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CAN TALENT ALLOCATION DRIVE TRANSFORMATION AND UPGRADING OF EXPORT TRADE THROUGH TECHNOLOGICAL INNOVATION UNDER LOW-CARBON BACKGROUND

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Abstract. Under the low-carbon background, regional talent allocation and transformation and upgrading of export trade are all important issues of common concern among academic circles in the stage of sustainable economic and environmental development. This paper explores talent allocation's impact on the transformation and upgrading of export trade. Based on the results, the improvement in regional talent allocation level has significantly increased the percentage of regional general trade exports. It is conducive to the transformation and upgrading of export trade, and such an influence also shows the nonlinear characteristic of increasing "marginal effect". This conclusion still stands after a series of robustness tests. According to the influencing mechanism test results, the technological innovation brought by the improvement in regional talent allocation level is an important transmission channel for such improvement to facilitate the transformation and upgrading of export trade. Based on the multi-dimensional analysis of the results of transformation and upgrading of export trade, regional talent allocation has significantly enhanced the complexity of exported technologies and actively promoted innovation among exporters. The research provides important inspiration for further promoting the structural reform of regional talent allocation and facilitating the transformation and upgrading of export trade patterns.

Keywords: regional talent allocation, transformation and upgrading of export trade, technological innovation, low-carbon economy, sustainability.

JEL Classification: Q55, F16, F18, O32.

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1. Introduction

Under the low-carbon background, China, the largest developing country, is experiencing the transformation and upgrading of the export trade patterns continuously. Since its implementation of the opening-up policy in December 1978, with its strength of demographic dividend, China has actively participated in the global industrial division of labor and cooperation and successfully transformed from a closed economy to the world's largest exporter of goods. The processing trade has been crucial in China's trade growth for more than 40 years. However, it is characterized by "both ends abroad", meaning its growth is compromised by low-profit margins and added values. At present, China's ranking low in the global value chain leads to the failure to effectively enhance the productivity of its export sector (Cai & Han, 2022; Yu, 2015). The processing trade, as China's main trade mode, brings a large amount of carbon emissions along with its exports. With the increase in China's export volume, the surge in its energy consumption brings about the continuous growth of carbon dioxide emissions, and undesirable phenomena such as climate warming and ecological environment deterioration emerge frequently, producing an insidious influence on how we produce and live. Reducing carbon emissions and tackling global climate change have become common goals worldwide (Chang et al., 2019). Hence, promoting the transformation and upgrading of export trade is one of the key approaches to optimize the current trade mode to achieve the transformation to a low-carbon economy and achieve sustainable economic and environmental development.

Talents have always served as the foundation for building a country, and giving play to their role can largely guarantee the longevity of a country and region. Socioeconomic development depends on the average competence level of talents and their reasonable allocation (Strenze, 2013). With the increasing importance attached by the Chinese government to the cultivation of talents, the flow and distribution of talents have become an important part that cannot be ignored in regional population structure adjustment and technological innovation. Since 1978, China has accumulated abundant regional talent resources, but a certain imbalance still exists in the spatial distribution of highly skilled labor. In 2021, at the central conference on talent-related work in China, General Secretary Xi stressed the need to "form strategic strongholds and the flying geese pattern at a faster pace" as to talent distribution. Hence, it is one of the issues worthy of research in economics on how to allocate talents to maximize the contribution of human resources effectively. Reasonable talent distribution helps to create the competitive edge of human capital, energize technological innovation, improve regional social production efficiency, and encourage the transformation and upgrading of the export trade patterns.

Over the past two decades, all-level governments in China have made efforts to implement local talent policies from extensive to precise types. The impact of talent policies on the supply of highly skilled labor has provided a research condition for us. So, we can explore how enhancing regional talent allocation impacts and drives the transformation and upgrading of export trade.

As the regional talent allocation level improves, the quantity of employment will rise in scientific research, the technology service industry, and educational institutions, and more highly skilled talents can be produced for society. With more highly skilled talents available for enterprises to hire, the short supply of skilled talents in enterprise transformation and upgrading can be ameliorated. Meanwhile, the proportion of employment in the technology service industry will increase and give rise to sci-tech popularization and rapid development of the application service industry. As the integration of emerging technologies like Cloud Computing, Internet of Things, and Mobile Internet deepens in the sci-tech service sector, enterprises driven by new industrial models have increased their R&D investment in emerging sci-tech fields such as AI, 5G, and chips, which has brought rapid growth of the R&D service industry. From one perspective, as the supply of highly skilled labor increases, enterprises transform gradually from manufacturing labor-intensive goods to those that are more reliant on human capital. Then, their resources also transfer gradually to human capital-intensive industrial sectors, with the quality of traded products improved gradually – that is, the Rebutzins effect (Vandenbussche et al., 2006), which will have a sustained influence on the export competitiveness and trade pattern of the manufacturing market. From another perspective, as the skilled labor increases, enterprises tend to invest in the application of new technologies and skill-biased technologies, introduce advanced equipment to process high-quality products, and ultimately achieve technology-skill complementation to enhance their productivity and achieve the trade pattern transformation (Acemoglu, 1998; Liu & Tie, 2020). To what degree does enhancing the distribution of regional talent benefit the evolution and enhancement of the export trade pattern? How does it influence the transformation and upgrading of the export trade patterns? The research on these issues has a bearing on the step-by-step propelling of low-carbon transformation and the realization of sustainable economic and environmental development.

2. Literature review

The first strand of literature related to this paper focused on the factors influencing the transformation and upgrading of export trade under the increasingly maturing digital infrastructure and trade opening. The Internet can improve the quality and feasibility of export products, thus facilitating export upgrading (Li et al., 2023; Huang & Song, 2019). Trade liberalization has had a positive impact on changes in the structure of exports and the quality of exports (Stojčić et al., 2018). Both imports and FDI by transnational enterprises have strong potential influences on the reform of export trade structure (Harding & Javorcik, 2012; Amighini & Sanfilippo, 2014; Fu et al., 2021). To enhance global openness and foster economic restructuring and advancement, the Chinese government has implemented the policy of free trade zones (FTZs) (Ge et al., 2023). The creation of Pilot Free Trade Zones (PFTZs) has notably shifted the trade balance towards more general trade and away from processing trade within the zones, thereby facilitating a shift and enhancement in trade patterns and improving the quality of regional trade (Chen et al., 2022b).

