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Determinants and spatial spillover of inter-provincial carbon leakage in China: The perspective of economic cycles

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ABSTRACT

Measuring and analysing carbon leakage are the foundation for improving environmental responsibility. Based on the origin–destination approach and spatial spillover analysis, this study explores factors of China's inter-provincial carbon leakage. A multiregional input–output model was used to obtain the carbon footprint of consumption, and the factors of carbon leakage were assessed. The results revealed that the economic development and environmental regulations of the origin and destination have opposite effects on carbon leakage. Accordingly, provinces with high-energy intensity and abundant energy resources are mainly net-exported carbon, whereas provinces with underdeveloped secondary industries are mainly net-imported carbon. Notably, a positive spillover effect of energy intensity exists at the origin, and a negative one occurs at the destination. Moreover, a positive spillover affects the origin's energy output, and the surrounding areas' energy endowment can create favourable conditions for carbon leakage at the origin. Finally, corresponding policy suggestions are presented based on the above analysis.

1. Introduction

Measuring carbon leakage requires constructing consumption-based footprint databases. The interlinkages among multiple regions further complicate this issue if the entire supply chain needs to be tracked, which may involve multiple regions. The consumption-based carbon footprint and carbon leakage must be adequately measured to address one of the significant concerns regarding climate change, which can be achieved by integrating input–output models and econometric tools. In particular, spatial spillover effects may interest policymakers as groups of regions that enjoy or suffer from carbon leakage may emerge. Indeed, effective policies should be developed to reduce carbon costs across regions to minimise carbon leakage.

These issues are of potential concern in major economies highly focused on primary and secondary industries. China is particularly interesting because it is the largest carbon dioxide emitter in the world. China set a crucial plan in 2020, accelerating the construction of a new development pattern with the domestic cycle as the main body, with the domestic and international cycles mutually reinforcing each other. The regions smooth the links of production, distribution, circulation and consumption and form value transfers to meet the demand for production and consumption in domestic circulation. In this process, the transfer of product value also transfers the carbon footprint. In other words, from the perspective of economic circulation, the carbon footprint considers final demand to be the driver of carbon emissions, including the sum of direct and indirect carbon emissions caused by final demand (Feng et al., 2013). Therefore, scientifically analysing the scale of the carbon footprint transfer and its determinants under the regional economic cycle is the premise of the scientific accounting of regional carbon responsibility and reasonable allocation of carbon emission rights. It is also conducive to forming a favourable situation of source governance and coordinated control to promote carbon emission reduction.

With sustainable development and a low-carbon economy as the ultimate goals, research on transforming a low-carbon economy into a green economy is constantly enriched (Saraji et al., 2021; Yu et al., 2020; Zhang and Ding, 2022). Energy, a vital source of carbon footprint and carbon leakage, is also a research hotspot (Streimikiene et al., 2021; Zhu et al., 2021). As a byproduct of energy consumption and the economic cycle, with the deepening division of labour and collaboration of

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production activities between regions, the problem of carbon footprint transfer has become increasingly prominent. Scholars have increasingly begun to discuss carbon footprint transfer and the factors influencing it (Xu et al., 2022; Ran et al., 2022), using gravity model or MRIO to measure regional carbon footprint (Song and Zhang, 2019; Liang et al., 2007), and using decomposition or Quadratic Assignment Procedure techniques to analyse the social, economic and environmental factors of carbon footprint transfer (Dong et al., 2022; Huo et al., 2022). However, there are several limitations to the existing research.

The extant literature has not adequately addressed the following problems. First, measuring the carbon footprint transfer scale is biased. Several scholars use the gravity model to measure the scale of carbon footprint transfer in research on the factors influencing the carbon footprint transfer network (Song and Zhang, 2019); however, this model lacks sufficient economic theoretical support. The determinants of bilateral flows chosen in the gravity model are limited (Wang and Feng, 2017), and it is difficult to consider the complexity and diversity of social phenomena. Further problems, such as assumptions of conditions and uncertainties of social factors, lead to bias in measuring the carbon footprint transfer scale.

Second, differences in carbon footprint origins and destinations were ignored in the analysis of carbon footprint transfer. No characteristic factor distinguishes carbon footprint sources and sinks for the scale network of the carbon footprint transfer, either using factor decomposition or regional differences (or correlations) (Wang et al., 2017; Li and Li, 2022). Bilateral origin and destination (OD) flow must consider the unique characteristics of the origin and destination. That is, the characteristics of the demand and supply sides and the spatial interaction between the two sides must be considered common determinants of carbon footprint transfer flows (Marrocu and Paci, 2013).

Third, spatial spillover of the carbon footprint transfer was not considered. Factors such as energy and the economy in China's provinces are spatially dependent, and different regions have different resource allocations; hence, carbon footprint transfer may have a spatial spillover effect (Peng et al., 2020). Thus, evaluating the determinants of bilateral OD flows should be done in a framework considering neighbouring areas' influence (Marrocu and Paci, 2013).

Therefore, this study aims to measure the scale and determinants of carbon footprint transfer, as analysed using the multiregional input–output (MRIO) model and OD-based spatial interaction models, from the perspective of an economic cycle. The main innovations of this study are as follows. First, based on the MRIO model, a framework for analysing the determinants of inter-provincial carbon footprint transfer from the perspective of the economic cycle is proposed. Second, aimed at the two-way network of carbon footprint transfer, the characteristics of source and sink places are incorporated into the spatial interaction model; the differences in the determinants between source and sink places are studied. Third, the analysis framework incorporates the spatial spillover effect of the determinants and quantifies the influence of the characteristics of the surrounding areas on the inter-provincial carbon footprint transfer of source and sink areas.

The remainder of this paper is structured as follows. Section 2 provides a literature review and relevant literature on the determinants of inter-provincial carbon footprint transfer. Section 3 discusses the ideas of this study, while Section 4 describes the methodology, introduces the models and methods for estimating inter-provincial carbon footprint transfer, studies the determining factors and analyses spatial spillover. Section 5 presents the results and discussion and analyses the characteristics of inter-provincial carbon footprint transfer, the influencing effect of determining factors on carbon footprint transfer and its spatial spillover. Finally, Section 6 provides conclusions and policy implications.

2. Literature review

The inter-provincial carbon footprint transfer forms a close and complex network. There are many driving factors behind this, summarised as energy endowment factors and economic, geographical and environmental regulation factors.

Energy endowment factors refer to the richness of regional energy resources. According to the factor endowment theory, energy abundance determines energy prices and regional energy-consumption patterns (Adom and Adams, 2018). For example, the low supply cost in energy-rich areas loosens the resource constraints of enterprises, easily leading to extensive energy use and low energy efficiency, thus directly increasing carbon emissions (Wu et al., 2021).

Moreover, rich natural resources tend to distort regional industrial structures, resulting in high-energy consumption and emissions from regional industries (Wang et al., 2019); therefore, for regions with high resource endowments, reducing energy-consumption intensity or improving energy-consumption efficiency is the key to reducing the carbon footprint (Chen and Zhu, 2019; Kyriakopoulos, 2021). Technological progress can reduce energy waste by improving energy efficiency (Tetteh et al., 2021; Ahmed et al., 2021; Kyriakopoulos, 2021) as an indirect means or cause the relocation of high-energy industries by promoting industrial transformation (Xia et al., 2022). This approach effectively improves regional energy-consumption efficiency (Chen et al., 2020).

Economic factors refer to the influence of regional economic circulation through economic structure and level of economic development, which then influences the transfer of the regional carbon footprint contained in economic circulation (Lei et al., 2017; Yang et al., 2022) through channels such as the value-added economic rate, the industrial structure, the population size, urbanisation (Xia et al., 2022; Dong et al., 2022; Khan et al., 2022). The level of economic development somewhat reflects the economic status of each region, and provinces with similar economic statuses are more likely to produce carbon transfers because of the flow of resource factors (Ma et al., 2019). In other words, the greater the difference in economic level between the carbon footprint transfer origin and destination, the lower the possibility of carbon footprint transfer (Shao and Wang, 2021).

Furthermore, industrial structure optimisation is beneficial for energy conservation and emissions reduction (Zhao et al., 2022; Zhu and Shan, 2020). For example, regions upstream of the industrial structure and the value chain division of labour tend to export more carbon-intensive products (Fang et al., 2022), which is the net transfer of carbon footprint out of provinces. In contrast, downstream regions should import carbon-intensive products from upstream industrial areas to meet production and living needs; therefore, these regions are more likely to be net transfer positive for the carbon footprint. Moreover, cross-regional industrial structure optimisation, including industrial transfer, is more conducive to reducing carbon emissions than single-region industrial structure optimisation (Zhu and Zhang, 2021), affecting the entire region's carbon footprint transfer.

