} = \alpha + \alpha_1 PR_{it} + \alpha_2 M + \beta_{02}PR_{it}{}^*M + \beta_1 X + \mu_t + \nu_f + \varepsilon_{ift} \tag{9}$$

Among them, $\alpha_1$ and $\alpha_2$ denote the coefficients of the main effect term, $\mathrm{PR}_{it}{}^*M$ represents the interaction between production automation and enterprise division of labor. This setting can identify the impact of production automation on the skill premium of enterprises with different degrees of division of labor, excluding the possibility of PR changes causing changes in the degree of enterprise division of labor, and then affecting the skill premium. The regression results are shown in Table 6, the main effect coefficients are all significantly positive, and the coefficients of the interaction terms of production automation and enterprise specialization index and value chain division of labor are all significantly positive at the 5% level, indicating that increasing the degree of production automation in the context of deepening the division of labor in the enterprise will more significantly expand the skill premium, which confirms that there is a knock-on and ripple effect of production automation on the

**Table 6 The linkage and spillover effects of production automation on skill premiums in the context of deepening enterprise division of labor.**

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| | SP | SP | SP |
| PR | 0.0036*** (0.0009) | 0.0007*** (0.0007) | 0.0042*** (0.0014) |
| VSI | 0.0874*** (0.0026) | | |
| PR*VSI | 0.0021** (0.0036) | | |
| GVC_lv | | 0.0081*** (0.0008) | |
| PR*GVC_lv | | 0.0032** (0.0014) | |
| GVC_ui | | | 0.0014*** (0.0003) |
| PR*GVC_ui | | | 0.0007** (0.0004) |
| Control variable | Yes | Yes | Yes |
| Fixed year | Yes | Yes | Yes |
| Fixed firm | Yes | Yes | Yes |
| Obs | 344,669 | 344,669 | 344,669 |
| $R^2$ | 0.288 | 0.277 | 0.277 |

** and *** denote significant at the 5% and 1% levels, respectively.

skill premium in the perspective of deepening the division of labor in the enterprise at multiple levels.

**Heterogeneity test**. The study revealed that the adoption of production automation greatly enhances the skill premium for businesses. It also demonstrates a cascading and ripple effect on the skill premium, particularly in the context of intensifying hierarchical labor segmentation. However, it has not been taken into account whether there is a heterogeneous impact in enterprises with different trade methods, regions, and ownership systems. Therefore, this article classifies the entire sample from the following three aspects.

Select a sample of enterprises whose trade mode is processing trade or general trade for heterogeneity analysis. None of the coefficient values for production automation in columns (1)–(4) of Table 7 for processing trade firms are significant, nor are the coefficients of the interaction terms in the proxies for the multidimensional division of labor in firms in columns (2), (3), and (4), indicating that overall, there is no cascading and ripple effect of production automation on the skill premium in processing trade firms. A likely explanation is that processing trade firms primarily import raw materials and parts, leveraging China's abundant and inexpensive workforce to specialize in low-value-added production within the global supply chain. The demand for unskilled labor is greater than skilled labor. The application of production automation in processing trade enterprises needs to be deepened, and the chain and spillover effects of production automation on skill premiums are not obvious in the context of deepening the division of labor among enterprises. The coefficient values of production automation and firm division of labor are significantly positive in columns (5)–(8) for general trading firms, and the coefficients of the interaction term between the proxy variables of firms' multilevel division of labor and production automation are also significantly positive in columns (6), (7), and (8), suggesting that there is a cascading and rippling effect of production automation on skill premiums under the deepening of firms' multilevel division of labor perspective in general trading firms. This is due to the fact that general trading enterprises mainly import intermediate products with a certain technological content, and the good complementarity between technology and skilled workers increases the demand for skilled labor. The higher the degree of production automation, the stronger the company's capital strength. The complementarity between capital and skilled labor further drives the company's skilled labor bias, thereby significantly increasing the skill premium.

