

Article

Driving Mechanism of Tourism Green Innovation Efficiency Network Evolution: A TERGM Analysis

Jun Fu ¹, Heqing Zhang ^{1,*}  and Le Li ²¹ Management School, Guangzhou University, Guangzhou 510006, China; fujun678@gzhu.edu.cn² School of Economics and Management, University Putra Malaysia, Serdang 43400, Malaysia; gs72876@student.upm.edu.my

* Correspondence: lyzhq8007@gzhu.edu.cn

Abstract

Under the background of global green sustainable development and the urgent need to understand complex regional innovation systems, it is crucial to scientifically assess China's Tourism Green Innovation Efficiency (TGIE) as a dynamic networked system and reveal its system-level evolution driving mechanism. This article presents the construction of the TGIE evaluation indicator system, measures the inter-provincial TGIE in China in 2011–2023 based on the three-stage super-efficiency SBM-DEA model, analyzes the spatial correlation network characteristics of TGIE by using the motif analysis method and the social network analysis method, and explores the evolutionary driving mechanism by using the time-exponential random graph model (TERGM). The study shows the following: (1) The TGIE of China exhibits a regional distribution pattern characterized by “high in the east and low in the west.” The efficiency of the eastern coastal region is significantly higher than that of the central and western regions, and the overall efficiency shows a fluctuating upward trend. (2) The local structure of China's TGIE network is dominated by the chain structure, and the partially closed structure is gradually enhanced. It indicates that the bridge role of intermediary nodes in the cross-regional flow of innovation resources is becoming more and more significant. (3) The overall network evolves from a single center to a polycentric collaboration model. High-efficiency regions attract low-efficiency regions to collaborate through high connectivity, and intermediary nodes play a key role in connecting high- and low-efficiency regions. (4) The evolution of China's TGIE network is driven by both exogenous and endogenous dynamics, showing significant path dependence and path creation characteristics. This study enhances the theoretical framework of complex systems in tourism innovation and offers theoretical support and policy insights for optimizing the network structure of China's TGIE as a complex adaptive system and maximizing regional cooperation networks.

Keywords: tourism green innovation efficiency; time-exponential random graph model; spatial correlation network; evolutionary driving mechanism



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1. Introduction

In the 21st century, global climate change has emerged as one of the most significant concerns that humanity is now confronting. Studies have shown that global carbon emissions from tourism account for about 8% of total greenhouse gas emissions and continue to grow at a rate of 2.7% per year [1]. Especially in the post-COVID-19 era, the rapid recovery of tourism has further aggravated the environmental pressure [2]. Meanwhile, as

a pillar industry of the national economy, tourism plays an irreplaceable role in promoting employment, boosting consumption, and driving regional development [3]. In China, the green transformation of the tourism industry is facing unprecedented opportunities and challenges with the introduction of the “dual-carbon” goal and the in-depth promotion of ecological civilization construction. On the one hand, China’s tourism industry is in a critical period of transformation and upgrading, and the scale of the industry continues to expand, but resource consumption and environmental pressure are also becoming increasingly prominent [4]. On the other hand, problems such as unbalanced development among regions and obstacles to the circulation of innovative resources are seriously constraining the overall improvement of the TGIE level [5]. Especially at the inter-provincial level, owing to the disparities in natural endowments, economic foundations, and innovation capabilities, regions present complex network linkage characteristics in promoting tourism green innovation [6]. Therefore, how to realize green innovation development while maintaining economic growth in tourism has become an important issue of global concern.

To address the issue of measuring efficiency, academics have gone through an evolution of research from simple to complex. Traditional DEA methods have been questioned for their difficulty in dealing with undesired outputs [7]. With the deepening of research, an integrated measurement framework that encompasses environmental pollution and resource consumption has emerged [8]. This framework was further refined in subsequent studies, especially the inclusion of carbon emission indicators, which made the efficiency measurement more comprehensive [9]. However, these measures still fail to effectively deal with the effects of environmental factors and random errors, and most of them are limited to static analysis, which is difficult to reflect the dynamic characteristics of efficiency evolution. The role of environmental regulation has been controversial in the study of efficiency improvement mechanisms. The results of quasi-natural experiments show that moderate environmental regulation can indeed stimulate the innovation drive of tourism firms [10]. However, empirical studies based on the firm level have found that overly stringent environmental regulations may inhibit innovation incentives in SMEs [11]. This divergence not only reveals the non-linear link between environmental regulation and innovation efficiency, but also indicates the need to understand the mechanism of innovation efficiency enhancement in a broader perspective. A fresh angle on the question of how efficient innovation is has emerged with the popularity of regional collaborative innovation. The introduction of social network analysis not only reveals the formation mechanism of regional innovation networks [12], but also confirms the path dependence characteristics of innovation networks through long-term panel data [13]. Studies from the multidimensional proximity perspective have further enriched the field by revealing the important impact of geographic proximity and structural proximity on the formation of regional innovation networks [14]. These studies show that the enhancement of regional innovation efficiency is a complex systematic project that needs to consider both the interactions between regions and the influence of exogenous factors. With the development of network science, the application of the Exponential Random Graph Model (ERGM) has opened up new avenues for the study of innovation networks. ERGM is able to consider both the exogenous and endogenous dynamics of the network simultaneously, which provides a systematic analytical tool for understanding the formation mechanism of innovation networks [15]. However, such studies are still limited to the static analysis at a particular point in time, failing to capture the complex adaptive dynamics and emergent properties of system evolution over time. Especially in such a rapidly developing field as tourism, the study of dynamic changes in network relationships is particularly important. Despite tourism’s increasing role in carbon emissions and innovation policy discourse, existing research has seldom addressed how efficiently tourism regions pursue green innovation,

especially in a spatial, networked context. Most current studies tend to examine either the environmental performance or the innovation behavior of tourism destinations in isolation, rather than focusing on the efficiency with which tourism-related innovation inputs are translated into green outputs. This lack of focus on efficiency is particularly problematic in the context of China's dual-carbon goals, where regional governments face mounting pressure to deliver sustainable outcomes with limited innovation resources. Therefore, it becomes imperative to investigate not only the performance gaps across regions, but also the underlying mechanisms—both spatial and relational—that influence the evolution of TGIE over time. Building on these foundations, this study extends prior research by exploring three core questions: (1) What spatiotemporal evolution patterns characterize China's inter-provincial TGIE? (2) How do local network structures, captured through motif evolution, reflect regional collaboration modes in the TGIE network? (3) How do exogenous and endogenous dynamics jointly drive the systemic evolution of the TGIE network?

In view of this, this paper first employs the three-stage super-efficiency SBM-DEA model to assess China's inter-provincial TGIE, effectively mitigating the impact of environmental variables and stochastic errors. The spatial correlation network is then established using the gravity model. On this basis, TERGM is used to explore the complex system evolutionary dynamics mechanism of China's inter-provincial TGIE as an evolving networked system from 2011 to 2023, capturing both micro-level interactions and macro-level emergence. The following are the main contributions of this study: (1) Expanding the research perspective of TGIE, constructing a dual analytical framework including exogenous and endogenous dynamics by introducing the dynamic network analysis method and systematically analyzing the dynamic mechanism of the evolution of the TGIE network. (2) Employing motif analysis to characterize the dynamic evolution of local network configurations from a microstructure perspective, this approach overcomes limitations of traditional macro-level network metrics and provides a novel analytical dimension for understanding regional tourism innovation collaboration patterns. (3) By constructing the spatial correlation network of inter-provincial TGIE, it reveals the evolutionary characteristics of the spatial pattern of TGIE and provides empirical evidence for optimizing the regional TGIE network structure. This study enhances the theoretical framework of TGIE and offers theoretical support and policy insights for improving green innovation in China's tourist sector and maximizing regional cooperation networks.

2. Theoretical Foundations and Research Hypotheses

In the present setting of heightened focus on global green and sustainable development, tourism, as an important pillar of economic development [16], the enhancement of the efficiency of its green innovation is particularly critical. Green innovation in tourism not only concerns environmental protection and sustainable development, but also affects the transformation and upgrading of regional economies [17]. Therefore, exploring the network evolution mechanism of TGIE not only possesses academic value, but also provides useful guidance for policy making and industry practice.

Innovation networks, as the core force driving technological progress and industrial upgrading, have been thoroughly explored in global studies [18]. The formation and evolution of its network show a unique complexity. In the open innovation system, the relationship between various innovation actors in the tourism industry gradually tends to be multilateral and complex, and these interactions are not only the driving force of innovation, but also the key to TGIE enhancement. As pointed out by the theory of resource endowment and multidimensional proximity, the differences in green innovation behaviors among regions are not only closely related to geospatial constraints, but also to the configuration of multidimensional factors such as capital, technology, knowledge,

and human resources. Therefore, the evolution of the TGIE network cannot be analyzed purely at the micro-level, but the joint role of exogenous and endogenous factors should be explored from the perspective of spatial and temporal dimensions.

Exogenous dynamics, as a key factor driving the efficiency of green innovation, usually derive from external conditions such as the policy environment, changes in market demand, and technical standards [19–21]. China's new policy framework, which actively promotes a green economy and low-carbon growth, has significantly bolstered green innovation in tourism [22]. These policies are not only reflected in financial support and subsidies for green tourism projects, but also cover measures for the construction of environmental protection facilities and carbon emissions trading mechanisms. The strength of the policies directly affects the ability of each tourist organization in the region to have access to green innovation resources, which in turn has an impact on the development of their innovation efficiency. In addition to exogenous dynamics, endogenous dynamics reflect self-organizing principles intrinsic to the system, where micro-level interactions (e.g., reciprocity, triadic closure) generate emergent macro-structures. Endogenous dynamics mainly originate from the interconnection and collaboration among the subjects in the network. As revealed by the path dependence theory, the decision-making of each micro-subject in the network is influenced by historical accumulation and previous behaviors, which in turn has a far-reaching impact on the macro-network structure. The social network theory theorizes that the superposition of interdependent micro-decision-making processes is reflected in macro-inter-provincial relations, making regional nodes embedded in specific network endogenous structures. This structural embeddedness shapes regional innovation endowments, which in turn react to micro-subjective behavior, thereby leading to the reinforcement of local configurations in mutual feedback. In the TGIE network, resource sharing and cooperation among regional subjects form a specific path dependency effect. This effect not only shapes the current shape of the network, but also influences the trajectory of future evolution. The construction and growth process of the TGIE network is not a single linear process, but a system full of dynamic changes. The subjects in the network are constantly adjusting and optimizing according to the changes in the external environment, and the role of historical paths and innovativeness in the evolution of the network is particularly prominent in this process.

