



Factor Mobility, Industrial Transfer and Industrial Carbon Emission: A Spatial Matching Perspective

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This paper proposes a dynamic industrial transfer index for the first time to characterize the spatial matchability of factor mobility and industrial transfer, and then explores the correlation between factor mobility, industrial transfer and industrial carbon emission intensity by using panel data from 30 provinces in China during 2004–2019. The results show that China’s ability to reduce carbon emissions is improving, and the intensity of industrial carbon emission has dropped by 44.84%. In addition, there is an obvious spatial mismatch between factor mobility and industrial transfer. Specifically, production factors generally flow from high-carbon emission intensity areas to low-carbon emission intensity areas, while the direction of industrial transfer is generally opposite to that of factor mobility. And the empirical analysis finds that the interaction between factor mobility and industrial transfer will affect the carbon reduction. If the direction of capital mobility is the same as that of capital-intensive industries, it is unfavorable to the carbon emission reduction. While the carbon reduction effect will be enhanced if the directions of labor and technology mobility are consistent with those of labor-intensive and technology-intensive industrial transfer, respectively. Finally, based on the findings, some recommendations are provided for governments to formulate policies.

Keywords: factor mobility, industrial transfer, carbon emission intensity, dynamic industrial transfer index, spatial matchability

INTRODUCTION

The greenhouse effect is a common challenge for human society (Anwar et al., 2020), and CO₂ accounts for the largest proportion among the six greenhouse gas (GHG) emissions. In 2010, global CO₂ emissions accounted for 76% of global GHG emissions (IPCC, 2014). Since then, global GHG emissions have increased by an average of 1.4% per year, and the total GHG emissions (including those from land-use activities) reached a record 59.1 billion tons of CO₂ equivalent (GtCO₂e) in 2019 (UNEP, 2020). Therefore, reducing CO₂ emissions has become an important goal of global environmental policy. As the second largest economy and the largest emitter of CO₂ in the world (Ma et al., 2019), China is taking active measures to reduce CO₂ emissions by adjusting its energy structure and upgrading its industrial structure, and proposing a series of carbon emission reduction goals. In 2015, China put forward the “China’s 2030 Emission Reduction Plan to Address Climate Change,” and planned to decrease CO₂ emissions per unit of GDP by 60–65% compared to 2005. On 29 October 2020, the “Recommendations of the Central Committee of the Communist Party of China on Formulating the 14th Five-Year Plan for National Economic and Social Development and Long-term Goals for 2030” proposed that it is necessary to formulate an action plan to reach the peak of carbon emissions by 2030 and become carbon neutral by 2060.

Then on 12 December 2020, at the Climate Ambition Summit, Chinese President Xi Jinping proposed a new goal of reducing CO₂ emissions per unit of GDP by more than 65% by 2030 compared to 2005, which will further increase the autonomous contribution of China.

With the introduction of China's carbon emission reduction goal, carbon emission reduction has become one of the key issues facing China's economic and social development and industrial restructuring in the future. As an important economic pillar, rapid industrialization has led to an increase in energy consumption and CO₂ emissions in the industrial sector, which contributes 85% of CO₂ emissions in China (Li et al., 2019). Therefore, reducing industrial carbon emissions has become an important task for the sustainable development of industrial economy. In addition, compared with the post-industrialization of developed countries, China is still in the stage of rapid industrialization (Jia et al., 2020). There are obvious differences in industrial structures and development stages between areas in China, which will lead to uneven distribution of carbon emissions and carbon reduction capabilities. Therefore, industrial transfer will inevitably cause changes in the spatial structure of carbon emissions.

Besides, the spatial allocation of production factors is closely related to the spatial layout of industrial structure. Production factors are important basis for economic and social development, and their utilization and distribution are crucial to the realization of carbon emission reduction goals. Generally speaking, if production factors flow freely, they will tend to flow to areas with high returns under the guidance of regional resource endowment differences and market laws (Chen et al., 2021), which is also the basic feature of the factor mobility in China. For a long time, the major production factors in China, such as labor and capital, have been concentrated in the eastern coastal areas, however, the manufacturing industry has shown a trend of transferring from the southeastern coast areas to the inland areas (Sun et al., 2018), which is contrary to the direction of the factor mobility. Generally, industrial transfer may lead to changes in regional industrial structure and factor demand structure, while the changes in factor supply structure lag behind the changes in the demand structure. Therefore, the mismatch between factor mobility and industrial transfer will act on the spatial pattern of carbon emissions. As China is simultaneously promoting factor market allocation reform, industrial restructuring and carbon emission reduction, the interaction between factor mobility, industrial transfer and carbon emission reduction is related to the realization of policy goals. Therefore, exploring the impact of the interaction of factor mobility and industrial transfer on carbon emission reduction from the perspective of spatial matchability is crucial to the policy coordination of factor allocation, industrial transformation and low-carbon development. In addition, the case study of China can also provide a reference for other developing countries to solve the problem of reducing emissions from industrial restructuring.

The main contributions of this paper are as follows: First, we improve the industrial transfer index (Sun et al., 2018) into a dynamic industrial transfer index, and measures the dynamic transfer trends of labor-intensive, capital-intensive, and

technology-intensive industries in China from 2004 to 2019 by using sub-sectors data. Second, some articles point out that the factor mobility does not match the industrial transfer in China (Wang, 2021), on this basis, we further use regional data to carve out and visualize the distribution characteristics of the spatial mismatch. Third, we explore the heterogeneous impact of different types of factor mobility and industrial transfer on industrial carbon emission intensity from the spatial matchability of factor mobility and industrial transfer, and analyze the heterogeneous impact of spatial matchability on carbon emissions under different carbon emission intensities. Finally, we put forward some recommendations to promote carbon emission reduction from the perspective of factor mobility and industrial transfer.

This paper is organized as follows: *Literature Review and Research Hypothesis* introduces the relevant literatures and research hypotheses. *Method and Data* describes the data and main methods. *Description of Objective Facts* describes the characteristic facts of factor mobility, industrial transfer and industrial carbon emissions. *Results and Discussions* is the empirical results, and *Conclusion and Policy Recommendations* is conclusions and policy recommendations.

LITERATURE REVIEW AND RESEARCH HYPOTHESIS

Literature Review

Recent years, factor mobility, industrial transfer and carbon emission intensity have been the research hotspots in academia. The studies on the relationship between factor mobility and economic activities can generally be divided into two categories. On the one hand, some studies discuss the relationship of factor mobility on economic activities from a single factor, such as the impact of capital mobility on energy consumption (Qamruzzaman and Wei, 2020), the impact of technology mobility on innovation efficiency (Yu et al., 2019), and the relationship between labor mobility and economic growth (Alonso-Carrera and Raurich, 2018). On the other hand, there are also some studies focusing on the effects of factor mobility on the economic growth and regional coordination. Zhang and Wu (2019) point out that factor mobility not only promotes factor gains in inflowing areas, but also increases factor gains in outflowing areas. However, Li et al. (2020) take the opposite view and argue that there is heterogeneity in the role of factor mobility on regional equilibrium development, that is, capital and technology mobility can promote regional equilibrium development while labor mobility will lead to the expansion of the gap in regional economic development.

Over the years, scholars have never stopped paying attention to industrial transfer. The measurement of industrial transfer (Wang et al., 2021), industrial transfer efficiency (Luo and Dai, 2019), economic effects and environmental effects of industrial transfer (Liu et al., 2020) have received extensive attention. At the same time, the relationship between factor mobility and industrial transfer is also frequently discussed, which mainly includes the

following views: First, the combined effect of mobile labor, capital and technology is the main driving force to promote industrial transfer (Zhai, 2016). Second, industrial transfer can play the “reservoir effect” to promote factor mobility (Chen and Chen, 2007). In summary, the existing studies show that there is a close connection between factor mobility and industrial transfer, so it is necessary to discuss them within the same framework.