Another type of related studies focuses on the factors influencing the transformation and upgrading of export trade in the context of the financial sector. Bank competition accelerates enterprises' gradual shift from processing mode to general trade (Wang & Mao, 2024). Xu et al. (2020) discovered that the reduced distance between banks and enterprises has elevated the share of general trade exports by businesses, thereby fostering a shift and enhancement in export trade patterns. This contains two essential transmission mechanisms, namely, the lowering of financing costs and the strengthening of risk control. Manova and Yu (2016) highlighted the influence of financing constraints on the transformation and upgrading of export trade earlier. They argue that during the transition from processing trade based on supplied materials to the use of imported materials and eventually to general trade, export enterprises will gradually have their demands for working capital rise, and a higher financing constraint will restrict the transformation of enterprises from processing with supplied materials to that with imported materials and from the processing trade to the general trade.

In addition, many existing researches have probed into the influences of talents and R&D innovation on the product mix optimization, transformation and upgrading of export trade. Based on the research conducted by Wei and Zhou (2022), the inflow of international talents has remarkably facilitated the technological structure optimization of Chinese enterprises' export products. The information transfer effect, technology spillover effect and R&D facilitating effect are the main channels for the inflow of international talents to promote the technological structure optimization of enterprises' export products. In economies with significant human capital, innovation of greater quantity and higher quality is seen in industries with higher R&D intensity. More than an essential source for enterprises to develop technologies and innovate knowledge, human capital can also enhance the application efficiency of technologies and the productivity of other production factors, thus facilitating the upgrading of the processing trade enterprises (Wang & Yu, 2023; Che & Zhang, 2018). An increase in R&D investment helps to improve the degree of forward-looking participation of a country's manufacturing industry in the global value chain. The integration of innovative R&D and the manufacturing industry can propel the market demand for R&D progress and raise the domestic added value of product exports. Enterprises' independent innovation activities can lower their production and manufacturing costs and ultimately promote the improvement in the quality of export products, and at the same time, innovation as an intermediary channel has a particular influence on the dynamic transformation of export trade (Zhou et al., 2022; Jiang & Jia, 2022; Amable et al., 2016; Crowley & McCann, 2018; Lu et al., 2023).

According to the above analyses and based on the low-carbon background, this paper first analyzes the effect direction and mechanism of the improvement in the regional talent allocation level on the transformation and upgrading of export trade from a theoretical perspective. The core explanatory variable – talent allocation – is the product of the current year's regional talent employment structure and adjustment factor. A higher product value indicates an elevated level of talent allocation. The variable being explained, transformation and upgrading of export trade, primarily concerns the transformation and upgrading of the export trade patterns. With the adoption of the matched data from CSYD (National Bureau of Statistics, 2012–2021), DRCNET (DRCNET Statistical Database System, 2011–2021) and CSMAR (China Stock Market & Accounting Research Database, 2011–2021), this paper empirically tests the degree of influence of the improvement in regional talent allocation level on the transformation and upgrading of export trade. It concludes that such an influence has the nonlinear characteristic of increasing "marginal effect". This paper comes to relatively reliable conclusions through the lag of explained variables, exclusion of coastal provinces, and treatment of endogenous problems. According to the test result, the technological innovation brought by the improvement in regional talent allocation level is an important transmission channel for such improvement, which facilitates the transformation and upgrading of export trade. Finally, from the multifaceted outcomes of export trade upgrading and transformation, it is clear that higher levels of regional talent allocation have a positive effect on the complexity of exported technologies and export firm innovation.

We contribute and usefully add to research in related areas in the following ways. Firstly, based on the technological innovation effect, this paper has depicted the theoretical logic that the improvement in regional talent allocation level can significantly facilitate the transformation and upgrading of export trade patterns and serves as a valuable supplement to theoretical frameworks of talent allocation and trade. Secondly, in terms of empirical tests, with the adoption of the matched data from various databases, this paper has comprehensively built quantitative indicators of the explained variable – transformation and upgrading of export trade – and the explanatory variable – regional talent allocation. Most importantly, this paper brought attention to how regional talent allocation influences the transformation and upgrading of export trade patterns instead of focusing on the export volume to better respond to China's urgent needs for the transformation and upgrading of trade patterns under the low-carbon economic background. Thirdly, in addition to constructing an indicator evaluation system for the transformation and upgrading of export trade concerning relevant literature, this paper has established a multi-dimensional indicator evaluation system – complexity of exported technologies and export firm innovation – for the transformation and upgrading of export trade and provided empirical evidence for the influences of regional talent allocation on the transformation and upgrading of export trade in more fields, which will offer critical parameters for further quantitative researches in the future.

3. Materials and methods

3.1. Theoretical analysis

Improving human capital greatly benefits foreign trade transformation and upgrading; the human capital improvement effect is one of the critical transmission mechanisms for the digital transformation of the manufacturing industry to promote export trade optimization (Grossman & Maggi, 2000; Grossman, 2004; Zhou et al., 2019; Geng & Bai, 2019; Chen et al., 2022a). All know that talents stand for a country's core competitiveness. In the recent twenty years, with the extensive application of talent policies, their implementation idea has evolved gradually from extensive development to precise promotion. The talent allocation in each region tends to be progressively rationalized, through which the competitive edge of human capital has been created. An increase in the level of regional talent allocation helps to strengthen cooperation and competition among regional enterprises, makes it easier for them to establish bonds and share resources and knowledge, and helps to form a close tie between the industrial chain and the supply chain, to spur the technological innovation and knowledge spillover effect among regional enterprises. On this basis, trades across different regions are becoming closer and closer, and the general technological productivity of each factor has increased, which will produce a remarkable and robust facilitating effect on the transformation and upgrading of export trade.

Meanwhile, technological innovation will create a threshold effect on regional talent allocation, facilitating the transformation and upgrading of export trade. Technological innovation can boost productivity and enhance enterprise cooperation. In the case of insufficient technological innovation intensity and a low use rate of technologies, the marginal effect of talent allocation on transformation and upgrading of export trade through technological innovation is relatively tiny. As the intensity of technological innovation rises, the impact of talent allocation facilitating the transformation and upgrading of export trade will grow. Accordingly, we formulate hypothesis 1 as follows.

