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RESEARCH ARTICLE

# Unleashing the mechanism among environmental regulation, artificial intelligence, and global value chain leaps: a roadmap toward digital revolution and environmental sustainability

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## Abstract

Strengthening environmental regulation and adhering to the green as well as sustainable development of China's manufacturing industry has become an inevitable trend. Technological innovation leads to industrial transformation, and artificial intelligence becomes a new driving force for core competitiveness and value chain upgrading. Is there a link between environmental regulation, artificial intelligence, and the jump in global value chains? Does AI have a mediating effect? This paper draws the following conclusions through panel estimation: environmental regulation plays a positive role in global value chains, and artificial intelligence has improved the level of global value chains as well. Further analysis of the mediation effect of artificial intelligence finds that artificial intelligence replaces low-end labor, reduces labor costs for enterprises, and promotes the leap of the global value chain. The strengthening of environmental regulation has greatly improved the total factor productivity of enterprises, artificial intelligence has significantly improved production efficiency, and total factor productivity has shown a positive influence on the global value chain as well.


**Keywords** Environmental regulation · Mediation effect · Artificial intelligence · Global value chain leap

## Introduction

With China's economic reform and opening up for 40 years, the manufacturing industry in China has made remarkable achievements. In the past 3 decades, the share of Chinese manufacturing value added in the world economy had gradually jumped from 3 to 28%. More than 200 industrial products are made in China, among over 500 major industrial varieties in the world. However, the rapid economic development has also brought serious environmental problems to China (Irfan et al. 2022; Fang et al. 2022; Sun et al. 2022). The extensive traditional development model has brought about severe waste, severe pollution, severe emissions as well as severe energy consumption (Irfan and Ahmad 2021; Ali et al. 2022). The long-term, large-scale haze has affected the health and quality of life of residents. For all-round green economic development, the central government and local municipal governments have issued corresponding policies to control and control pollution. From 2003 to 2019, among the 407 key monitoring sections of the seven major river systems in China, the sections that meet the water quality requirements of classes I–III have increased from 38.1 to 79.1%, and the sections belonging to the inferior class V water quality have dropped from 29.7 to 3%. Although the environmental quality has been improved through years of efforts, many scholars are still worried. Strict environmental regulations force a large number of polluting enterprises to reduce or stop production, which will seriously affect the local development of the economy (Razzaq et al. 2020; Wen et al. 2022).

Dealing with the problem of pollution issue, although the state has introduced various measures to restrict manufacturing growth, it is not a long-term solution for a rapidly developing manufacturing country like China. While the growth of Chinese manufacturing is facing the internal pressure of environmental pollution, the external competition pressure in the international market is even more serious. On the one hand, affected by the repatriation

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of manufacturing industries in developed countries, China is facing pressure in foreign trade; by contrast, with the disappearance of demographic dividend, China itself suffers from unreasonable industrial structure distribution, low product added value, and "stuck neck" technology. Due to the lack of problems, developing countries take advantage of cost advantages to squeeze the development space of China's manufacturing industry. However, some scholars are optimistic that strict environmental regulation policies will force polluting enterprises to transform and upgrade innovative technologies, and the production capacity will be gradually transferred from high-pollution enterprises to low-pollution enterprises, realizing the transformation and local industrial structural upgrade. The global manufacturing industry is undergoing drastic changes. Traditional comparative advantages are difficult to make Chinese manufacturing continue to move forward, be away from the extensive development model, and accelerate industrial transformation and upgrading to achieve a global value chain, which has been a very tricky issue to solve.