Under the goal of global carbon reduction, carbon emissions have gradually become one of the focal topics in academia. The accounting for carbon emissions (Kabir et al., 2021; Zhao et al., 2021), spatial layout of carbon emissions (Chen et al., 2021), carbon emission forecast (Gao et al., 2021), the carbon reduction effect of carbon tax (Liu et al., 2021), economic impact (Peng et al., 2021) and policy effects of carbon emissions (Xu, 2021; Wakiyama and Zusman, 2021) have received extensive attention. In addition, there are also some studies exploring the relationship between industrial transfer and carbon emissions. Li et al. (2021) analyze the relationship between industrial transfer and carbon emissions from the perspective of industrial chains, and identify the industrial paths that affects carbon emissions in China. Since energy consumption is the main source of carbon emissions (Rauf et al., 2020), and industrial transfer can change the spatial distribution of energy intensity by influencing the regional industrial structure (Zhao and Lu, 2019), industrial transfer not only promotes economic development, but also has a certain negative impact on the environment. In addition, Chinese industries, especially industrial industries, are gradually transferring from the coast to the mainland, which is also accompanied by carbon transfer (Wang et al., 2021). Due to industrial transfer or the movement of intermediate goods and services between industries, carbon emissions in some areas will be transferred to other areas, which will lead to hidden carbon emissions (Zheng, 2021). From the above studies, we can see that industrial transfer is closely related to carbon emissions.

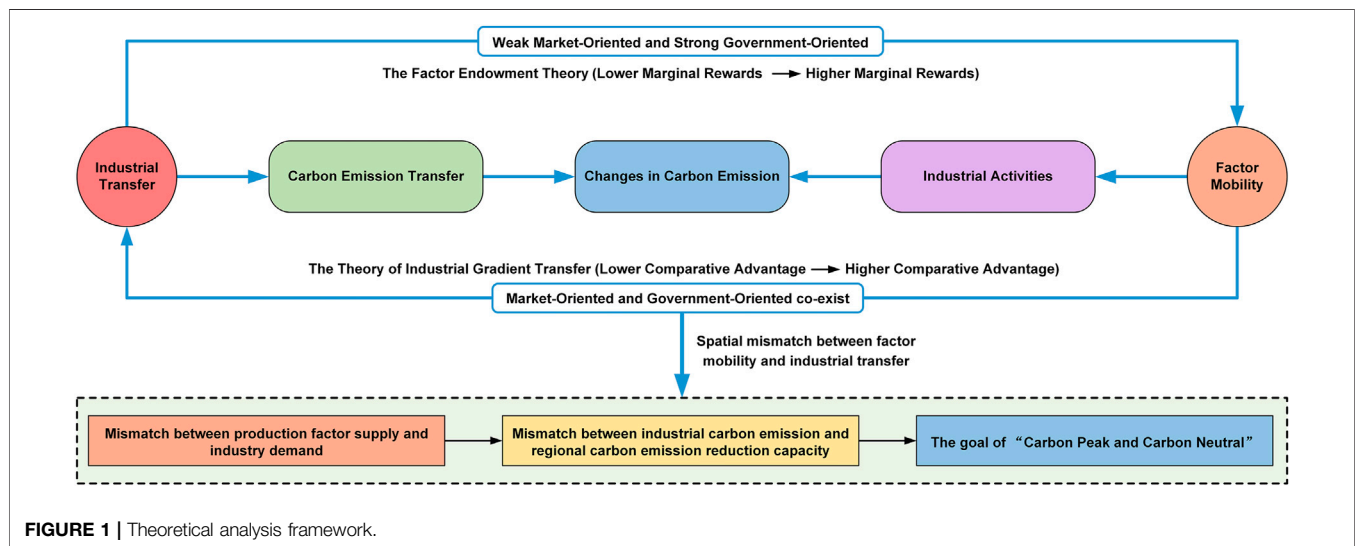
In summary, scholars have conducted extensive research on the impact of factor flow, industrial transfer and carbon emission intensity on economic development. Although these studies basically argue that carbon emission transfer will be accompanied by industrial transfer, and the spatial matchability of factor mobility and industrial transfer will hinder the process of industrial transfer, but the relationship between factor mobility, industrial transfer and carbon emission has not been fully explained. Therefore, we think that there are still several aspects need to be made up, so we carried out the following main works. First, we propose an improved dynamic industrial transfer index and characterize the spatial layouts and dynamic characteristics of interregional industrial transfer in China from 2004 to 2019 by using industrial data. Second, we compare the spatial matchability of factor mobility and industrial transfer, discuss the impact of factor mobility and industrial transfer on industrial carbon emission intensity from the perspective of spatial matchability, and then analyze the heterogeneity of this impact under different carbon emission intensities using quantile regression. Third, some policy recommendations are put forward to provide decision-making reference for improving the carbon emission reduction effect of industrial transfer and achieving the goal of “Carbon Peak and Carbon Neutrality”.

Research Hypothesis

Industrial activities are one of the main sources of CO₂ emissions (Li et al., 2019). There is significant heterogeneity in the carbon emission intensity of different industrial sectors due to differences in energy consumption structures. Among them, the industrial sectors using fossil energy such as coal, coke or oil and other energy-intensive sectors have higher carbon emission intensity. In addition, due to regional differences in technology endowment, scale effect, and environmental regulation intensity, the emission reduction capacity of different areas is not consistent, so the adjustments of industrial layout and changes in industrial structure may lead to adjustments and changes in carbon emissions (Yan and Yang, 2010). In general, the transfer of capital-intensive industries implies an increase in energy consumption, and a corresponding potential increase in carbon emission intensity (Zhao et al., 2020). While the transfer of technology-intensive industries may lead to an increase of regional technology level and a decrease of carbon emission intensity (Chen et al., 2020). In addition, technology-intensive and labor-intensive industries have lower carbon emission intensity compared to capital-intensive industries (Fu et al., 2021a). In other words, the impacts of different types of industrial transfer on carbon emissions may be heterogeneous. Accordingly, we propose the first research hypothesis of this paper.

H1: There is heterogeneity in the impact of different types of industrial transfers on industrial carbon emission intensity.

Production factors are the important basis of industrial activities, so the mobility and allocation of factors play a crucial role in industrial activities and will also have an impact on industrial carbon emissions accordingly. With the acceleration of economic system reform and marketization, the administrative barriers to resource allocation have gradually been broken. Based on the factor endowment theory, the quantitative and qualitative differences in production factors between different areas constitute an objective basis for factor mobility (Zhang, 2016). Due to the differences in economic development levels and industrial returns, the profit-seeking nature of production factors tends to make them cluster in areas or industries with higher marginal rewards (Zhao and Xu, 2020). However, the total amounts of production factors in economic activities, such as labor and capital, are limited. And factor mobility inevitably leads to the redistribution of production factors among areas and industries, which ultimately affects the layout and structure of industrial production. In addition, China’s factor markets have serious institutional barriers and low levels of factor market allocation (Lu and Wang, 2021), and industrial transfer is not always dominated by the market behavior of spontaneous factor mobility, government regulation is also one of the important factors leading to industrial transfer (Zhang et al., 2019). Therefore, the dual role of government and market may lead to serious misalignment problems between factor mobility and industrial transfer, which in turn will affect factor productivity and industrial carbon



emissions. Besides, according to the theory of industrial gradient transfer, developed areas with high factor abundance have stronger incentives to transform and upgrade their industries, thereby prompting industries that have lost comparative advantages or with high energy consumption and high pollution to transfer to developing areas, where they may still have comparative advantages. So industrial transfer can be used to achieve industrial progress in developed areas and industrial upgrading in developing areas (Sun and Hou, 2021). From this perspective, the process of industrial transfer will be accompanied by the spatial transfer of demand for production factors. Due to the imperfect market mechanism or information asymmetry, the flow direction of labor, capital and other production factors often cannot change in time with the direction of industrial transfer, which will lead to the problem of mismatch between factor mobility and industrial transfer and the imbalance between the supply and demand of factors. In turn, the imbalance between supply and demand of production factors will affect the process of industrial transfer. When the direction of factor mobility does not match that of industrial transfer, the contradiction between factor mobility, industrial transfer and carbon emission reduction will be strengthened. Therefore, we propose the second research hypothesis of this paper. **Figure 1** shows the theoretical analysis framework of this paper.