In columns (1)–(4) of Table 8 for Eastern and Central firms, the coefficient values of production automation and firm division of labor are significantly positive, and the coefficients of the interaction terms between the proxy variables for multilevel division of labor and production automation are also significantly positive in columns (2), (3), and (4), suggesting that there are cascading and ripple effects of production automation on skill premiums under the deepening of the multilevel division of labor in firms' perspectives in the East and Central firms. In columns (5)–(8) for western firms, the coefficient values of production automation and division of labor are not significant, and the proxy variables for the multilevel division of labor in firms in columns (6), (7), and (8) are not significant, suggesting that there are no knock-on and ripple effects in western firms. This may be due to the large geographical differences in enterprise production automation. The varying degrees of economic advancement and labor market maturity between eastern and central regions lead to distinct responses among businesses when it comes to how automation affects employment. These regional disparities inevitably shape how companies allocate roles and responsibilities within their workforce. Firms operating in the Middle Eastern markets, in particular, find themselves navigating a more dynamic and fiercely competitive commercial landscape. The complementarity between automation and skilled workers will enable enterprises to adjust the structure of labor factors in a timely manner when undertaking different tasks in the international market, increasing the demand for skilled workers, and thereby increasing the wages of skilled workers; Enterprises in the western region are limited to labor abundance and labor market perfection, and their degree of marketization is relatively weak. They remain largely unaffected by shifts in workforce dynamics resulting from automation, and struggle to promptly source qualified workers who can adapt to evolving labor divisions. Consequently, as businesses intensify their specialization, the ripple effects of automated production on skill-based wage gaps remain minimal.

In columns (1)–(4) of Table 9 of state-owned enterprises, the coefficient values of production automation and division of labor among firms are insignificant, and the proxy variables for multilevel division of labor among firms in columns (2), (3), and (4) are insignificant, indicating that there is no cascading and ripple effect in state-owned enterprises. In columns (5)–(8) of non-state-owned enterprises, the coefficient values of production

**Table 7 The impact of production automation on skill premiums in enterprises with different trading methods.**

| Variable | Improvement trade | | | | General trade | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| PR | 0.0013 (0.0008) | 0.0004 (0.0012) | 0.0008 (0.0011) | 0.0014 (0.0020) | 0.0030*** (0.0006) | 0.0050*** (0.0010) | 0.0011*** (0.0008) | 0.0057*** (0.0016) |
| VSI | | 0.0568*** (0.0037) | | | | 0.0946*** (0.0030) | | |
| PR*VSI | | 0.0077 (0.0050) | | | | 0.0055*** (0.0042) | | |
| GVC_lv | | | −0.0051*** (0.0012) | | | | 0.0138*** (0.0010) | |
| PR*GVC_lv | | | 0.0019 (0.0023) | | | | 0.0030* (0.0016) | |
| GVC_ui | | | | 0.0004 (0.0003) | | | | 0.0017*** (0.0003) |
| PR*GVC_ui | | | | −0.0001 (0.0007) | | | | 0.0010* (0.0005) |
| Control variable | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed firm | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs | 113,401 | 113,401 | 113,401 | 113,401 | 197,464 | 197,464 | 197,464 | 197,464 |
| $R^2$ | 0.167 | 0.175 | 0.168 | 0.167 | 0.147 | 0.161 | 0.15 | 0.147 |

* and *** denote significant at the 10% and 1% levels, respectively.