H1: *The improvement in regional talent allocation level positively facilitates the transformation and upgrading of export trade patterns, and such an influence shows the nonlinear characteristic of increasing "marginal effect" at different technological innovation levels.*

Romer (1986) and Lucas' (1988) new economic growth theory highlights that human capital accumulation greatly accelerates technological advancement and economic growth.

Human capital is a prerequisite for innovation since it can promote R&D investment, which may bring innovative achievements. The allocation of highly skilled talents to the country's production sector can facilitate technological innovation in the industry (Suseno et al., 2020; Kato et al., 2015; Murphy et al., 1991). Cinnirella and Streb (2017), Fonseca et al. (2019) and Ramírez et al. (2020) respectively took the literacy rate, the enrollment rate of secondary education, and other indicators as the proxy variable of human capital, the proportion of employees with the education attainment of undergraduate level and above as the proxy indicator of human capital, and the proportion of the number of R&D personnel in total employees as human capital. Based on these three different perspectives, they verified the positive contribution of human capital to technological innovation. Rong and Wu (2020) also used the exogenous policy impact of the supply of China's labor with university education attainment since 2003 to identify the influence of human capital on enterprise innovation. Consequently, a mismatch in human capital results in a decrease in a firm's ability to innovate (Huang et al., 2023). Hence, the key to raising regional sci-tech innovation is the accumulation and allocation of human capital. Enhancing regional human capital accumulation and optimizing human capital allocation can accelerate the aggregation and release of innovation factors such as technologies and knowledge in the region, give play to the capacity of independent innovation, and raise regional sci-tech innovation.

Akcigit and Kerr (2018) distinguished between the innovation inside and outside an enterprise. According to them, conscious innovation activities of enterprises have accelerated technical progress and ultimately determined the long-term economic growth rate; enterprise innovation favors an increase in the percentage of general trade, i.e., facilitates the shift of enterprises' export trade pattern from the processing trade to the general trade (Akcigit & Kerr, 2018; Yi & Cai, 2019). The processing traded products mainly go through three production and sales links, including the import of intermediate products from abroad, the reassembly and processing of these products, and re-exporting them abroad. In these links, domestic enterprises are only responsible for the simple assembly and processing of intermediate products and have no mastery of the core technologies of these products. However, when it comes to general traded products, enterprises need to master and be proficient in every link of their production. They also need to increase R&D investment and raise technological levels constantly to boost the quality of their export products, thereby ultimately enhancing the trade competitiveness of their products in the international marketplace. In conclusion, technical progress has raised productivity and thus boosted the possibility of enterprises transforming from the processing trade to the general trade pattern. The productivity threshold is an essential factor affecting whether enterprises choose to export their products and which export mode they choose. Generally, those with a low productivity threshold will choose the export mode of processing trade, whereas other enterprises will choose the export mode of general trade (Dai et al., 2014, 2016). Based on these views, we propose Hypothesis 2 as follows.

H2: *the improvement in the regional talent allocation level can boost the productivity of enterprises by raising the technological innovation level and is conducive to the transformation of export trade from the processing trade to the general trade pattern, which reflects the "technological innovation effect".*

3.2. Methods selection

(1) Base regression model

To examine the extent to which regional talent allocation affects the transformation and upgrading of export trade, we shall consider omitted variables that are individual-dependent and time-independent, and solve the problem of those time-dependent and individual-independent ones. Hence, we need to introduce the province-fixed effect and the year-fixed effect to solve these two existing problems. The double fixed effect model established is as follows.

$$Export_{it} = a_0 + a_1 talalloc_{it} + \sum a_2 controls_{it} + \nu_i + u_t + \varepsilon_{it}. \quad (1)$$

In Equation (1), $Export_{it}$ stands for the transformation and upgrading of export trade of province i in period t. The a_0 is the intercept term, $talalloc_{it}$ stands for the regional talent allocation level of province i in period t, and a_i is the to-be-estimated coefficient. If a_i is significantly positive, it implies that the regional talent allocation level is favorable to the transformation and upgrading of export trade patterns. $controls_{it}$ is the set of control variables, which represents a set of variables that may have an impact on the transformation and upgrading of export trade. It consists of the environmental regulation of province i in period t ($environ_{it}$), the governmental support for science and technology ($govtec_{it}$), the level of social consumption ($consume_{it}$), the digital economy ($digit_{it}$) and the transport accessibility ($access_{it}$). Since it's difficult for these 5 control variables to fully cover a series of factors affecting the transformation and upgrading of export trade patterns at the provincial level, the province fixed effect v_i and the year fixed effect u_t are added in this paper to absorb the influences of unobservable factors at the provincial level and in different years on the empirical results. The v_i stands for the time-independent province fixed effect of province i, u_t stands for year fixed effect, and ε_{it} stands for the stochastic disturbance term.

With the addition of the above five control variables at the provincial level, the province fixed effect and the year fixed effect, the problem of biased estimation results caused by omitted variables is alleviated to some extent in the Benchmark Model (1). However, endogenous issues still linger in the Benchmark Model. Firstly, endogenous issues are caused by some influencing factors at the provincial level and in different years. For example, factors such as macroeconomic policy adjustment and regional characteristics cannot be absorbed by the province-fixed effect and the year-fixed effect. If these factors affect the explained variable export trade pattern transformation and upgrading, the empirical result that the core explanatory variable regional talent allocation level affects the transformation and upgrading of export trade cannot be interpreted as a causal effect. Secondly, the OLS model has endogenous problems due to the existence of reverse causality in it. To alleviate endogenous issues, the following methods will also be adopted in this paper, including further lag of explained variables and exclusion of eastern coastal provinces, so successfully resolving the issue of reverse causation and biased estimation brought on by the omitted variables. To more effectively address endogenous problems, 2SLS regression is carried out utilizing population density as the instrumental variable of the regional talent allocation level.