Green sustainable development is one goal for Chinese manufacturing and innovation to lead the industrial transformation. Artificial intelligence has become an important module in the construction of core competitiveness. As a new type of productivity, artificial intelligence brings new kinetic energy to the global scientific and technological revolution and provides new technologies for the reconstruction of the global value chain. In this new wave of technological revolution, developed countries take advantage of the development of AI technology from the national strategic level to improve their own scientific and technological level. For China's own development, the realization of the application of artificial intelligence, a high-end technology, is an important condition for breaking through the technological bottleneck, changing the control of technology by others, and realizing the leap of the global industrial chain and value chain. Artificial intelligence has undoubtedly become a new battlefield for the technological revolution of various countries. In 2015, Chinese President Xi Jinping proposed the "robot revolution," which emphasized the importance of the development of the Chinese intelligent industry first. In the subsequent policy guidelines about the digital economy and internet economy, artificial intelligence has become the focus of national policy promotion. A series of measures by the Chinese government undoubtedly proves that the research and AI technology evolution will play a supporting as well as the leading role. Recently, with the epidemic developing, the global industrial chain growth has been greatly affected. The application of AI technology can enhance the standard of people's livelihood, and at the same time, it will bring opportunities for China to implement technological innovation and realize the leap of the global industrial chain. Artificial intelligence drives the informatization, automation, and personalization of production and sales, which is the key for enterprises to improve their technological level and directly affects a country's production efficiency, employment structure, and participation in the global value chain. Numerous research conclusions show that the use of artificial intelligence technology can not only reduce costs and improve total factor productivity but also directly improve labor productivity. The application of artificial intelligence technology has effectively improved the productivity of existing labor while creating new employment opportunities (Acemoglu and Restrepo 2019). However, existing research mainly focuses on the technology of AI to increase the productivity of existing labor, and there are few comments on the creation of new labor opportunities. It is believed that artificial intelligence brings more impact on existing employment, increasing the relative price of high-skilled labor and low-skilled labor and increasing social inequality. Frey and Osborne (2017) find that the employment of nearly half of the workers in the US is threatened due to the application of AI technology. Chen et al. (2019) is optimistic that reducing the existing labor demand with artificial intelligence can improve China's increasingly serious aging problem. More data from China shows that AI is positively influencing the participation of Chinese manufacturing in global value chains.

The manufacturing industry in China faces an environmental regulation problem but also faces the problem of using artificial intelligence in the manufacturing industry to improve the technical level and optimize the industrial structure of productivity. It seems that there is no correlation between the two, but there is a deep inner connection. Previous studies have not explained this internal link. The "Porter hypothesis" says companies will improve their technological innovation standard of the environment under the pressure of environmental regulation.

Tighter environmental regulations force technological innovation, which requires high-skilled labor to match it. The quality of the labor force is an important factor that determines the state of the department of the labor force in the GVC. The higher the degree of talent quality matching, the more conducive it is to promoting the rise of the global value chain. China's traditional "demographic dividend" relies on the advantage of the traditional low-cost labor force to rely on high professional skills and a high-quality labor force, which is an important goal of China's deep integration of the high-end global value chain. As a new development technology platform, artificial intelligence can not only replace the original low-end labor force but also create new labor. So environmental rules and artificial intelligence can solve each other to a certain extent.

At present, the downward pressure on the economy is increasing. Can environmental regulation and artificial intelligence bring about the innovation of technology, in order to achieve multiple goals of protection of the environment, optimization of domestic labor force structure, and global value chain leap? The main contributions here are the following: (1) Discuss the effects of environmental rules and artificial intelligence on the jump of the GVC. (2) Analyze the transmission of artificial intelligence as an intermediary variable as well as the effects of environmental regulation arising from the GVC.

## Literature review

With the gradual understanding of the regulation of the environment in academia, the economic effect and employment influence on environmental rules have become the focus of discussion. Some scholars find that polluting companies' costs will rise when strict rules of the environment carry out. Polluting companies may have a choice to somewhere with looser regulations (Condliffe and Morgan 2009; Gao 2021; Hou et al. 2013; Cai et al. 2016a). Greenstone (2002)'s research shows the TFP of American polluting companies decreased by 2.6% with the policy of the Clean Air Act, causing industry losses of $21 billion as well. Affected by environmental regulations, the production of polluting industries has been impacted and the economy has slowed down. Scholars who are positive about the economic effects brought about by environmental regulation believe the protection of the environment and the efficiency of the economy can both wins, and that strict environmental protection policies have a favorable impact on improving economic competitiveness (Beeker and Henderson 2000; Berman and Bui 2001a; Ambec et al. 2013). Li et al. (2010), Dong et al. (2011), Chen (2011) and Zhang and Bu (2011) also find similar results through the study of Chinese cases. Strict environmental regulation can allow polluting enterprises to reduce pollution and improve their total factor productivity through technological improvement and equipment upgrades. Some polluting enterprises can improve their profitability through technological innovation and ignore the cost increase caused by environmental regulation (Berman and Bui 2001b). Lanoie et al. 2011; Rassier and Earnhart 2015; Chen (2011); Zhang and Zhao 2012). Strict rules of the environment eliminate the problem of pollution discharge by companies, reduces the discharge of local wastewater and exhaust pollutants, improve the local ecological environment, and attract more investment in green and clean industries, such as the high-end service industry, real estate industry, tourism, and promotes the upgrading of local industrial structure (Li 2013; Gray and Shimshack 2001; Shimshack and Michael 2008; Gao and Gao (2019); Fang et al. 2013).

