

Article

The Dynamic Evolution of Agricultural Trade Network Structures and Its Influencing Factors: Evidence from Global Soybean Trade

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Abstract: Under the rapid advancements in information technology, the complex network characteristics of agricultural product trade relationships among global economies have exhibited increasing prominence. This study takes the soybean trade market as an empirical case, employing a combination of social network analysis to investigate the dynamic evolution of agricultural trade network structures; then, the Temporal Exponential Random Graph Model (TERGM) is adopted to analyse the factors influencing the soybean trade network. Based on comprehensive empirical data encompassing soybean trade data among 126 economies from 2000 to 2022, this research demonstrates several key findings: Firstly, the soybean trade network is characterised by pronounced trade agglomeration effects and “small-world” properties, accompanied by heightened trade substitutability. Secondly, the network’s structural configuration has undergone a distinct transformation, shifting from a traditional single-core-periphery structure to a more complex multi-core-periphery architecture. Thirdly, in response to external shocks impacting network topology, the core structure exhibits greater resilience and stability, whereas the periphery displays heterogeneous responses. Finally, the evolution of soybean trade relations is governed by a dual mechanism involving both endogenous dynamics and exogenous influences.

Keywords: agricultural trade network structure; dynamic evolution; influencing factors; social network analysis; temporal exponential random graph model



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1. Introduction

The rapid advancement of information technology has profoundly reshaped global agricultural trade patterns. Online e-commerce has overcome geographical barriers, enabling direct access to international consumers for agricultural products. Agricultural futures markets now leverage information technology for precise price forecasting and efficient risk management. Digital cold chain logistics and traceability systems enhance product quality and transport efficiency. However, these developments have intensified trade complexity, introducing an increasing number of participating countries/regions, rapidly changing market information, and multifaceted influencing factors. Among agricultural products, the soybean market stands as a representative case. As a vital global source of edible oil and protein, soybeans directly impact food security. Research on the soybean market, a key player in the international agricultural trade, contributes to understanding agricultural trade’s structural framework and operational logic.

The soybean trade has flourished with increasingly intertwined relationships, forming a complex trade network. According to the CEPII-BACI international trade database, frequent soybean trading activities occurred between 2000 and 2022, with expanding import–export volumes. This has established a pattern dominated by the United States and Brazil as primary exporters, while Asian countries operate as major importers. USDA data indicate that Brazil and the United States accounted for nearly 80% of global soybean production in 2022, highlighting the global impact of the soybean trade network. As the largest importer, China’s sustained demand growth primarily supports oil extraction and feed processing, addressing domestic edible oil consumption and livestock farming needs. Being a land-intensive crop requiring flat cultivation areas, most countries increasingly rely on international trade to meet demand as economies develop, resulting in import dependencies. A notable example is China: despite ranking as the world’s fourth-largest soybean producer, it depends on imports for over 80% of its requirements.

In recent years, an increasing number of scholars have adopted social network analysis methods to investigate the changes in agricultural product trade network structures under various event shocks. These studies primarily focus on analysing the impacts of such shocks on key structural features of trade networks, including connectivity, density, and centrality, thereby revealing the dynamic evolution and adaptability of trade networks in response to external disturbances.

From a methodological perspective, the existing literature predominantly employs social network analysis tools to abstract agricultural product trade relationships as either unweighted, weighted, or directed networks. For instance, some scholars constructed a directed trade network for agricultural products along the Belt and Road Initiative (BRI) and found that the COVID-19 pandemic significantly reduced network connectivity and density, leading to sparser trade relations [1]. Similarly, some researchers utilised near real-time global grain trade data to demonstrate that developed countries exhibited greater resilience due to higher connectivity and stronger trade alliances during the pandemic. In contrast, developing countries faced more significant challenges [2]. Regarding mathematical models, some scholars have employed the Temporal Exponential Random Graph Model (TERGM) to analyse the influencing factors of agricultural product trade networks and assess their resilience to external shocks [3].