(2) Panel threshold model

Threshold effect is the phenomenon whereby attaining a specific value for one economic parameter causes a sudden shift in another economic parameter towards other forms of development. The critical value that is the causative phenomenon is called the threshold (threshold value). If the object of study of the model contains multiple individuals and multiple years, then it is a panel threshold model. In this paper, the technological innovation level may also indirectly affect the nonlinear dynamic spillover of regional talent allocation, facilitating the transformation and upgrading of export trade. To deepen the analysis of the nonlinear influence of improvement in regional talent allocation level on the transformation and upgrading of export trade, we take technological innovation as the threshold variable, and based on the practice of Hansen (1999), we have established the following fixed effect panel threshold regression model.

$$\begin{aligned} Export_{it} &= \beta_0 + \beta_1 talalloc_{it}.I(innov_{it} \le r_1) + \beta_2 talalloc_{it}.I(r_1 < innov_{it} \le r_2) + \\ &\beta_3 talalloc_{it}.I(innov_{it} > r_2) + \sum \beta_4 controls_{it} + v_i + u_t + \varepsilon_{it}. \end{aligned} \tag{2}$$

In Equation (2), $innov_{it}$ is the threshold variable, and based on the practice of Wu and Deng (2023), the technology market turnover/gross regional production is used to measure technological innovation (constant price in 2011, the same as below). $I(.)$ is the indicative function, r_1 and r_2 are to-be-estimated threshold values, with the rest variables the same as those in Equation (1). ε_{it} is independent and identically distributed. Equation (2) is a multi-threshold model, and will become a single-threshold model if the estimation of the intermediate $r_1 < innov_{it} \le r_2$ is reduced.

(3) Instrumental variables method

Endogenous problems possibly existing at the regional talent allocation level and transformation and upgrading of export trade lead to biased estimations of regression results. Based on the spirit of the 2021 central conference on talent-related work in China, Chinese governments have been implementing policies to promote talent flow and improve the regional talent allocation level, which has significantly facilitated the transformation and upgrading of export trade. Then, the enhancement in transformation and upgrading of export trade has also increased regional demands for highly skilled labor, promoted regional technical progress and economic growth, and thus attracted more talents to settle down; that is, there is bidirectional causality between regional talent allocation level and transformation and upgrading of export trade. Hence, we have adopted the instrumental variable method to test the result of regional talent allocation further, facilitating the transformation and upgrading of export trade. By referring to the research of Angrist and Krueger (1991), we have established the following instrumental variable model based on Equation (1).

$$\text{cov}(z_{it}, talalloc_{it}) \ne 0; \tag{3}$$

$$\text{cov}(z_{it}, \varepsilon_{it}) = 0. \tag{4}$$

Equation (1) is the baseline regression model. Equation (3) and (4), the effective instrumental variable (z_{it}) shall meet two conditions at the same time, that is, the instrumental variable and the core explanatory variable are related to each other, and $\text{cov}(z_{it}, talalloc_{it}) \ne 0$

meets the criteria of instrumental variables, while the instrumental variables are not correlated with random perturbations, and $\mathrm{cov}(z_{it}, \varepsilon_{it}) = 0$ meets the exogenous conditions of instrumental variables. Finally, two-stage least squares method has been used to inspect the correlation and exogeneity of the instrumental variables.

(4) Data source, variable selection and processing

By combining various data sources such as the CSYD (National Bureau of Statistics, 2012–2022), DRCNET (DRCNET Statistical Database System, 2011–2021) and CSMAR (China Stock Market & Accounting Research Database, 2011–2021) , we established a panel sample of 30 provinces from 2011 to 2021. DRCNET is a series of large-scale database clusters launched after years of R&D, optimization, and integration by the Development Research Center of State Council, which comprehensively integrates various types of data related to China's economic operation provided by China's statistical functionaries at all levels. It is one of the most authoritative, comprehensive, and scientific statistical databases that provides quantitative information on China's economy. DRCNET involves three categories, namely "General Trade", "Processing Trade", and "Other Trade". This paper retains only the "General Trade" and "Processing Trade" patterns for subsequent research. With a combination of the collected details of the explained variable – transformation and upgrading of export trade – and the demand for the variable establishment, the Tibet Autonomous Region has been excluded from this paper. Regarding the core explanatory variable – regional talent allocation level, the human capital has been measured using the proportion of people with higher education attainment in the total population or the average schooling year in most academic literature. However, considering that the highly educated personnel may not necessarily facilitate the export trade pattern transformation and upgrading, it's the highly skilled personnel who work in scientific research, the technology service industry, and educational institutions/departments that genuinely have a facilitating effect on the export trade pattern transformation and upgrading. Therefore, based on the China Statistical Yearbook data (National Bureau of Statistics, 2012–2022), this paper has made statistics on urban employment by industries in 30 provinces from 2011 to 2021. The product of regional talent employment structure (x) and adjustment factor (y) of the current year has been used to measure the regional talent allocation level in the same year (see Equation 5). The greater the product value, the higher the regional talent allocation level of the current year.

The explained variable $Export_{it}$ stands for the transformation and upgrading of export trade patterns of province i in period t. It is measured using the proportion of general trade exports (general trade exports/total exports of general trade and processing trade) in this paper by referring to the practice of Brandt and Morrow (2017). Suppose the proportion of general trade volume in total export trade volume rises in province i during period t. In that case, it is considered that the regional export trade pattern gradually transforms from the processing trade to the general trade. So, this region realizes its export trade pattern transformation and upgrading step by step.

Regarding the core explanatory variable $talalloc_{it}$ (regional talent allocation level), Lai and Ji's (2015) practice has been used as a reference. Firstly, the regional talent employment structure (x) is represented by the proportion of the sum of employment in scientific research, technology service industry, and educational units in each province of the current year in the sum of such jobs in 30 provinces countrywide in the same year.

Secondly, the regional talent allocation adjustment factor has been determined. Based on the "relative monopoly degree" of industries put forward by Jin (2005), the talent allocation fitting indicator has been determined using the ratio of the sum of employment in scientific research, technology service industry, and educational institutions in each province of the current year to the total employment in each industry in each province in the same year. Referring again to the practice of the China Economic Growth Group (Zhang et al., 2014), the first-level adjustment coefficient (y) for regional talent allocation is determined by dividing the above-fitted index by the share of each province's current-year GDP value added in the sum of the current-year GDPs of the 30 provinces.