Therefore, this paper is based on the logical framework of “bottom-up” and “internal and external.” Starting from the resource endowment theory and multidimensional proximity theory, we analyze the exogenous dynamics of the TGIE network evolution. The endogenous dynamics of TGIE network evolution are analyzed from the social network and path dependence theories, which are shown in the analytical framework in Figure 1. On this basis, the potential influence mechanism of China's TGIE network and its hypotheses are proposed.

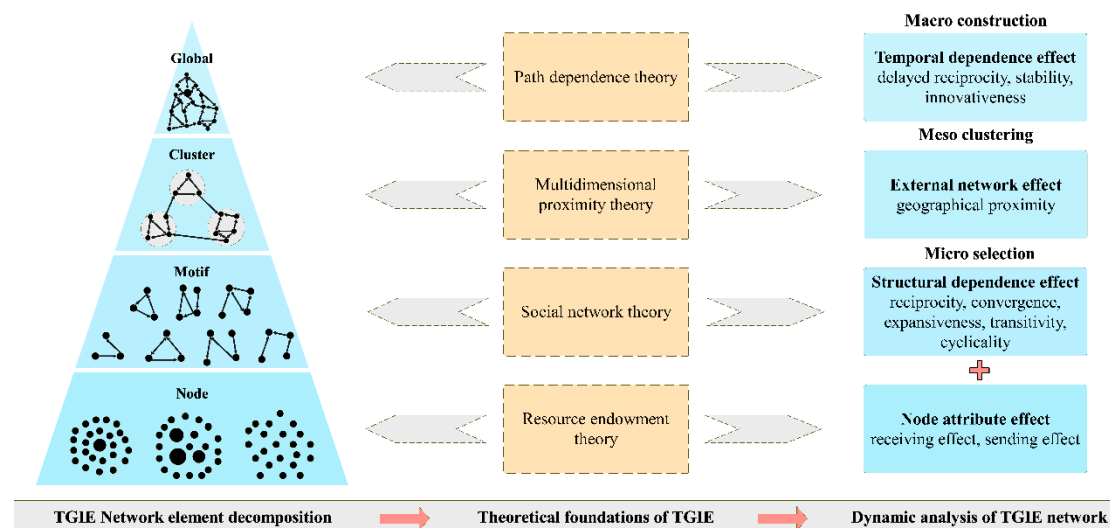


Figure 1. Analysis framework of the TGIE network evolution mechanism.

2.1. Exogenous Dynamics and TGIE Network Evolution

Lusher et al. [23] stated that the exogenous dynamics of the network include node attributes and exogenous contextual factors. Node attributes are categorized as the sender effect, receiver effect, convergence, or divergence between senders and receivers. Exogenous contextual factors include the entrainment effect of other networks and spatial factors. This coincides with the city node attribute effect and inter-city relationship attribute effect, which are concerned with urban innovation networks. In the TGIE network, the region node attribute can correspond to the receiver effect and the sender effect. Regional relational attributes usually refer to the institutional, organizational, cognitive, and geographic proximity between regions. These can correspond to covariate networks such as convergence as well as spatial factors. Thus, exogenous mechanisms of network evolution have been more abundantly tested in traditional regressions [24].

During the evolution of the TGIE network, node attributes have a profound impact on the network structure through the receiving effect and the sending effect. From the standpoint of the receiving effect, regions with lesser economic growth may exhibit a heightened need for efficiency enhancement and are more predisposed to pursue collaboration with high-efficiency regions. Regions facing the pressure of industrial structure transformation have a more urgent need to enhance the efficiency of green innovation. Regions characterized by high transportation accessibility demonstrate an enhanced capacity to assimilate innovation resources, and it is easier to acquire and digest external innovation experience. Regions with a relatively backward level of green technology can realize technological catch-up faster through network connection. In terms of the sending effect, regions exhibiting advanced economic development are more inclined to take the initiative to establish innovation cooperation with other regions due to the possession of sufficient innovation resources and stronger resource allocation capacity. Regions with a high degree of industrial structure optimization have a first-mover advantage in green innovation and are more likely to export advanced experiences to other regions. Regions with high transportation convenience can more effectively reduce the cost of innovation resource flow and promote cooperation. Regions with leading green technology levels tend to have stronger demonstration effects and are more likely to attract other regions to actively seek cooperation. This two-way mechanism reveals the complexity and multidimensionality of node attributes in network evolution. This paper proposes the following hypotheses based on the preceding analysis:

H1a. *The level of economic development, optimization of industrial structure, accessibility, and green technology level play a positive role in the receiver effect of the region in the network.*

H1b. *The level of economic development, optimization of industrial structure, accessibility of transportation, and level of green technology play a positive role in the sender effect of the region in the network.*

In terms of inter-city relationship attributes, multidimensional proximity has been identified as a key force influencing exchange and cooperation [25], for example, geographic proximity, which measures the spatial proximity of the cooperating parties. In the evolution of the TGIE network, geographic proximity, as an important relational attribute, has a significant impact on the formation and development of the network structure [26]. Geographically proximate provinces tend to have more convenient transportation conditions and more frequent economic interactions. This spatial accessibility can reduce the cost of innovation resource flows and facilitate inter-regional experience exchange and technology diffusion. Second, geographic proximity may also influence network evolution through demonstration and competition effects. Innovation practices and successful experiences among neighboring provinces are more likely to generate demonstration and driving effects, while healthy competition among regions can also motivate provinces to continuously improve their TGIE levels. This paper proposes the following hypothesis based on the preceding analysis:

H2. *Geographic proximity plays an active role in the formation of the TGIE network.*

2.2. Endogenous Dynamics and TGIE Network Evolution

The endogenous dynamics of a network refer to the fact that network relationships can form certain local subgraphs or microstructures through the process of self-organization, thus promoting the formation of other relationships in the network, and the recurrent effects of many micro-rules drive the essential changes in the global structure [27]. According to the social network theory, these micro-configurations can be effectively identified and parameterized as endogenous structural variables of the network to simulate the network evolution process [28]. For directed networks, endogenous dynamics include edge effects, reciprocity effects, structure-dependent effects, and time-dependent effects. Among them, the edge effect is the basic effect for forming relationships, which is used to control the network size, and the practical interpretation is similar to the intercept term in linear regression.

The reciprocity effect reflects the tendency for two-way reciprocity in a network [29]. If there is a correlation between region *i* and region *j*, there is a tendency to establish a corresponding reverse linkage between region *j* and region *i*, as well. Bidirectional exchanges may facilitate the comprehensive circulation and optimum distribution of resources. When a reciprocal relationship is formed between two regions, they can share experiences and exchange technologies in their respective areas of specialization. For example, one region may have an advantage in tourism human resource management while another region excels in environmental pollution control. Through reciprocal cooperation, both regions can realize complementary advantages and common enhancement. Second, reciprocal relationships help establish a more stable and lasting cooperation mechanism. Compared with unidirectional relationships, two-way reciprocal cooperation can enhance trust and commitment between regions and reduce cooperation risks and transaction costs. Such stable cooperative relationships enable regions to engage in more in-depth innovation exchanges, including joint R&D activities, sharing of innovation facilities and human resources, etc. Since this paper will track the time-series evolution of the network, the

reciprocity effect is categorized into current reciprocity and delayed reciprocity, and the following hypotheses are proposed:

H3a. *Unidirectional TGIE correlations established between regions in the current period tend to transform into reciprocal relationships within the same period.*

H3b. *Unidirectional TGIE correlations established between regions in the current period tend to transform into reciprocal relationships in the next period.*

Typical manifestations of structural dependence effects in networks are the preference attachment effect and the ternary closure effect. The preferred attachment effect refers to the propensity of a newly added node in a network to link more often to nodes with many existing connections, typically assessed by the geometrically weighted centrality distribution of the node. The statistic itself can be interpreted as inverse preferential attachment, and to avoid logical transformations, its opposite is taken in the model so that a positive coefficient indicates the presence of preferential attachment. In directed networks, it can be subdivided into a geometrically weighted centrality distribution of in-degree and a geometrically weighted centrality distribution of out-degree, portraying convergence and dilatancy, respectively. Convergence, on the other hand, is embodied as the clustering effect of associative relationships in the TGIE network. Inter-regional collaboration can effectively promote TGIE, and regions with higher absorption and utilization capacities are more inclined to establish close ties with regions with higher efficiency levels. This collaborative pattern enhances the driving effect of high-efficiency areas on low-efficiency regions, potentially intensifying the “the strong getting stronger and the weak getting weaker” phenomena inside the network. Expansion is reflected in the star-shaped distribution of collaborative relationships in the inter-regional TGIE network. As the policy of ecological prioritization and green development continues to deepen, some regions have become the core nodes for resource export and technology diffusion due to their significant advantages in TGIE. These regions usually gather higher-quality scientific research resources, a higher level of policy support, and a stronger industrial base, attracting other regions to take the initiative to establish collaborative relationships, thus driving the whole network to show a tendency of expanding from the core region to the periphery, presenting an axial amplitude spatial radiation effect. Therefore, this paper puts forward the following hypotheses:

H4a. *Inter-regional TGIE correlations have a tendency towards preference attachment and the network is characterized by convergence.*

H4b. *Inter-regional TGIE correlations have a tendency towards preference attachment and the network is characterized by expansiveness.*