As for the specific events examined, existing studies primarily focus on the impacts of the COVID-19 pandemic, the Russia–Ukraine conflict, and other economic disruptions on trade networks. For instance, some researchers constructed a multilayer network model to analyse the effects of the Russia–Ukraine conflict on the global grain trade network, revealing that sunflower oil and corn trade losses reached 89% and 85%, respectively. In comparison, poultry meat exports were directly impacted by 25% [4]. While some analysed the impacts of food crises and financial crises on agricultural product trade networks between 2000 and 2016, concluding that these events had relatively limited effects and exhibited significant heterogeneity across countries [5]. Furthermore, the structural characteristics of global grain trade networks for four major crops (soybeans, wheat, rice, and corn) are investigated, finding that the global grain trade network is transitioning toward greater interconnectivity and resilience in response to the dual shocks of COVID-19 and the Russia–Ukraine conflict [6].

Additionally, some scholars have utilised the Quadratic Assignment Procedure (QAP) to study the self-organising structures of agricultural product trade networks. These studies primarily explore how factors such as geographic distance, natural endowments, economic development, trade policies, and political stability influence the formation and evolution of trade networks [7,8]. In addition, QAP has been applied to analyse trade networks at regional and commodity-specific levels. Some researchers employed QAP regression to investigate the drivers of agricultural trade networks within the Regional Comprehensive Economic Partnership

(RCEP), identifying four distinct blocks: net gainers, mutual spillover zones, intermediary hubs, and net spillers. The study revealed that spillover effects between blocks are transitive and that geographic distance, economic and social conditions, resource endowments, and language proximity significantly influence RCEP agricultural trade network structures [9]. Some utilised QAP to explore the evolution mechanisms of global cereals trade networks, finding that economic disparities, resource endowments, and regional free trade agreements positively influenced network evolution. At the same time, cultural similarities and political differences had negative impacts on trade patterns [10]. From a regional perspective, the QAP model has been applied to identify key influencing factors of agricultural product trade networks in specific regions, which provides valuable implications for understanding their structural dynamics [11,12]. However, the QAP model also has certain limitations. When analysing trade networks, the QAP model often requires integration with other methodologies, such as the gravity model, to complement its limitations. While the gravity model can explain trade relationships by leveraging node attribute characteristics (e.g., GDP, market size) and exogenous mechanism variables (e.g., geographic distance), it assumes trade relations are independent of each other, thereby overlooking the structural characteristics of complex trade networks. This limitation, to some extent, restricts a comprehensive understanding of the self-organising structure of trade networks.

There is relatively little existing literature on the soybean trade network, and it mainly focuses on analysing the dynamic structural characteristics of the soybean trade network. Based on the method of complex trade networks, some scholars have constructed a global soybean trade network and found that the scale of the network is continuously expanding, the number of trading countries is steadily increasing, and the trade connections between countries are gradually deepening. South America has become the global soybean export centre, and Asia has become the global soybean import centre. The trade status of North America has declined [13]. Some other scholars have not only analysed the structural evolution characteristics of the soybean trade network but also examined the impact of sudden events on individual nodes [14,15]. The results show that the soybean trade network is gradually becoming more complex, exhibiting small-world characteristics and scale-free network properties. Some major soybean-producing countries such as the United States dominate the global soybean trade. Moreover, when some uncertain factors emerge, such as trade frictions and changes in the policy decisions of importing and exporting countries, China's soybean trade is vulnerable to the threat of strict control by other countries. In addition to studying the structural characteristics of soybean trade, some scholars have also investigated the influencing factors of soybeans' virtual water trade network. Some scholars have constructed the virtual water trade networks of wheat, rice, corn, and soybeans for 29 major grain trading countries in 2012 and 2022 and measured their network indicators and virtual water flow patterns. They have studied the influencing factors of grain products' virtual water trade network from four dimensions: economic scale, geographical features, resource endowment, and policy agreements. In terms of economic scale, the gross domestic product (GDP) is the largest core driving factor for the virtual water trade networks of all grain products, followed by the per capita arable land area, which is a factor related to resource endowment [16].