Geographical factors, including distance and location, can affect the transfer of carbon footprints between regions through economic linkages, transportation costs and efficiency. According to the first law of geography, in terms of spatial distribution, geographical objects or attributes are related; the closer the distance, the closer the connection (Tobler, 1970). Therefore, geographically adjacent provinces can form an economic circle owing to a close association; convenience within the economic circle promotes the flow of economic value more frequently, making the transfer of the carbon footprint between regions more closely connected. Geographical distance also plays a decisive role in transportation costs and efficiency. The closer the distance, the lower the cost yet higher the efficiency; thus, carbon transfer is more likely to occur between neighbouring regions (Shao and Wang, 2021).

Environmental regulation factors protect the environment and regulate all types of behaviours that pollute the environment. Such regulation determines the production costs and development of enterprises. In response to strict environmental regulations, enterprises can improve their energy efficiency through technological innovation and directly reduce their regional carbon footprints (Pan et al., 2017). Enterprises can also choose industrial transfers to areas with low environmental regulation to avoid environmental production costs, which affect the carbon footprints of the two regions. From the perspective of difference, the greater the variance in the level of environmental regulation, the more likely an up–down industrial chain relationship exists between the two regions; thus, the carbon transfer relationship is closer (Yu and Gong, 2020). Nonetheless, regions with similar levels of environmental protection have closer economic ties and greater associations with carbon transfer (Bai et al., 2020). Given the lag in environmental regulation, its impact on the carbon emissions network may have a threshold, showing a nonlinear relationship (Jiang and Ma, 2021).

3. Theoretical framework

This study aims to calculate the scale of hidden carbon emission transfer in the process of the economic cycle, explore the influence of the characteristics of carbon footprint transfer sources and sinks on inter-provincial carbon footprint transfer and analyse the influence of factors on carbon footprint transfer in surrounding areas from the perspective of spatial spillover.

The carbon footprint is a concept based on the ecological footprint and is applied to measure carbon emissions. From a narrow perspective, the carbon footprint refers only to the direct carbon emissions generated by fossil fuel combustion. From a broad perspective, the carbon footprint refers to the total CO_2 emissions directly and indirectly caused by production activities. The carbon footprint can be transferred between regions in many ways, such as through air circulation, photosynthesis and natural material circulation; however, the carbon footprint shift generated by the economic cycle is the most crucial component. Economic circulation refers to the virtuous cycle driven by domestic demand in every economic activity link, including production, distribution, circulation, investment and consumption. In domestic economic circulation, various regions perform activities to meet the demand for production and consumption, such as exchanging production materials and distributing production value and consumption, forming a value transfer chain.

Furthermore, the transfer of carbon emissions hidden in the value chain cannot be ignored. According to the consumer principle of carbon emissions accounting, producers provide products and services to departments in other regions, and the responsibility for the carbon emissions should be attributed to consumers. Therefore, this study considers the carbon footprint as the complete carbon emissions caused by the region's final demand, including the transfer of embodied carbon emissions caused by transferring products and services in and out of regions during economic circulation.

Inter-provincial carbon footprint transfer is a two-way time transfer network comprising directional flows between origins and destinations, the size of which is affected by both its origin and destination. Moreover, the impacts of origin and destination characteristics on carbon footprint transfer differ significantly. Regarding carbon footprint transfer origins, regions with excellent energy endowments are typically the main areas of energy consumption, and their energy intensity is relatively high. In these regions, energy consumption is the direct cause of carbon emissions, and the possibility of carbon footprint transfer is high; therefore, the energy factor is a key factor affecting the carbon footprint transfer of origin.

For the transfer destination, industrial products with high-energy consumption imported for production and consumption demand are the main components of carbon footprint transfer. Regions with tertiary industries as the primary industrial structure and a high economic level lack the local supply of such products and have a great demand from foreign provinces. Therefore, economic factors will likely affect the carbon footprint transfer destination; however, at the economic level, the effects of carbon transfer in and out may be the same because embodied carbon transfer mainly relies on economic flow. The higher the economic level, the more frequent the economic flow, which promotes both carbon transfer and carbon transfer-out.

The determinants affect the local region's carbon footprint transfer and surrounding areas through the spatial spillover effect. From an economic perspective, spillover refers to the externality of economic activities, realised through four paths: demonstration, competition, aggregation and factor mobility effect (Hong et al., 2020; Fosfuri et al., 2001). The demonstration effect refers to the convergence phenomenon formed by the interaction and influence between regions, generating spatial spillovers through imitation. For example, the 'environmental dividend' brought by a region with strict environmental regulation causes other regions to follow and improve the level of environmental regulation, thus affecting the transfer of the inter-provincial carbon footprint. The competition effect, or the crowding effect, occurs when an excessive concentration of enterprises leads to mutual disadvantage; accordingly, enterprises spread to the surrounding areas to avoid competition, resulting in spatial spillover.

Under the influence of the competition effect, changes in industrial structure and energy intensities in surrounding areas may lead to changes in the scale of carbon footprint transfer. The agglomeration effect is the phenomenon of the spatial accumulation of enterprises with a division of labour and cooperation in a specific region, which generates spatial spillover through industrial agglomeration. For example, the areas surrounding a region with energy endowment advantages are often gathering places for enterprises with high-energy consumption; attracting enterprises with high-energy consumption can increase the scale of carbon footprint transfer. The factor mobility effect refers to the connection or interaction between neighbouring regions through technology, personnel and capital flows (Hao et al., 2021), resulting in spatial spillovers. In other words, the flow of personnel, technology and capital can cause changes in the industrial structure of both regions and affect the scale of inter-provincial carbon footprint transfer.

Based on the above theoretical foundation, this study's research framework comprises three parts. (1) This study measures the carbon footprint transfer scale. The premise of studying the factors influencing carbon footprint transfer is to measure the scale of the carbon footprint transfer. (2) This study calculates the inter-provincial carbon footprint transfer behind the economic cycle based on MRIO and examines the factors influencing carbon footprint transfer. Several factors influence carbon footprint transfer, such as energy, economic factors and the geographical environment, and the effects of origin and destination are different. This study explores the impact of economic factors, geographical environment and energy on carbon transfer from the perspectives of origin and destination. (3) Finally, this study investigates the spatial spillover effects of factors affecting carbon footprint transfer. The characteristic factors of a region affect the carbon transfer of surrounding areas through demonstrations, competition, industrial agglomeration, factor flow and other effects. Therefore, this study analyses the influence of origin and destination characteristics on the carbon footprint transfer of surrounding areas through the spatial spillover effect (Fig. 1).

4. Methodology

4.1. The calculation model of carbon footprint transfer

From the economic cycle perspective, sectors in different regions are related through intermediate inputs, and carbon emissions are transferred accordingly, forming a close spatial transfer network of the carbon footprint. The input–output analysis provides a basic method for measuring the economic links between regions and sectors. Therefore, this study uses the MRIO model to measure inter-provincial carbon footprint transfer, which is the basis and premise of research on the determinants of carbon footprint transfer.

The multiregional input–output table contains three quadrants. The first quadrant is the intermediate goods flow matrix, the second quad-