Scholars with negative attitudes say that rules of environment have a significant part in enhancing corporate research and development, but it has a negative influence on research and development. The affect of the total factor productivity of enterprises is not significant, and the tightening of environmental regulation cannot bring about economic development (Lanoie and Patry 2001; Rubashkina et al. 2015; Gao 2021); someone still think that the connection between the two environmental regulation and international competitiveness is not yet clear (Li et al. 2013; Li and Tao 2012; Yu and Hu 2016).

In an early study of the employment effects of environmental regulation, researchers find that the rules of environment imperil the employment (Morgenstern et al. 2002). However, more recent studies find that environmental protection can lead to employment opportunities. Environmental regulation has two impacts: on the one hand, environmental protection brings increased costs, which will reduce employment; on the other hand, environmental protection promotes the research and development of environmental protection technologies, creating new jobs. The two cancel each other out, resulting in a positive net employment effect (Marx 2010; Bezdek et al. 2008). Empirical research in China finds that the rules of the environment as well as creating job opportunities do not contradict; in addition, the connection between them presents a smile curve. Regulations of the environment have a "threshold." When labor costs increase, rules of the environment in rising employment are weakened (Gao and Song 2018; Gao et al. 2020; Li 2015; Lu 2011; Mi et al. 2012; Lv et al. 2020; Porter 1991; Wang et al. 2013).

There is heterogeneity in the influence of enterprises on environmental regulation. First, regulations of the environment influence Chinese state-owned companies more than non-state-owned companies. They are not only constrained by production costs but also subject to strict control at all levels and higher-level departments. State-owned enterprises have the responsibility to fulfill stricter social responsibilities and will be more standardized in pollution discharge, requiring higher standards and emission control, more stringent. Different from state-owned enterprises, in order to maximize profits, non-state-owned enterprises choose cost-saving extensive production and reduce investment in environmental protection technology research and development (Luo and Qi 2021; Young et al. 2004). Second, compared with non-state-owned companies, the pollution control cost of state-owned companies is greater. Strict environmental regulations force companies to invest a lot of money to adopt new environmental protection technologies, upgrade environmental protection equipment, and improve production processes. Chinese state-owned enterprises have more credit guarantees and financial support than non-state-owned enterprises.

Environmental regulation affects the local industrial structure. Environmental regulation enables resources to be transferred from non-state-owned enterprises with poor financing capacity and high pollution to state-owned enterprises with strong financing capacity and low pollution, thereby promoting the development of the local banking industry. Rules of the environment have a significant effect on the banking development where state-owned companies are occupied (Luo and Qi 2021). Li (2013) and (Yu and Sun 2017) find that due to the promotion pressure of government officials, strict environmental regulations make government managers take the initiative to require local enterprises to develop less polluting, clean, and green industries, thereby local industrial structures are optimized as well as being upgraded. Li (2013) and (Zhang et al. 2020) say that rules of the environment have certain externalities, and the tightening of environmental regulation is conducive to the development of related tertiary industries such as accommodation and catering, real estate, and tourism.

With the rise of artificial intelligence, the informatization and automation of production and sales have gradually led companies to improve the direction of technological upgrading and continue to affect a country's production efficiency, labor structure, and mode of joining in the GVC. Numbers of existing articles say artificial intelligence replaces part of the labor force, reduces the demand for intermediate jobs, and can also create new labor jobs, which leads to inequality in the proportion of labor income (Acemoglu and Restrepo 2019; Frey and Osborne 2017; Chen et al. 2019). Guo (2019) and Chen et al. (2019) find that artificial intelligence promotes the efficient flow of production factors between various sectors, artificial intelligence reduces labor demand, improves capital return and total factor productivity, and affects changes in industrial structure and the division of labor income brought about by changes in sectoral structures. Liu and Dai (2018) analyzed that artificial intelligence replaces low-skilled workers to reduce labor costs, which significantly improves the level of Chinese enterprises' participation in global value chains. Artificial intelligence has brought about the transformation of the population structure, and the advanced labor force enables companies in China to promote their high-quality employment, which enhances the position of their GVC. AI technology has greatly improved corporate productivity as well as facilitated Chinese companies' joining the GVC division of labor. Chen et al. (2019) think that artificial intelligence improves the automated production process and the replacement of labor by intelligent systems and equipment is greater than that of mechanical automation, thereby reducing labor demand. Through empirical research on the US economy, it is found that increasing the use of robots in the production process will reduce the demand for labor. If artificial intelligence can reach the average human labor level, in America over 50% of employment will be replaced by artificial intelligence (Zhao et al. 2014). AI can improve return on capital, savings, and investment rates. When artificial intelligence in the production process develops well, the capital factor gradually replaces the labor factor, the return on investment of capital gradually increases, and productivity is improved. At the same time, the advancement of artificial intelligence promotes technological upgrading, thereby enhancing the improvement of TFP as well as further improving the return on capital (Chen et al. 2019).