Those studies provide a solid theoretical foundation and empirical support for this research. However, most of the existing literature focuses on studying the topological structural characteristics of the agricultural product trade network. There is relatively little analysis of the network's core-periphery structure, and few studies explore the impact of unexpected events on the network structure. In the analysis of network influencing factors, most research efforts concentrate on using the Quadratic Assignment Procedure to study the impact of exogenous network factors. At the same time, there is less exploration of the endogenous structural aspects of the network. This research aims to contribute to two key areas based on

previous studies. Firstly, it comprehensively analyses the dynamic evolution characteristics of the soybean trade network from multiple dimensions, including the characteristics of the core–periphery structure. Secondly, it systematically studies how various event shocks affect the evolution of the soybean trade network structure and applies the Temporal Exponential Random Graph Model (TERGM) to explore the influencing factors of the network. The structural arrangement of this paper is shown in Figure 1.

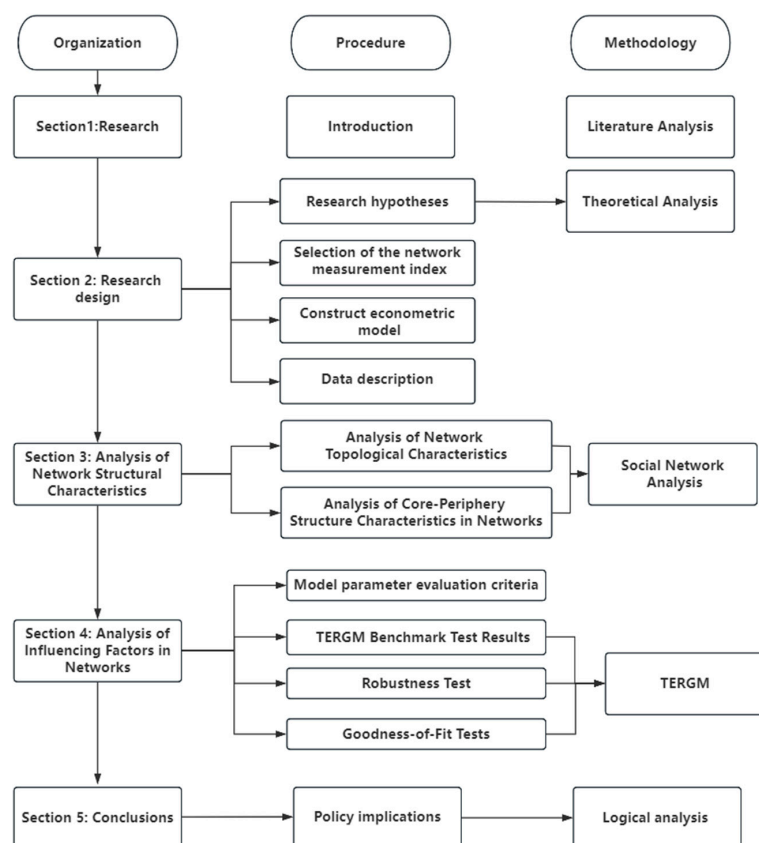


Figure 1. Organisation of this paper.

2. Research Design

2.1. Theoretical Hypotheses

The soybean trade network, a complex and evolving structure, is continuously influenced by external events, with the degree of impact varying across different countries. This paper provides a detailed explanation of these dynamics. Due to the limited theoretical research specifically on soybeans, this study expands its analysis to the broader category of agricultural trade to which soybeans belong. The structure of the soybean trade network, as revealed by this study, is significant and can potentially influence future research in this field.

First, the scale of global agricultural trade networks is expanding, and trade complexity is increasing [17]. Different agricultural trade networks exhibit hidden trade clustering characteristics [18]. The global agricultural trade landscape is gradually being reshaped, with the European economic bloc and the United States still dominating the network control, demonstrating a clear “core advantage” hierarchy [19]. From a regional perspective, agricultural trade among countries along the “Belt and Road” is highly concentrated in regions and types [20], with import trade dispersed and export trade concentrated. Trade intensity is particularly high among neighbouring countries. The agricultural trade network of RCEP countries shows significant spatial correlation [9], exhibiting strong stability and

“small-world” characteristics. Based on this, the following hypothesis is proposed regarding the topological structure of the soybean trade network:

Hypothesis 1. *The soybean trade network exhibits trade agglomeration effects and “small-world” characteristics.*