H2: The matchability of factor mobility and industrial transfer will affect the carbon emission reduction effect of industrial transfer.

METHOD AND DATA

Estimation of Factor Mobility

According to the Cobb-Douglas production function, technology, labor, and capital are the main factors that determine the level of

industrial development. Therefore, in this paper, we mainly focus on the impact of labor, capital, and technology mobility on carbon emissions.

Labor mobility (lf)

China conducts a population census as well as migrants statistics every 10 years, and conducts a migrant population dynamic survey (CMDS) every year, but the coverage of the dynamic survey is small, with a sample size of about 200,000 households, which only accounts for about 0.04% of China's total population. In other words, there is no continuous official data on labor mobility that covers the whole country in China. Considering the lack of official statistics, we learn from the common practice of scholars and use net population change after excluding natural growth factors (Lin and Wang, 2006) to measure the macro-level population mobility. From the 2010 census in China, the proportion of labor force in the mobile population is about 90%. Therefore, this paper uses the net population change after excluding the natural growth factor multiplied by the proportion of labor force in the mobile population to measure inter-provincial labor mobility, which is defined as follows:

$$lf_{i,t} = \left(\frac{L_{i,t} - L_{i,t-1}}{L_{i,t-1}} - n_{i,t} \right) \times 0.9 \quad (1)$$

where $L_{i,t}$ represents the total population of province i at the end of year t , and $n_{i,t}$ is the natural growth rate of province i in year t .

Capital mobility (cf)

Since there are no official public data on inter-provincial capital mobility in China, we follow the common practice of Chinese scholars to approximate the inter-provincial capital mobility by using the expenditure approach principles of national economic accounting (Hu and Wu., 2012). According to the formula of national economic accounting, GDP can be decomposed into final consumption (C), capital

formation (I) and net outflow of goods and services (X), where X can be assumed to be the consumption of goods and services in the province by residents outside the province (including other domestic provinces and abroad). Therefore, based on the principle that the direction of goods and services mobility is opposite to that of capital mobility, the size of inter-provincial capital mobility is approximated by the net outflow of goods and services minus the net export of foreign trade. In this paper, the ratio of the size of inter-provincial capital mobility to GDP is used as a proxy variable for capital mobility, which can also be used to capture domestic market trade.

Technology mobility (tf)

Technology market transaction is a suitable indicator to measure inter-regional technology mobility (Yu et al., 2019). However, it is worth noting that, unlike labor and capital mobility, technology outflow does not lead to a decline in the technology level of the outflowing area, so technology market transactions in inflowing areas can be used as a proxy variable for inter-provincial technology mobility, specifically measured by the ratio of technology market transactions to GDP.

Estimation of Industrial Transfer

Manufacturing transfer is the main form of industrial transfer. Developed countries have well-developed information on the location of enterprises and can directly judge the scale and direction of industrial transfer based on changes in the location of enterprises (Arauzo-Carod et al., 2010), while such information is difficult to obtain in China, so industrial transfer in China is usually measured in an indirect way. Zhao and Yin (2011) propose a method to measure industrial transfer based on the idea of share transfer. Sun et al. (2018) point out that the change in the number of enterprises cannot accurately reflect the transfer of manufacturing industries, so they make some improvements based on Zhao's study by using the change in production scale after excluding the natural growth of industries to reflect industrial transfer, which is defined as follows:

$$IR_{ci,t} = P_{ci,t} - P_{ci,t_0} \\ = \frac{q_{ci,t}}{\sum_{c=1}^n q_{ci,t}} / \frac{\sum_{i=1}^m q_{ci,t}}{\sum_{i=1}^m \sum_{c=1}^n q_{ci,t}} - \frac{q_{ci,t_0}}{\sum_{c=1}^n q_{ci,t_0}} / \frac{\sum_{i=1}^m q_{ci,t_0}}{\sum_{i=1}^m \sum_{c=1}^n q_{ci,t_0}} \quad (2)$$

where $IR_{ci,t}$ denotes the industry transfer index of industry i of area c in year t , $P_{ci,t}$ and P_{ci,t_0} denote the total production scale of industry i in year t and year t_0 (base period), respectively. m presents the number of industries, $q_{ci,t}$ denotes the production scale of industry i in area c in year t , and $\sum_{i=1}^m q_{ci,t}$ denotes the overall production scale. Eq. 2 examines the industrial transfer related to a specific year, however, the industrial transfer examined by a fixed base period cannot better reflect the dynamics of industrial transfer. Moreover, in order to make the industrial transfer index relatively comparable to the factor mobility based on the previous year, we improve Eq. 2 by defining the industrial transfer index as the difference between the relative

proportion of production scale in the current year and the relative proportion in the previous year, and defining the index as a dynamic industrial transfer index, which can be expressed as follows:

$$IR_{ci,t}^d = P_{ci,t} - P_{ci,t-1} \\ = \frac{q_{ci,t}}{\sum_{c=1}^n q_{ci,t}} / \frac{\sum_{i=1}^m q_{ci,t}}{\sum_{i=1}^m \sum_{c=1}^n q_{ci,t}} - \frac{q_{ci,t-1}}{\sum_{c=1}^n q_{ci,t-1}} / \frac{\sum_{i=1}^m q_{ci,t-1}}{\sum_{i=1}^m \sum_{c=1}^n q_{ci,t-1}} \quad (3)$$

When $IR_{ci,t}^d = 0$, the industry is not transferred. If $IR_{ci,t}^d > 0$, it means that industry i of area c in year t undergoes transfers in relative to the previous year. Otherwise, the industry is relatively transferred out.

Estimation of Industrial Carbon Emission Intensity

Carbon intensity is usually defined as CO₂ emissions per unit of GDP (Zhou et al., 2019). Accordingly, industrial carbon intensity (ci) can be defined as CO₂ emissions per unit of industrial outputs, and the combustion of fossil energy is the main source of CO₂ emissions (Zhao and Luo, 2018). Based on the general approach of existing studies, the consumption of fossil energy is used to estimate CO₂ emissions according to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, as shown in Eq. 4.

$$C = \sum AD_i \times NCV_i \times EF_i \times O_i \times \frac{44}{12} \quad (4)$$

where C denotes CO₂ emission and i denotes energy type. In this paper, the fossil energy mainly includes raw coal, washed coal, other washed coal, coal, coke, coke oven gas, blast furnace gas, other gas, crude oil, gasoline, kerosene, diesel, fuel oil, naphtha, lubricating oil, paraffin, solvent oil, petroleum asphalt, petroleum coke, liquefied petroleum gas, refinery dry gas, natural gas, other petroleum products and other coking products, etc., AD_i , NCV_i , EF_i and O_i represent energy consumption, average low level heat content, carbon content per unit calorific value and carbon oxidation rate, respectively.