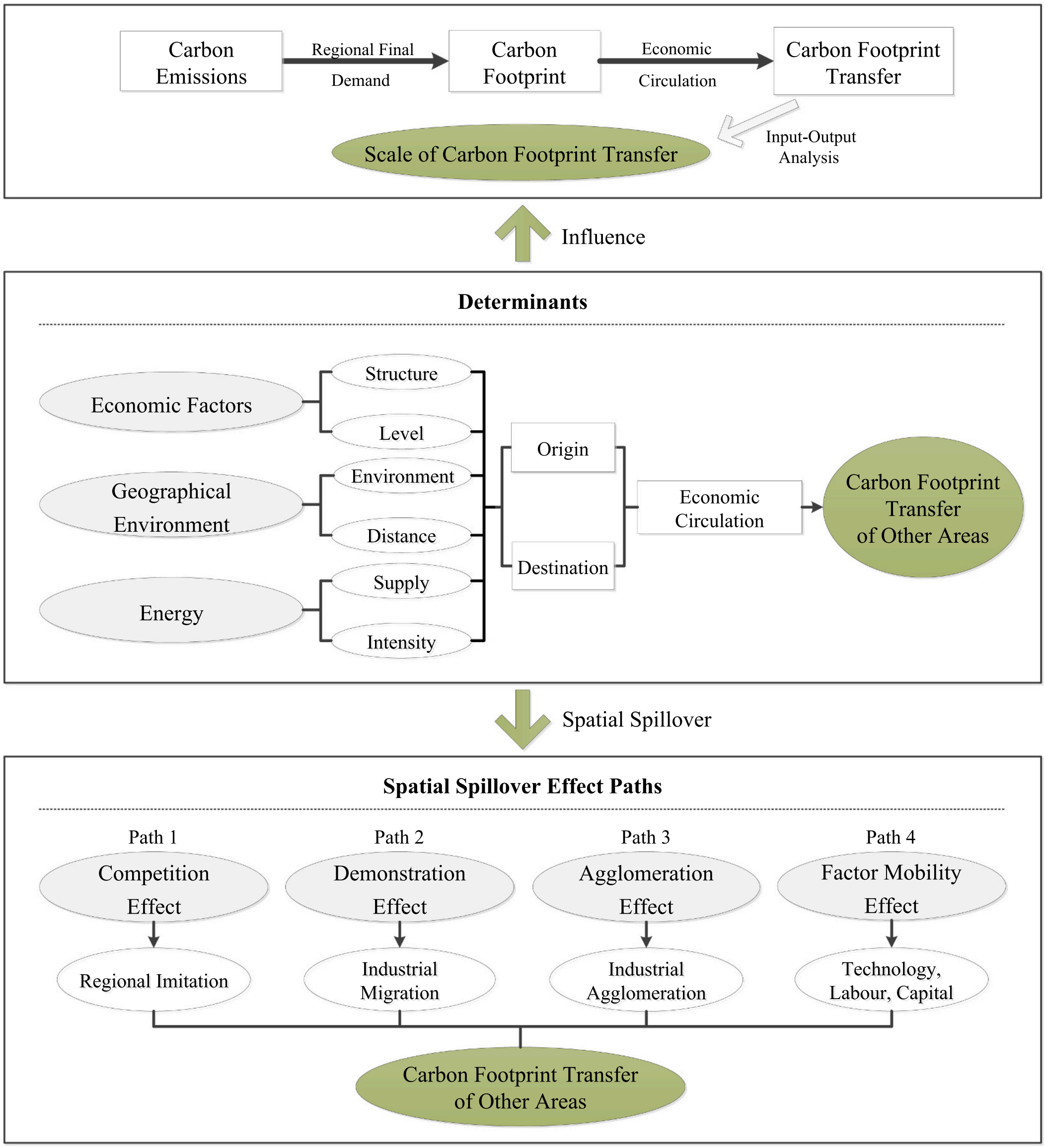

Fig. 1. The theoretical framework.
Note: Created by the author (*Visio*).

rant is the final use matrix, and the third is the value-added component. If the intermediate flow matrix has n departments and m provinces, the horizontal balance relationship is as follows:

$$\sum_{j=1}^{n}\sum_{s=1}^{m}x_{ij}^{rs}+\sum_{s=1}^{m}y_{i}^{rs}=x_{i}^{r} \tag{1}$$

where x_i^r represents the total output of sector i in region r. x_{ij}^{rs} represents the input of industry i in region r to the production process of industry j in region s, and y_i^{rs} represents the demand of region s for the final product of industry i in region r.

The direct consumption coefficient, a_{ij}^{rs}, represents the products of sector i in region r directly consumed by sector j in region s per unit of total output in the production process. It is calculated as follows:

$$a_{ij}^{rs}=x_{ij}^{rs}\Big/x_{j}^{s} \tag{2}$$

where x_{ij}^{rs} represents the input of industry i in region r in the production process of sector j in region s. x_j^s represents the total input of sector j in region s. Substituting the direct consumption coefficient into Eq. (1) and expressing it in matrix form, we obtain

$$A^{RS}X^{R}+Y^{RS}=X^{R} \tag{3}$$

where $A^{RS}=\left[a_{ij}^{rs}\right]$ is the matrix of the direct consumption coefficient. $X^{R}=\left[x_{i}^{r}\right]$ is the total output column matrix for each department in each province, and $Y^{RS}=\left[y_{i}^{rs}\right]$ is the final demand matrix. Under the condition that the technical conditions between regions remain unchanged, we transform (3) to obtain

$$X^{RS}=\left(I-A^{RS}\right)Y^{RS} \tag{4}$$

where $\left(I-A^{RS}\right)^{-1}$ is the Leontief inverse matrix, also known as the complete demand matrix and denoted by $B^{RS}=\left(I-A^{RS}\right)^{-1}$. The element b_{ij}^{rs} represents the input of sector i in region r required to meet the unit final product demand of sector j in region s.

Inter-provincial carbon footprint transfer is the transferal of carbon emissions accompanied by interregional and intersectoral flows of goods and services. These processes occur in two stages: intermediate input and final use. Taking the two regions as examples, Fig. 2 depicts the

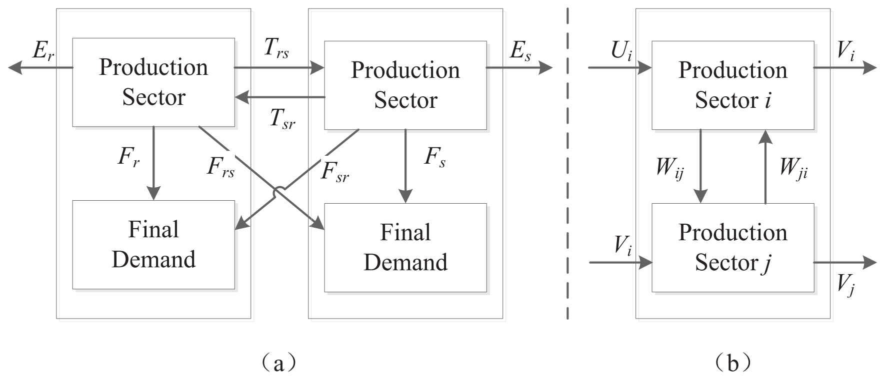

Fig. 2. The transfer of carbon emissions between regions and sectors.
Note: Created by the author (*Visio*).

carbon footprint transfer resulting from the relationship between goods and service flows between sectors and regions.

In Fig. 2 (a), F_r and F_s represent the carbon emissions generated by production and final use in regions r and s. F_{rs} and F_{sr} represent, respectively, the carbon transfer caused by production in regions r and s and the final use in regions s and r. T_{rs} and T_{sr} represent, respectively, the carbon transfer caused by intermediate inputs from production sectors in regions r and s to production sectors in regions s and r. E_r and E_s represents the carbon transfer that occurs when carbon is produced in regions r and s and exported to foreign countries. Fig. 2 (b) shows a region's carbon transfer caused by intersectoral intermediate inputs. W_{ij} and W_{ji} represent, respectively, the carbon transfer caused by intermediate inputs from production sectors i and j to production sectors j and i in region r. U_i and U_j are the sums of the carbon transfer caused by the intermediate use of sectors i and j in region r from all other regions. V_i and V_j include, respectively, the carbon transfer caused by intermediate inputs from sectors i and j in region r to all other regions, final use outside the province and foreign countries.

The direct carbon emission coefficient was introduced into the multiregional input–output model to measure the inter-provincial carbon footprint transfer scale. The direct carbon emission coefficient is

$$ac_j^r = c_j^r \Big/ x_j^r \tag{5}$$

where ac_j^r represents the carbon dioxide emitted per unit of the total output of sector j in region r. c_j^r represents the carbon emissions of sector j in region r, and x_j^r represents the total output of sector j in region r. The direct carbon emission coefficients of ac_j^r m and n sectors were arranged in a diagonal matrix to obtain the direct carbon emission coefficient matrix, A_c, covering n sectors in m regions.

The complete carbon emission coefficient is the sum of the direct and indirect carbon emissions per unit of the final product; its matrix is obtained by multiplying the direct carbon emission coefficient matrix A_c by the Leontief inverse matrix, namely the complete demand matrix B^{RS}. The complete carbon emission coefficient matrix E^{RS} is

$$E^{RS} = A_c \times B^{RS} = A_c\left(I - A^{RS}\right)^{-1} \tag{6}$$

The inter-provincial carbon footprint transition matrix, T^{RS}, was obtained by multiplying the complete carbon emission coefficient matrix, E^{RS}, by the final demand matrix, Y^{RS}.

$$T^{RS} = E^{RS}Y^{RS} = B^{RS}Y^{RS} = A_c\left(I - A^{RS}\right)^{-1}Y^{RS} \tag{7}$$

where $T^{RS} = \left[t_i^{rs}\right]$ t_i^{rs} represents the carbon transfer from industry i in region r to region s.