Finally, the product of regional talent employment structure (x) and adjustment factor (y) has been used to represent the regional talent allocation level variable, with the calculation Equation as follows:

$$talalloc_{it} = \frac{talent_{it}}{\sum_{1}^{30} talent_{it}} \times \left(\frac{talent_{it}}{L_{it}} \div \frac{gdp_{it}}{\sum_{1}^{30} gdp_{it}} \right). \tag{5}$$

In the above Equation, $talalloc_{it}$ stands for regional talent allocation level of province i in period t. $talent_{it}$ stands for the sum of employment in sci-tech research, technology service industry and educational institutions of province i in period t. $\sum_{1}^{30} talent_{it}$ stands for the sum of such employment in 30 provinces in period t. L_{it} stands for the total employment in each industry of province i in period t. gdp_{it} stands for the GDP value added of province i in period t, and $\sum_{1}^{30} gdp_{it}$ stands for the sum of GDP of 30 provinces in period t.

Control variables and Mechanism variables are as follows. (1) Environmental regulation ($environ_{it}$). Drawing on the study of Chen et al. (2018), this paper manually collects government work reports of 30 Chinese provinces from 2011 to 2021. Second, word-splitting is used for the government work report content. Lastly, the frequency of words concerning the environment is counted, and the percentage of those words' total frequency in government reports is computed. Environmental protection, pollution, energy consumption, emissions reduction, low carbon, air, chemical oxygen demand, sulfuric acid, carbon dioxide, PM10 in particular, and PM2.5 are among the phrases connected to the environment. (2) Government support for science and technology ($govtec_{it}$). Referring to the study of Qin and Gao (2020), this paper measures the proportion of government S&T expenditures to fiscal expenditures in each province. (3) Social consumption level ($consume_{it}$). The ratio of total retail sales of consumer goods to gross domestic product (GDP) has been calculated for each province (Ruan & Zhang, 2020). (4) Digital economy ($digit_{it}$). Referring to Zhao's et al. (2020) practice, the comprehensive development level of the digital economy has been measured mainly from Internet development and digital financial inclusion. The four former aspects considered in this paper are the Internet popularity rate, cellphone use rate, percentage of relevant employees, and total telecommunications per capita. In terms of digital financial inclusion, the Digital Financial Inclusion Index of China has been used in this paper. This index is developed by the Institute at Digital Finance Peking University in cooperation with Ant Financial Group (Guo et al., 2020). In this paper, the analysis with the entropy weight method has been applied for a multi-dimensional evaluation of the data of five indicators above to get the comprehensive development level of the digital economy finally. (5) Transport accessibility (*$access_{it}$*). We used the total provincial road area/provincial resident population to measure this indicator (Zhang & Wang, 2014). (6) Technological innovation level (*$innov_{it}$*). The measurement of the technological innovation level of the mechanism variable is explained in Equation 2.

To guarantee that the regression results are robust, all the aforesaid variables are indented by 1 percent in this paper. Table 1 shows the findings of the descriptive statistics.

As shown in Table 1, the means of transformation and upgrading of export trade and regional talent allocation levels are 68.78% and 17.50%, respectively, and their standard deviations are 20.83% and 8.89%, respectively. Their differences in maximum and minimum are significant. This indicates notable differences among 30 provinces in the transformation and upgrading of export trade and regional talent allocation level, and similar characteristics are also shown in control variables such as environmental regulation, government support for science and technology, social consumption level, digital economy, and transport accessibility, which indicate apparent disequilibrium among 30 provinces in the development levels of economy, politics, education and transportation.

(5) Relevance analysis

This study's control variables may interact, leading to biased results. Therefore, a multicollinearity test is required. Before the regression estimation, the correlation between the control variables in this paper was tested. The results are shown in Table 2.

Table 1. Descriptive statistics

Variable	N	Unit	Mean	S.D.	Minimum	Maximum
Export	330	(%)	68.78	20.83	26.51	99.49
talalloc	330	(%)	17.50	8.89	4.19	42.51
environ	330	(%)	6.80	2.00	0.31	1.24
govtec	330	(%)	2.14	1.48	0.56	6.24
consume	330	(%)	38.00	6.80	22.70	52.57
digit	330	—	0.18	0.12	0.02	0.64
access	330	square meters/person	16.22	4.92	4.11	26.20
innov	330	(%)	1.64	2.89	0.02	17.50

Table 2. Results of correlation test

Variable	environ	govtec	consume	digit	access
environ	1.000				
govtec	–0.031	1.000			
consume	0.176^{***}	0.348^{***}	1.000		
digit	0.051	0.542^{***}	0.199^{***}	1.000	
access	0.147^{***}	$–0.154^{***}$	$–0.171^{***}$	–0.040	1.000

Note: ***, ** and * indicate that the test is significant at the level of 1%, 5% and 10% respectively.

According to the regression results, the correlation coefficient between the variables of the digital economy and government support for science and technology is 0.542, which is a medium correlation. There is either no connection or a weak association between the other variables, as the correlation coefficient does not rise over 0.4. The above analysis concludes that no severe multicollinearity exists between the control variables and that further empirical studies can be conducted.

4. Empirical results and analysis

4.1. Benchmark regression results

Table 3 presents the estimation results of the benchmark regression in this paper. In Column (1), the province fixed effect has been controlled in this paper to exclude the impact of unobservable factors at the provincial level, and the robust standard error has been used for testing, with no control variable added. The result reveals that the regression coefficient of the increase in the level of regional talent allocation on the transformation and upgrading of export trade is 0.9282, and at 1%, it is significantly positive. This suggests that regional talent allocation significantly contributes to the transformation and upgrading of export trade. However, the transformation and upgrading of export trade may be affected by other factors. So, based on regression in Column (1), we have further controlled environmental regulation, government support for science and technology, social consumption level, digital economy level, and transport accessibility, and get the regression result in Column (2), the coefficient drops

Table 3. Benchmark regression results

Variable	Explained variable: Export			
	(1)	(2)	(3)	(4)
talalloc	0.9282*** (0.2019)	0.8845*** (0.2359)	0.7409*** (0.2242)	0.8199*** (0.2538)
environ		1.7895 (2.5537)		3.8930 (3.5529)
govtec		3.6511*** (0.8628)		3.1625*** (0.9048)
consume		–0.3147** (0.1269)		–0.2174* (0.1211)
digit		0.1746*** (0.0544)		0.5237*** (0.1072)
access		–0.0073*** (0.0027)		–0.0065** (0.0032)
year fixed effect			Yes	Yes
province fixed effect	Yes	Yes	Yes	Yes
R^2	0.8609	0.8771	0.8658	0.8847
N	330	330	330	330