To discuss the influence of labor quality on the Chinese global value chain division of labor, Moran (2011) points out that when China and other developing countries absorb foreign direct investment, the technical knowledge spillover effect on their own countries is insufficient, and the main reason for this problem is the host country's human resources. Insufficient capital absorption capacity. Hua (2006) finds that China's low-skilled labor force has certain difficulties in absorbing the knowledge and technology spillovers generated by foreign direct investment, which caused China's "market-for-technology strategy failure." Therefore, it can be seen that the quality matching of factors has an important effect on dividing the work in GVC. The essence of dividing the work in the GVC is the division of labor of various elements of different intensities (such as labor, capital, technology, knowledge, and so on) in each production link. The factor endowment structure is an important factor for a country to be in different positions in the GVC. Countries with high-end factor endowment comparative advantages are correspondingly at the top of the GVC, as well as countries with rich low-end factor endowment comparative advantages are correspondingly in the global value chain. (Deadorff 2001; Lu 2004; Zhang and Fang 2005; Porter 2013; Liu et al. 2016). Through the human capital accumulation method of "learning by doing," human capital can greatly improve the level of a country's join in the global division of labor and obtain more benefits from the division of labor through technological knowledge spillovers. The key to a country's success in international competition is to concentrate its existing resources to produce and export products with human capital advantages. Lu and Luo (2010) point out that human capital has the dual characteristics of regeneration and dynamism at the same time, which has an important impact on the level of division the labor in the GVC. A country's ability to absorb advanced technology and knowledge diffusion is affected by the country's human capital. The relatively low level of human capital in developing countries restricts its ability to absorb advanced technology, which in turn affects the division of the work in the GVC. Through two channels of trade opening and FDI, human capital actively acts as an intermediary and a threshold and promotes the rise of the global value chain by improving the ability of technology absorption and diffusion (Caselli and Coleman 2006; Chen and Zhao 2014). The misallocation of factors caused by the deviation of resource allocation will affect total factor productivity, which is not conducive to economic growth (Yu and Sun 2017). When there is a deviation in the allocation of labor quantity or labor quality mismatch in an industry, it will seriously affect the productivity of this industry. Insufficient factor allocation and mismatch imbalance will bring about low production efficiency (Gao and Gao 2019).

## Theoretical analysis and research assumptions

With the impact of environmental pollution on people's lives, the extensive economic development model with severe pollution as well as severe energy consumption cannot meet the requirements of modern economic development, and a green and clean economy will take its place. Environmental regulation has become a difficult problem that every country needs to solve. Developing countries, limited by resource endowment and technology, mainly produce and export primary products and low-value-added manufactured goods, and the factor allocation of a large number of low-skilled labor matches their own productivity. Strict environmental regulations will cause a large number of enterprises to go bankrupt because they cannot bear the cost of environmental protection, and a large number of the labor force will be unemployed. Therefore, some enterprises may choose "environmental protection" and choose areas with relatively loose environmental regulations for production. The endowment of production factors is an important determinant of a nation's joining in the dividing of the work in the GVC. The extensive economy matched with low-skilled labor can only produce products with relatively low added value and is at a disadvantage in dividing the work in the GVC. The application of AI systems will substitute low-skilled employees, reduce labor costs, improve enterprise production efficiency, and increase product-added value.

When a country's degree of environmental regulation is relatively weak, the demand for low-skilled labor increases, and the country will undertake the transfer from industries with higher pollution levels, forming "brown employment." On the contrary, when a country's degree of environmental regulation is relatively strong, due to green production requires a lot of new technology support, and the demand for high-skilled labor increases, forming "green employment" (Zhang et al. 2020). Artificial intelligence can replace low-skilled workforce, reduce the required quantity for low-skilled employees, reduce labor costs, improve return on capital, and improve enterprise productivity, thereby achieving a leap in the global value chain. This paper puts forward the first hypothesis:

Hypothesis 1: Losing environmental regulations, artificial intelligence replaces low-skilled labor and promotes the jump of the global value chain.