The ternary closure effect is an important endogenous mechanism that influences the selection of relationships between nodes and drives the development of network clusters, which is manifested in the stabilization of the network structure, the formation of tightly-knit communities, and the characteristics of “small worlds.” From the studies of knowledge cooperation networks [30] and emerging technology networks [31], it is found that the triadic closure mechanism plays an important role in the formation and maintenance of network relationships. Broekel et al. [32] point out that the triadic closure can be regarded as a kind of “social capital,” which can enhance the relationship between participants.” This in turn enhances trust and cooperation among participants. In the TGIE network, the ternary closure effect can also improve the overall utilization efficiency of green innovation resources by promoting cooperation and mutual trust, information exchange, and resource

sharing among regions, which is a key direction for the evolution and development of the network. At present, with the promotion of China's tourism green development strategy and regional integration process, inter-regional green innovation cooperation relationships have gradually deepened, and the association effect, agglomeration effect, and "small world" characteristics of the network structure have become more and more obvious. Considering the directionality of the relationship, this paper divides the triadic closure into transmission closure and cyclic closure. Transmission closure refers to the fact that in the TGIE network, region A influences region B through cooperation, region B then influences region C through cooperation, and region A directly influences region C ($A \rightarrow B$, $B \rightarrow C$, $A \rightarrow C$). This closure relationship reflects the hierarchical structure of the TGIE network. Cyclic closure means that in the TGIE network, region A influences region B, region B influences region C, and region C in turn influences region A ($A \rightarrow B$, $B \rightarrow C$, $C \rightarrow A$). This closed relationship reflects the flattening and equalization of the network structure. Therefore, this paper proposes the following hypotheses:

H5a. *Inter-regional TGIE networks have a tendency for transmission closure.*

H5b. *Inter-regional TGIE networks have a tendency for cyclic closure.*

The time-dependent effect is a measure of the tendency of a network to keep relationships stable or change at different moments. Wang et al. [33] and Liu et al. [34] point out that relationships in a network are not only affected by structural dependence, but are also closely related to their past states. On the one hand, the TGIE network is a product of nested inter-regional resource flow preferences and cooperative relationships with some historical continuity and path dependence. The stability of this network relationship may stem from the trust base and interest association of long-term cooperation, which contributes to the tendency of the TGIE network to maintain the existing structural characteristics. On the other hand, with the ongoing advancement of green development policies and the enhancement of the government's involvement in directing regional coordinated development, the regions may show dynamic adjustment and innovative development characteristics in the cooperative relationship. For example, at different stages of green tourism development, regions may choose new partners or strategies according to their own development goals, promoting the continuous evolution and optimization of the network relationship. This paper proposes the following hypotheses based on the preceding analysis:

H6a. *The TGIE networks between regions exhibit stability, and the relationships demonstrate path dependence characteristics.*

H6b. *The TGIE networks between regions exhibit innovation, and the relationships demonstrate path creation characteristics.*

3. Data and Methods

3.1. Construction of the Indicator System and Data Sources

TGIE denotes the environmental advantages attained via the execution of innovative activities and the use of innovation inputs, specifically the proportionate correlation between innovation inputs and the resultant resource and environmental outputs. It indicates the extent to which innovation inputs contribute to innovation outputs, and its objective assessment aids in minimizing input redundancy and optimizing the distribution of innovation resources. The three-stage super-efficiency SBM-DEA model integrates the benefits of conventional data envelopment analysis with stochastic frontier analysis [35]. While carrying out multi-input, multi-output efficiency measurement, it eliminates the influence

of external uncontrolled variables and stochastic errors, and can better evaluate the efficacy of decision-making units. The precise procedure for calculating is as follows:

(1) First Stage

The first stage is a super-efficient SBM model based on undesired outputs. The model treats each provincial administrative unit as a decision-making unit (DMU), which includes M input factors x_m , L desired outputs y_l and K non-desired outputs u_k . The linear programming formulation of the super-efficient SBM model with undesired outputs is as follows:

$$\rho = \min \frac{\frac{1}{M} \sum_{m=1}^M \frac{s_m^x}{x_{m0}}}{\frac{1}{L+K} \left(\sum_{l=1}^L \frac{s_l^y}{y_{l0}} + \sum_{k=1}^K \frac{s_k^u}{u_{k0}} \right)} \quad (1)$$

$$s.t. \begin{cases} x_{m0} \geq \sum_{j=1, \neq 0}^n \lambda_j x_{mj} - s_m^x, \forall m \\ y_{l0} \leq \sum_{j=1, \neq 0}^n \lambda_j y_{lj} - s_l^y, \forall l \\ u_{k0} \geq \sum_{j=1, \neq 0}^n \lambda_j u_{kj} - s_k^u, \forall k \\ s_m^x \geq 0, s_l^y \geq 0, s_k^u \geq 0; x_i \geq 0, y_i \geq 0, u_i \geq 0, \lambda_i \geq 0; \forall m, l, k, i \end{cases} \quad (2)$$

where ρ is the efficiency value to be measured; s_m^x , s_l^y , and s_k^u denote the slack variables for input, desired output, and undesired output variables, respectively; and λ is the vector of weights. The magnitude of the value shows a positive correlation with the value of this DMU. In order to make the measured efficiency value closer to the actual efficiency value, as well as to solve the inter-period comparability problem in the DEA model, this paper sets the DMU value as conditioned on the scale efficiency variable and global reference.

(2) Second Stage

In the second stage, the SFA model is used to account for the impact of management inefficiency, external factors, and random mistakes on the slack values of the input variables. This is important because these factors might prevent the measured input-output levels from being maximized. Therefore, the SFA model is used in the subsequent phase to mitigate the impact of environmental factors and random discrepancies, thereby isolating the duplication of decision units solely attributable to management inefficiencies. The precise formula is as follows:

$$S_{mi}^t = f(E_{mi}^t, \eta_m) + v_{mi}^t + \xi_{mi}^t, i = 1, 2, \dots, N; m = 1, 2, \dots, N; t = 1, 2, \dots, T \quad (3)$$

where S_{mi}^t is the slack variable for the m -th input; E_{mi}^t is the environmental variable, and η_m is its coefficient; $v_{mi}^t + \xi_{mi}^t$ denote the mixed error term and the two terms are independent of each other, representing random mistakes and managerial inefficiency, respectively. In addition, the estimate of the random error term is used to strip out the managerial inefficiency term and the random error term, which ultimately approximates the specific estimate of the random error factor, and the following formula is applied to adjust the initial inputs:

$$x_{mi}^{t'} = x_{mi}^t + [\max(v_{mi}^t) - v_{mi}^t] + [\max(f(E_{mi}^t, \eta_m)) - f(E_{mi}^t, \eta_m)] \quad (4)$$

where $x_{mi}^{t'}$ is the adjusted input value; x_{mi}^t is the pre-adjusted input value; $[\max(v_{mi}^t) - v_{mi}^t]$ denotes the exclusion of random error effects; and $[\max(f(E_{mi}^t, \eta_m)) - f(E_{mi}^t, \eta_m)]$ denotes the exclusion of the effect of external uncontrollable factors.

(3) Third Stage

In the third stage, the modified data obtained from the second stage is used to re-evaluate the measurement using the highly efficient SBM model for undesired output.

The efficiency numbers acquired at this step have eliminated the impact of the external environment and random mistakes, allowing for a more precise representation of the actual degree of efficiency.

The particular measurement indices are chosen as follows:

- (1) Input indicators. Based on the new economic growth model, human and capital inputs are the most basic production factors [36]. Meanwhile, considering the increasingly prominent energy supply problem [37], this paper selects human, capital, and energy input indicators as the core input factors to measure TGIE. Tourism research and development (R&D) people are the implementers of tourism innovation initiatives, reflecting the innovative potential of the regional tourist sector. The personnel of tourist organizations are essential to advancing the high-quality growth of the tourism sector and sustaining innovative capabilities. Therefore, this paper selects tourism R&D personnel and tourism organization employees to characterize human input. Financial input is the fundamental guarantee for green innovation in tourism, and R&D expenditure is usually adopted internationally to reflect the degree of investment in science and technology innovation. This paper selects tourism R&D expenditure to characterize the financial input. Energy input is an important prerequisite for tourism industry to carry out green innovation; this paper selects the total energy consumption of tourism industry to characterize the energy input.
- (2) Output indicators. Desired output is the positive output of the implementation of innovation activities in the tourism industry. This paper selects the two indicators of total tourism revenue and the number of tourism patent applications to measure the economic benefits and innovation benefits obtained by the tourism industry in the implementation of green innovation, respectively. The gross revenue from tourism is the most immediate indication of the benefits derived from the implementation of green innovations in the tourist sector. The number of tourism patent applications is the core of the tourism industry's scientific and technological assets. The undesired outputs are selected as tourism carbon emissions, tourism sewage emissions, and tourism garbage emissions, since there are no relevant statistics on carbon emissions and energy consumption in tourism in domestic databases and statistical yearbooks. In this paper, the bottom-up method of decomposition and then totalization are adopted to account for the carbon emissions and energy consumption of the tourism industry, based on Becken et al.'s method of dividing the tourism industry into three major sectors, namely, tourism transportation, tourism accommodation, and tourism activities [38]. The formula is as follows:

$$C_{i(\text{transport})}^t = \sum_{j=1}^4 T_{ij}^t P_j \theta_j \quad (5)$$

$$C_{i(\text{accommodation})}^t = B_i^t L_i^t \alpha \beta \quad (6)$$

$$C_{i(\text{activities})}^t = \sum_{q=1}^5 N_i^t A_q^t \mu_q \quad (7)$$

$$C_i^t = C_{i(\text{transport})}^t + C_{i(\text{accommodation})}^t + C_{i(\text{activities})}^t \quad (8)$$

In the formula, subscript i denotes a region, and subscript j represents the four types of tourist transportation modes: Aviation, Highway, Railway, and Waterway. The variable T_{ij}^t signifies the passenger turnover for tourist transportation mode j in province i during year t ; P_j indicates the passenger share utilizing transportation mode j ; θ_j denotes the carbon emission factor per unit for mode j ; and B_i^t quantifies the bed capacity in star-rated tourist hotels within province i in year t , with L_i^t representing the annual occupancy

rate. The parameter α corresponds to energy consumption per unit, while β indicates carbon emissions per bed per night. Tourist activity types are categorized by subscript q , comprising sightseeing, leisure vacation, business meetings, and visiting friends, and others. N_i^t designates the total tourist arrivals in province i during year t . A_q^t signifies the proportion of tourists engaging in activity type q , with μ_q representing the carbon emission factor for activity q . The aggregate tourism carbon emissions for province i in year t are quantified by C_i^t .