Note: ***, ** and * indicate that the test is significant at the level of 1%, 5% and 10% respectively. Standard error is listed in brackets. The same applies below.

a bit and remains statistically significant positive at 1%. Based on the regression in Column (1), we have controlled the year-fixed effect in Column (3) with no control variable added. At 1%, the primary explanatory variable's coefficient, 0.7409, is considerably positive. In Column (4), the paper adds five control variables and applies double fixed effects. Using robust standard errors, the coefficient of the core explanatory variable is 0.8199 and is still significantly positive at 1%. In conclusion, the regional talent allocation level improvement has shown a significant positive facilitating effect on the transformation and upgrading of export trade.

Besides, in Column (2) and Column (4), the regression coefficients for the control variable environmental regulation are insignificant. Environmental regulations usually increase the production costs of enterprises, such as investment in environmental protection equipment and the application of pollution control technologies. These additional costs may weaken the price competitiveness of exporting enterprises in the international market, making it difficult for them to gain an advantage in the export market. At the same time, the implementation of environmental regulation needs to be coordinated with other policies (e.g., trade policy, industrial policy, etc.). Suppose environmental regulations are too strict and other supportive policies fail to keep pace. In that case, exporters may face greater operating pressure and find it difficult to transform and upgrade their export trade. The regression coefficients for government support for science and technology are positive, as is the regression coefficient for the digital economy. Government support for science and technology can promote the diffusion of knowledge and technology and bring about knowledge spillover effects. It can enhance the international competitiveness of export products and promote the transformation and upgrading of export trade by improving the quality of export products and innovation capacity. Digital technologies have reduced information asymmetries and transaction costs. Through e-commerce platforms, digital payment systems, and blockchain technology, enterprises can conduct cross-border transactions more efficiently, reducing information search, negotiation, and fulfillment costs. This makes it easier for SMEs to participate in international trade as well, thus facilitating the transformation and upgrading of export trade.

Furthermore, the social consumption level regression coefficients are significantly negative in columns (2) and (4). Higher levels of social consumption imply increased demand in the domestic market, and firms may tend to satisfy growing domestic demand rather than take on the additional costs and risks associated with exporting. In this case, resources may be allocated more to satisfying the domestic market than tapping external markets, thus inhibiting the transformation and upgrading of export trade. Regression coefficients of transport accessibility are significantly negative at 1% and 5%, respectively, which suggests that, other things being equal, an increase in transport accessibility may lead to the opening and expansion of the market, attracting more enterprises to compete. If market saturation increases, it may lead to increased market competition, squeezing the export trade profits of enterprises and making it challenging to achieve trade transformation and upgrading.

4.2. Nonlinear effect analysis

Considering the nonlinear influence of regional talent allocation level on transformation and upgrading of export trade at different technological innovation levels, we introduced a threshold variable. We first tested the existence of a panel threshold using the method of Hansen (1999).

After repeated sampling 1000 times by bootstrap, we performed single-threshold and double-threshold tests based on the original hypothesis. There is one threshold for the impact of regional talent allocation on the transformation and upgrading of export trade, as Table 4 illustrates. The single threshold is substantial at the 10% level, while the double threshold is insignificant.

Table 4. Threshold effect test results

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	1.6143	0.0051	27.87	0.077	25.6446	32.1716	46.3606
Double	1.5435	0.0048	14.62	0.168	27.9814	47.0356	81.9731

Note: RSS denotes residual sum of squares; MSE denotes mean square error; Fstat denotes F-value; Prob denotes P-value; Crit10 denotes 10% critical value; Crit5 denotes 5% critical value; Crit1 denotes 1% critical value.

The threshold is 0.1471. According to the estimation results of panel threshold parameters in Table 5, when the technological innovation level is lower than 0.1471, the coefficient of influence of regional talent allocation level on the transformation and upgrading of export trade is 0.8392 and is significantly positive at the level of 5%. When the technological innovation level is higher than 0.1471, the impact of regional talent allocation on the transformation and upgrading of export trade is substantial, with a coefficient of 1.8495 and a significant positive effect at 1%. The facilitating impact of regional talent allocation on the transformation and upgrading of export trade is adjusted by the threshold effect of technological innovation level; when the level is high, the positive influential effect of regional talent allocation on the transformation and upgrading of export trade will be enhanced. Thus, Hypothesis 1 has gained support.

Table 5. Threshold regression results

<table>
<tr><th colspan="3">Variable: Export</th></tr>
<tr><td rowspan="2">talalloc</td><td>(innov ≤ 0.1471)</td><td>0.8392**</td></tr>
<tr><td>(innov > 0.1471)</td><td>1.8495***</td></tr>
<tr><td colspan="2">C</td><td>0.6519***</td></tr>
<tr><td colspan="2">control variables</td><td>Yes</td></tr>
</table>

Note: The single threshold value for innov was 0.1471.

4.3. Robustness tests

Robustness tests performed on benchmark regression results in this paper are as follows:

(1) Lagged the explained variables. The next period of the explained variables may also be affected by the core explanatory variables of the current period. This study employs a lagged explained variable for the transformation and upgrading of export trade to examine the effect of current regional talent distribution on the subsequent period's transformation and upgrading of export trade. The results have passed the robustness test in Column 1 of Table 6.

(2) Exclusion of eastern coastal provinces. Eastern coastal provinces have more frequent and larger-volume trade contacts with overseas target markets. As a result, local export enterprises have solid capacities for independent innovation, R&D, and technological upgrading of traded products, as well as a more extraordinary transformation and upgrading of export trade rate. In this paper, eastern coastal provinces have been excluded to ensure the robustness of test results, and the results have passed the robustness test, as shown in Column 2 of Table 6.