4.2. Study design of determinants of inter-provincial carbon footprint transfer

The formation of the inter-provincial transfer of the carbon footprint is affected by several factors. This study selects explanatory variables from three aspects: energy endowment, economic factors, and environmental regulation. Furthermore, this study constructs an OD-based spatial interaction model from the gravity model to explore the determinants of inter-provincial carbon footprint transfer. This approach allows us to distinguish the influence differences of various characteristic factors between origins and destinations and to consider the spatial spillover effect.

4.2.1. Model

The gravity model, derived from Newton's law of universal gravitation, has been widely used in studying international trade, geographical economies and regional networks. Traditional gravity models usually only analyse individuals in space without considering the spatial influence characteristics of the surrounding areas. Griffith (2007) pointed out that bilateral spatial flows have spatial autocorrelation and are not independent; therefore, he proposed a spatial gravity model. This model analyses paired-flow data between two places in space, where each region can be an origin or destination. This model studies the correlation between the origin and destination and the determinants of the flow level. Assuming that O_i, D_j and $F(I,j)$ represent the origin, destination and spatial separation functions, respectively, the flow levels at the origin and destination can be expressed as

$$\Omega(i,j) = C \times O(i) \times D(j) \times F(i,j). \tag{8}$$

Owing to the directional changes in the origin and destination of inter-provincial carbon footprint transfer, using the gravity model to explore the determinants of the carbon footprint transfer scale of the origin and destination is suitable. The expression form of Eq. (8) is transformed, and the gravity model based on the ordinary linear model (LM) is expressed as follows:

$$Y = \alpha\tau_n + X_o\beta_o + X_d\beta_d + D\beta + \varepsilon \tag{9}$$

where Y is the explained variable, namely the inter-provincial carbon footprint transfer amount. X_o is the set of characteristic variables of the origin, and X_d is the set of characteristic variables of the destination. D is the geographical distance from the origin to the destination. A and μ are constant and error terms, respectively, while τ_n represents the column vector with element 1.

The gravity model of Eq. (9) uses only the characteristics of carbon footprint transfer origin, destination and geographical distance to explain the scale of carbon footprint transfer; it does not consider the spatial distribution pattern and spatial interaction among regions. Given the spatial correlation of inter-provincial carbon footprint transfer and reflecting spatial dependence, this study combines the spatial econometric model with the gravity model to construct an OD-based spatial interaction model by referring to the spatial OD model proposed by LeSage and Pace (2008).

The spatial interaction effect has three primary forms. The first is the interaction effect between explained variables of different samples, and the second is the interaction effect between explanatory variables. Third, the interaction effect is transmitted through an intersample error term. A general nested model (GNS), including all spatial interaction effects, is expressed as follows:

$$\begin{cases} Y = \rho W_1 Y + \alpha\tau_N + X\beta + W_2 X\theta + \mu \\ \mu = \lambda W_3 \mu + \varepsilon \end{cases} \tag{10}$$

where Y is the explained variable, and X is the explanatory variable. W_1, W_2 and W_3 are the spatial weight matrices describing the spatial correlation between the explained variable, explanatory variable and error term, respectively. ρ, θ and λ are the three spatial effect parameters. E and μ are the error terms.

Common spatial econometric models include the spatial lag model (SAR), spatial error model (SEM), spatial Durbin model (SDM) and spatial Durbin error model (SDEM). When $\rho \neq 0$, $\theta = 0$ and $\lambda = 0$ (that is, there is only an interaction effect between explained variables), Eq. (10) is the SAR. When $\rho = 0$, $\theta = 0$ and $\lambda \neq 0$ (that is, there is only an interaction effect between error terms), Eq. (10) is the SEM. When $\rho \neq 0$, $\theta \neq 0$ and $\lambda = 0$ (that is, there is an interaction effect between explained variables and explanatory variables), Eq. (10) is the SDM. When $\rho = 0$, $\theta \neq 0$ and $\lambda \neq 0$ (that is, there is an interaction effect between explanatory variables and the error term), Eq. (10) is the SDEM.

Inter-provincial carbon transfer in China mainly depends on other provincial factors, such as economic factors, energy endowment and the geographical environment. Therefore, it is necessary to add the spatial lag term of the influencing factors of carbon transfer, namely the spatial Durbin term, into the model. By adding a spatial Durbin term, this study builds a spatial OD interaction model based on the SDM and SDEM. The specific model is expressed in Eqs. (11) and (12).

$$Y = \rho W_{od} Y + \alpha\tau_N + X_o\beta_o + X_d\beta_d + D\beta + W_{od}X_o\theta_o + W_{od}X_d\theta_d + W_{od}D\theta + \mu \tag{11}$$

$$\begin{cases} Y = \alpha\tau_N + X_o\beta_o + X_d\beta_d + D\beta + W_{od}X_o\theta_o + W_{od}X_d\theta_d + W_{od}D\theta + \mu \\ \mu = \lambda W_{od}\mu + \varepsilon \end{cases} \tag{12}$$

Eq. (11) is the SDM, and Eq. (12) is the SDEM, where Y is the explained variable, namely the inter-provincial carbon footprint transfer. X_o is the set of characteristic variables of the origin, and X_d is the set of characteristic variables of the destination. D is the geographical distance. The α constant term, ε and μ are error terms. ρ, θ and λ are the spatial effect parameters of the explained, explanatory, and error variables, respectively. τ_N represents a column vector containing one element. W_{od} is a spatial weight matrix constructed based on the spatial correlation of the double contiguity of origin and destination. This matrix is built by performing the Kronecker product of the spatial weight matrix W of 30 provinces constructed based on the geographical distance between provinces (i.e. $W \otimes W$) and finally obtaining the W_{od}.

Based on the above analysis, this study uses the gravity model based on the ordinary linear regression (LM) model, namely Eq. (9), as the benchmark model. The spatial OD interaction model based on the SDM and SDEM, namely Eqs. (11) and (12), was used to explore the factors influencing carbon footprint transfer from the perspective of spatial spillover.

4.2.2. Variables

The dependent variable of this study's OD-based spatial interaction model was bilateral flow data calculated from the inter-provincial carbon footprint transfer scale. Furthermore, starting from the three aspects of energy endowment, economic factors and geographical environment, six indicators (energy output, economic level, industrial structure, energy intensity, environmental regulations and geographical distance) were selected as explanatory variables.

Energy Output (EP): As mentioned above, regions with excellent energy endowments are often the main provinces with carbon footprint transfers, and the impact of energy output on carbon footprint transfers cannot be ignored. The calculation method of energy output is as follows. The energy production of each province is converted into standard coal using the discounted coal coefficient, then summed and the logarithm is taken.

Energy Intensity (E): Energy intensity is closely related to the regional energy structure and technological level, and differences in energy structure and technology level promote cross-regional cooperation, thus bringing about interregional economic value flow. Energy intensity is the total regional energy-consumption ratio to gross domestic product (GDP).

Environmental regulations (P): Environmental regulations restrict regional economic development. High levels of environmental regulation imply high production costs for enterprises with high-energy consumption and emissions. After weighing the advantages and disadvantages, enterprises consider industrial transfer to areas with a low level of environmental regulation, which can affect the transfer of carbon footprint. Environmental regulation is the ratio of a completed investment in regional industrial pollution control to regional industrial added value.

Industrial Structure (I): Provinces with developed secondary industries export more carbon-intensive products, thereby affecting the transfer of the inter-provincial carbon footprint (Chen et al., 2020). The industrial structure is the ratio of the added value of the regional secondary industry to the GDP.

Geographic distance (D): Geographical distance negatively affects inter-provincial carbon footprint transfers. The greater the geographical distance, the greater the transportation cost, the lower the transportation efficiency and the smaller the carbon footprint transferred. Furthermore, geographically adjacent provinces form an economic circle, and the flow of economic value within this circle is more frequent owing to the influence of various policies; therefore, carbon transfer is more likely to occur between adjacent provinces. Geographical distance is taken as the spherical distance between the capital cities of the two provinces and then as the reciprocal.

Economic Level (G): Economic development reflects each region's economic status and frequency of economic activity. The higher the economic level, the more frequent the economic activities and the greater the possibility of carbon footprint transfer. In this study, GDP refers to the regional economic level and a logarithmic operation is performed.

4.3. Model of spillover analysis

Determinants have a feedback effect and simultaneity, and considering only spatial coefficients cannot accurately determine the spillover effect of the determinants (Anselin, 2010). Therefore, a partial differential estimation method was adopted to decompose the spatial effects of independent variables into direct and indirect effects to analyse the determinants of inter-provincial carbon footprint transfer.