In addition, there are no statistics on tourism wastewater discharge and tourism waste. Referring to an existing study [39], the conversion was made using the share of total tourism revenue to GNP. Regarding the natural environmental factors, forest parks and nature reserves not only enhance the attractiveness of tourism, but also have a greater impact on the absorption and purification of carbon dioxide, domestic wastewater, etc., thus affecting the measurement of TGIE. Therefore, two indicators, forest park area and nature reserve area, are selected to characterize the spatial heterogeneity of natural environmental factors in different regions. The construction of the indicator system is detailed in Table 1.

Table 1. Indicator system for TGIE.

Index	Specific Index	Indicator Description
Input	Labor	Number of employees in tourism institutions (unit: 10,000 persons)
		Number of tourism R&D personnel (unit: 10,000 persons)
	Capital	Expenditure on tourism R&D (unit: CNY 10,000)
	Energy	Total energy consumption in the tourism industry (unit: 100 million MJ)
Desired output	Economic	Total tourism revenue (unit: CNY 100 million)
	Innovation	Number of tourism patent applications (unit: units)
Undesired output	Tourism environmental pollution	Tourism carbon emissions (unit: 10,000 tons)
		Tourism wastewater discharge (unit: 10,000 tons)
		Tourism waste discharge (unit: 10,000 tons)
External uncontrollable factors	Natural environmental factors	Area of forest parks (unit: 10,000 hectares)
		Area of nature reserves (unit: 10,000 hectares)

The data used in this paper are mainly derived from the China Tourism Statistical Yearbook, China Tourism Sample Survey Data, China Transportation Statistical Yearbook, China Environmental Statistical Yearbook, and China National Bureau of Statistics. Missing data were supplemented by mean value or linear interpolation. Thirty provinces in China (excluding Hong Kong, Macao, Taiwan, and Tibet) were chosen for the research because data were not available in some regions, and the validity of the data was not guaranteed.

3.2. Spatial Correlation Network Construction

Currently, the methods for constructing networks in the literature mainly include the minimum spanning tree method [40], the VAR model [41], and the gravity model [29]. The minimum spanning tree method can only generate a simple connectivity graph consisting of $N-1$ edges and N nodes, which cannot comprehensively reflect the multi-level connections among subjects. The VAR model is too responsive to the selection of lag order and fails to adequately represent the network topology. The gravity model is more suitable for dealing with aggregate data and exploring the dynamic progression of the network compared to the previous two models. The precise calculation formula is as follows:

$$F_{ij} = k_{ij} \times \frac{c_i \times c_j}{d_{ij}^2}, \quad k_{ij} = \frac{c_i}{c_i + c_j} \quad (9)$$

where F_{ij} is the correlation strength of TGIE; k_{ij} is the gravity coefficient; c_i and c_j denote the TGIE levels of provinces i and j , respectively; and d_{ij} is the geometric center distance between provinces. Using the results of gravitational model measurement to construct the gravitational matrix w_{ij} (30×30) and using the mean value of each row of the matrix as the threshold to construct a directed asymmetric binary adjacency matrix, the binary network w_{ij} of the spatial association of TGIE in China is obtained.

3.3. Network Motif Analysis

The network motif is the basic unit of complex structure inside a network, representing the typical pattern of efficiency correlation among nodes. Motif analysis can reveal the specific paths and network characteristics of efficiency correlation among different regions. The frequency of the motif is much higher than its frequency in random networks with the same distribution of nodes and connection strengths, which suggests that the motif has an important role in the structure of the network. The importance of motifs can be quantified by calculating the Z-value of the motif. The formula for the Z-value is given below:

$$Z_i = \frac{N_{reali} - N_{randi}}{\sigma_{randi}} \quad (10)$$

where Z_i denotes a specific motif; N_{reali} is the number of times the motif Z_i appears in the actual network; N_{randi} is the number of occurrences of motif Z_i in the random network; σ_{randi} is the standard deviation; in terms of Z_i , the larger the value, the higher the importance of the motif in the network. In TGIE networks, motifs can not only reflect the structural properties of efficiency associations among provinces, but also reveal the potential development direction of the network. For example, the transfer-type motif ($A \rightarrow B \rightarrow C$) may indicate the existence of multi-level efficiency-driven relationships among provinces. The closed-loop motif ($A \leftrightarrow B \leftrightarrow C \leftrightarrow A$), on the other hand, may reflect the equilibrium and tightness of efficiency linkages among regions. The motif analysis helps elucidate the fundamental mechanisms and evolutionary traits of the TGIE network.

3.4. Measurement of Variables

- (1) Dependent variable. The dependent variable studied in this study represents the presence or absence of inter-provincial linkages in the TGIE network (i.e., whether there is a linkage or not, which takes the value of 1 when it exists, and 0 otherwise), and is used to characterize the distribution of linkages in the inter-provincial TGIE.
- (2) Explanatory variables. This study is based on the hypothesis of the formation process of the TGIE network and the extrapolation of its dynamic development trajectory, alongside the trajectory of conventional research [34,42]. The following explanatory variables are added to the model: edges, mutual, delrecip, gwidegree, gwodegree, ttriple, ctriple, stability, and innovation, and the explanations of the specific indexes are shown in Table 2. Mutual is used to measure whether inter-regional TGIE affiliations tend to form reciprocal relationships during the same period. It measures whether province j gives back to form a bidirectional reciprocal relationship in the same period when province i has a unidirectional correlation relationship to province j . Delrecip is used to measure whether unidirectional correlation relationships between regions are characterized by cross-period reciprocity, and to detect whether a unidirectional relationship formed in the previous period gives back to form a bidirectional relationship in the next period. The correlation relationship is directed as follows: the sender is the one who sends out the correlation relationship, and the receiver is the one who receives the correlation relationship; usually the receiver is in a more favorable position in the network. In this paper, we use gwidegree to measure the preference attachment effect, which describes the distributional tendency

of province i to receive correlations sent by multiple provinces. Gwodegree measures the preference radiation effect, which reflects the possibility that some core provinces may have formed a “core-edge” structure through their influence on neighboring nodes. Ttriple tests the transmissive closure effect between three nodes in the network and measures the tendency of indirect inter-provincial linkages, while ctriple reflects the tendency of three nodes to form a closed-loop relationship, which describes the closeness of multi-directional interactions in the network. Stability is used to measure the tendency of the network relationships to remain unchanged in period t in period $t + 1$, reflecting the path dependence characteristics of the network. Innovation tests whether network relationships change over time, measures the generation of new relationships or the disappearance of old relationships in the network, and reflects the innovative development characteristics of the network.

- (3) Control variables. In this study, we refer to the related literature [27,42–44] and include important exogenous mechanism drivers as control variables in the model. Economic development level (EDL), Industrial structure (IS), Transport convenience (TC), Green technology level (GTL), and Geographical distance (GD) all affect the TGIE correlations, and these factors together drive the formation of network relationships by the exogenous mechanisms.

Table 2. Variable specification of TERGM.

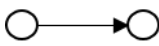
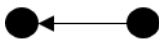
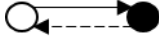
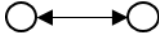
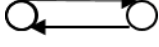
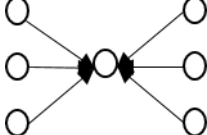
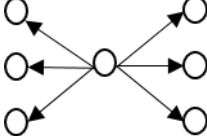
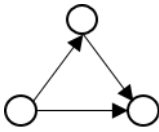
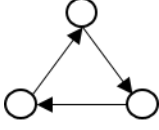
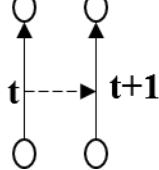
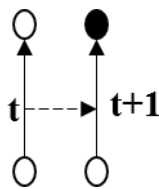
Effect	Variable	Diagram	Statistical Significance	Hypothesis
Basic effect	Edges		Network density as an indirect reflection; the baseline tendency for relationship formation	/
Node attribute effect	Nodeicov		Measures the impact of a node's regional attribute on incoming relationships between regions	H1a
	Nodeocov		Measures the impact of a node's regional attribute on outgoing relationships between regions	H1b
External network effect	Edgecov		Measures the impact of an external relational network on the formation of efficient relationships	H2
Reciprocity effect	Mutual		The tendency of unidirectional relationships to receive reciprocal feedback in the current period	H3a
	Delrecip		The tendency of unidirectional relationships to receive reciprocal feedback in the next period	H3b
Structural dependence effect	Gwidegree		The tendency of efficient relationships to distribute concentratively	H4a
	Geodegree		The tendency of efficient relationships to distribute expansively	H4b

Table 2. Cont.

Effect	Variable	Diagram	Statistical Significance	Hypothesis
Temporal dependence effect	Ttriple		The tendency to form hierarchical transitive efficient relationships among three regions	H5a
	Ctriple		The tendency to form flat cyclic efficient relationships among three regions	H5b
	Stability		The tendency for the overall network pattern in period t to remain stable in period t + 1	H6a
	Innovation		The tendency for the overall network pattern in period t to undergo variation in period t + 1	H6b

3.5. Modeling

ERGM and its extension TERGM have garnered significant interest and acknowledgment from academics as novel network statistical methodologies [33,45]. The distinctive feature of TERGM is that it is appropriate for dynamic observation network studies and considers the time-dependent characteristics of network data [34].

Therefore, in this paper, TERGM captures the co-evolution of endogenous self-organizing mechanisms and exogenous control parameters in networked systems, covering four longitudinal observation periods (2011 to 2023, with each observation cycle spanning four years). By simulating micro-level interaction rules and macro-level emergent patterns, TERGM reveals how local collaborative behavior drives system-level correlation evolution and uncovers the path dependence of green innovation efficiency in spatial configuration. The specific observation of TGIE spatial correlation network in year t is denoted by y^t , and a K-order Markov correlation is constructed by the principle of discrete-time Markov chain TERGM:

$$P(Y^t = y^t | Y^{t-k}, \dots, Y^{t-1}, \theta) = \frac{\exp\left[\sum_H \theta_H g(y^t, y^{t-1}, \dots, y^{t-k})\right]}{c(\theta, y^{t-k}, \dots, y^{t-1})} \quad (11)$$

where $P(\cdot)$ denotes the probability that the observed network y occurs in all possible networks; Y . $c(\cdot)$ denotes the normalized constant that ensures the probability is between 0 and 1; H is the set of variables that affect the formation and evolution of the network; θ_H is the vector of coefficients; and $g(\cdot)$ is the network statistic corresponding to H .