Control Variables

Refer to existing researches, we choose economic externality (eo), technological innovation (inv), industrial structure (ind), urbanization rate ($urban$), fiscal self-sufficiency rate (fss), and environmental regulation ($mier$) as control variables. eo , ind , and $mier$ are all relative indicators, which are measured by the proportion of total exports and imports in GDP (Waugh and Ravikumar, 2016), the proportion of secondary industry output in GDP, and the proportion of resource tax, vehicle use tax, and environmental tax (sewage charge) related to environmental protection in GDP (Jorgenson and Wilcoxon, 1990), respectively. inv , $urban$, and fss are expressed as the number of invention patent applications per 10,000 people, the proportion of urban population, and the proportion of budget revenue to budget expenditure (Zou et al., 2019), respectively.

Data Source

After combing through the sustainable development and low-carbon emission reduction policies of China, we found that the Scientific Outlook on Development, introduced in July 2003, is of great significance to China's energy conservation and to the sustainable development. Therefore, 2004 is chosen as the starting point of this paper. The energy consumption data used to calculate CO₂ emissions are from the China Energy Statistical Yearbook (2005–2020). The year-end population and natural growth rates required for labor mobility and the data required for capital mobility are from the China Statistical Yearbook (2004–2020), where data on “net outflows of goods and services” for 2019 are missing for some provinces, and we use the average growth rates of the last 5 years for estimation. The technology market transactions in the inflowing areas required for technology mobility are obtained from the China Statistical Yearbook on Science and Technology (2005–2020). The manufacturing industries are divided into labor-intensive, capital-intensive and technology-intensive according to the intensity of production factors. The data on industrial output value required for industrial transfer come from the China Industry Statistical Yearbook (2004–2020), wind database and statistical yearbooks of relevant provinces. The data required for the control variables are from the China Statistical Yearbook (2005–2020) and the Finance Yearbook of China (2005–2020). The VIF test shows that the variance inflation coefficients of all variable are less than 10, which can prove that there is basically no multicollinearity in these variables (Hair et al., 1995).

Method

Moderating Effect Model

In this paper, the panel fixed effects model is used to examine the relationship between factor mobility, industrial transfer and industrial carbon emissions. Combined with the theoretical analysis, the impact of the interaction between factor mobility and industrial transfer on carbon emissions is the focus of our attention. Therefore, in addition to factor mobility and industrial transfer, the interaction term of these two indicators is added to the model to examine the effect of their interaction on industrial carbon emissions, and the model is shown in Eq. 5.

$$ci_{it} = \alpha_0 + \alpha_1 ff_{it} + \alpha_2 \times int_{it} + \alpha_3 ff_{it} \times int_{it} + \alpha \sum X_{it} + u_i + \lambda_t + \varepsilon_{it} \quad (5)$$

where ci represents industrial carbon emission intensity, ff denotes factor mobility, which include labor mobility (lf), capital mobility (cf), and technology mobility (tf), respectively. int is industrial transfer, including labor-intensive industry transfer (lit), capital-intensive industry transfer (cit), and technology-intensive industry transfer (tit). X denotes a set of potential control variables, u_i denotes individual fixed effects, λ_t denotes time fixed effects, and ε_{it} denotes a random error term.

Quantile Regression Model

Considering that the industrial carbon emission intensity may represent the ability to reduce emissions, the impacts of factor

mobility and industrial transfer on industrial carbon emission intensity may be heterogeneous at different industrial carbon emission intensities. Quantile regression is one of the effective methods to examine the heterogeneous impacts of explanatory variables on the explained variables at different quantile levels, and it uses the conditional expectation of the explained variable to obtain a regression equation in any quantile level of the explained variable by adding the absolute value of the minimum residual weights (Koenker, 2004). The formula for the quantile regression is as follows:

$$Q_{\tau}(y_i | x_i) = X_i^T \beta_{\tau} \quad (6)$$

Following Alvarado et al. (2021), we use the panel quantile regression approach to estimate the heterogeneous impacts of the factor mobility and industrial transfer on industrial carbon emission intensity at different quantile levels. We specify the quantile τ th ($0 < \tau < 100$) of the dependent variable's conditional distribution as a function of a set of explanatory factors X_{it} . The equation is shown in Eq. 7.

$$Q_{\tau} \left(\frac{ci_{it}}{X_{it}} \right) = \alpha_{\tau} + X_{it} \beta_{\tau} + \alpha_{\tau} \varepsilon_{it} \quad (7)$$

The matrix X_{it} is the set of all the explanatory and control variables, and ε_{it} is the error term. In this paper, the model of quantile regression can be specifically expressed as Eq. 8.

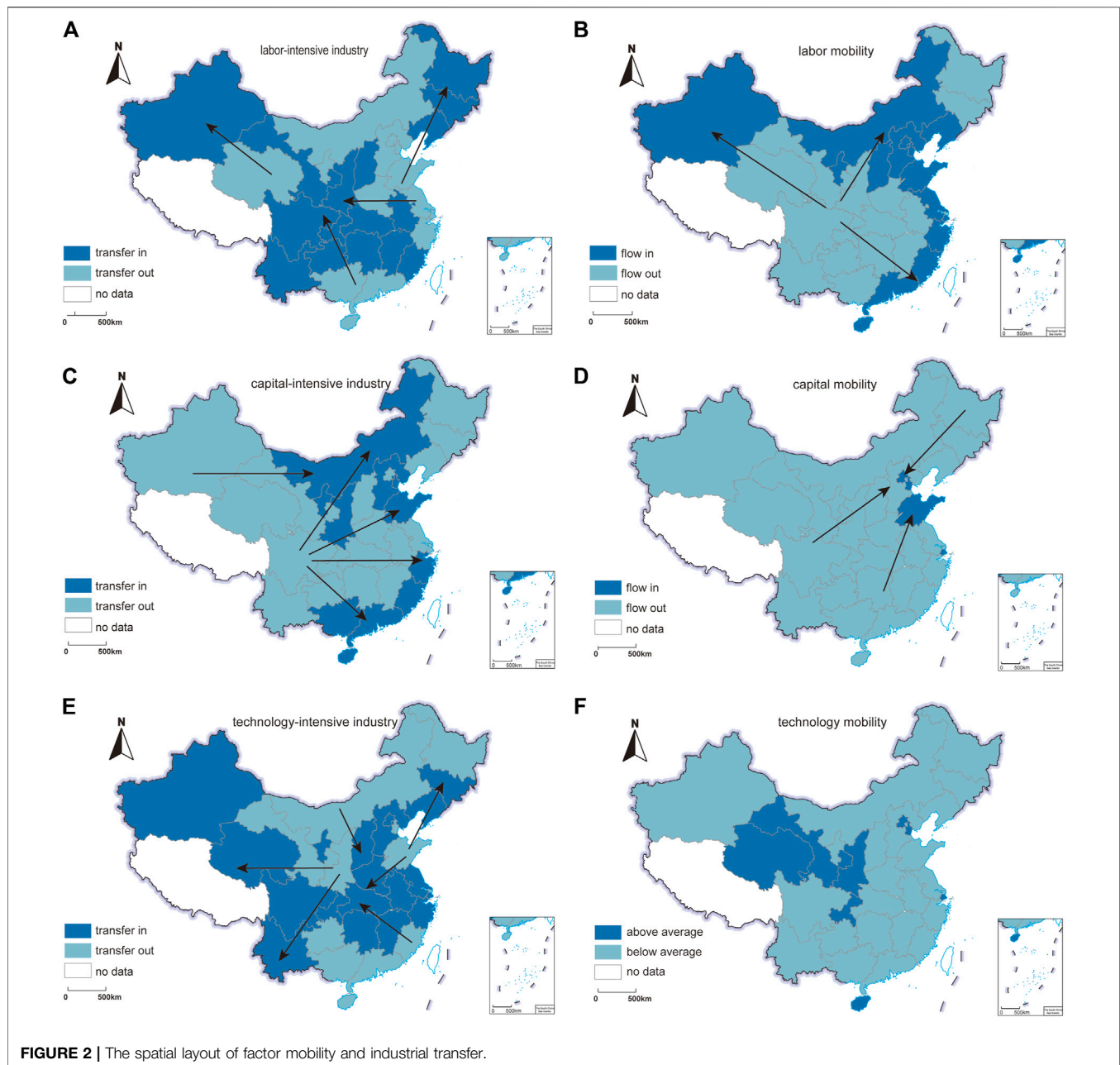
$$Q_{(\tau)}(\tau | \alpha_i, \varepsilon_t, X_{it}) = \alpha_i + \varepsilon_t + \beta_{1\tau} ff_{it} + \beta_{2\tau} int_{it} + \beta_{3\tau} ff_{it} \times int_{it} + \beta_{4\tau} eo_{it} + \beta_{5\tau} inv_{it} + \beta_{6\tau} ind_{it} + \beta_{7\tau} urban_{it} + \beta_{8\tau} fs_{it} + \beta_{9\tau} mier_{it} \quad (8)$$