Agricultural trade networks have formed a distinct core–periphery structure [9]. Countries such as China, Australia, Japan, Thailand, and Vietnam, with their large trade volumes, serve as essential trade nodes and are in the core areas of the network. The periphery regions exhibit a “three-core, multi-node” structure, with Malaysia, the Philippines, and Singapore as the core areas and Brunei, Cambodia, Laos, Myanmar, and New Zealand as secondary nodes. Overall, secondary node regions in the periphery account for a significant proportion, and these countries have weak trade connections with both intra- and extra-cluster nations. From a sectoral perspective, the global grain trade network also demonstrates a significant core–periphery structure [10], with the United States, Japan, Mexico, Egypt, South Korea, and Colombia as core countries, evolving from a single-core to a multi-core structure. Similarly, the dairy trade network exhibits a clear core–periphery structure, with core import regions shifting from Europe, East Asia, and the Americas to North America, the Middle East, and East Asia, while core export regions remain relatively unchanged. In the land flow trade network [21], a few economies play a hub role in large-scale land transfers, resulting in a typical core–periphery structure. Therefore, the following hypothesis is proposed:

Hypothesis 2. *The soybean trade network exhibits a distinct core–periphery structure, evolving from a single-core to a multi-core structure.*

Agricultural products are highly susceptible to natural disasters; thus, agricultural trade networks are also vulnerable to the impact of sudden events. Based on the types of sudden events, they can be broadly categorised into two types: First, international conflict events. In the context of the Russia–Ukraine conflict, the complete loss of agricultural production in Ukraine has had varying impacts on different countries [4], indicating heterogeneity in the effects across nations. The impact is smaller on major grain-exporting countries and larger on major grain-importing countries. Additionally, the effects can be traced along a single linear axis, where initial minor declines in food supply have escalated into market panic, exacerbating inflation and food insecurity in import-dependent regions [22]. Second, natural disaster events. Studies simulating the impact of sudden declines in U.S. wheat production due to natural disasters such as sandstorms on the global agricultural trade network [23] found that such events generally affect global trade networks by impacting the reserves of major grain-producing countries. A reduction in U.S. exports led other countries to utilise their reserves to meet demand, resulting in a 31% decline in global wheat reserves.

These studies indicate that the impacts of sudden events on different countries are heterogeneous. For major producing countries, while abrupt shocks may reduce agricultural output, the adverse effects of such events are likely to be transferred to other countries through market transmission mechanisms. As a result, major producing countries only bear the risk of reduced food exports, and the impact of this risk on their market position appears to be marginal. In contrast, for major food-importing countries, the negative consequences of sudden events propagate domestically through market channels. Owing to their heavy reliance on imported food, these nations are confronted not only with steep price surcharges but also with unforeseeable food emergencies. Building on these observations, the following hypothesis is advanced:

Hypothesis 3. *The impact of sudden events on core structures tends to stabilise, while the impact on peripheral structures exhibits heterogeneity.*

The agricultural product trade network is jointly influenced by a variety of factors. According to existing theories, these influencing factors can be divided into two categories. One category consists of exogenous factors. For example, in the dairy products sector, exogenous factors such as per capita income gap, geographical distance gap, and standard language have always affected the dairy trade relationships among countries [8]. In the global grain trade network, geographical distance, economic gap, resource endowment, and regional free trade agreements have a positive impact on the evolution of the grain trade network. In contrast, cultural similarity and political differences have a negative impact on the pattern of the grain trade network [10]. In the global egg trade network, exogenous factors, including geographical distance, natural endowment, economic development, trade policies, and political stability, have a significant impact on the evolution of the egg trade network. The other category is endogenous factors. This type of research mainly starts from the topological structure of the network, believing that the topological structure formed by the network itself will affect the formation and evolution of the network. For example, in a study on the influencing mechanisms of the agricultural trade network of Shanghai Cooperation Organization countries, in addition to researching exogenous factors such as geography, culture, and economy, the study also examined the impact of the network's own structural characteristics on the overall network, such as network structural characteristics like reciprocity, multiple connectivity, and stability mechanisms. Finally, it was found that these network structural characteristics also significantly affect the network's evolution [3]. The existing literature shows that the agricultural product trade network is affected by both endogenous and exogenous factors. Based on this, the following hypothesis is proposed in this paper:

Hypothesis 4. *The soybean trade network is jointly influenced by both endogenous and exogenous factors.*

Based on the above four hypotheses, this paper will conduct an in-depth study. However, in order to more clearly demonstrate the internal relationships between Hypotheses 1 to 4 and the research objectives of this paper, this paper provides a more vivid mind map, as shown in Figure 2.