4. Results

4.1. Analysis of TGIE Measurement Results

The measured results of China's TGIE between 2011 and 2023 are shown in Figure 2a. In the first stage, the average value of national TGIE is 0.8072, with an overall fluctuating upward trend. Specifically, it rises from 0.8237 in 2011 to 0.8446 in 2023. Shanghai has been

on the efficiency frontier side, with an average value of efficiency as high as 1.2038, while that of Liaoning is only 0.3327, which highlights the significant differences in TGIE between regions. However, the effects of natural environmental factors and random errors are not removed at this stage, and the efficiency measurements have some errors.

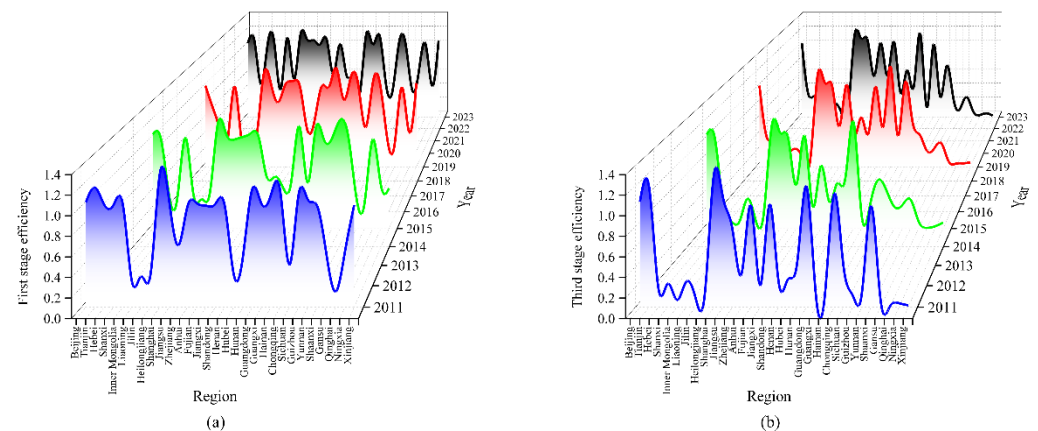


Figure 2. (a) First stage efficiency. (b) Third stage efficiency.

The third stage adjusts the input data from the first stage through the SFA stochastic frontier regression model. The calculation results are shown in Figure 2b. After adjustment, the national average of overall efficiency drops to 0.4763, indicating that environmental variables and stochastic errors mask the true picture of efficiency to some extent. In terms of time trends, the overall efficiency in the eastern region is higher and remains relatively stable. In Jiangsu, for example, its efficiency value grew from 1.0757 in 2011 to 1.0874 in 2023, showing a steady upward trend. The performance of Fujian and Zhejiang is also more outstanding, with the average efficiency value of 1.0293 in Fujian and 0.9653 in Zhejiang during the study period. In contrast, the efficiency value of the central and western regions is relatively low and fluctuates greatly. Qinghai has the lowest efficiency value in the country, growing from 0.0048 in 2011 to 0.0241 in 2023, but still significantly lower than the national average. Xinjiang's efficiency value fluctuates less, declining from 0.0196 in 2011 to 0.0182 in 2023, with almost no growth. The low efficiency of these regions reflects their shortcomings in tourism innovation resource input and green technology level.

Taken together, China's TGIE shows significant differences in time and space, with the efficiency value of the eastern coastal region significantly higher than that of the central and western regions, presenting a spatial pattern of “high in the east and low in the west.”

4.2. Local Motif Analysis of TGIE Networks

To investigate the microstructure and network organization of China's TGIE network, this paper launches a study through motif analysis, where motifs with $p < 0.05$ ($|Z| > 1.96$) were considered statistically significant. The top six most frequent motifs across all observation years were prioritized for analysis based on occurrence frequency ranking (Table 3). This dual criterion—statistical significance and frequency ranking—ensures both methodological rigor and empirical relevance to tourism innovation networks.

From the results of the ternary structure, motif 12 appears with the highest frequency in all years, and its frequency shows a year-on-year upward tendency, indicating that the dominant role of the chain structure in the network is continuously strengthening. This chain structure reflects that many provinces form unidirectional indirect links through intermediary nodes. It reflects that intermediate nodes play a crucial bridging function in the cross-regional movement of innovation resources. Motif 166, as a bridging structure, has a relatively stable frequency, showing that some provinces have realized efficient inter-

regional links through bridge nodes, and its two-way flow characteristics further promote the diversification of resource sharing and collaboration modes. Meanwhile, the frequency of motif 174 fluctuates and rises during the study period. As a partially closed structure, its directional characteristics indicate a significant enhancement of bidirectional interactions in the TGIE network. Such interactions contribute to the efficiency of collaboration and strengthen the regional integration of innovation resources. However, the frequency of fully closed motif 238 is consistently lower across years. This suggests that the role of fully interactive collaboration patterns in the TGIE network is relatively limited, but still has some value in promoting network stability and deep collaboration.

Table 3. Motif analysis of China's TGIE network from 2011 to 2023.

Year		2011			2015			2019			2023		
Structure	ID	Motif	Frequency/%	ID	Motif	Frequency/%	ID	Motif	Frequency/%	ID	Motif	Frequency/%	
Ternary Structure	12		11.4500	12		12.9710	12		13.0520	12		15.9390	
	166		10.8560	166		11.4500	166		10.9860	166		10.8640	
	174		9.0156	174		7.9729	174		8.1690	174		9.8842	
	38		6.8997	46		7.5488	46		6.6667	46		6.5004	
	46		5.7958	38		5.9372	38		5.2582	38		5.9662	
	238		4.1398	238		4.1561	238		4.8826	238		4.2743	
	392		3.6012	392		3.7254	392		4.2027	392		4.2280	
Quaternary Structure	10372		3.0179	18572		2.9829	18572		3.4673	10372		3.9095	
	18572		2.6826	10372		2.9439	10372		3.3482	8588		2.8344	
	2188		2.3181	2202		2.8787	17238		2.5446	18572		2.6250	
	74		2.2890	590		2.1753	74		2.3661	4694		2.4853	
	2202		2.2306	710		2.0711	2202		2.3512	536		2.4435	

Among the results of the quadruple structure, motif 392 maintains the highest frequency in all years and shows a continuous upward trend. The directional characteristics of this single-intermediary node chain structure indicate that in the collaboration of the four nodes, resources and information are mainly transferred directly or indirectly between regions through intermediary nodes, which fully reflects the importance of cross-region and multi-level collaboration. The higher frequency of motif 10372, which is a multi-intermediary node chain structure, reflects that some of the core nodes play the role of resource pooling and leading collaboration in the network role. Similar to motif 166 in the ternary structure, the directional relationship of motif 10372 highlights the ability of core provinces to integrate innovation resources through unidirectional or bidirectional flows. The frequency of motif 18572 decreased after 2019, showing that the partially closed ternary structure is gradually replaced by the polycentric collaboration model of the multi-intermediary node chain structure, a change that reflects the innovation net-

work's evolutionary flexibility and adaptability. Meanwhile, the emerging chain motif 8588 and partially closed motif 4694 appear and increase in frequency in 2023, marking the sophistication and diversification of cross-regional collaboration forms in the TGIE network, and these new motifs further emphasize the tendency of optimal allocation of resources between regions through intermediary nodes.

From the overall evolution trend, the driving mechanism of the TGIE network gradually shifts from the core node-dominated monocentric model to the polycentric collaboration model. The chain structure and partially closed structure serve as the primary impetus for network evolution.

4.3. TGIE Network Overall Evolutionary Analysis

In this paper, the structure of China's TGIE directed network in 2011, 2015, 2019 and 2023 is measured and plotted according to the gravity model (Figure 3). Among them, the size of the circle represents the size of the node degree value. The degree value includes the degree of connecting in and connecting out.

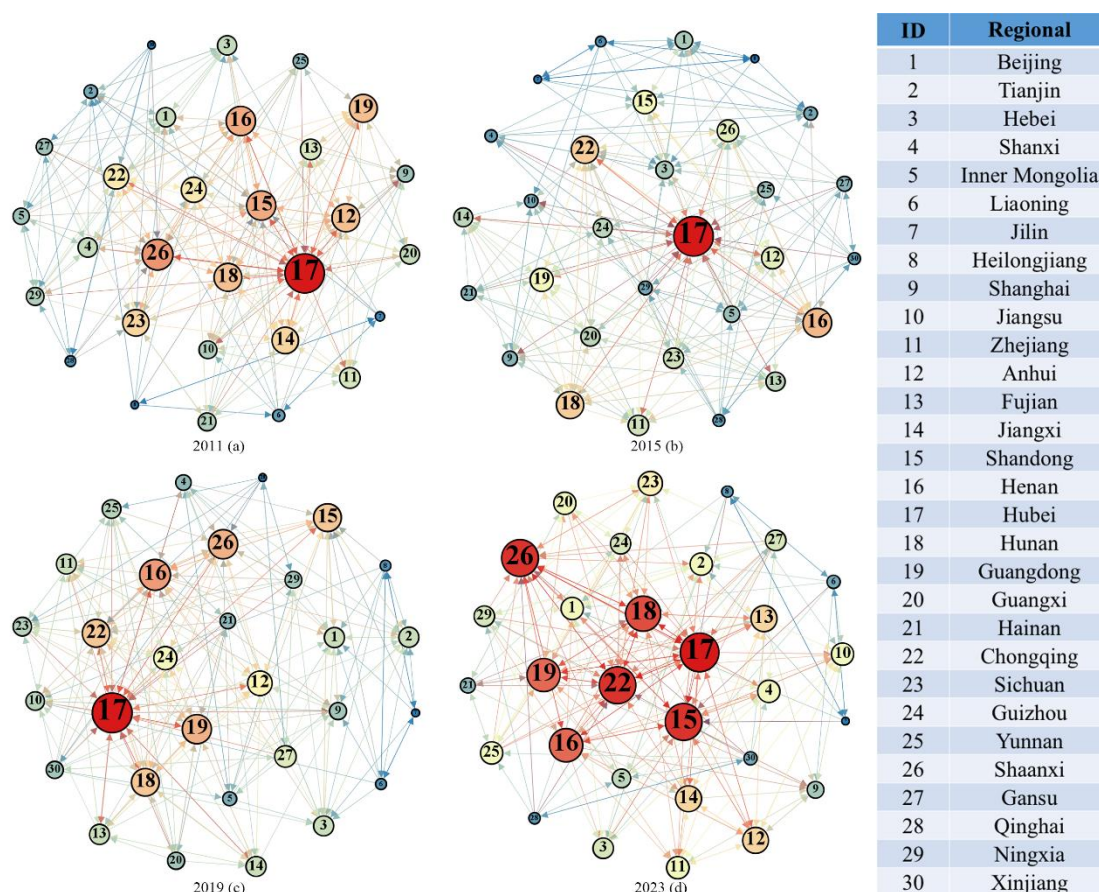


Figure 3. Structure of the TGIE network from 2011 to 2023.