**Table 8 Impact of production automation on skill premium in enterprises in different regions.**

| Variable | Eastern and Central enterprises | | | | Western enterprises | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| PR | 0.0023*** (0.0005) | 0.0034*** (0.0009) | 0.0005*** (0.0007) | 0.0040*** (0.0014) | −0.0097 (0.0169) | −0.0182 (0.0229) | −0.0085 (0.0146) | 0.0004 (0.0249) |
| VSI | | 0.0889*** (0.0026) | | | | 0.0667 (0.0650) | | |
| PR*VSI | | 0.0015* (0.0037) | | | | 0.0964 (0.1522) | | |
| GVC_lv | | | 0.0082*** (0.0008) | | | | 0.0254 (0.0211) | |
| PR*GVC_lv | | | 0.0035** (0.0014) | | | | −0.0001 (0.0269) | |
| GVC_ui | | | | 0.0014*** (0.0003) | | | | 0.0075 (0.0075) |
| PR*GVC_ui | | | | 0.0006* (0.0004) | | | | −0.0039 (0.0115) |
| Control variable | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed firm | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs | 336,811 | 336,811 | 336,811 | 336,811 | 7858 | 7858 | 7858 | 7858 |
| $R^2$ | 0.280 | 0.291 | 0.281 | 0.280 | 0.882 | 0.883 | 0.883 | 0.883 |

*,** and *** denote significant at the 10%, 5%, and 1% levels, respectively.

**Table 9 Impact of production automation on skill premium under different enterprise ownership systems.**

| Variable | State-owned enterprise | | | | Non state-owned enterprises | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| PR | 0.0012 (0.0054) | 0.0043 (0.0081) | −0.0002 (0.0074) | 0.0023 (0.0150) | 0.0024*** (0.0005) | 0.0041*** (0.0009) | 0.0006* (0.0007) | 0.0041*** (0.0014) |
| VSI | | 0.0494*** (0.0109) | | | | 0.0878*** (0.0028) | | |
| PR*VSI | | −0.0100 (0.0313) | | | | 0.0044* (0.0038) | | |
| GVC_lv | | | 0.0101*** (0.0033) | | | | 0.0073*** (0.0009) | |
| PR*GVC_lv | | | 0.0024 (0.0114) | | | | 0.0036** (0.0015) | |
| GVC_ui | | | | 0.0003 (0.0013) | | | | 0.0013*** (0.0003) |
| PR*GVC_ui | | | | −0.0004 (0.0047) | | | | 0.0006* (0.0004) |
| Control variable | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed firm | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs | 31,993 | 31,993 | 31,993 | 31,993 | 312,676 | 312,676 | 312,676 | 312,676 |
| $R^2$ | 0.735 | 0.737 | 0.735 | 0.735 | 0.287 | 0.298 | 0.288 | 0.287 |

*, ** and *** denote significant at the 10%, 5%, and 1% levels, respectively.

automation and enterprise division of labor are significantly positive, and the coefficients of the interaction terms between the proxy variables of enterprise multilevel division of labor and production automation are also significantly positive in columns (6), (7), and (8), suggesting that there are cascading and ripple effects of production automation on skill premiums under the perspective of deepening enterprise multilevel division of labor in non-state-owned enterprises. This may be due to the low degree of monopoly and high market sensitivity of non-state owned enterprises, which can quickly grasp the dynamics of market changes. In order to improve productivity and increase enterprise profits, it will stimulate enterprises to expand the use of automated capital, promote the deepening of enterprise division of labor, thereby undertaking more skilled intensive production tasks with high added value, increase the demand for skilled workers, and reduce the demand for unskilled workers, The skill premium has expanded (Raveh and Reshef 2016). However, state-owned enterprises generally have labor protection systems, and the substitution rate for unskilled workers is low. Some workers who have been replaced by automation will continue to work in posts with low degree of automation through job transfer or vocational training (Hu et al. 2021). The wages of employees in state-owned enterprises are less flexible with market changes, factor marketization lags behind, and the degree of linking wages to enterprise performance is relatively low (Sheng and Hao 2021), These factors are not conducive to deepening the division of labor in enterprises, and the wage gap between skilled and unskilled labor is not significant. Therefore, there is no chain and spillover effect in state-owned enterprises.