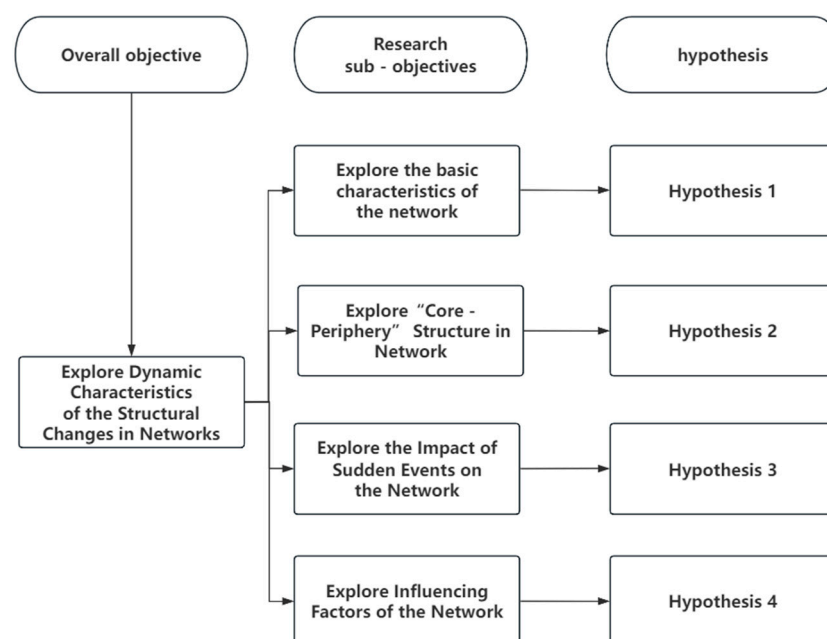


Figure 2. Mind map of theoretical hypotheses.

2.2. Construction of Social Network Model

This section begins by constructing a soybean trade network model based on social network analysis. Subsequently, appropriate network statistical models are selected based on trade network theory to study the network's evolution characteristics and influencing factors.

2.2.1. Construction of the Soybean Trade Network

To comprehensively understand the global soybean trade landscape and its evolution trends, this study employs complex network methods, treating each country participating in soybean trade as a network node and the trade relationships between countries as network connections, thereby constructing a global soybean trade network. In the soybean trade network, the size of a node is represented by its degree, which is measured by the number of soybean trade relationships an economy has with other economies in the network. The larger the node, the greater the volume of soybean trade the economy sends or receives, indicating its more significant position in the soybean trade network. The thickness of the edges represents the degree of trade dependency between economies, with thicker edges indicating a higher level of soybean trade dependency between the two economies. The trade dependency value draws on the approach of [24], measuring the “irreplaceability” in trade, that is, the degree of dependency of one country on soybean trade with another. The higher the dependency value, the stronger the irreplaceability of the trade relationship.

Therefore, before constructing the soybean trade network, it is necessary to calculate the trade dependency indicators between economies. The specific calculation is as follows: the soybean trade dependency of Economy i on Economy j is equal to the import dependency value of soybean trade between the two economies, expressed as

$$Bimtd_{ij} = R_{ij}^2(C_{ri}/C_{pj}) \quad (1)$$

Among them, $Bimtd_{ij}$ represents the degree of soybean import dependence of country i on country j , R_{ij} is the proportion of the amount of soybeans imported by country i from country j to its total soybean imports, C_{ri} is the soybean import concentration of country i , and C_{pj} is the soybean export concentration of country j .