Environmental regulation can effectively guide enterprises to strengthen cleaner production and green manufacturing. To achieve this goal, it is necessary to improve its own technical level, realize the effective use of resources, and adhere to the production mode of manufacturing sustainably developed. Technological progress leads to the differentiation of demand for advanced employment and a disadvanced workforce to a certain extent. When environmental regulations are tightened, enterprises need to bear high environmental protection costs, and enterprises need to improve their own production efficiency and obtain high profits. This will force enterprises to introduce new technologies, improve production lines and production processes, and breakthrough "green barriers." Achieving technological innovation undoubtedly requires a large number of scientific and technological personnel, expanding the demand for high-skilled labor, raising the salary of the advanced workforce, and employment market price guiding disadvantaged workforce to advantage workforce, increasing the supply of high-skilled labor. Artificial intelligence improves the mean level of the workforce, as well as production factors of high-tech labor and high-tech industries, are matched to each other, producing products with higher added value and finally realizing the leap of the global value chain. Secondly, tightening the rules of the environment increases the companies' internal costs and gradually eliminates high-cost enterprises. Advantageous enterprises in the market survive, competitive labor and capital elements are reallocated through the market, and high-quality resources are redistributed. As a scarce resource, artificial intelligence is concentrated in advantageous enterprises, reducing companies' production costs, improving enterprises' productivity, producing more products with high added value, improving the competitiveness of the international market, and realizing the leap of the global value chain. Finally, with the tightening of environmental regulations, enterprises use artificial intelligence technology to improve productivity, enhance the added value of enterprise technology, and achieve a jump in the global value chain. This paper puts forward the second hypothesis:

Hypothesis 2: Tightening environmental regulations, artificial intelligence improves production efficiency and promotes the leap of the global industrial chain.

## Model setting and variable description

### Model settings

Combined with the theoretical analysis above. Drawing on the research method of Chen (2011), this paper sets the following equations to empirically test the connection between environmental regulation, artificial intelligence, and the rise of the global value chain:

(1) Artificial intelligence replaces low-skilled labor

$$\text{staff}_{it} = \beta_0 + \beta_1 \ln \text{market}_{it} + \sum \text{control}_{it} + \text{year}_t + \varepsilon_{it} \tag{1}$$

$$\text{RCA}_{it} = \beta_0 + \beta_1 \ln \text{ER}_{it-1} + \beta_2 \ln \text{market}_{it} + \beta_3 \text{staff}_{it} + \sum \text{control}_{it} + \text{year}_t + \varepsilon_{it} \tag{2}$$

(2) Artificial intelligence improves productivity

$$\text{lnt fplp}_{it} = \beta_0 + \beta_1 \ln \text{market}_{it} + \sum \text{control}_{it} + \text{year}_t + \varepsilon_{it} \tag{3}$$

$$\text{RCA}_{it} = \beta_0 + \beta_1 \ln \text{ER}_{it-1} + \beta_2 \ln \text{market}_{it} + \beta_3 \ln \text{tfplp}_{it} + \sum \text{control}_{it} + \text{year}_t + \varepsilon_{it} \tag{4}$$

### Variable description

In the above model, *i* is the industry, and *t* is the year. The RCA index is the relative ratio of the proportion of industry exports to total exports and the world's industry exports to total exports; ER represents environmental regulation variables, expressed as the ratio of the sum of annual operating costs of wastewater, waste gas, and investment in pollution control to the total output value of the industry (Dong et al. 2011). Considering that environmental regulation has a certain lag on artificial intelligence, the article uses the first-order lag term as an explanatory variable; lnmarketit represents artificial intelligence, which is expressed by the robot intensity of industry *i* in year *t* (Graetz and Michaels 2018). The artificial intelligence level is measured by the logarithm of robot density (lnmarket), that is, the number of robots working per million hours; Σcontrolit represents other control variables in Table 1; staff represents the number of employees; lntfplp represents total factor productivity (Dong et al. 2011).

### Data sources

The article uses 28 manufacturing panel data between 2000 and 2014 as a sample for empirical testing. The data comes from China Statistical Yearbook, China Industrial Statistical Yearbook, China Environmental Statistical Yearbook, China Labor Statistical Yearbook, China Science and Technology Statistical Yearbook, as well as the United Nations UNcomtrade database.

## Results

### Benchmark regression results

As shown in Table 2, column (1) shows the benchmark regression results when the year and industry fixed effects are controlled, respectively. Column (2) represents the results of the benchmark regression controlling for only the year-fixed effects.

**(1) The impact of environmental regulation on global value chains** Since there is a certain time hysteresis from the implementation of the regulatory environment to its actual effect, this paper introduces the rules of the environment's first-order lag term into the model. As it is shown in Table 2, the variables were significant at the 1% level, which means that the rules of the environment have a positive influence on global value chains. The traditional theory believes that rules of the environment induce the deepening of the internalization of environmental costs, and the growing cost makes companies overburdened, diverts the efficiency of enterprise resource investment, and reduces the competitiveness of enterprises. However, the "Porter hypothesis" believes that the tightening of environmental regulations makes enterprises have to improve technology for green production. This "innovation compensation effect" and "first-mover advantage" form the fresh competitiveness of companies. Constrained by environmental regulations, forward-looking