(3) Discussion of endogenous problems. In this paper, population density is used as an instrumental variable for the level of regional talent allocation in this province. Population density ($density_{it}$) is measured as the total population of the administrative division at the end of the year/area of the administrative division. There is a specific correlation between population density and regional talent allocation. Generally, regions with higher population density tend to have more employment opportunities. This can not only attract a large number of talents to these regions but also make timely adjustments to talent employment and reduce the talent skill-job mismatch rate through knowledge spillover effects, labor market matching, urbanization and infrastructure, industrial clusters, housing and cost of living, as well as government policies and public services, thus forming a higher talent allocation level. On the other hand, the regional talent allocation level will also affect the population density. High-quality talents gathered in a particular region will increase economic development and employment opportunities, thus attracting more people to the area and growing population density. Therefore, population density and talent allocation are strongly correlated and satisfy the correlation requirement of instrumental variables. Meanwhile, although population density may indirectly affect regional economic activities by influencing factors such as infrastructure, labor market, and urbanization, there is no direct causal relationship between it and regional transformation and upgrading of export trade. The transformation and upgrading of export trade mainly depend on R&D investment and technological innovation. Therefore, the instrumental variable has exogenous requirements. The findings of the 2SLS regression in Table 6's column 3 demonstrate that the regional talent allocation level, after introducing population density as an instrumental variable to eliminate endogeneity issues further, significantly promotes the transformation and upgrading of export trade. Additionally, this test result passed the unidentifiable and weak instrumental variable tests, proving instrumental variables' effectiveness. These three robustness test results are compatible with the benchmark regression's findings.

Table 6. Robustness tests

Variable	Explained variable: Export		
	(1)	(2)	(3)
talalloc	0.4903* (0.2793)	0.6580** (0.2547)	4.2405*** (0.6467)
control variables	Yes	Yes	Yes
year/province fixed effect	Yes	Yes	Yes
R^2	0.9071	0.9054	0.8113
N	300	209	330

Note: The KP-F statistic in Column (3) is 45.18, larger than 10, indicating no weak instrumental variable problems.

5. Mechanism test and extended analysis

5.1. Mechanism test

Effective allocation of talents is essential for exerting talents' innovation capacity, and technological innovation is a key mechanism by which regional talent allocation influences the transformation and upgrading of export trade. This paper $innov_{it}$ stands for the technological innovation of province i in period t. The mechanism model is set up as follows:

$$innov_{it} = a_0 + a_1 talalloc_{it} + \sum a_2 controls_{it} + \nu_i + u_t + \varepsilon_{it}. \tag{6}$$

The regression was conducted concerning the methodology of the Model (1), where the level of technological innovation ($innov_{it}$)was defined as the explained variable, and the other variables remained unchanged.

Table 7. Mechanism test results

Variable	innov	innov
	(1)	(2)
talalloc	0.0650** (0.0299)	0.0514** (0.0258)
control variables	No	Yes
year/province fixed effect	Yes	Yes
R^2	0.9085	0.9409
N	330	330

The impact of regional talent allocation on technological innovation is further demonstrated by Table 7, where the estimation coefficients of the explanatory variable in Columns (1) and (2), 0.0650 and 0.0514, respectively, are significantly positive at the significance levels of 5%. From the results in Table 7, the improvement in regional talent allocation level has indeed accelerated technological innovation, which is one of the critical factors for crossing the productivity threshold and facilitating the transformation and upgrading of export trade. The empirical results of this mechanism have verified the validity of Hypothesis 2 in this paper.

5.2. Extended analysis

From a broader perspective, the transformation and upgrading of export trade covers reflects not only the optimization of the trade pattern but also the complexity of exported technologies and the sustainable development of export trade. With combination of the *Guiding Opinions of the CPC Central Committee and the State Council on Promoting the High-quality Development of Trade* issued and implemented by the CPC Central Committee and the State Council on November 19, 2019, two indicators have been selected in this paper, namely the complexity of exported technologies of products in 22 industries (T01–T22) in 30 provinces from 2011 to 2021, and the non-financial A-share-listed exporting enterprises in Shanghai and Shenzhen, in 30 provinces of China, from 2011 to 2021 two main types of indicators of innovation.

(1) Complexity of exported technologies. To achieve the transformation and upgrading of the export trade patterns, enterprises can increase the proportion of exported high-tech products to enhance their international competitiveness. So, can the improvement in regional talent allocation level facilitate the increased complexity of exported technologies? To answer this question, we set up the regression model as follows:

$$\ln \exp yit_{it} = a_0 + a_1 talalloc_{it} + \sum a_2 controls_{it} + \nu_i + u_t + \varepsilon_{it}. \quad (7)$$

We refer to the methodological regression of model (1), where the explained variable $\ln \exp yit_{it}$ is replaced by the logarithmic value of the province's export technological complexity ($\exp yit_{it}$) in the period, and the other variables remain unchanged. For the measurement of complexity of exported technologies, we have referred to the ideas of Hausmann et al. (2007) and calculated the complexity of exported technologies of products in 22 industries (T01-T22) in 30 provinces from 2011 to 2021. The calculation Equation is:

$$prody_{ijt} = \sum_{i=1}^{n} \frac{(x_{ijt} / X_{it})}{\sum_{i=1}^{n} (x_{ijt} / X_{it})} \ln pergd_{it}, \quad (8)$$

where $prody_{ijt}$ denotes the complexity of exported technologies of province i in a sub-sector of 22 industries in period t, j denotes the commodity export category, x_{ijt} denotes the value of export trade in the products of the j sub-sector in province i in period t. X_{it} denotes the total exports of the province i in period t. x_{ijt} / X_{it} denotes the share of exports of products of the j sub-sector of province i in period t in the total exports of the province. $\ln pergd_{it}$ denotes the logarithmic value of per capita in each province in period t after deflating the price index. After measuring the export technological complexity of each industry in province i in period t, by weighting and summing the export technological complexity of each sub-industry, we can derive the export technological complexity of the products of 22 industries (T01–T22) in each province and the calculation Equation is as follows:

$$\exp tc_{it} = \sum_{j=1}^{m} \frac{x_{ijt}}{X_{it}} prody_{ijt}. \quad (9)$$

At the 1% significant level, Column (1) of Table 8 regression coefficient, 0.5577, is positive, demonstrating the positive facilitating effect of regional talent allocation on the increased complexity of exported technologies.