Both C_{ri} and C_{pj} are constructed through the standardised Herfindahl–Hirschman Index (HHI) method, which can reflect the influence of other economies in the soybean trade dependence relationship. The calculation methods are as follows:

$$C_{ri} = \frac{\sqrt{\sum_{k=1}^n \left(\frac{X_{ki}}{X_i}\right)^2} - \sqrt{\frac{1}{n}}}{1 - \sqrt{\frac{1}{n}}}, C_{pj} = \frac{\sqrt{\sum_{k=1}^n \left(\frac{X_{jk}}{X_j}\right)^2} - \sqrt{\frac{1}{n}}}{1 - \sqrt{\frac{1}{n}}} \quad (2)$$

Next, based on the soybean trade dependency index, the soybean trade network from 2000 to 2022 is constructed to explore the structural characteristics of soybean trade among various economies during the sample period. Specifically, the soybean trade network is defined as $G = (V, E, W, T)$, where V represents the set of all nodes; E represents the set of all trade connections; W represents the trade weights indicated by the trade dependency values; and T represents the trade network for each year. Since the soybean trade network is a weighted network, with edge information including the degree of dependency, practical information is extracted and prepared for empirical analysis by following other scholars' approaches in extracting the backbone network structure. Referring to [25], network nodes are screened, resulting in 77 representative agricultural trade economies. Based on the method of [26] and considering that each economy has a small number of key agricultural trade partners, this study retains the top three edges with the highest trade dependency indices. Ultimately, the number of network edges each year is around 165, sufficient to capture the top

one to three important trade partners of each economy in the trade network. Since simplifying the network structure may lead to a certain degree of deviation, to ensure the accuracy of the results, this paper will conduct further tests on the obtained conclusions later.

2.2.2. Measurement Indicators for the Soybean Trade Network

This study employs a series of network statistical indicators to describe the overall structural characteristics of the soybean trade network among 126 major global economies.

The clustering coefficient (CC) measures the degree of interconnection and clustering among economies within the soybean trade network, as shown in Equation (3):

$$CC = \frac{1}{N} \sum_{i=1}^N \frac{2 \times e_i}{N(N-1)} \quad (3)$$

In Equation (3), e_i represents the number of trade partner economies that have actual soybean trade relationships with Economy i . It measures the global clustering of the trade network, reflecting the closeness of connections among the trade partners of each country. A higher clustering coefficient indicates a greater degree of clustering among economies in the network, suggesting closer cooperation in soybean trade.

Average path length (APL) measures the average of the shortest paths between economies in the soybean trade network. It reflects the average minimum number of steps required for any economy in the trade network to establish a trade relationship with another economy. In Equation (4), q_{ij} represents the shortest path between Economy i and Economy j . A shorter average path length (APL) indicates higher efficiency of information transmission in the soybean trade network, making soybean trade interactions more convenient.

Network density (ND) measures the strength of relationships among economies in the soybean trade network. The network density value will be higher if there are more soybean trade relationships between economies. Since the soybean trade network is a directed one, the maximum possible number of relationships between economies is $N(N-1)$, where N is the number of economies. Thus, the directed network density can be calculated as follows:

$$ND = \sum_{ij} ITD_{ij} / N(N-1) \quad (4)$$

In Equation (5), $\sum_{ij} ITD_{ij}$ represents the actual number of soybean trade relationships in the network, and the maximum distance between any two economies in the network is defined as the network diameter.

Network centralisation measures the overall tendency of the network to concentrate around specific nodes. A higher value indicates greater network centralisation, meaning that a small number of nodes control a significant portion of trade resources. The formula for overall network centralisation is as follows:

$$P_K = P(k \geq K) = \sum_{k=K}^{K_{max}} p(k) \quad (5)$$

where k_{max} is the maximum degree in the network. By distinguishing between in-degree and out-degree, the in-degree centralisation and out-degree centralisation of the network can be calculated separately.

2.3. Temporal Exponential Random Graph Model Construction

This study has two core objectives. First, it systematically examines the dynamic evolution of the soybean trade network from 2000 to 2022, focusing on its core-periphery structural characteristics and the network characteristics it exhibits under the impact of significant events. Through this analysis, this study aims to comprehensively summarise

the dynamic evolution patterns of the global soybean trade network. The second key objective is to deeply explore the mechanisms behind the formation of trade network relationships and their primary influencing factors.