**Table 1** Description of other control variables

| Control variables | Description |
|---|---|
| Level of capital agglomeration (lnkl) | The average annual balance of net fixed assets is divided by the number of employees in the enterprise, and then the logarithm is taken |
| Age | Subtract the year the business was founded from the current year, then add 1 |
| External financing capacity (extFinCap) | Ratio of interest expense to capital requirement |
| Industry agglomeration level (hhi) | Herfindahl index for industry |
| Enterprise size (lnassets) | Gross value of fixed assets and logarithm |

**Table 2** Benchmark regression results

| | (1)RCA | (2)RCA |
|---|---|---|
| lnER | 0.0512***<br>(0.0002) | 0.0222***<br>(0.0015) |
| lnmarket | 0.0033***<br>(0.0003) | 0.0012***<br>(0.0003) |
| lnkl | 0.0087***<br>(0.0008) | 0.0005<br>(0.0005) |
| Age | −0.0020***<br>(0.0002) | −0.0008***<br>(0.0002) |
| extFinCap | −0.0037***<br>(0.0001) | 0.0002<br>(0.0003) |
| hhi | 0.0999***<br>(0.0210) | 0.0011<br>(0.0088) |
| lnassets | 0.0199***<br>(0.0005) | 0.0101***<br>(0.0006) |
| Year fixed effect | Yes | Yes |
| Industry fixed effects | Yes | No |
| Number of samples | 510,001 | 500,213 |
| $R^2$ | 0.0350 | 0.0301 |

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

companies have introduced new types of polluting equipment and improved production lines and process levels in order to meet the standards, thereby breaking through the "green barriers," enhancing international competitiveness, and realizing a leap in the GVC.

**(2) The impact of artificial intelligence on the GVC** As shown in Table 2, the influence coefficients of artificial intelligence on the GVC are 0.0033 as well as 0.0012, both of which are significant at the 1% level, which represents that artificial intelligence has improved the level of the global value chain. On the one hand, the application of artificial intelligence systems replaces low-skilled labor, reduces the cost of labor input, improves the profitability of enterprises, and improves labor productivity, which is conducive to the production of high-value-added products and improves the dividing of the workforce in the GVC. On the other hand, the application of artificial intelligence makes some low-skilled laborers turn to high-skilled laborers through training, "learning by doing" and other methods. High-skilled labor brings the innovation of technology as well as enhances the productivity of enterprises. At the same time, the mutual matching of high-tech industries and high-skilled labor has further upgraded the industry and realized the leap of the global value chain. The production automation, efficiency, and intelligence brought by artificial intelligence have promoted the upgrading of the industry, enhanced the international competitiveness of Chinese manufacturing enterprises, and improved the level of Chinese companies joining the GVC.

**(3) The impact of other variables on global value chains** In Table 2, the level of capital agglomeration has a positive and significant influence on the GVC (0.0087), which indicates that capital agglomeration reduces the cost of using funds for enterprises and improves the production efficiency and competitiveness of enterprises. First of all, when environmental regulations are tightened, companies are forced to carry out technological innovations, and capital needs to increase. Companies with strong competitiveness gradually eliminate companies with weak competitiveness, resources are optimized, and capital is once again concentrated in high-quality companies, which contribute to the added value of products, the realization of industrial upgrading, and the leap of the global value chain. Secondly, state-owned enterprises have more social responsibilities for environmental protection than others. Meanwhile, state-owned companies have more financial strength and talent reserves than other companies and can have financial support from the market. Innovative technologies can improve the level of technological production, enhance quality products, as well as increase the division of the workforce in the GVC.

The level of industry agglomeration has a positive and significant influence on the GVC (0.0999), which indicates that industrial agglomeration produces technology as well as knowledge spillovers, enhances innovation of technology capability of enterprises, and improves the production capacity of enterprises, making enterprises climb to both ends of the global value chain. Environmental regulation enables industries in the region to share public goods with each other, free flow of high-tech labor in the region and realizes the effects of knowledge as well as technology spillover. The dissemination of knowledge in the agglomeration area is beneficial to the companies' innovation technology as well as to producing stronger international products for enterprises. Competitive products lay the foundation.

Firm size significantly affects GVCs (0.0199), which indicates that larger firm size has a stronger impact on GVC jumps. As discussed above, state-owned companies are less influenced by the rules of the environment than non-state-owned. In addition, state-owned companies have more dominant in enterprise-scale than other companies. Larger enterprises can attract more high-quality talents and financial support. These elements are necessary conditions for enterprises to achieve high-quality production, and industrial optimization and upgrading are also important factors for realizing the leap of the global value chain.