DESCRIPTION OF OBJECTIVE FACTS

Spatial Matchability of Factor Mobility and Industrial Transfer

From the spatial matchability of factor mobility and industrial transfer, production factors generally flow from the central and western areas to the eastern areas, while the direction of industrial transfer is opposite. Especially labor-intensive industries and technology-intensive industries generally transfer from the eastern areas to the central and western areas, and there is a relatively obvious spatial mismatch between the direction of factor mobility and the trend of industrial transfer.

Figures 2A, B reflect the spatial layout of labor mobility and labor-intensive industrial transfer, respectively. As can be seen from the China Census in 2010, employment is the main factor of labor mobility across provinces, accounting for 77.2%. More than 55.4% of the mobile labor force is employed in manufacturing industries, and the labor force with a college degree or above is less than 11.6%. Overall, labor-intensive industries are the main industries absorbing low-skilled labor. Comparing Figures 2A, B, we can find that, during 2004–2019, labor-intensive industries basically show a trend of transferring from the eastern areas to the central, western, and northeastern areas, while labor force shows a trend of moving from the central and western areas to the



eastern areas. Although the trend of labor inflow in eastern provinces such as Beijing, Shanghai and Shandong slows down after 2016, and there is even a net outflow, the labor force in some central and western areas begin to return at the same time, the contradiction between labor supply and demand in the central and western areas remains prominent with the transfer of labor-intensive industries to central and western areas.

Figures 2C, D reflect the basic situation of capital mobility and capital-intensive industry transfer. And we can see that, from 2004 to 2019, capital flows from the central and western areas to the eastern areas, while capital-intensive industries do not show a clear trend of transferring from the eastern to the central and western areas, just like the findings of (Fu et al.,

2021b). In general, capital-intensive industries in the eastern provinces such as Tianjin, Hebei, Shandong, Zhejiang, Fujian, Guangdong and Hainan remain net inflows. Comparing the regional input-output tables of China, we find that Beijing, Tianjin, Shanghai, Jiangsu, Shandong and Fujian generally show net outflows of domestic and provincial capital-intensive products, while the central and western areas mostly show net inflows of domestic and provincial capital-intensive products, indicating that the eastern areas are still the main production base for capital-intensive products. It also indicates that although capital mobility and capital-intensive industry transfer are more consistent in some provinces, the matchability between them still needs to be improved.

TABLE 1 | Average industrial carbon emission intensity in various provinces in China from 2004 to 2019 (tons/million).

No.	Low-carbon areas			High-carbon areas		
	Area	<i>C_i</i>	No.	Area	<i>C_i</i>	No.
1	Guangdong	3.0382	9	Hubei	6.2271	1
2	Fujian	3.6593	10	Sichuan	6.3628	2
3	Zhejiang	3.6751	11	Hunan	6.4236	3
4	Jiangsu	4.2196	12	Tianjin	7.5717	4
5	Shanghai	4.9240	13	Henan	7.7095	5
6	Chongqing	5.4303	14	Guangxi	7.7609	6
7	Jiangxi	5.6533	—	—	—	7
8	Beijing	5.6771	—	—	—	8

It can be seen from **Figures 2E, F** that technology-intensive industries transfer from the eastern areas to the central and western areas, which is like the findings of Cao and Zhang. (2021). However, there is still a mismatch between technology mobility and technology-intensive industry transfer in terms of technology market transactions. The main manifestation is that technology-intensive industries mainly transfer to areas where technology inflows are lower than the national average. Next, we examine the independent innovation capacity of areas that absorb technology-intensive industries. Among them, the number of invention patent applications per 10,000 people in eastern coastal areas such as Beijing, Shanghai, Jiangsu, and Zhejiang exceeded 2, however, it is less than 0.5 in the central and western areas. The above information shows that there is also an imbalance in the spatial layout and innovation level of technology-intensive industrial transfer. Although some technology-intensive industries have transferred into the central and western areas where the level of independent innovation is relatively weak due to industrial layout adjustment, the direction of technology mobility represented by technology market transactions and the transfer direction of technology-intensive industries cannot be matched in time.

Basic Performance of Industrial Carbon Emission Intensity

According to the national average industrial carbon emission intensity from 2004 to 2019 (the average value is 8.1382), the 30 provinces are divided into low carbon emission intensity areas (low-carbon areas) and high carbon emission intensity areas (high-carbon areas). From **Table 1**, we can see that the industrial carbon emission intensity of China shows obvious regional distribution characteristics, with a spatial pattern that the east is lower than the west, and the south is lower than the north. Among them, the southeast coastal area has the lowest carbon emission intensity. From the perspective of industrial carbon emission intensity trends, the carbon emission intensity of all provinces decreases significantly from 2004 to 2019. The overall industrial carbon emission intensity of China decreases from 11.5210 to 6.3521, with a decrease of about 44.87%. The average industrial carbon emission intensity of low-carbon areas decreases from 7.3773 to 3.2648 with a decrease of about 55.75%. The average industrial carbon emission intensity in high-carbon areas decreases from 19.1107 to 12.8883, with a decrease of

TABLE 2 | Results of the panel unit root test.

Variables	LLC test		ADF-Fisher test	
	Statistic	<i>p</i> -value	Statistic	<i>p</i> -value
<i>ci</i>	-7.5425***	0.0000	109.0661***	0.0001
<i>lf</i>	-7.4093***	0.0000	243.3295***	0.0000
<i>cf</i>	-3.0962***	0.0010	155.2880***	0.0000
<i>tf</i>	-3.1674***	0.0008	143.9097***	0.0000
<i>lit</i>	-3.0554***	0.0011	147.5111***	0.0000
<i>cit</i>	-4.1994***	0.0000	133.3901***	0.0000
<i>tit</i>	-3.8887***	0.0001	147.0320***	0.0000
<i>eo</i>	-2.2931**	0.0109	147.0443***	0.0000
<i>inv</i>	-7.4075***	0.0000	177.9160***	0.0000
<i>ind</i>	-4.8320***	0.0000	147.2384***	0.0000
<i>urban</i>	-3.5233***	0.0002	138.3170***	0.0000
<i>fss</i>	-4.8094***	0.0000	175.0018***	0.0000
<i>mier</i>	-6.0502***	0.0000	137.1842***	0.0000

32.56%. Thus, we can see that the central and western areas with high carbon emission intensity are still the key areas for carbon emission reduction in China.