The GNS equation is rewritten as follows:

$$Y = (I - \rho W)^{-1}(X\beta + WX\theta) + R \tag{13}$$

where R represents the intercept and is the error term. The partial derivative of the expected value of Y concerning X is expressed as

$$\left(\frac{\partial E(Y)}{\partial x_{1r}} \cdots \frac{\partial E(Y)}{\partial x_{nr}}\right) = S_r(W) = \begin{pmatrix} \frac{\partial E(y_1)}{\partial x_{1r}} & \cdots & \frac{\partial E(y_1)}{\partial x_{nr}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(y_n)}{\partial x_{1r}} & \cdots & \frac{\partial E(y_n)}{\partial x_{nr}} \end{pmatrix} = (I_n - \rho W)^{-1} \begin{pmatrix} \beta_r & w_{21}\theta_r & \cdots & w_{1n}\theta_r \\ w_{21}\theta_r & \beta_r & \cdots & w_{2n}\theta_r \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1}\theta_r & w_{n2}\theta_r & \cdots & \beta_r \end{pmatrix} \tag{14}$$

where I_n the identity matrix of order n, $r = 1, 2, \ldots, k$, k is the number of explanatory variables, and w_{ij} is the (i, j) element of the spatial weight matrix W. β_r is the regression coefficient of the r-th explanatory variable, and θ_r represents the estimated coefficient of the r-th variable of WX.

The direct and indirect effects of different observations vary; thus, a comprehensive index was used to measure their direct and indirect effects. The average direct effect is that of the r-th independent variable in region i on the dependent variable in region i averaged over $S_r(W)_{ii}$. The average indirect effect cannot be obtained directly but only by subtracting the average direct effect from the average total effect.

Based on the above principles, spatial effect decomposition of the spatial OD interaction model can be performed. The influence of the local region was interpreted as the direct effect, the influence on other regions as the indirect effect, and the sum of the direct and indirect effects as the total effect.

4.4. Data collection and processing

First, the data basis for calculating the inter-provincial carbon footprint transfer scale was the 2017 interregional input–output table for 31 provinces and cities in China (Zheng et al., 2020). Considering data availability, the 42 industries in the input–output table were combined into 6 industries, consistent with the industry classification in the energy balance table. The six major industries include farming, forestry, animal husbandry and fisheries; manufacturing; construction; wholesale, retail, accommodation and catering; transport, storage and postal services; other industries.

Second, because of the lack of energy balance sheet data, this study examined 30 provinces in China, excluding Tibet, Hong Kong, Macao and Taiwan. After stripping Tibet's data from the input–output table, a multiregional input–output table of 30 provinces and 6 major industries was finally obtained. Moreover, data for 17 types of energy consumption were sourced from the terminal consumption of the *2017 provincial energy balance sheet*, including raw coal, cleaned coal, other washed coal, briquette coal, coke, coke oven gas, other gas, crude oil, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas, refinery dry gas, other petroleum products, other coking products and natural gas. Among them, the energy used as raw materials and materials in industries where such materials are not burned to release carbon must be removed. Furthermore, because electricity and heat, as secondary energy sources, do not directly emit carbon dioxide, the fuel consumption used for thermal power generation and heating in processing conversion is included in industrial carbon emission accounting.

Third, energy data were obtained from the *2017 provincial energy balance sheet*. The carbon dioxide emission factor was calculated using energy data from the *Guidelines for Compilation of Provincial Greenhouse Gas Inventories (Trial)*, and the missing energy data refer to the carbon emission factor calculated by Sun et al. (2015). The calculation of carbon emissions for each region and sector was based on the *Guidelines for Compilation of Provincial Greenhouse Gas Inventories (Trial)*, summarised in Eqs. (15) and (16).

$$F_\alpha = LC_\alpha \times CPC_\alpha \times CO_\alpha \times \frac{44}{12} \tag{15}$$

$$C = \sum_{\alpha=1}^{l} F_\alpha \times EC_\alpha \tag{16}$$

where F_α represents the carbon dioxide emission factor of the α-th energy. LC_α is the average low calorific value of the α-th energy, CPC_α is the carbon content per unit calorific value of the α-th energy and CO_α is the carbon oxidation rate of the α-th energy. C represents the carbon dioxide emissions of all energy fuels, and EC_α is the consumption of the α-th energy fuel.

Lastly, data on the variables are from the *China Energy Statistical Yearbook* of 2017 and the 2017 *China Statistical Yearbook*. The spherical distance between the two provincial capitals was obtained using autonomous calculations.

5. Results and discussion

5.1. Measurement of inter-provincial carbon footprint transfer

Carbon footprint transfer includes transfer-in and transfer-out, which refer to the transfer of embodied carbon emissions caused by the transfer of goods to or from other provinces. The total carbon footprint transfer of all provinces in 2017 was estimated to be 34.51×10^8 t, and significant differences exist in the transfer of the carbon footprint of different industries in different provinces.

5.1.1. Industrial distribution of carbon footprint transfer

Fig. 3 presents the carbon transfer-outs for each industry. It is not difficult to determine that the carbon transfer is mainly concentrated in the manufacturing industry, and its transfer amount is as high as 30.05×10^8 t, far exceeding the carbon transfer amount of nonmanufacturing industries. Furthermore, almost all provinces, except Beijing, had the highest proportion of carbon transfer from industry, indicating that the industrial sector is mainly responsible for China's energy consumption and carbon emissions. Owing to the characteristics of energy consumption, industry inevitably has the highest amount of carbon transfer in all provinces, which plays a decisive and key role in the transfer of carbon footprint. Accordingly, the determinants of carbon footprint transfer should focus on industrial characteristics.

5.1.2. Inter-provincial flows of carbon footprint transfers

The carbon footprint transfer network was directed. A flow direction diagram of the inter-provincial carbon footprint transfer is shown in Figs. 4 and 5 to analyse the flow direction characteristics of China's inter-provincial carbon footprint transfer.

Fig. 4 shows the inter-provincial flow direction of large-scale carbon footprint transfer. Large-scale carbon footprint transfer (above 0.3×10^8 t) occurs in the carbon transfer from Inner Mongolia to Hebei, Zhejiang and Henan and from Liaoning to Guangdong. As a significant energy province, Inner Mongolia is the main province of carbon transfer, while Liaoning and Guangdong are coastal cities with frequent economic flows. Large-scale (0.2–0.3 $\times 10^8$ t) and medium-scale (0.15–0.2

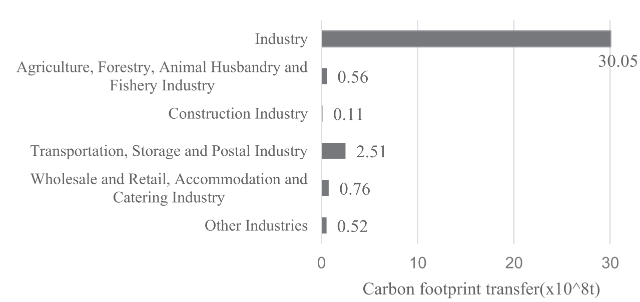

Fig. 3. Carbon footprint transfer-out industry distribution.
Note: Created by the author based on the scale of carbon footprint transfer.