Regarding the temporal dynamics of the comprehensive network evolution, the dynamics of the TGIE network in China between 2011 and 2023 show a trend of increasing regional collaboration and gradual complexity of the network structure. In 2011, the overall density of the network was low, with high-efficiency regions (e.g., Shanghai, Guangdong) as the core. These regions have attracted more linkages from low-efficiency regions through higher connectivity, demonstrating a strong attraction to collaboration. This characteristic suggests that high-efficiency regions do not only act as resource exporting nodes, but also become the main targets for other regions to seek cooperation by virtue of their innovation resource endowment, technological advantages and economic development level, forming

“centers of attraction” for resources and innovation factors. By 2015, the chain structure in the network had further emerged, and the frequency of the ternary structure had increased significantly. Highly efficient regions at this stage continue to strengthen their role as attraction nodes through high connectivity, with some regions (e.g., Jiangsu and Zhejiang) showing particular strength in their ability to attract green innovation resources. Meanwhile, regions like Henan, Hubei, and Chongqing gradually develop into important intermediary nodes that promote inter-regional collaboration by connecting high-efficiency nodes with low-efficiency nodes. In 2019, the complexity of the network further increases, and the frequency of the multi-intermediary node chain in the quaternary structure significantly increases. Some regions (e.g., Henan, Shaanxi, and Chongqing) exhibit resource output and network coordination through higher connectivity. High-efficiency regions still rely on high connect in degrees to maintain strong attractiveness. This pattern reflects the bidirectional nature of collaborative relationships in the network. High-efficiency regions attract low-efficiency regions to establish connections, while intermediary nodes facilitate resource redistribution through multi-directional connections, further promoting multi-level interactions in the network. In 2023, the TGIE network enters a highly networked stage, with overall connectivity further enhanced. High-efficiency regions still maintain a high degree of connectivity, indicating that their attractiveness continues to play a role in the network. These regions have not only enhanced the integration efficiency of innovation resources through collaboration with neighboring nodes, but also gradually strengthened their direct links with other high-efficiency regions, forming a pattern of multi-center interaction. At the same time, intermediary nodes (e.g., Hubei, Henan, Chongqing, and Shandong) play a crucial role as bridges between inefficient and efficient regions, further optimizing the efficiency of resource flows and promoting the balanced development of the network as a whole.

In terms of the relationship between degree value and efficiency, the level of degree does not exactly correspond to the level of efficiency. High-efficiency regions (e.g., Shanghai and Guangdong) show that they are attracting other node regions to collaborate with them through their high degree of connectivity rather than simply acting as output nodes of resources. In contrast, some regions with high outward connectivity but medium efficiency (e.g., Henan and Hunan) show stronger resource mediation and coordination functions through multi-directional connectivity. This dynamic relationship suggests that the collaboration mechanism in the network not only depends on the efficiency level of the nodes, but is also influenced by their structural location and functional positioning. Combined with the analysis of local motifs, the frequency of chained and partially closed structures continues to increase over the four periods, suggesting that the evolution of the network is increasingly dependent on the role of intermediary nodes. These intermediary nodes facilitate the flow of resources between inefficient and efficient regions through high connectivity, while efficient regions continue to maintain their core attraction in the collaborative network through high connectivity.

Overall, the evolution of the TGIE network not only reflects the spatial distribution pattern of node efficiency, but also demonstrates the dynamic changes in node functions in resource flow and collaborative relationships.

4.4. Analysis of the Dynamics of the Evolution of the TGIE Network

In this paper, the TERGM simulation of China’s TGIE network from 2011 to 2023 is performed. The results of its parameter estimate are shown in Table 4. Regardless of whether it is an exogenous or endogenous dynamics model, the TERGM simulation needs to incorporate the base effect edges to control the network size. Model 1 mainly incorporates the exogenous dynamics variables of the node attribute effect and external network effect

to test the exogenous mechanism hypothesis. Model 2~Model 6 take the exogenous dynamics as a control variable and incorporate the endogenous dynamics variables one by one to explore the endogenous mechanism of network evolution. The formation and evolution of the TGIE network are a result of the joint action of exogenous dynamics and endogenous dynamics (Figure 4). Exogenous dynamics drive the formation of the foundation of the network through the mechanism of resource endowment differences and geographic proximity. Endogenous dynamics further strengthen the stability and dynamic characteristics of the network through the mechanism of network self-organization.

Table 4. TGIE network TERGM estimation results.

Effect	Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Basic Effect	edges	−1.5601 *** (0.2044)	−1.8577 *** (0.2062)	−2.6602 *** (0.2474)	−2.6553 *** (0.2499)	−4.3596 *** (0.2512)	−4.3315 *** (0.2480)
	nodeicov (EDL)	1.1839 *** (0.3527)	1.6201 *** (0.3634)	2.6364 *** (0.4709)	2.6659 *** (0.4865)	2.6303 *** (0.4917)	2.6476 *** (0.4722)
Node Attribute Effect	nodeicov (IS)	0.2381 *** (0.0425)	0.2536 *** (0.0438)	0.3325 *** (0.0555)	0.3309 *** (0.0561)	0.3315 *** (0.0565)	0.3288 *** (0.0551)
	nodeicov (TC)	0.0567 *** (0.0052)	0.0530 *** (0.0034)	0.0408 *** (0.0061)	0.0415 *** (0.0064)	0.0457 *** (0.0063)	0.0454 *** (0.0069)
	nodeicov (GTL)	1.1180 *** (0.0943)	1.1502 *** (0.0931)	1.2308 *** (0.1100)	1.2291 *** (0.1100)	1.2305 *** (0.1142)	1.2306 *** (0.1118)
	nodeocov (EDL)	2.1700 *** (0.3528)	2.5168 *** (0.3614)	3.1722 *** (0.4836)	3.2027 *** (0.4848)	3.1796 *** (0.4721)	3.1680 *** (0.4825)
	nodeocov (IS)	−0.0531 (0.0407)	−0.0813 (0.0433)	−0.0562 (0.0542)	−0.0563 (0.0529)	−0.0569 (0.0532)	−0.0595 (0.0519)
	nodeocov (TC)	0.0226 (0.0493)	0.0304 (0.0503)	0.0293 (0.0568)	0.0244 (0.0587)	0.0301 (0.0578)	0.0313 (0.0581)
External Network Effect	nodeocov (GTL)	0.0520 (0.0758)	0.2076 ** (0.0763)	0.3834 *** (0.0976)	0.3817 *** (0.0983)	0.3791 *** (0.0990)	0.3899 *** (0.1017)
	edgecov (GD)	3.8927 *** (0.1534)	3.1468 *** (0.1753)	2.4155 *** (0.2018)	2.4311 *** (0.2020)	2.4242 *** (0.2042)	2.4340 *** (0.2049)
Endogenous Structural Effect	mutual		1.3161 *** (0.1926)	1.2075 *** (0.2173)	1.2131 *** (0.2239)	1.1924 *** (0.2196)	1.2283 *** (0.2164)
	delrecip			1.5026 *** (0.1678)	1.5131 *** (0.1687)	1.5046 *** (1.1574)	1.5032 *** (0.1644)
	gwidegree				0.2314 *** (0.0129)	0.0414 *** (0.0023)	0.0140 *** (0.0010)
	geodegree				0.1047 *** (0.0099)	0.0090 *** (0.0008)	0.0013 *** (0.0001)
	ttriple					0.0353 *** (0.0039)	0.0452 *** (0.0062)
	ctriple					−0.5039 *** (0.0277)	−0.3800 *** (0.0235)
Log Likelihood	stability						3.1622 *** (0.0992)
	innovation						3.5151 *** (0.1368)
AIC		3088	2730	1959	2263	1479	888
BIC		3172	2792	2043	2346	1484	894
Log Likelihood		−1533	−1355	−967	−1119	−738	−443

Note: *** and ** enote statistical significance at the 1% and 5% levels, respectively. Values in parentheses represent standard errors.

In terms of exogenous dynamics, the formation of the TGIE network is first driven by the mechanism of resource endowment differences. This “source power” is manifested in the inter-regional differences in EDL, IS, TC, and GTL. The analysis of node attributes shows that the coefficient of reception effect of EDL is 2.6476. The probability of a region with a higher level of economic development to receive resources is 14.12 times higher than that of a region with a lower level of economic development ($\exp(2.6476) = 14.12$, hereinafter the same), while the coefficient of reception effect of GTL is 1.2306, which corresponds to the probability multiplier of 3.42 times. The contribution of TC and IS to the reception effect is relatively small but still significant. This suggests that regions with high levels of economic development and green technology are more inclined to attract the inflow of external resources, validating H1a. As for the sending effect, the coefficient of EDL is 3.1680, indicating that the probability of forming an output relationship in regions with high EDL is as high as 23.74 times, whereas the coefficient of GTL as a sender is 0.3899, with a probability multiplier of only 1.48 times. This indicates that EDL has a more substantial influence on the sender effect, validating H1b. However, IS and TC have no substantial influence on the sender effect, rejecting some of the hypotheses. Geographic proximity significantly influences the establishment of the TGIE network, and becomes a “determining force” for resource flows. The coefficient of GD is 2.4340, which indicates that the probability of forming green innovation efficiency correlations between neighboring regions is 11.39 times higher than that of distant regions, which verifies H2. This suggests that geographic proximity not only reduces the cost of innovation resource flows, but also enhances the willingness of inter-regional cooperation through spatial proximity.