RESULTS AND DISCUSSIONS

Baseline Regression

Before performing empirical analysis, we conduct a panel unit root test using the LLC test and the ADF-Fisher test. The results in **Table 2** show that the original hypothesis of the existence of a unit root for each variable is strongly rejected, so the panel series is stationary.

Table 3 is the analysis results of full samples. Col. (1) indicates that labor force inflow can exacerbate industrial carbon intensity, which is similar to the findings of Liu et al. (2021). One possible reason is that the cross-regional labor mobility is accompanied by the adjustment of labor structure, which is mainly manifested in the transfer of rural labor and the transfer of labor from the primary industry to the secondary and tertiary industries. Especially, the increase in employment in the secondary industry implies the expansion of the industrial scale and the increase in energy consumption and carbon emission intensity. Col. (2) and Col. (3) show that labor-intensive industrial transfer contributes to the reduction of industrial carbon emission intensity. The negative estimated value of the interaction term

TABLE 3 | Results of baseline regression.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>lf</i>	0.0016* (1.93)	—	0.0018** (2.12)	—	—	—	—	—	—
<i>lit</i>	—	-0.0019*** (-3.25)	-0.0020*** (-3.43)	—	—	—	—	—	—
<i>lf*lit</i>	—	—	-0.0001* (-1.85)	—	—	—	—	—	—
<i>cf</i>	—	—	—	-0.0013 (-1.42)	—	-0.0015 (-1.64)	—	—	—
<i>cit</i>	—	—	—	—	0.0095*** (9.42)	0.0103*** (9.55)	—	—	—
<i>cf*cit</i>	—	—	—	—	—	0.0001** (2.44)	—	—	—
<i>tf</i>	—	—	—	—	—	—	-0.0736*** (-3.57)	—	-0.0472** (-2.34)
<i>tit</i>	—	—	—	—	—	—	—	-0.0046*** (-5.32)	-0.0014* (-1.85)
<i>tf*tit</i>	—	—	—	—	—	—	—	—	-0.0017*** (-4.34)
<i>eo</i>	0.0390 (1.03)	0.0413 (1.11)	0.0308 (0.82)	0.0588 (1.53)	0.0868** (2.51)	0.1060*** (3.01)	0.0292 (0.78)	0.0844** (2.27)	0.0489 (1.33)
<i>inv</i>	-0.1430*** (-6.59)	-0.1584*** (-7.29)	-0.1541*** (-7.09)	-0.1450*** (-6.69)	-0.1661*** (-8.35)	-0.1580*** (-7.83)	-0.1364*** (-6.32)	-0.1535*** (-7.29)	-0.1332*** (-6.40)
<i>ind</i>	-0.6098*** (-5.44)	-0.6083*** (-5.51)	-0.6442*** (-5.78)	-0.5583*** (-5.00)	-0.7157*** (-6.97)	-0.6934*** (-6.77)	-0.6198*** (-5.62)	-0.6848*** (-6.24)	-0.7433*** (-6.40)
<i>urban</i>	-0.6621*** (-3.63)	-0.4231** (-2.33)	-0.5031*** (-2.71)	-0.6335*** (-3.49)	-0.1961 (-1.17)	-0.3311* (-1.91)	-0.5564*** (-3.18)	-0.4243** (-2.43)	-0.6011*** (-3.44)
<i>fss</i>	-0.0272*** (-3.38)	-0.0291*** (-3.64)	-0.0296*** (-3.71)	-0.0253*** (-3.11)	-0.0399*** (-5.32)	-0.0364*** (-4.83)	-0.0189** (-2.28)	-0.0339*** (-4.27)	-0.0263*** (-3.27)
<i>mier</i>	0.0471 (1.27)	0.0250 (0.68)	0.0361 (0.98)	0.0313 (0.85)	0.0316 (0.94)	0.0316 (0.93)	0.0547 (1.49)	0.0390 (1.09)	0.0602* (1.72)
<i>cons</i>	10.4450*** (13.14)	4.8604*** (6.33)	5.3112*** (6.64)	10.1321*** (13.22)	4.4845*** (6.40)	4.9563*** (6.84)	10.1525*** (13.51)	5.2384*** (7.10)	6.2149*** (8.37)
Area fixed	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time fixed	yes	yes	yes	yes	yes	yes	yes	yes	yes
<i>F</i> ²	0.5444	0.5513	0.5567	0.5426	0.6172	0.6240	0.5534	0.5681	0.5949
Obs	480	480	480	480	480	480	480	480	480
<i>F</i> -value	75.16***	77.74***	61.54***	75.09***	102.05***	81.31***	78.42***	83.25***	71.95***

Note: *, ** and, *** indicate that the statistical value is significant at the 10%, 5%, and 1% levels, respectively.

between labor mobility and labor-intensive industrial transfer indicates that the emission reduction effect of labor-intensive industrial transfer can be strengthened with the inflow of labor. The reason may be that labor-intensive industries such as food processing, furniture manufacturing, and textiles have lower carbon emission intensity compared with capital-intensive industries such as metal products and chemical raw material processing (Fu et al., 2021a). While the spatial mismatch between labor-intensive industry transfer and labor mobility will lead to a structural shortage of labor, forcing labor-intensive industries to undergo automation and intelligent transformation and upgrading. In addition, due to the natural labor-dependent attributes of labor-intensive industries, the return of labor will alleviate the contradiction between labor supply and demand in areas where labor-intensive industries are transferred in. Therefore, with the increase of labor inflow, the carbon emission reduction effect of labor-intensive industry transfer areas is strengthened.

In **Table 3**, col. (4)–(6) show that the estimated value of capital mobility is negative but not significant, the capital-intensive industries transfer aggravates the industrial carbon emission intensity, and the interaction term between the two indicators indicates that the negative impact of capital-intensive industrial transfer on carbon emission reduction is enhanced by the capital inflow. Generally speaking, capital inflows are conducive to promoting the adjustment of the industrial structure, and promoting the transformation of industries that have lost their comparative advantages and high energy-consuming industries, thus promoting carbon emission reduction. However, capital inflows represent a net outflow of trade in goods and services, it means that the areas with goods outflows bear the carbon emissions from the production of goods for other areas (Seo et al., 2015). The more the capital inflows, the higher the implied carbon emissions, which in turn may weaken the emission reduction effect of capital inflow. From the industrial perspective, since capital-intensive industries often have the characteristics of high energy consumption and high pollution (Hu et al., 2021), the transfer of capital-intensive industries is actually accompanied by the transfer of carbon emissions, so industrial carbon emissions intensity will increase with the transfer of capital-intensive industries, which is consistent with the theoretical analysis. In addition, since the capital mobility examined in this paper reflects the trade of goods and services in the domestic market, combined with the direction of capital mobility and capital-intensive industry transfer in **Figure 2**, it can be seen that the areas of capital inflow are mainly those with low carbon emission intensity. Although capital inflow can provide the basic conditions for industrial transformation and upgrading, however, capital inflow makes the area bear the carbon emissions generated in the production of goods exported to other areas. Capital inflow areas such as Shandong and Tianjin are also areas where capital-intensive industrial are transferred in. The directions of capital mobility in these areas are relatively matched with that of capital-intensive industry transfer, which also exacerbates the negative impact of capital-intensive industry transfer on carbon emission reduction.

In **Table 3**, col. (7)–(9) show that both technology mobility and technology-intensive industrial transfer are conducive to reducing industrial carbon emission intensity, and the interaction of the two indicators further enhances the effect of carbon emission reduction, indicating that technology mobility and technology-intensive industrial transfer are effective ways to promote carbon emission reduction and achieve “Carbon Peak and Carbon Neutrality”. The result of the control variables show that independent innovation also significantly reduces industrial carbon emission intensity, which can further demonstrate that technological progress is an important way to achieve carbon emission reduction goals (Sun et al., 2021).