Notably, traditional statistical and econometric methods typically rely on the assumption that the research objects are independent of one another. This approach overlooks the potential influence of other relationships within the network on specific relationships [25]. For instance, the QAP (Quadratic Assignment Procedure) analysis method mentioned earlier fails to fully account for the structural characteristics of complex trade networks, which, to some extent, limits our comprehensive understanding of the self-organising structure of trade networks. However, soybean trade networks exhibit highly complex relational characteristics. If traditional statistical and econometric methods are still applied, the interdependence among observational errors may lead to biased results, undermining the accuracy of the findings [27–29]. Therefore, this study directly models soybean trade relationships as the topological structure of trade networks and employs the temporal exponential random graph model [30–32], which is suitable for analysing network data to conduct an empirical test of the influencing factors.

TERGM (Temporal Exponential Random Graph Models) is an extension of ERGM (Exponential Random Graph Models). While traditional ERGM models can explain the mechanisms underlying network formation at specific points in time, they struggle to account for the temporal dependencies inherent in network data. To address this limitation, the TERGM model was developed. TERGM introduces parameters from previous network realisations into the ERGM framework, enabling the analysis of temporal dependencies in longitudinal network data. Secondly, TERGM further explores the impact of endogenous mechanism effects on network evolution, such as structural effects like reciprocity, multi-connectivity, and transitive closure. Compared with previous research methods, this further expands the scope of research on network influencing factors.

Currently, several versions of the TERGM model have been developed. The analysis in this study is based on the TERGM framework proposed by Leifeld et al. [33]. This framework is grounded in the definition of discrete-time Markov chains, creating a Markovian network configuration where each soybean trade network configuration at time t depends only on the network state at the previous time step $t - 1$. Specifically, the model assumes that the soybean trade network configuration at time t is related only to the network configurations of the previous k periods. The general form of this model can be represented as follows:

$$P(N^t | N^{t-k}, \dots, N^{t-1}, \theta) = \frac{\exp(\theta^T h(N^t, N^{t-1}, \dots, N^{t-k}))}{c(\theta, N^{t-k}, \dots, N^{t-1})}, k \in \{0, 1, \dots, T-1\} \quad (6)$$

Within the TERGM framework, N represents the network, conceptualised as an adjacency matrix where $N_{ij} = 1$ if there is a trade relationship between nodes i and j , and $N_{ij} = 0$ otherwise. The variable t denotes time, θ represents the coefficient matrix, and $c(\theta) = \sum_{i=1}^N \exp(\theta^T N_i)$ is a non-Markovian constant ensuring probabilities remain within the range $[0, 1]$. $h(N)$ is a vector of network statistics based on the structural characteristics of the network. The TERGM model incorporates various variables, including endogenous network structural variables (e.g., reciprocity), actor attributes (e.g., type of trading partner), and exogenous covariates (e.g., other relationships between nodes). This study integrates complex network theory with the classical gravity model of trade, resulting in the following TERGM model:

$$\begin{aligned}
P(BD^t | BD^{t-1}, \theta) = & \left(\frac{1}{c}\right) \exp(\theta_0 Edges + \theta_1 Reciprocity + \theta_2 Expansiveness + \theta_3 Multiple_2_paths \\
& + \theta_4 Triadic_closure + \theta_5 Stability + \theta_6 Variability + \theta_{r1} \ln GDP + \theta_{r2} \ln_pop + \theta_{s1} \ln_GDP \\
& + \theta_{s2} \ln_pop + \theta_{a1} \ln_GDP + \theta_{a2} \ln_pop + \theta_7 NCov_colony + \theta_8 NCov_contig \\
& + \theta_9 NCov_distcap)
\end{aligned} \quad (7)$$

where BD^t and BD^{t-1} represent the global soybean trade networks at time t and $t - 1$, respectively. The dependent variable is the logarithm of the probability that an economic entity establishes a soybean trade network connection. The coefficient is interpreted as a log-advantage ratio. *Edges* represents the number of edges, and its coefficient is generally not specifically interpreted. *Reciprocity*, *Expansiveness*, *Multiple_2_paths*, *Triadic_closure*, *Stability*, and *Variability* are endogenous structural variables. $\ln_GDP$ and $\ln_pop$ represent the actors' attributes, where the subscripts r , s , and o indicate the receiver, sender, and shared attributes, respectively. *NCov_colony*, *NCov_contig*, and *NCov_distcap* are external network covariates. Each variable's specific meanings and construction methods will be discussed in detail in the following text. The TERGM model uses pseudo-maximum likelihood estimation for fitting, and the parameters are adjusted through estimation, simulation, comparison, and improvement steps to obtain relatively stable estimation results.