## Discussion

**Conclusions and policy recommendations**. This article uses matching data from the International Robotics Federation IFR data, Chinese industrial enterprise data, and Chinese customs data from 2001 to 2014 to test the impact of production automation on enterprise skill premiums, and the impact of production automation on skill premiums through deepening enterprise division of labor. The research results show that the improvement of production automation level has expanded the skill premium of enterprises. The conclusion is still valid after considering the endogenous problems and robustness tests in various situations. The mechanism test shows that production automation can promote the deepening of enterprise division of labor, and the impact of production automation on skill premium is achieved through changes in enterprise division of labor. In the context of deepening enterprise division of labor, improving the degree of production automation will significantly expand the skill premium, which confirms the existence of the interlocking and spillover effect. Heterogeneity testing shows that the chain and spillover effects have different strengths and weaknesses in the skill premium of general trading enterprises, enterprises in the Middle East, and non-state owned enterprises. In processing trade enterprises, western enterprises, and state-owned enterprises, the chain and spillover effects of production automation on skill premiums are not significant.

The policy implications obtained from the article are as follows: First, when enterprises introduce automation technology, it is possible to bring about large-scale unemployment. Therefore, on the one hand, the government should continue to improve income redistribution policies such as unemployment insurance stabilization and return, vocational training subsidies, broadening the scope of benefit from skill upgrading subsidies, and minimum wage protection, to build a strong safety net for unemployment protection; On the other hand, due to the introduction of automation, which has changed the skill set required for occupations, the risk of low skilled workers being replaced by automation is greater. Therefore, the government should guide enterprises to organize job transfers for low skilled workers and targeted job placement training for new technology fields, and provide special funds to encourage enterprises to carry out regular vocational skill training to meet the needs of automation technology through skills competitions, online learning, promotion incentives, and other means. Second, part of the reason for the expansion of the skills premium is the imbalance between supply and demand in the labor market caused by the insufficient supply of skilled labor. Therefore, the government should increase the scale of education investment, encourage enterprises to cooperate with universities and colleges in running schools, reasonably guide universities and colleges in dynamically adjusting their curriculum based on the actual needs of enterprise production and development. Thus, to cultivate more high-quality applied talents that meet the needs of enterprises, to improve the overall skill level of the labor force, to increase the supply of skilled labor, and to alleviate the worsening of the income gap caused by the imbalance between supply and demand. Third, the rise of production automation will disproportionately benefit general trade firms, hybrid trade businesses, companies based in the Middle East, and privately-owned enterprises by substantially boosting their skill premium. the government should accurately implement policies based on specific regions and enterprise types, and reasonably formulate tax policies, employment training policies, etc. to prevent further expansion of the skill premium. Fourth, in the wave of automation reform, enterprises should strengthen their ability to digest and absorb technology, enhance their technological innovation capabilities, and enhance their embeddedness and embedding position in the global value chain, in order to undertake more skilled production tasks with high added value and attract more highly skilled workers for employment.

**Contributions**. Compared with existing studies, the marginal contributions of this paper are (1) This paper portrays the degree of enterprise division of labor deepening from the multi-dimensional perspective of vertical specialization level, GVC level and GVC position, which enables a multi-dimensional and all-encompassing understanding of the relationship between enterprise division of labor deepening, production automation, and skill premium. (2) Instead of discussing production automation or enterprise division of labor separately from each other, this paper integrates production automation and enterprise division of labor within a framework to explore the mechanism of production automation that expands the skill premium by increasing the degree of enterprise division of labor, providing a new research perspective to explain the formation of the skill premium. (3) In terms of research data, this paper does not continue the previous practice of using macro data at the national or industry level, but adopts matched data from the International Federation of Robotics (IFR) data, China's industrial enterprise data, and China's Customs data, to construct a data sample used to study the interaction among production automation, the division of labor in enterprises, and the skill premium. (4) While most of the existing literature examines the skill premium at the macro-national level, this paper goes deeper into the micro perspective of enterprises and explores the micro mechanism of the skill premium from the perspective of enterprises' participation in the specialized division of labor, which is conducive to capturing the micro evidence of the heterogeneous impacts of automation of production and the mechanism of its effects on the skill premium. (5) Taking China as an example, this paper studies the impact of production automation on the skill premium of enterprises, and the chain and ripple effects of production automation on the skill premium under the perspective of the deepening of the multilevel division of labor in enterprises, which provides useful references for China and other countries in the world to improve the income distribution policy and correctly deal with the relationship between production automation and the skill premium in the context of the division of labor in enterprises.