The above analysis shows that the matching of labor mobility and labor-intensive industrial transfer, and the matching of technology mobility and technology-intensive industrial transfer are both conducive to carbon emission reduction. While the matching of capital mobility and capital-intensive industrial transfer is unfavorable to carbon emission reduction in areas where capital-intensive industries are transferred in. Combining with the spatial matchability of factor mobility and industrial transfer in **Figure 2**, it can be found that, during the 2004–2019, the matchability of labor mobility and labor-intensive industrial transfer, and that of technology mobility and technology-intensive industrial transfer is poor, while the matchability of capital mobility and capital-intensive industrial transfer is better. This result indicates that there is a fragmentation between factor mobility and industrial transfer, which makes factor allocation ineffective in serving the needs of industrial layout adjustment and cannot effectively play the positive role of carbon emission reduction mechanism of industrial transfer.

Endogeneity Discussion and Robustness Test

Although some control variables and fixed effects are added in the model to reduce the estimation bias caused by omitted variables, the potential endogeneity caused by reverse causality still needs to be considered. In this paper, we mainly explore that, under the pressure of carbon emission reduction in China, local governments may adjust their industrial transfer strategies according to carbon emissions, thus affecting the spatial layout of industries transfer.

The average listing price of industrial land can be used as an instrumental variable for industrial transfer (Hou and Liang, 2021). The cost of industrial land is an important factor in the process of industrial transfer, and in order to maximize corporate profits, enterprises tend to move to regions with low industrial land costs, so industrial transfer is closely related to the listing price of industrial land. Besides, the average listing price of industrial land is generally not affected by carbon emission intensity, so it can be used as an instrumental variable for industrial transfer. We crawled 381,161 industrial land transaction data from 2004 to 2019 from the China Land Market website using crawler technology. After that, based on the industrial classification criteria in this paper and the “industry type” in the land transaction information, we divide the listing

TABLE 4 | Results of endogeneity discussion and robustness tests.

Variables	2sls			Replacing proxy variables of factor mobility			Replacing proxy variables of industry transfer		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>lf</i>	0.0036** (1.97)			0.0018** (2.16)			0.0017* (1.96)		
<i>lit</i>	-0.0184* (-1.72)			-0.0020*** (-3.39)			-0.0021*** (-4.07)		
<i>lf*lit</i>	-0.0001** (-2.02)			-0.0003** (-2.09)			-0.0001* (-1.70)		
<i>cf</i>		-0.0009 (-0.69)			-0.0043 (-1.33)			-0.0009 (-0.94)	
<i>cit</i>		0.0220*** (5.31)			0.0096*** (4.22)			0.0084*** (8.30)	
<i>cf*cit</i>		0.0001** (2.55)			0.0020** (2.28)			0.0001** (2.42)	
<i>tf</i>			-0.0496* (-1.74)			-0.0604*** (-3.98)			-0.0552*** (-2.71)
<i>tf*tf</i>			-0.0007** (-2.06)			-0.0029** (-3.10)			-0.0009* (-1.85)
<i>tf*tf*tf</i>			-0.00017** (-2.16)			-0.00005** (-2.44)			-0.00014*** (-3.36)
Control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes
Area fixed	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time fixed	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2				0.5560	0.6234	0.6093	0.5614	0.6052	0.5817
Obs	480	480	480	480	480	480	480	480	480

Unrecognizable tests and weak instrumental variable tests

K-P rk LM (p-value)	12.13* (0.0717)	3.60*** (0.0048)	9.58*** (0.0020)
K-P rk Wald F (10% threshold)	10.31 (7.03)	18.10 (7.03)	15.79 (7.03)

Note: *, **, *** indicate that the statistical value is significant at the 10%, 5%, and 1% levels, respectively.

price of industrial land into listing price of labor-intensive industrial land, listing price of capital-intensive industrial land and listing price of technology-intensive industrial land, which were then used as instrumental variables for labor-intensive industrial transfer, capital-intensive industrial transfer and technology-intensive industrial transfer, respectively. And then we use the 2sls method to estimate them. The higher the listing price of industrial land, the less conducive to industrial transfer. Therefore, we use the opposite value of the listing price of industrial land in the endogeneity discussion to compare with the baseline regression results. As shown in Col. (1)–(3) of **Table 4**, although the regression results of the 2sls model are slightly different from the baseline regression results in the estimates of some explanatory variables, the signs and significance of the coefficients are basically consistent, which can indicate that the regression results are still robust after considering the interference of endogeneity problems.

In addition, we adopt the method of replacing key variables for robustness tests to test the reliability of the experimental results. Since factor mobility and industry transfer are the key explanatory variables in this paper, the choice of their proxy variables is crucial to the empirical results. We replace the proxy variables for factor mobility and industrial transfer, respectively, and the results are shown in **Table 4**. Col. (4)–(6) are the results after replacing proxy variables of factor mobility. We replace labor mobility, capital mobility, and technology mobility with the changes in the proportion of the labor force in each province to the total national labor force (Chen and Bai, 2019), the changes in the proportion of fixed asset investment in each province to the total national investment (Qiang and Hu, 2022), and relative share of technology market transactions to GDP, respectively. Col. (7)–(9) are the results after replacing proxy variables of industrial transfer, we recalculate the industrial transfer index by replacing the total industrial output value with the industrial sales value. As can be seen from **Table 4**, the relationship between factor mobility, industrial transfer and industrial carbon emission intensity does not change substantially after replacing the explanatory variable, and the signs of other estimated variables are consistent with that of baseline regression and remain significant. Therefore, we believe that the results of this paper are basically robust.

Discussion on the Heterogeneity of Carbon Emissions Intensity

Yu et al. (2018) shows that industrial carbon emission intensity can reflect the carbon reduction capacity of the industrial sector in an area. A lower carbon intensity may represent a greater ability to reduce emissions, and then reducing the negative impact of transferring high carbon industries to the area. Conversely, areas with high industrial carbon emission intensity and weak emission reduction capacity may be more negatively affected by the transfer of high-carbon industries. In other words, the influence of the interaction of factor mobility and industrial transfer on industrial carbon emission intensity may be heterogeneous at different industrial carbon emission levels, and the panel

TABLE 5 | Results of quantile regression.

Variable	Quantiles				
	10	30	50	70	90
<i>lf</i>	0.0017 (1.15)	0.0017* (1.66)	0.0018** (2.16)	0.0018* (1.82)	0.0019 (1.23)
<i>lit</i>	-0.0023** (-2.32)	-0.0022*** (-3.07)	-0.0020*** (-3.59)	-0.0019*** (-2.72)	-0.0017 (-1.60)
<i>lf*lit</i>	-0.0001 (-0.92)	-0.0001** (-2.07)	-0.0001** (-2.06)	-0.0001*** (-2.63)	-0.0001 (-0.31)
<i>cf</i>	-0.0019 (-0.96)	-0.0017 (-1.25)	-0.0016 (-1.36)	-0.0014 (-1.00)	-0.0012 (-0.53)
<i>cit</i>	0.0097*** (5.18)	0.0100*** (7.74)	0.0103*** (9.40)	0.0106*** (7.96)	0.0110*** (5.21)
<i>cf*cit</i>	0.0001 (0.49)	0.0001* (1.85)	0.0001** (2.13)	0.0001** (2.05)	0.0001* (1.77)
<i>tf</i>	-0.0281 (-0.82)	-0.0376 (-1.59)	-0.0467** (-2.40)	-0.0556** (-2.30)	-0.0670* (-1.79)
<i>tit</i>	-0.0020 (-0.99)	-0.0017 (-1.23)	-0.0015** (-2.26)	-0.0012* (-1.83)	-0.0009** (-2.38)
<i>tf*tit</i>	-0.0018*** (-2.87)	-0.0017*** (-4.07)	-0.0017*** (-4.85)	-0.0017*** (-3.82)	-0.0016** (-2.40)

Note: *, ** and, *** indicate that the statistical value is significant at the 10%, 5%, and 1% levels, respectively.

quantile regression is one of the effective methods to verify the above point (Opoku and Aluko, 2021). The results reported at different quantiles of industrial carbon emission intensity are shown in **Table 5**.