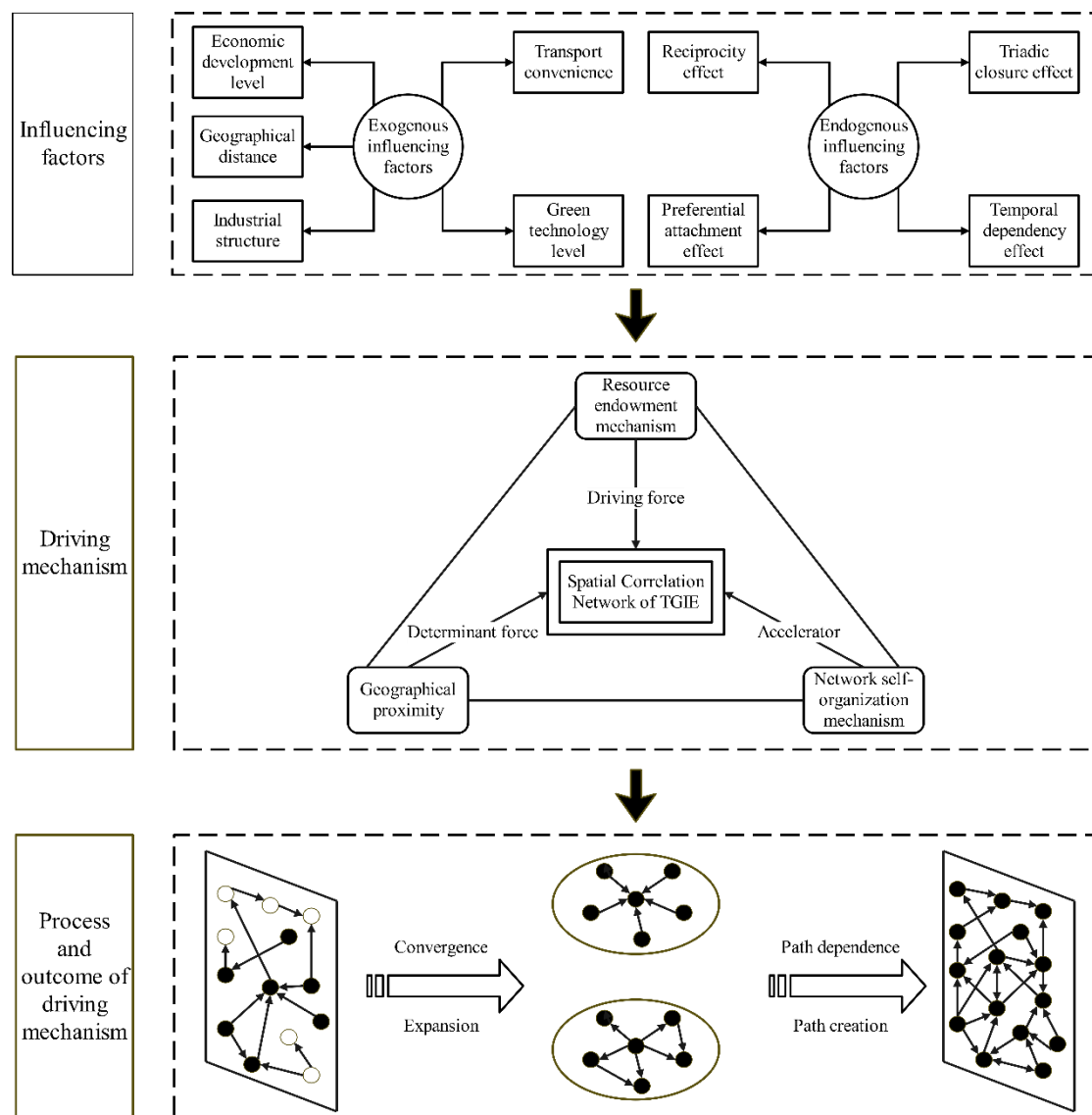


Figure 4. Evolution mechanism of the TGIE spatial association network.

Endogenous dynamics provide an important “gas pedal” for the TGIE network through the network self-organization mechanism. The mutual coefficient of the reciprocal effect is 1.2283, indicating that two-way relationships have a strong tendency to form during the same period; delrecip has a coefficient of 1.5032 and a probability multiplier of 4.50 times, which further suggests that unidirectional associations tend to evolve into reciprocal relationships at a later stage, and thus strengthen the stability of the network. H3a and H3b are both validated. The gwidegree in the preference attachment effect and the geodegree in the preference radiation effect are both significantly positive, and the dual roles of efficient nodes in attracting cooperative relationships and diffusing resources are manifested. The attraction of core nodes to peripheral nodes enhances the resource clustering and radiation functions of the network, validating H4a and H4b. Meanwhile, gwidegree is stronger than geodegree, which indicates that the affiliation relationship in the TGIE network prefers core nodes with high attraction ability. In the ternary closure effect, the coefficient of ttriple is markedly positive, but the coefficient of ctriple is substantially negative, thereby corroborating hypothesis H5a and refuting hypothesis H5b. It indicates that TGIE presents a network formation mode mainly thanks to the increase in transfer closure structure, while cyclic closure structure is less easy to form and maintain. The

time-dependent effect is an important driver of TGIE network evolution. The coefficients of stability and innovation in Model 6 are 3.1622 and 3.5151, respectively, and both are significant, verifying H6a and H6b. It indicates that the TGIE network presents an obvious path dependence effect, and its evolutionary process has path creation characteristics.

For model fit goodness-of-fit, the smaller the AIC and BIC, the better, while the larger the Log Likelihood, the better. It can be seen that the model accuracy is greatly improved when the endogenous mechanism is considered. The Goodness-of-fit (GOF) test, i.e., 1000 simulations based on the estimated parameters of Model 6, is performed on Model 6, which contains all variables and has the best fit (Figure 5). The key features are dyad-wise shared partners, edge-wise shared partners, degree, and indegree, and the geodesic distances of the simulated network are compared and analyzed with the real network. It can be found that the five types of key network features are close to the 95% confidence interval of the simulated network, indicating that the simulated network can explain the real network well. In addition, the ratio of true positive prediction rate to false positive prediction rate of the ROC curve is near the upper left corner. It indicates that the model simulates the structural features of the real network well and is able to capture the dynamic evolution mechanism of the network.

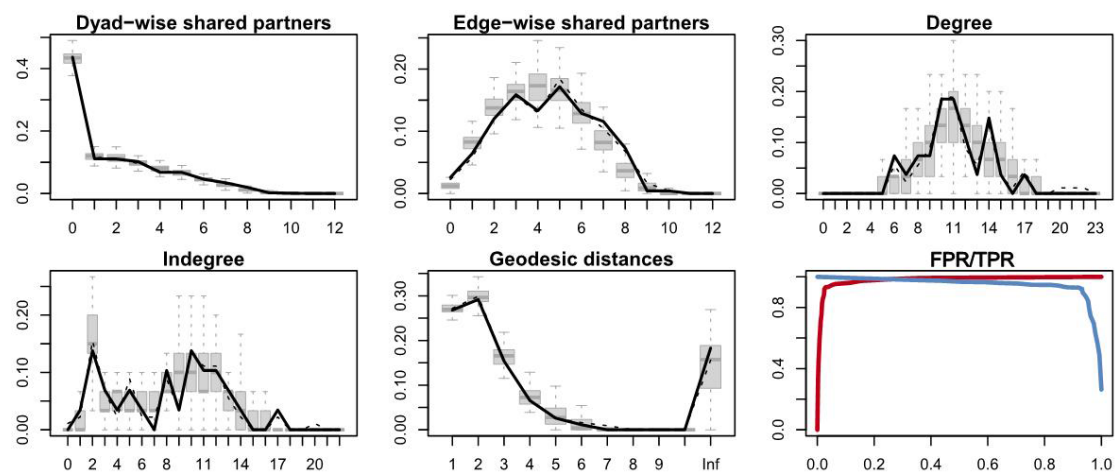


Figure 5. Goodness-of-fit plots. Note: edge-wise and dyad-wise in the figure correspond to the standard terminology edge-wise and dyad-wise.

5. Discussion

The evolution of the TGIE network in China embodies a complex dynamic mechanism. This study reveals the joint role of exogenous and endogenous dynamics through TERGM. First, the findings indicate that the eastern area exhibits higher green technology attractiveness in the TGIE network by virtue of its economic developedness and green technology advantages. This is consistent with existing studies that emphasize the centrality of economically developed regions in innovation networks [46]. However, in contrast to the traditional view, this study finds that intermediary nodes (e.g., Henan and Hubei) exhibit a key role in cross-regional cooperation. It significantly facilitates resource flows and collaboration by connecting efficient and inefficient regions. This finding continues the discussion on the importance of network bridge nodes [47]. It further suggests that the function of intermediary nodes may be particularly important in the field of innovation, as they not only undertake resource allocation, but also play a guiding role in shifting collaboration patterns [48]. The reciprocity effect shows a significant facilitating role in network evolution, which is manifested in the gradual evolution of unidirectional associative relationships into bidirectional reciprocal relationships. This relationship not only strengthens the trust and collaboration among nodes, but also improves the overall stability of the network by

enhancing the bidirectionality of resource flow. This outcome is in accordance with the research conducted by Yan et al. [49], which suggests that the reciprocity effect is crucial in enhancing cooperation within innovation networks. In addition, the reciprocity effect is uneven across regions, with high-efficiency regions (e.g., Shanghai, Guangdong) more likely to attract collaborative relationships in return. And intermediary nodes further consolidate their bridging role in the network through two-way relationships. This indicates that the reciprocity effect depends not only on the resource endowment of the nodes, but also on their structural location within the network, thereby illustrating the complexity of network development.