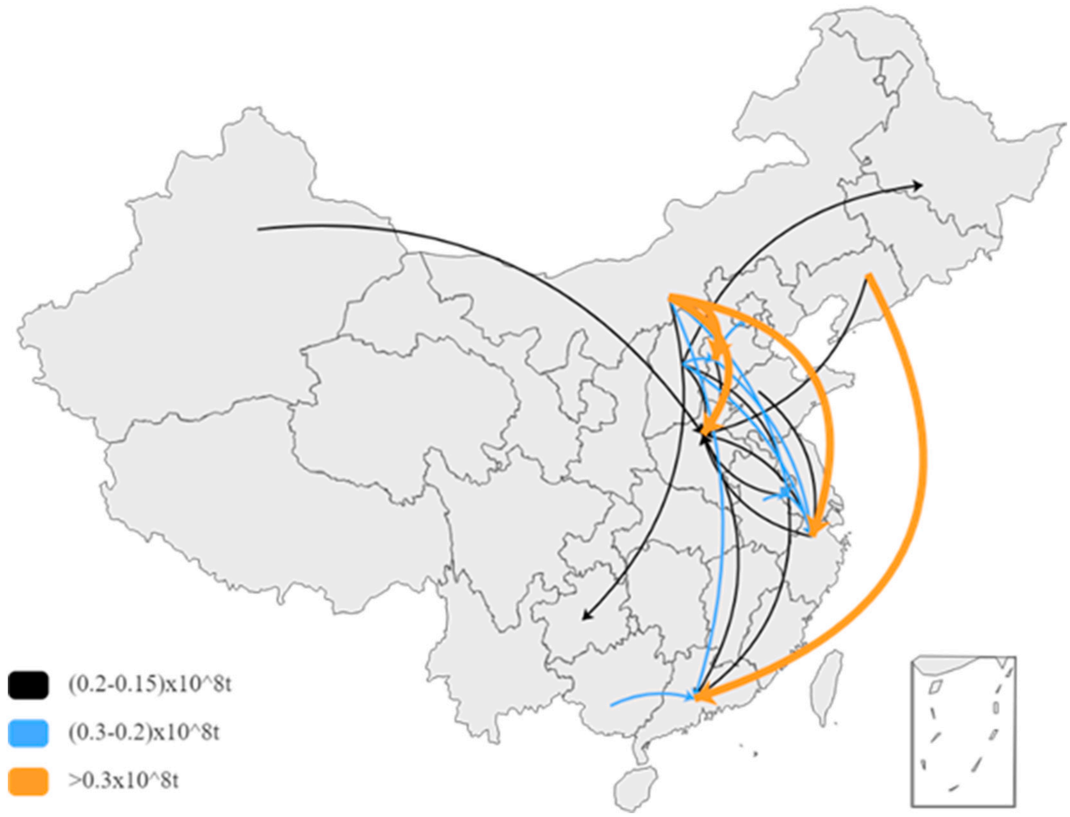

Fig. 4. Inter-provincial carbon footprint transfer (large-scale) flows in China.
Note: Created by the author based on the scale of carbon footprint transfer (programmed in *Python*).

Fig. 5. Inter-provincial carbon footprint transfer (small scale) flows in China.
Note: Created by the author based on the scale of carbon footprint transfer (programmed in *Python*).

$\times$ 10^8 t) carbon footprint shifts mainly occurred between Hebei and Beijing, Guangxi and Guangdong, as well as between Inner Mongolia, Shanxi, Zhejiang, Jiangsu and Guangdong.

Furthermore, the carbon transfer networks in the Yangtze River Delta region were relatively close. In summary, carbon transfer is more likely to occur between neighbouring regions, and there is a greater likelihood of carbon transfer between provinces with abundant energy resources and those with leading economies.

Fig. 5 shows the inter-provincial flowchart of carbon footprint transfer at a small scale (0.1–0.15 $\times$ 10^8 t). The origins and destinations of smaller carbon footprint transfers are more diversified and involve more provinces, among which North China, East China, and north-central China have higher network densities. The main provinces of carbon transfer were Inner Mongolia, Hebei and Liaoning, while the main provinces of carbon transfer were Zhejiang, Jiangsu, Guangdong and Yunnan. The inter-provincial carbon transfer network is complex, and the provinces are closely connected. Additionally, energy and industrial resources were the main determinants of carbon transfer.

5.2. Determinant analysis of inter-provincial carbon footprint transfer

5.2.1. Spatial autocorrelation test and model selections

The inter-provincial carbon footprint transfer is likely to be affected by neighbouring regions; therefore, it is necessary to use Moran's index to test whether spatial autocorrelation exists in the inter-provincial carbon footprint transfer. If this exists, a spatial econometric model is required. Table 1 lists the calculated results for the global Moran index, showing that Moran's $I = 0.117$ of carbon transfer is greater than 0, and its P value is much less than 0.01. This result indicates an apparent spatial aggregation effect of carbon transfer. Moran's indices of energy output, economic level, energy intensity and environmental regulation were all greater than 0, and the P value was far less than 0.01, indicating a significant positive spatial correlation; however, Moran's index of industrial structure is −0.061, and the P value is less than 0.01, indicating an obvious negative spatial correlation between industrial structures.

Fig. 6 shows Moran's I scattergram of the carbon footprint transfer, showing that most scattered points are located in the first and third quadrants, and the trend line slope is significantly higher than 0. These findings indicate that most provinces are located in the 'high–high' or 'low–low' region, and there is an evident clustering phenomenon in the geographical spatial distribution, meaning that the amount of carbon transfer in this region has a positive radiation effect on neighbouring areas (i.e. the spatial spillover effect).

The results of the spatial correlation test confirm the necessity of using a spatial econometric model; however, which spatial econometric model is more appropriate needs to be tested and compared. This study used the Lagrange multiplier method (LM) for the model selection of SAR and SEM, and the results are shown in Table 2. Both LMerr and LMlag are significant at the 1 % level, and RLMerr and RLMlag are significant at the 1 % level, indicating that SAR and SEM can be used. This study constructs a spatial OD interaction model based on SDM and SDEM to explore the spatial spillover effect of factors influencing carbon transfer. Simultaneously, a spatial OD interaction model based on SAR and SEM was constructed to compare and test the robustness of parameter estimates for each variable.

Table 1
Moran I for testing the spatial correlation.

Variable	Notation	Moran's I	$P(I)$
Carbon Footprint Transfer	T	0.117	0.000
Energy Output	EP	0.242	0.000
Economic Level	G	0.148	0.000
Industrial Structure	I	−0.061	0.000
Energy Intensity	E	0.306	0.000
Environmental Regulation	P	0.043	0.000

Note: Created by the author (*Stata*).

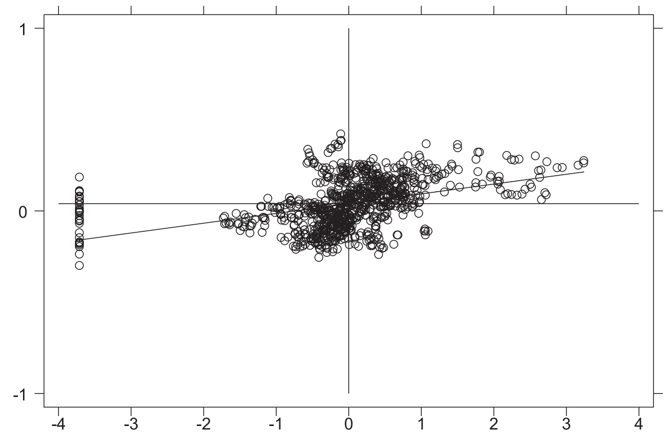

Fig. 6. Moras I scattergram of carbon footprint transfer.
Note: Created by the author (*Stata*).

Table 2
Lagrange multiplier method (LM) test results.

Statistic	Estimate	P value
LMerr	104.430	0.000
LMlag	11.027	0.000
RLMerr	102.520	0.000
RLMlag	9.108	0.002

Note: Created by the author (*R*).

5.2.2. The analysis of determinants

The spatial model cannot be compared according to the size of R^2; therefore, three statistics are provided to compare the models: log-likelihood (Log L), Akaike information criterion (AIC) and Schwarz Criterion (SC). This study used the log-likelihood (Log L) and Akaike information criterion (AIC) to determine the model's goodness of fit. The regression results are shown in Table 3. According to Log L and AIC, the SDEM-based spatial OD model was superior. At the same time, both the spatial influence coefficients ρ and λ are positively significant at the 1 % level, indicating a significant positive spatial dependence of carbon transfer.

The economic origin and destination effectively promote inter-provincial carbon transfer; the higher the economic level, the more frequent the carbon transfer. Table 3 shows that regardless of whether spatial correlation and spillover are considered, the economic levels of origin and destination positively affect carbon transfer at a significance level of 1 %. The coefficient values of the economic level of the origin are 0.552, 0.534, 0.369, 0.362 and 0.417, indicating that when the economic level of the origin area increases by 1 %, carbon transfer-out increases by 0.55 %, 0.53 %, 0.37 %, 0.36 % and 0.42 %, correspondingly.

The coefficient values of the economic level of the destination are 0.672, 0.687, 0.667, 0.432 and 0.446, indicating that when the economic level of the destination increases by 1 %, carbon transfer increases by 0.67 %, 0.69 %, 0.67 %, 0.43 % and 0.45 %. Carbon transfer is hidden behind the economic circulation, and regions with high economic levels usually have frequent economic activities; therefore, carbon transfer is more likely to occur. In terms of carbon origin, when the inter-provincial products are transferred out to obtain economic benefits, carbon is transferred out. Regarding destination, the supply of high-carbon products in provinces with higher economic levels is lower, so they need to be transferred from outside the province to form carbon transfers; therefore, carbon transfer is more likely to occur among provinces with similar economic levels (Ma et al., 2019), particularly among provinces with high economic levels.

Table 3
Estimation results.