**Limitations**. This study also has some limitations. First, due to data limitations, the data used in this study is up to 2014, which does not fully take into account the policy changes and firm development changes during the recent years of the COVID-19 pandemic. In future studies we try to expand the time span of the data as much as possible and add more recent years to further deepen the study of the production automation on the skill premium. Second, due to similar macroeconomic shocks, the selection of instrumental variables for the U.S. industrial robotics construct in this paper may be imperfect, and we expect to find more appropriate instrumental variables in future studies.

## Data availability

All underlying data used in this study are provided in the Supplementary file.

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## Note

1 Due to the adjustment of China's industry classification standards during the sample period, the classification of transportation equipment manufacturing industry was canceled after 2012, and it was divided into automobile manufacturing, railway, shipbuilding, aerospace, and other transportation equipment manufacturing industries. In order to maintain data consistency, the automobile industry and other transportation industries were excluded.

## References

Acemoglu D, Restrepo P (2020) Robots and jobs: evidence from US labor markets. J Political Econ 128(6):2188–2244
Antràs P, Chor D, Fally T et al. (2012) Measuring the upstreamness of production and trade flows. Am Econ Rev 102(3):412–416
Anwar S, Sun S (2012) Trade liberalisation, market competition and wage inequality in China's manufacturing sector. Econ Model 29(4):1268–1277
Autor DH (2015) Why are there still so many jobs? The history and future of workplace automation. J Econ Perspect 29(3):3–30
Autor DH, Levy F, Murnane RJ (2003) The skill content of recent technological change: an empirical exploration. Q J Econ 118(4):1279–1333
Bughin J, Seong J, Manyika J et al. (2018) Notes from the AI frontier: modeling the impact of AI on the world economy. McKinsey Global Institute
Chen B, Yu M, Yu Z (2017) Measured skill premia and input trade liberalization: evidence from Chinese firms. J Int Econ 109:31–42
Chen D, Yao D (2022) Has artificial intelligence widened the wage gap between enterprises—evidence from Chinese industrial enterprises Econ Sci 44(03):127–142
Chiacchio F, Petropoulos G, Pichler D (2018) The impact of industrial robots on EU employment and wages: a local labour market approach. Bruegel Working Paper Issue. Bruegel
Dai X, Liu M, Zhang WF (2017) How local market scale expansion leads value chain climb. World Econ 40(09):27–5
Frey CB, Osborne MA (2017) The future of employment: how susceptible are jobs to computerisation? Technol Forecast Soc Change 114:254–280
Graetz G, Michaels G (2018) Robots at work. Rev Econ Stat 100(5):753–768
Hu SM, Wang LH, Dong ZQ (2021) Industrial robot application and labor skill premium: theoretical hypothesis and industry evidence. Ind Econ Res 20(04):69–84
Hummels D, Jørgensen R, Munch J et al. (2014) The wage effects of offshoring: evidence from Danish matched worker-firm data. Am Econ Rev 104(6):1597–1629
Jiang X, Milberg W (2013) Capturing the jobs from globalization: trade and employment in global value chains. 2259668
Jung JH, Lim DG (2020) Industrial robots, employment growth, and labor cost: a simultaneous equation analysis. Technol Forecast Soc Change 159:120202