The study also reveals the dual characteristics of “path dependence” and “path creation” in network evolution. Historical partnerships significantly contribute to the stabilization of the present network structure, as corroborated by the research of Guo et al. [50]. This suggests that the evolution of the network is not only constrained by the existing resource endowment, but also influenced by the historical cooperation trajectory. Meanwhile, this study finds that the TGIE network exhibits a certain degree of flexibility in adjusting to the time dimension, and this “path creation” feature is particularly obvious under the regional policy and innovation-driven approach, which shows an important contribution to the dynamic progression of the network [51]. This finding provides a new perspective to explain the dynamic adjustment of inter-regional collaboration patterns, especially for regions with weak geographic proximity, where policy facilitation may be more critical than traditional resource endowment differences. In addition, this study explores the interplay between exogenous and endogenous dynamics. Geographic proximity, as an important factor of exogenous dynamics, significantly contributes to resource flows, congruent with the results of Ferretti et al. [26]. This suggests that geographic proximity may significantly lower resource flow costs and improve regional cooperation willingness. The preference attachment effect, as a manifestation of endogenous dynamics, further explains how efficient nodes strengthen their centrality in the network by attracting cooperative relationships from inefficient nodes. It is equally crucial to acknowledge that the ternary closure effect in the network exhibits significant fluctuations, with some regions displaying strong triangular relationships while others show weaker or even negative correlations. This may indicate differences in the level of trust and cooperation between regions at different stages of the network, further highlighting the challenge of achieving balanced development within the network.

Furthermore, it is valuable to contextualize our findings by critically comparing them with similar research in other countries or sectors. For instance, studies on green innovation networks in the manufacturing sector indicate that economically developed regions or core enterprises also typically dominate the innovation network structure, with peripheral actors depending heavily on intermediary nodes or central firms to integrate into the innovation ecosystem [52]. Similarly, research on the nuclear trade network in Europe has underscored the critical role of bridging nodes, highlighting how regions or firms positioned as network intermediaries significantly facilitate technology diffusion and resource integration [45]. However, compared to these sectors, tourism exhibits distinctive characteristics due to its inherent reliance on natural and cultural resources, higher sensitivity to geographic proximity, and the complexity of multi-stakeholder collaboration. These sectoral differences suggest that regional policymakers in tourism should place greater emphasis on tailored collaboration mechanisms and leverage local-specific resources when designing green innovation strategies.

In addressing practical implications more explicitly, this study highlights two critical aspects based on the findings. First, considering the pronounced spatial disparities observed in TGIE performance, regional governments facing low TGIE should adopt tar-

geted strategies rather than general approaches. Particularly, provinces with consistently low TGIE values, predominantly located in central and western China, should prioritize overcoming deficits in innovation inputs and green technological capabilities. Practical measures could include increasing direct investment in R&D projects focused on sustainable tourism, offering incentives or subsidies for businesses actively engaging in green innovation activities, and establishing dedicated training programs to improve local human capital specialized in green technologies. Such targeted interventions can help address the underlying resource constraints and promote regional innovation performance systematically. Second, peripheral provinces, currently positioned at the margins of the TGIE network, face the challenge of integrating effectively into a predominantly core-dominated network structure. As revealed by this study, intermediary nodes significantly enhance the efficiency of resource flow and regional collaboration. Thus, peripheral provinces should strategically utilize these intermediary nodes by strengthening connectivity—both physical and informational—with central and intermediate regions. Specifically, policy measures could include building or upgrading inter-provincial transportation and digital infrastructure to reduce transaction costs and facilitate efficient resource exchange. Furthermore, peripheral provinces can form alliances or cooperative frameworks with existing intermediary nodes to effectively participate in innovation collaboration, gain spillover benefits from developed regions, and eventually improve their centrality and integration within the broader TGIE network. These practical strategies align closely with the findings regarding network reciprocity and preferential attachment effects, which emphasize both resource endowment advantages and structural positions within networks. By adopting such targeted approaches, regional policymakers can more effectively address disparities in TGIE performance and facilitate broader, more balanced, and sustainable development within China's tourism innovation landscape.

However, there are some limitations in this study. One critical assumption underlying TERGM is the Markovian dependence, which presumes that network evolution is solely contingent upon its immediate past state. This assumption may overlook long-term dependencies or memory effects extending beyond the immediate past, potentially simplifying complex, path-dependent processes. Moreover, TERGM inherently assumes linear relationships between network evolution and driving factors, which may inadequately represent complex non-linear or threshold effects that exist in actual network dynamics. Thus, future research could benefit from employing alternative or complementary modeling approaches, such as dynamic stochastic actor-oriented models (SAOMs), which explicitly incorporate actor-level decisions and allow for greater flexibility in modeling non-linear relationships and memory effects. In addition, with the wide application of digital technologies and artificial intelligence in green innovation, the evolution of TGIE networks may be affected by more non-traditional variables. Such as the level of digital technology and the completeness of digital infrastructure, which have not been included in the analytical framework of this study. Future research could further extend the analytical framework of this study. For example, the potential role of digital technologies in shaping the evolution of the TGIE network is considered in conjunction with micro-level data to explore how collaboration patterns at the firm or industry level affect the dynamic evolution of the TGIE network.

6. Conclusions and Policy Implications

6.1. Main Conclusions

This paper combines the three-stage super-efficiency SBM-DEA model, motif analysis, and TERGM to conduct an in-depth study on the temporal changes, local structural characteristics, overall network evolution, and driving mechanisms of China's TGIE network from 2011 to 2023. The main conclusions are as follows:

(1) Significant spatial differences in China's TGIE. The national TGIE level is measured by the three-stage super-efficiency SBM-DEA model, and the results show that the overall national efficiency average is low but with a fluctuating upward trend. The efficiency differences between regions are significant. The eastern coastal region shows higher efficiency due to its green innovation resources and technological advantages, while the central and western regions are relatively inefficient due to insufficient resource inputs and lower technological levels, reflecting a distinctive spatial gradient characteristic.

(2) The evolution of the local network configuration is characterized by the dominance of the chain structure and the gradual strengthening of the partially closed structure. From 2011 to 2023, the local structure of China's TGIE network is gradually dominated by the chain structure, which indicates that the tendency to realize unidirectional and indirect linkages through intermediary nodes becomes more and more obvious. Intermediary nodes act as a bridge for cross-regional resource flows, significantly facilitating the integration of innovation resources. At the same time, the increase in partially closed structures reflects the gradual strengthening of two-way cooperative relationships. The evolution of these localized structures enhances the efficiency of resource sharing and collaboration within the network and promotes inter-regional innovation integration.

(3) The overall evolution of China's TGIE network shows a shift from a single center to a polycentric collaboration model. The overall connectivity and collaboration of the network have gradually increased, forming a pattern of transformation from a single center to a polycentric collaboration model. High-efficiency regions (e.g., Shanghai, Guangdong) attract low-efficiency regions (e.g., Qinghai, Xinjiang) to participate in collaboration through high connectivity. Intermediary nodes (e.g., Henan, Hubei, Chongqing) play a bridging role by connecting inefficient and efficient regions. This polycentric collaboration model improves the integration efficiency of innovation resources and enriches the connectivity model.

(4) The TGIE network evolution is driven by both exogenous and endogenous dynamics. Exogenous dynamics drive network formation and resource flows mainly through resource endowment differences (e.g., EDL, IS, TC, GTL) and geographic proximity. For example, regions with higher EDL tend to attract more resources, while regions with higher GTL show stronger resource exporting ability. Geographic proximity, on the other hand, plays a decisive role in network formation by reducing the cost of resource flows and enhancing the willingness to cooperate. Among the endogenous dynamics, the reciprocity effect and preference attachment effect drive efficient nodes to attract inefficient nodes, which strengthens the stability of the network. The ternary closure effect promotes the collaborative deepening of the network. The time-dependent effect, on the other hand, exhibits significant path dependence and path creation characteristics. The evolutionary process of the network reflects the continuous influence of historical paths on current network relationships, while the network structure shows significant flexibility in adjusting under policy-driven and innovation-driven circumstances.

6.2. Policy Implications

Based on the analysis of the evolution mechanism of China's TGIE network, in order to enhance the level of TGIE, optimize the network structure, and promote the sustainable development of tourism, the following policy proposals are presented:

(1) The eastern coastal region leads in TGIE with its resource and technological advantages, while the central and western regions lag significantly behind due to insufficient resource inputs and lower technological levels. In order to improve this spatial gradient characteristic, it is necessary to build a tourism green innovation pattern of synergistic development in the east, central and west regions through the establishment of a special

support fund, the strengthening of technical assistance, and the sharing of green innovation results. Emphasis should be placed on supporting the technological catch-up and efficiency enhancement of the central and western regions in the construction of green scenic spots, low-carbon tourism projects, and resource-saving facilities.

(2) The evolution of the TGIE network suggests that intermediary nodes have a key role in promoting cross-regional resource integration and tourism innovation cooperation. It is recommended to set up cross-regional tourism green innovation centers in intermediary nodes such as Henan, Hubei, and Chongqing to support the joint actions of tourism R&D institutions and higher education institutions. At the same time, by upgrading the transportation and information infrastructure of intermediary nodes, we can promote the flow of green tourism technology and experience sharing, and promote the clustering effect of cross-regional tourism innovation networks.

(3) Exogenous dynamics significantly influence the evolution of the TGIE network, in particular, resource endowment differences and geographic proximity have a significant effect on the flow of resources for tourist green innovation. It is recommended to reduce the cost of resource flows by reducing or exempting taxes and fees for cross-regional green tourism cooperation, providing transportation and logistics subsidies, and promoting cross-regional joint development of low-carbon tourism products. At the same time, we encourage the joint formulation of green tourism policies among neighboring regions to form a coordinated innovation ecosystem, in order to fully unleash the facilitating effect of geographic proximity on the green development of tourism.

(4) Endogenous dynamics of the TGIE network are mainly reflected in the reciprocity effect, preference dependence effect, ternary closure effect, and time dependence effect. In order to strengthen the stability and vitality of the tourism green innovation network, cross-regional two-way cooperation should be encouraged through incentive policies, such as supporting the sharing of green tourism R&D results and carrying out inter-regional tourism talent mobility programs, in order to enhance the viscosity and depth of network cooperation. At the same time, polycentric collaboration in green tourism should be supported to deepen the efficiency of integration of innovation resources in chain and closed networks, and to ensure that the network evolves dynamically under historical path dependence and innovative drive.

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