Coefficient	Model 1	Model 2	Model 3	Model 4	Model 5
	LM	SLM	SAR	SDM	SDEM
Intercept	14.533***	−15.301 **	−13.924***	−7.096*	−15.800***
	(−19.034)	(−18.823)	(−15.384)	(−1.900)	(−4.200)
G_o	0.552***	0.534***	0.369***	0.362***	0.417***
	(9.540)	(9.345)	(7.376)	(4.954)	(5.557)
EP_o	0.315***	0.311***	0.320***	0.302***	0.263***
	(10.080)	(10.055)	(11.490)	(11.152)	(8.351)
I_o	1.311***	0.993**	0.707*	−0.995*	−0.970
	(2.755)	(2.064)	(1.884)	(−1.649)	(−1.295)
E_o	0.253*	0.293**	0.135	0.230	0.291*
	(1.907)	(2.211)	(1.180)	(1.404)	(1.695)
P_o	0.003*	0.001	−0.003**	−0.008***	−0.006***
	(1.857)	(0.839)	(−2.237)	(−3.993)	(−2.792)
G_d	0.672***	0.687***	0.667***	0.432***	0.446***
	(11.615)	(11.982)	(13.336)	(6.025)	(5.940)
EP_d	0.11***	0.105***	0.044	0.108***	0.168***
	(3.517)	(3.409)	(1.579)	(3.901)	(5.332)
I_d	−0.56	−0.928*	−0.788**	−0.518	−1.911**
	(−1.177)	(−1.921)	(−2.100)	(−0.865)	(−2.551)
E_d	0.151	0.300**	0.275**	−0.223	−0.213
	(1.141)	(2.178)	(2.406)	(−1.373)	(−1.245)
P_d	−0.005***	−0.007***	−0.008***	−0.008***	−0.009***
	(−3.186)	(−4.122)	(−5.013)	(−3.845)	(−4.152)
D	0.625***	0.605***	0.741***	0.869***	0.883***
	(31.503)	(26.696)	(32.238)	(35.137)	(35.566)
Lag. G_o				0.586**	1.071***
				(2.494)	(4.640)
Lag. EP_o				−0.065	−0.059
				(−0.715)	(−0.637)
Lag. I_o				0.765**	1.704
				(0.659)	(1.243)
Lag. E_o				1.056***	2.320***
				(2.010)	(4.535)
Lag. P_o				0.026***	0.038***
				(4.690)	(6.784)
Lag. G_d				−0.832***	−0.510**
				(−3.636)	(−2.210)
Lag. EP_d				0.472***	0.647***
				(5.524)	(7.013)
Lag. I_d				2.286**	−1.102
				(1.924)	(−0.804)
Lag. E_d				−1.639***	−1.313**
				(−3.171)	(−2.567)
Lag. P_d				0.014***	0.013**
				(2.623)	(2.262)
Lag. D				−1.155***	−1.017***
				(−13.841)	(−9.319)
ρ		0.234***		0.447***	
λ			0.949***		0.914***
AIC	2217.3	2209.6	2129.1	1933.6	1880.5
Log L		−1090.812	1050.571	−941.788	−915.272

Note: Values in parentheses are t-statistics. ***, ** and * represent significance at the 1 %, 5 % and 10 % levels, respectively. Created by the author (*R*).

Provinces with high-energy intensity and excellent energy endowments are dominated by carbon transfer-out, whereas provinces with a small proportion of secondary industries are dominated by carbon transfer-in. In the optimal spatial OD interaction model, the origin energy intensity and energy output have a significantly positive impact on carbon transfer at confidence levels of 10 % and 1 %, respectively, where the coefficient values of energy intensity and energy output are 0.291 and 0.263, respectively. When the source energy intensity and energy output levels increased by 1 %, carbon transfer increased by 0.30 % and 0.26 %, respectively. Provinces with high-energy intensity and excellent energy endowments have low energy-consumption structures (Chen et al., 2018) and generally develop relatively developed high-energy-consuming industries. For example, in Hebei, Inner Mongolia, Shanxi, Liaoning and other provinces rich in energy resources and with high-energy consumption, the output is mostly transferred out of the province in the form of carbon transfer, such as in the Yangtze River Delta region, to meet the needs of production and life outside the province. The coefficient value of the industrial structure of the destination is −1.911, which is less than 0 and significant at the 1 % confidence level, indicating that the smaller the proportion of the secondary industry, the greater the carbon transfer at the destination. As the primary province of carbon transfer, the industrial structure is generally dominated by the tertiary industry, and the industrial output cannot meet the demand in the province; therefore, it needs to be imported from outside the province to cause carbon transfer-in.

Environmental regulation inhibits carbon transfer; however, its effect is negligible. In the SDM and SDEM, origin and destination environmental regulations were significantly negative at the 1 % confidence level, but the influence coefficient was small. Among them, the environmental regulation coefficient values of the source are −0.006 and −0.008, and the environmental regulation coefficient values of the sink are −0.009 and −0.008. Environmental regulation helps China's industrial technology move closer to green progress (Chen et al., 2022), and progress in emission reduction technology helps reduce carbon emissions and indirectly reduces carbon transfer; however, enterprises with high-energy consumption and emissions tend to be located in areas with low levels of environmental regulation. Therefore, the higher the environmental regulation is, the smaller the amount of carbon transfer is; however, its impact is limited.

The positive and significant effect of geographical distance on carbon transfer indicates that the longer the geographical distance, the higher the transportation cost and risk, the lower the time efficiency and the less likely carbon transfer is to occur. Furthermore, the energy output variable at the destination has a significantly positive impact on carbon transfer, indirectly indicating that the primary sector of carbon transfer is the industrial sector, which depends on energy resources. The regions with lower energy production have correspondingly smaller industrial demand.

5.3. Spillover analysis of the determinants of inter-provincial carbon footprint transfer

Owing to the existence of spatial dependence, when a variable changes, it will cause changes in the amount of carbon transfer in the local area and changes in the amount of carbon transfer in adjacent areas, which are transmitted back through the spatial feedback effect. The partial differential decomposition decomposed the spatial spillover effect into direct and indirect effects. The decomposition results for the spatial effects are presented in Table 4. The SDEM does not have a spatial lag term of the explained variable; thus, its spillover effect is the regression coefficient of the spatial lag term of the explanatory variable. The following section focuses on the indirect effect (i.e. the spillover effect).

The surrounding area's economic level promotes or inhibits carbon transfer. In the spatial OD interaction model, the indirect effect values of the source area's economic level were 1.342 and 1.071, which were significantly positive at the 1 % confidence level. The indirect effect coefficients of the economic level of the sink are −1.146 and −0.51, which are significantly negative at the 5 % confidence level. Interestingly, the economic level has a positive spillover effect in terms of carbon transfer-out and a negative spillover effect in terms of carbon transfer. Regions with a high economic level often focus on upgrading their industrial structure and developing downstream industries, such as high-tech and light industries. To meet production and living needs, transferring specific scales of upper and middle-stream products from the surrounding areas is necessary to promote carbon transfer. Simultaneously, industrial migration occasionally occurs when upgrading the industrial structure of regions with high economic levels. Some midstream enterprises are more likely to move to the surrounding areas to increase output supply and reduce demand outside the province, thereby reducing the scale of carbon transfer in the surrounding areas.

Regarding origin, there is a positive spillover effect of energy intensity, and an increase in energy intensity in the surrounding areas effectively promotes carbon transfer. According to the data in Table 4, the indirect effect coefficients of the energy intensity of origin are 2.081 and 2.32, which are significant at confidence levels of 5 % and 1 %, respectively. High-energy intensity generally means high-energy consumption and relatively low economic output. Heavy industries with high-energy consumption and high emissions are the primary industries. Forming regional industrial clusters around provinces with excellent energy endowments is easy. Through the path of industrial agglomeration in the spatial spillover effect, the regions with higher energy intensity exert the 'siphon effect', inducing the midstream enterprises to gather in the surrounding areas, thus effectively promoting the carbon transfer out of the surrounding areas.

Regarding destination, there is a negative spillover effect of energy intensity, and a reduction in energy intensity in the surrounding areas effectively promotes carbon transfer. The data in Table 4 indicate that the indirect effect coefficients of energy intensity at the sink are −3.121 and −1.313, and both are significant at the 5 % confidence level. Furthermore, the reduction of energy intensity in the surrounding areas promotes carbon transfer into the destination, which may be related to the economic structure of the surrounding areas. For example, Beijing and other regions with high economic levels can transfer midstream industries, such as industries with high-energy consumption and emissions, to surrounding areas (Yuan and Zhou, 2021). Consequently, the energy intensity and industrial concentration in the region decreased while midstream industries in the surrounding areas developed, thus promoting carbon transfer in the surrounding areas.

Energy output has a positive spillover effect on carbon transfer at the destination; that is, the excellent energy endowment in the surrounding areas provides favourable resource conditions for carbon transfer. The indirect effect coefficients of the energy output at the destination were 0.934 and 0.647, respectively, significantly greater than zero at the 1 % confidence level, indicating that the energy endowment in the surrounding areas had a positive spatial spillover effect on carbon transfer. On the one hand, the energy industry breeds. To save energy

Table 4
Spatial effect decomposition results.