## Analysis of the mediation effect of artificial intelligence

### Artificial intelligence replaces low-skilled labor

As shown in Table 3, environmental regulation has a negative significance (− 0.0013) for low-end labor at a 1% level, which indicates that relaxed regulations of the environment have increased the demand for low-skilled labor. First, when a region has strict environmental regulations, it will bring certain pressure on environmental protection costs to local enterprises. For extensive and low-factor endowment industries, they choose to withdraw and transfer to regions with relatively loose environmental regulations. Extensive enterprises gather in areas with loose environmental regulations, which brings demand for low-skilled labor. Secondly, non-state-owned enterprises choose to agglomerate in areas with looser environmental regulations than state-owned companies because of the lack of capital, technology, and high-end labor. The looser the environmental regulations, the more concentrated non-state-owned enterprises, and the larger quantity of demand for low-end labor.

The influence coefficient of AI on the low-end workforce of companies is − 0.0012, at a 5% level, which indicates that artificial intelligence replaces the low-end labor force and reduces the labor cost of enterprises. The application of artificial intelligence systems can save labor time, reduce the demand for simple labor, reduce labor costs, expand corporate profits, and improve corporate production efficiency. The use of artificial intelligence is essential to simplify cumbersome processes through robots, improve efficiency, and solve the growing labor cost problem caused by labor shortages.

Low-skilled labor has a negative effect on the GVC at a 5% level (− 0.0005), which suggests that reducing low-skilled workers promotes global value chain jumps. The development of artificial intelligence replaces low-skilled labor and reduces the production cost of enterprises. The demand for low-skilled labor has been greatly reduced, prompting the labor force to shift to high-skilled labor through training, enhancing the competitiveness of enterprises and realizing the leap of the global value chain. Artificial intelligence systems can replace complex and dangerous processes that require many years of experience, replace labor with by robots, and replace labor comparative advantages with capital comparative advantages to achieve industrial upgrading.

### Artificial intelligence improves productivity

In Table 4, the effect of environmental regulation on total factor productivity is positive (0.0034) at a 1% level, which indicates the strengthening of environmental rules significantly improves the TFP of enterprises. Strict environmental regulations make enterprises have to adopt advanced technologies, improve technological processes, and reduce environmental pollution. The use of

**Table 3** AI mediation effect (labor force)

| | (1) Staff | (2) RCA |
|---|---|---|
| lnER | − 0.0013*** (0.0002) | 0.0222*** (0.0015) |
| lnmarket | − 0.0012** (0.0005) | 0.0012*** (0.0003) |
| Staff | | − 0.0005** (0.0002) |
| lnkl | 0.0007 (0.0001) | 0.0005 (0.0005) |
| Age | − 0.0006* (0.0003) | − 0.0008*** (0.0002) |
| extFinCap | 0.0009 (0.0002) | 0.0002 (0.0003) |
| hhi | 0.0001 (0.0003) | 0.0011 (0.0088) |
| lnassets | 0.0234** (0.0002) | 0.0101*** (0.0006) |
| Number of samples | 234,890 | 500,213 |
| $R^2$ | 0.0288 | 0.0301 |

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

**Table 4** The mediating effect of artificial intelligence (total factor productivity)

| | (1) lntfplp | (2) RCA |
|---|---|---|
| lnER | 0.0034*** (0.0001) | 0.0018*** (0.0002) |
| lnmarket | 0.0016*** (0.0002) | 0.0022*** (0.0005) |
| lntfplp | | 0.0006** (0.0001) |
| lnkl | − 0.0036 (0.0006) | − 0.00012 (0.0008) |
| Age | 0.0023* (0.0001) | − 0.0018*** (0.0009) |
| extFinCap | − 0.0009 (0.0008) | − 0.0072 (0.0012) |
| hhi | − 0.0034 (0.0002) | 0.0071 (0.0008) |
| lnassets | 0.0004** (0.0001) | 0.0001*** (0.0006) |
| Number of samples | 345,980 | 450,210 |
| $R^2$ | 0.0218 | 0.0321 |

***, **, and * indicate significant at the 1%, 5%, and 10% levels, respectively advanced technology requires companies to employ high-quality labor, thereby greatly increasing the productivity of enterprises. Enterprises with clean, environmentally friendly, and green production can get more financial support, and the input of a large amount of capital once again provides conditions for technological innovation and further enhances the total factor productivity of enterprises.

AI has a positive correlation with TFP at a 1% level (0.0016), which shows that artificial intelligence has dramatically improved the productivity of enterprises. The use of artificial intelligence is essentially the replacement of ordinary workers by robots, simplifying complex procedures and improving production efficiency. Artificial intelligence has replaced low-end labor, but the design and maintenance of artificial intelligence still require high-tech labor and a lot of capital. The use of high-end factors provides a firm's TFP.