Lankisch C, Prettner K, Prskawetz A (2017) Robots and the skill premium: an automation-based explanation of wage inequality. Hohenheim Discussion Papers in Business, Economics and Social Sciences. University of Hohenheim
Levinsohn J, Petrin A (2003) Estimating production functions using inputs to control for unobservables. Rev Econ Stud 70(2):317–341
Liu B, Pan T (2020) Research on the impact of artificial intelligence on the division of labor in the value chain of manufacturing industry. Quant Econ Tech Econ Res 37(10):24–44
Liu JM, Tang HL, Wu JG (2017) The impact of the comprehensive implementation of replacing business tax with value-added tax on corporate profitability, investment, and specialization: an analysis based on the PSM-DID model of listed companies in Hunan Province. Financ Res 38(12):75–88
Liu Y (2016) Has participation in global value chains widened the income gap-a panel analysis based on cross-country cross-industry. Int Trade Issues 42(04):27–39
Lv Y, Luo W, Liu B (2015) Heterogeneous enterprises and global value chain embedding: a perspective based on efficiency and financing. World Econ 38(08):29–55
Lv Y, Gu W, Bao Q (2020) Artificial intelligence and Chinese enterprises' participation in the division of labor in global value chains. China Ind Econ 38(05):80–98
Nie HH, Jiang C, Yang RD (2012) Current situation and potential problems in the use of Chinese industrial enterprise databases. World Econ 35(05):142–158
OECD (2013) Interconnected economies: Benefiting from global value chains. OECD Publishing
Olley GS, Pakes A (1996) The dynamics of productivity in the telecommunications equipment industry. Econometrica 64(6):1263–1297
Raveh O, Reshef A (2016) Capital imports composition, complementarities, and the skill premium in developing countries. J Dev Econ 118:183–206
Sheng B, Hao BR (2021) Global value chain embedding and skill premium: an empirical analysis based on China's microenterprise data. Int Trade Issues 47(02):80–95
Shepherd B (2013) Global Value chains and developing country employment: a literature review. OECD Trade Policy Papers No. 156. OECD Publishing
Shi BZ, Li JT (2020) Does the internet promote division of labor: evidence from Chinese manufacturing enterprises. Manag World 36(04):130–149
Tang YH, Zhang PY (2018) Research on the location and change mechanism of Chinese enterprises embedded in global production chains. Manag World 34(05):28–46
Wang LH, Hu SM, Dong ZQ (2020) Can artificial intelligence technology induce labor income inequality? Model deduction and classified evaluation. China Ind Econ 38(04):97–115
Yan XL, Zhu BK, Ma Ch (2020) Industrial Robot Use and Manufacturing Employment: Evidence from China. Statistical Research 37(01):74–87
Yao D, Chen D, Zhang YL (2023) Artificial intelligence and intra-firm wage gap: task bias or skill bias. Econ Theory Econ Manag 43(09):99–112
Yu M (2015) Processing trade, tariff reductions and firm productivity: evidence from Chinese firms. Econ J 125(585):943–988
Yu MJ, Zhi K (2016) Import liberalization and corporate profitability. Econ Res 51(08):57–71
Yuan C, Xiao TS, Geng CX, Sheng Y (2021) Digital transformation and enterprise division of labor: specialization or vertical integration. China Ind Econ (09):137–155. https://doi.org/10.19581/j.cnki.ciejournal.2021.09.007
Zhang C (2020) Clans, entrepreneurship, and development of the private sector in China. J Comp Econ 48(1):100–123
Zhang X, Li GQ (2022) Industrial intelligence and the embedding degree of urban global value chains. Sci Res 40(09):1598–1607

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## Author contributions
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## Competing interests
The authors declare no competing interests.

## Ethical approval
This article does not contain any studies with human participants performed by any of the authors.

## Informed consent
Informed consent was obtained from all authors for this article.

## Additional information
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