As shown in **Table 5**, the estimated value of labor mobility is always positive but significant only at the 30th to 70th quartiles. The process of labor mobility across areas is also accompanied by labor transfers between rural and urban areas, and between agricultural and non-agricultural sectors. The higher the ratio of the labor force working in the non-agricultural sector, the higher the carbon emissions (Hao et al., 2021). Therefore, in general, labor mobility exacerbates the intensity of industrial carbon emission. In contrast, the estimated value of labor-intensive industry transfer is negative and its absolute value decreases as the quantile increases, indicating that the labor-intensive industry transfer can reduce industrial carbon emission intensity (Fu et al., 2021b). And the lower the industrial carbon emission intensity, the stronger the emission reduction capacity, the more obvious the emission reduction effect of labor-intensive industries transfer. While at the 90th quartile level, the emission reduction effect of labor-intensive industries is no longer significant. Looking at the interaction term of labor mobility and labor-intensive industry transfer, the magnitude of the estimated value does not change significantly at each quartile level, but the significance of the estimated value is the same as that of labor mobility, which indicates that the carbon reduction effect of labor-intensive industries can be strengthened with labor inflow.

The estimated value of capital mobility is negative but insignificant, while the estimated value of capital-intensive industry transfer is significantly positive at all quartile levels, and gradually become larger as the quartile increases. This result indicates that the negative effect of capital-intensive industry transfer on carbon emission reduction gradually increases with the increase of industrial carbon intensity. The interaction term between capital mobility and capital-intensive industrial transfer is significantly positive at the 30th to 90th quartiles, but the estimated value does not change significantly, which is similar to the baseline regression results, indicating that capital mobility exacerbates the negative impact of capital-intensive industrial transfer on carbon emission reduction again.

When the industrial carbon emission intensity is at the 50th to 90th quartiles, technology mobility has a significant positive effect on industrial carbon reduction, and the absolute value of the coefficient increases as the quartile level increases. Technology-intensive industrial transfer also has a positive effect on industrial carbon reduction, but it is only significant at the 50th to 90th quartiles, and the emission reduction effect of technology-intensive industrial transfer gradually decreases with the increase of carbon emission intensity. One possible reason is that, compared with low carbon emission areas, high carbon emission intensity areas have relatively weaker emission reduction capacity and a relatively lower overall technology level. Therefore, although the transfer of technology-intensive industries can reduce industrial carbon emission intensity, the technology level in these areas may not be able to meet the needs of technology-intensive industry development in a short time. Besides, since the supporting facilities required for technology-intensive industry development are inadequate, the emission reduction effect of technology-intensive industry transfer continues to weaken as industrial carbon emission intensity increases.

CONCLUSION AND POLICY RECOMMENDATIONS

Reducing industrial carbon emission intensity is an important way to promote carbon emission reduction and achieve the goal of “Carbon Peak and Carbon Neutrality”. This paper proposes a dynamic industrial transfer index and discusses the impact of the spatial matchability of factor mobility and industrial transfer on industrial carbon emission intensity by using Chinese provincial panel data from 2004 to 2019. There are several findings as follows.

First, there is an obvious spatial mismatch between the direction of factor mobility and the trend of industrial transfer in China. Taking the national average industrial carbon emission intensity as the basis for division, production factors generally flow from high-carbon to low-carbon areas, labor-intensive and technology-intensive industries generally transfer from low-carbon to high-carbon areas. However, the transfer of capital-intensive industries is relatively lagging behind, and low-carbon

areas are still the main production bases for capital-intensive products. Second, China's carbon emission reduction capacity has been improving, and the industrial carbon emission intensity has decreased significantly, with the national average industrial carbon emission intensity decreasing from 11.5210 to 6.3521 (a decrease of about 44.87%). Third, the interaction between factor mobility and industrial transfer can affect the industrial carbon emission intensity. When the directions of labor mobility and technology mobility are consistent with that of labor-intensive and technology-intensive industrial transfer, respectively, the carbon emission reduction effect of industrial transfer will be strengthened. When the direction of capital mobility is consistent with capital-intensive industrial transfer, the capital inflow will aggravate the negative impact of capital-intensive industry transfer on carbon emission. Finally, the impacts of factor mobility, industrial transfer, and the matchability of the two on industrial carbon emission intensity are heterogeneous, the carbon reduction effects of labor-intensive and technology-intensive industries are more obvious in low-carbon areas, while the negative effects of capital-intensive industrial transfer on emission reduction are more obvious in high-carbon areas.

In response to the above findings, we propose the following recommendations. First, it is necessary to make reasonable use of the “invisible hand” of the market and the “visible hand” of the government. On the one hand, it is necessary to play the decisive role of the market in factor allocation, speed up the reform of factor market prices, and promote the optimal allocation of factors according to market rules and market prices. On the other hand, in the process of promoting the government's role to change from “setting prices” to “setting rules,” it is necessary to promote the coordination of the market-oriented reform of factor allocation and regional coordinated development policies to alleviate the problem of regional factor mismatch.

Second, the strategic arrangement of industrial transfer should focus on the “trinity” of industrial structure upgrading, spatial layout adjustment and carbon emission reduction targets to achieve technological and structural emission reduction of industrial transfer. The central and western areas should raise the environmental access threshold and implement stricter environmental supervision policies to force the transformation and upgrading of the “high-pollution and high-consumption industries” and avoid becoming a “pollution refuge” for

domestic industrial transfer. At the same time, it is necessary to strengthen the planning of industrial transfer to weaken the negative impact of the transfer of the “high-pollution and high-consumption industries” on carbon emission reduction in terms of the location of transferred industries, supporting facilities, and the construction of industrial parks. The eastern areas should give full play to its advantages of strong independent innovation capability, high energy efficiency and industrial concentration, take the lead in promoting green transformation, and promote industrial emission reduction through industrial upgrading.

Third, a green and low-carbon modern industrial pattern should be actively built. On the one hand, it is necessary to accelerate the adjustment of energy structure and increase the proportion of renewable energy in the final energy consumption. At the same time, pay more attention to green independent technology innovation, and take the energy saving and clean technology as the focus of research, so as to promote the process of clean production. On the other hand, it is necessary to speed up the adjustment of industrial structure, curb the “high-pollution and high-consumption industries,” and focus on the development of strategic emerging industries and high-tech industries. In addition, it is necessary to give full play to the role of the carbon trading market and carbon tax in reducing carbon emissions. The coverage of the carbon emissions trading market needs to be gradually expanded, more attention should be paid to the role of fiscal policy in carbon emission reduction, and the introduction of the “carbon tax” should be actively explored.

DATA AVAILABILITY STATEMENT

The datasets can be obtained from the National Bureau of Statistics of China. <http://www.stats.gov.cn>.

AUTHOR CONTRIBUTIONS

XZ: Conceptualization, Methodology, Software, Data Curation, Validation, Writing—Original Draft, Visualization. HY: Formal analysis, Resources, Writing—Review and Editing. LY: Writing—Review and Editing, Supervision, Project administration.

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