TFP has a positive effect on the GVC, and it is significant at 5%, which represents the improvement of TFP contributes to the jump of the GVC. The strengthening of environmental regulation has forced enterprises to introduce new production technologies, expand the demand for a high-end labor force, improve the overall quality of the labor force, improve enterprise productivity, and finally realize the leap of the global value chain. The improvement of total factor productivity enables enterprises to have more profit space, and enterprises are more capable of seeking high-tech labor and high-end technology. These more advanced production factors provide feedback to enterprises, increase the added value of products, and upgrade the industrial structure. The industry climbs to both ends of the global value chain.

## Conclusion

This article takes the panel data of 28 Chinese manufacturing between 2000 and 2014 as samples. Based on the data from the UNcomtrade database of the United Nations, this paper empirically examines the connection between rules of environment, artificial intelligence, and the jump of the global value chain. There are several conclusions below:

Firstly, the first-order lag term of rules of the environment in the model empirical test finds that environmental regulation has a positive influence on global value chains. AI has improved the GVC. Judging from the impact of other variables on the GVC, the level of capital agglomeration has a positive and significant effect on the GVC, which represents that capital agglomeration reduces the cost of using funds for enterprises and improves the production efficiency and competitiveness of enterprises; industry agglomeration has a positive as well as a significant influence on the GVC, which represents that industrial agglomeration produces knowledge and technology spillovers, enhances the technological innovation capability of enterprises, improves the production capacity of enterprises, and makes enterprises climb to both ends of the GVC; the scale of enterprises significantly affects the global value chain. This suggests that larger firms have a stronger influence on GVC jumps.

Secondly, the analysis of the mediation effect of artificial intelligence finds that artificial intelligence replaces low-end labor, decreases the labor cost of firms, as well as reducing low technology to promote the jump of the global value chain. Rules of the environment have a negative significance on low-end labor at a 1% level, representing that relaxed rules of the environment have increased the demand for low-skilled labor; artificial intelligence has a negative impact on low-end labor at 5%. It is significant at the level of 5%, which represents that artificial intelligence replaces low-end labor and reduces the labor cost of enterprises; low-skilled labor has a negative influence on the GVC at the 5% significance level, which shows that reducing low-skilled labor promotes global value chains jump.

Finally, the strengthening of rules of the environment has dramatically improved the total factor productivity of enterprises. Artificial intelligence has significantly improved the productivity of firms, and total factor productivity has shown a positive influence on the global value chain. The influence of rules of the environment on TFP is 0.0034 at a 1% significance level, which represents that the strengthening of rules of the environment has significantly improved the total factor productivity of enterprises; artificial intelligence has a significant effect on total factor productivity at the 1% significance level. A positive correlation means that artificial intelligence has significantly improved the production efficiency of enterprises; total factor productivity has a positive impact on the GVC at a 5% significance level, which represents the improvement of total factor productivity contributing to the global value chain jump.

Combined with the research conclusions, this paper proposes the following policy implications:

(1) Strengthen environmental control and build a long-term mechanism for cleaner production in the industry. The government needs to formulate and improve regulatory policies, adjust the relative prices of factors by setting a resource tax, and force enterprises to transform to an intensive and clean way; encourage technological research and development of enterprises, and provide research and development subsidies and tax relief for enterprises that implement clean production technology. Regulatory

policies are more conducive to exerting the positive effect of rules of the environment on the rise of the global value chain.

(2) Strengthen the training of high-end skilled talents and realize the leap of the global value chain by obtaining "talent bonus" and strengthening environmental regulation. Tighter environmental regulations have increased the demand for high-quality labor, which will become a new driving force in the transformation as well as the development of Chinese manufacturing. In order to avoid the mismatch between labor skills and market demand, the government has to combine major national strategic needs with personnel training, make full use of educational resources, promote the training of high-skilled personnel, and enhance international competitiveness.

(3) Seizing the opportunity of the rapid upgrading of AI, the advantages of traditional low-skilled labor have gradually disappeared. Using a new generation of Chinese AI technology is a key way to optimize the manufacturing structure, resist the competition of low-cost labor in developing countries, and break through the technological barriers of developed countries' paths. How to rely on artificial intelligence for "intelligence + manufacturing" will be the key to promoting Chinese enterprises to join the division of workforce in the GVC.

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**Materials availability** The datasets generated and/or analyzed during the current study are not publicly available due to the confidentiality agreement of the patent data but are available from the corresponding author on reasonable request.

## Declarations

**Ethical approval** Not applicable.

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