	Direct effect		Indirect effect		Total effect	
	SDM	SDEM	SDM	SDEM	SDM	SDEM
G_o	0.371***	0.417***	1.342***	1.071***	1.714***	1.489***
	(5.366)	(5.557)	(3.093)	(4.640)	(3.587)	(5.107)
EP_o	0.303***	0.263***	0.126	−0.059	0.429**	0.204*
	(11.230)	(8.351)	(0.648)	(−0.637)	(2.194)	(1.787)
I_o	−0.991*	−0.970	0.575	1.704	−0.416	0.734
	(−1.681)	(−1.295)	(0.236)	(1.243)	(−0.153)	(0.361)
E_o	0.245	0.291*	2.081**	2.320***	2.326**	2.611***
	(1.512)	(1.695)	(2.111)	(4.535)	(2.138)	(4.030)
P_o	−0.008***	−0.006***	0.040***	0.038***	0.032**	0.032***
	(−3.811)	(−2.792)	(3.209)	(6.784)	(2.406)	(4.620)
G_d	0.424***	0.446***	−1.146**	−0.510**	−0.722	−0.064
	(5.683)	(5.940)	(−2.221)	(−2.210)	(−1.361)	(−0.220)
EP_d	0.115***	0.168***	0.934***	0.647***	1.048***	0.815***
	(4.332)	(5.332)	(3.947)	(7.013)	(4.385)	(7.128)
I_d	−0.493	−1.911**	3.687	−1.102	3.195	−3.013
	(−0.686)	(−2.551)	(1.397)	(−0.804)	(1.080)	(−1.481)
E_d	−0.245	−0.213	−3.121**	−1.313**	−3.366**	−1.527**
	(−1.518)	(−1.245)	(−2.393)	(−2.567)	(−2.430)	(−2.358)
P_d	−0.007***	−0.009***	0.020*	0.013**	0.012	0.004
	(−3.678)	(−4.152)	(1.788)	(2.262)	(1.101)	(0.567)

Note: ***, ** and * represent significance at the 1 %, 5 % and 10 % levels, respectively. Created by the author (with *R*).

transportation costs, enterprises with high-energy consumption gather in the surrounding areas of provinces with excellent energy endowments, such as Hebei Province, which is backed by Inner Mongolia and is adjacent to Shaanxi Province in the west. It is necessary to transfer industrial raw materials from surrounding areas with excellent energy endowments to promote carbon transfer and meet the demand for industrial production. On the other hand, the areas with high-energy endowments are mainly concentrated in the northern regions such as Heilongjiang, Inner Mongolia, Shanxi, Ningxia and other northern regions; that is, the energy resources have spatial aggregation, showing a positive spillover impact on carbon transfer.

The environmental regulation in the surrounding areas negatively affects carbon transfer. In the spatial OD interaction model, the coefficient values of the indirect effect of environmental regulation at the origin and destination were all greater than zero and significant at different levels. According to the 'pollution haven' hypothesis, with the continuous improvement of environmental regulation levels in a particular region, high-emission industrial enterprises prioritise the surrounding areas with relatively low environmental regulation levels for industrial migration, thus promoting carbon transfer in the surrounding areas.

6. Conclusion and policy implications

6.1. Conclusion

Under the 'dual carbon' policy, starting from the economic cycle, this study investigates the current situation of China's inter-provincial carbon footprint transfer. It reveals the factors influencing the origin and destination of spatial carbon footprint transfer, which is of great practical significance for cross-regional coordinated development and emission reduction policy formulation. Meanwhile, it is of great theoretical significance to creatively use the perspectives of origin, destination and spatial spillover to enrich the research on carbon footprint transfer. This study first calculates the carbon footprint transfer of six provincial departments using the multiregional input–output model. It then establishes an OD-based spatial interaction model to analyse the determinants and spatial spillover of carbon footprint transfer from the perspective of the origin and destination.

The results exhibit the following. First, the economic level and environmental regulation of the origin and destination have the same effect on carbon transfer in and out; the former promotes carbon transfer, while the latter inhibits it. Second, provinces with high-energy intensity and excellent energy endowments mainly transfer carbon out. In contrast, provinces with a small proportion of secondary industries mainly transfer carbon. Third, regarding the origin, there is a positive spillover effect of energy intensity, and an increase in energy intensity in the surrounding area effectively promotes carbon transfer. Regarding destination, there is a negative spillover effect of energy intensity, and a reduction in energy intensity in surrounding areas effectively promotes carbon transfer. Fourth, a positive spillover effect exists on the origin's energy output, and the surrounding areas' energy endowment can create favourable basic conditions for the carbon transfer of the origin. In conclusion, differences and similarities exist in the factors influencing the inter-provincial carbon footprint on carbon transfer in and out. Moreover, the factors influencing inter-provincial carbon footprint transfer can affect the surrounding areas through the spatial spillover effect.

6.2. Policy implications

The above research shows that the realisation of the 'dual carbon' goal cannot only consider a single province but should start from the regional linkage network as a whole and develop a suitable long-term collaborative emission reduction mechanism. Therefore, we propose the following policy suggestions.

The calculation of regional carbon emission responsibilities should consider the transfer of the carbon footprint between regions. According to this study's calculations, the inter-provincial carbon footprint transfer scale is enormous; thus, the inter-provincial carbon footprint hidden behind the economic cycle should be paid attention to. Provinces should share environmental responsibilities while generating revenue through cross-regional industrial cooperation. Based on the principle of fairness, the total carbon footprint is considered an indicator of cumulative carbon emissions to reflect the emission reduction responsibilities of industries. This approach considers direct and indirect carbon emissions in the measurement system, which helps clarify the emission reduction tasks of provinces and realise cross-regional collaborative governance.

An energy structure transformation policy should be implemented for the core provinces of carbon transfer. The leading role of energy endowment and energy intensities on carbon transfer means that its emission reduction status in the 'dual carbon' process deserves attention. Furthermore, the optimisation of the energy structure of the origin and reduce coal consumption to a certain extent should be promoted, along with the development of new and renewable energy. Additionally, dependence on fossil energy should be reduced, the diversification of the energy structure and low-carbon energy structure should be realised, and provinces must fundamentally achieve the effect of emission reduction.

Full play should be given to the inhibition effect of environmental regulations on the transfer of the carbon footprint and implement environmental regulation strategies. For example, a pollution charge system should be formulated, and enterprises that exceed prescribed discharge standards can charge fees to exceed the standard discharge. Pollutant discharge fees can also be levied on all polluters. Based on specific local pollution conditions, a tiered pollution fee system should be designed to raise charges, and market-driven environmental laws and regulations should be used to encourage enterprises to realise a low-carbon transition.

Multiple measures should be taken to curb undesirable spatial spillovers and promote benign ones. The spatial spillover of the carbon footprint transfer is significant. Thus, it is necessary to strengthen coordinated development among regions from the perspective of spatial spillover effects. On the one hand, the 'siphon effect' occurs in areas with high-energy endowment and intensity. Therefore, the surrounding areas can formulate the immigration threshold criteria for enterprises, such as setting the upper limit of energy consumption per unit output value to filter out enterprises with high-energy consumption. Moreover, regional cooperation should be improved, economic ties within the region should be strengthened, strategic alliances and cross-regional economic entities should be formed and the interregional flow of capital should be promoted along with labour and technological resources. All of these measures could drive the region's overall coordinated development.

6.3. Limitations and future research directions

This study has some limitations, which provide directions for future research. First, the data cover only one year, so it is difficult to ascertain the trend of the influencing factors of carbon footprint transfer over time. Future studies should combine the spatial OD interaction model with panel data to analyse the carbon footprint transfer on a timescale. Second, the OD-based spatial interaction model was used to study carbon footprint transfer at the provincial level, which confirms the necessity of discussing the difference between origin and destination. This method can also be applied to carbon footprint transfers between countries and departments based on data availability. Finally, the spatial spillover effect of inter-provincial carbon footprint transfers is unequivocal; thus, spatial spillover decomposition technology could be used in further studies in the future.

CRediT authorship contribution statement

Chonghui Zhang: Methodology; Writing - Original Draft; Jiamiao Ji: Formal analysis; Runting Li1: Investigation; Dongcai Zhang: Data collection; Investigation; Validation; Dalia Streimikiene: Writing-Review & Editing.

Declaration of competing interest

The authors declare that this study was conducted without any commercial or financial relationships that could be construed as potential conflicts of interest.

Data availability

Data will be made available on request.

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