(2) Innovation in exporting firms. Under the background of economic transformation, the realistic requirement for achieving sustainable export trade development is to transform the driving force for growth from elements to innovation. Based on the sustainable development of export trade, we investigated the impact of regional talent allocation on export firms' innovation. This paper adopts innovation output ($\ln input_{it}$) that draws on the literature of (Yang et al., 2024), i.e., it adopts the number of patent applications filed by exporting firms and takes the logarithmic value to measure it. Furthermore, invention, utility model, and design patents are the three categories into which China has classified patents, considering the different contribution weights of these three types of patents to the enterprise and then adopting the weights of 3:2:1 to allocate, and finally using the number of the three types of patent applications weighted total number of patents plus 1 of natural logarithms for the measurement of (ln$input_{it}$). In addition, the number of patents granted is an indicator that can better reflect a firm's innovation output (Li et al., 2024), which is measured in this paper by the natural logarithm of the weighted total of the number of patents granted of the three types plus one, based on the calculation above (ln$output_{it}$). The specific regression model is set up as follows:

$$\ln input_{it} = a_0 + a_1 talalloc_{it} + \sum a_2 controls_{it} + \nu_i + u_t + \varepsilon_{it}; \tag{10}$$

$$\ln output_{it} = a_0 + a_1 talalloc_{it} + \sum a_2 controls_{it} + \nu_i + u_t + \varepsilon_{it}. \tag{11}$$

We refer to the method regression of model (1), where the explained variables are replaced by ln$input_{it}$ and ln$output_{it}$ respectively, leaving the other variables unchanged. Two regression coefficients in Column (2) and Column (3) of Table 8, 1.5174 and 1.9079, are significantly positive at the significance level of 10% and 5%, indicating the positive facilitating effect of improvement in regional talent allocation level on the innovation in export firms.

Table 8. Other performances of transformation and upgrading of export trade

Variable	lnexpyit	lninput	lnoutput
	(1)	(2)	(3)
talalloc	0.5577*** (0.1697)	1.5174* (0.8050)	1.9079** (0.7947)
control variables	Yes	Yes	Yes
year/province fixed effect	Yes	Yes	Yes
R^2	0.9491	0.9645	0.9648
N	330	330	330

6. Conclusions and policy implications

6.1. Discussion and conclusions

Many studies have examined the connection between human capital and trade patterns since the 20th century's close, when higher education began to spread (Harris & Robertson, 2013; Chen & Liu, 2024; Du et al. 2023). In particular, Du et al. (2023) argue that increased human capital has a considerable negative effect on the domestic value-added rate for processing trade. We support and extend their arguments in the context of the transition to a low-carbon economy.

As China's regional economy grows and human capital continues to be enhanced, introduction of highly skilled labor has become an essential part of population structure adjustment. Research on human capital shall switch from the perspective of accumulation in quantity to that of spatial allocation and from the idea of total quantity to structure.

We have evaluated the impact of increased regional talent allocation levels on the transformation and upgrading of export trade based on matched data from the CSYD (National Bureau of Statistics, 2012–2021) DRCNET (DRCNET Statistical Database System, 2011–2021) and CSMAR (China Stock Market & Accounting Research Database, 2011–2021). According to empirical research findings, the improvement in regional talent allocation level has significantly raised the proportion of general trade exports. It is conducive to the transformation and upgrading of export trade. Also, with adopting the threshold model, the positive influence of improvement in regional talent allocation levels on the transformation and upgrading of export trade has been found with the characteristic of nonlinear increasing "marginal effect". The benchmark regression results still stand after a series of robustness tests, including the one-phase lag of the explained variable, exclusion of eastern coastal provinces, and treatment of endogenous problems. This research has also profoundly dug into the mechanism for the improvement in regional talent allocation levels to play a role and found that technological innovation is an important transmission channel for improving in regional talent allocation levels to facilitate the transformation and upgrading of export trade. This is a great reference value for implementing regional talent policies and building a new development pattern.

6.2. Policy implications

Firstly, it's necessary to establish a long-term mechanism for training and introducing highly skilled talents. Policies shall be implemented in a targeted and precise way to build talent patterns in different regions, and financial and resource investments shall gradually increase in the training of highly skilled talents. A sound higher education system must be established to train high-quality talents to meet the needs of export trade transformation. The employment and security of the medium- and low-skilled labor force shall be carefully considered, and vocational training must be provided actively to adapt to the new form of socioeconomic development.

Secondly, it's necessary to build an innovation-driven ecosystem. Specifically, an ecosystem that supports technological innovation must be built, including establishing technological innovation and cooperation platforms, technological transfer centers, and scientific research institutions for the export trade transformation and providing innovation project support and R&D funds for regional talents. Enterprises shall be encouraged to establish joint R&D cooperation mechanisms with universities and research institutions, boost knowledge flow and technological transfer, and enhance industry-university-research cooperation. Meanwhile, incentive mechanisms must be established for technological innovation, including patent and IPR protection, and financial support systems must be established to offer loans and venture capital for innovation projects.

Finally, under the background of a low-carbon economy, China must adjust the industrial structure of its processing trade, vigorously propel the development of the low-carbon economic trade industry, reinforce governmental policy guidance and support, encourage the growth of low-carbon industries while preventing access to high-carbon ones. Efforts shall be made to strengthen reasonable talent allocation in enterprises and enhance their capacity for independent innovation. The export trade structure with low technology content, environmental protection standards, and added value shall be adjusted. High-tech products with low energy consumption and emission shall be supported to meet global requirements for low-carbon economic development, enhance export competitiveness, and steadily propel sustainable economic and environmental development.

This study has made significant contributions, but some things could still be improved. On the one hand, the research object in this paper is the largest developing country – China, and the research results apply to a large number of countries and regions, except a small portion of countries and areas that may be restricted in application due to different national conditions. In the future, we will further break national and regional restrictions, expand the scope of research and application, and make positive contributions to the environment's and humanity's sustainable development in a setting of low carbon. On the other hand, most of the data used in this research are macroeconomic statistics because of the constraints of information technology and microdata platforms, and the data on general trade and processing trade are in severe shortage and updated very slowly in micro-databases. In the future, as the micro-databases keep updating and the information technology keeps improving gradually, we will further enrich and optimize our research.

Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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