2.4. Data Sources and Explanation

Selecting appropriate data is a critical component of investigating an industry's global production and trade dynamics. The primary data source for this study is the CEPII-BACI database from the French Institute for International Economic Studies. This database is a refined variant of the highly classified trade data from the United Nations Comtrade Database (UN Comtrade), encompassing import and export values and quantities in standard units for 251 economies at the HS-6-digit product level. The advantages of this database include timely updates and the provision of detailed and reliable product trade information. Therefore, soybean trade data under the HS code 120100 from the CEPII-BACI database is selected for this study. Since this research aims to examine the impact of specific sudden events on the network structure, annual data are required. Considering data availability and timeliness, the study period is set from 2000 to 2022. Meanwhile, due to the large volume of data and the absence of soybean trade data for many countries, to meet the specific requirements of the subsequent analysis model of network influencing factors and take into account research efficiency, after a screening process, we finally obtained the soybean trade data of 126 countries within 22 sample periods.

3. Analysis of the Evolutionary Characteristics of the Soybean Trade Network Structure

Building on the network model constructed in the previous section, this section analyses the structural evolution of the soybean trade network, focusing on two main aspects: the topological structure and the core-periphery structure.

3.1. Analysis of Network Topological Structure Characteristics

Based on the network statistical indicators selected in Section 2, this section calculates the statistical characteristic parameters of the soybean trade network for 12 periods from 2000 to 2022, using a 2-year interval. These calculations are used to analyse topological structure characteristics of the soybean trade network, as presented in Table 1.

Table 1. Calculation results of network metrics.

Year	Clustering Coefficient	Average Path Length	Density	Number of Edges	Mean Trade Dependency	In-Degree Centralisation	Out-Degree Centralisation
2000	0.167	2.950	0.023	935	0.1721	0.0144	0.0410
2002	0.145	2.898	0.027	1016	0.1779	0.0182	0.0473
2004	0.212	2.816	0.027	1013	0.1807	0.0170	0.0231
2006	0.185	2.953	0.024	1113	0.1881	0.0199	0.0218
2008	0.203	2.796	0.025	1263	0.1912	0.0177	0.0270
2010	0.201	2.651	0.027	1329	0.1693	0.0163	0.0136
2012	0.191	2.644	0.026	1360	0.1441	0.0163	0.0129
2014	0.233	2.586	0.028	1506	0.1579	0.0115	0.0168
2016	0.232	2.488	0.028	1458	0.1683	0.0179	0.0126
2018	0.282	2.537	0.028	1463	0.1607	0.0198	0.0096
2020	0.210	2.496	0.028	1580	0.1611	0.0201	0.0107
2022	0.290	2.505	0.030	1657	0.1588	0.0230	0.0116

The soybean trade network has been continuously expanding. During the sample period, the number of trade edges increased from 935 to 1657, and the network density rose from 0.023 to 0.03. This indicates an overall expansion trend in the soybean trade network, with trade activities between countries becoming more active and connections growing tighter.

The soybean trade network exhibits trade agglomeration effects. The clustering coefficient, also known as the transitivity coefficient, measures the proportion of closed triads in the network and reflects the degree of clustering and stability among nodes. The clustering coefficient ranges between 0.145 and 0.290. Although there are fluctuations in some years, the overall trend is upward, suggesting an increase in the number of closed triads in the network.

The soybean trade network demonstrates “small-world” characteristics. The average path length ranges from 2.488 to 2.953, indicating that any economy *i* can establish a soybean trade relationship with another economy *j* through an average of two to three steps. This reduces the difficulty of cooperation between countries, confirming Hypothesis 1.

The gap between in-degree and out-degree centralisation is narrowing. Centralisation reflects the overall tendency of the network to concentrate around specific nodes. A higher centralisation value indicates greater network concentration, with a few nodes controlling a significant share of trade resources, and suggests the presence of a core–periphery structure. The results show that the network’s centralisation is on an upward trend, indicating an evolving “core–periphery” structure. In-degree centralisation represents import concentration, while out-degree centralisation reflects export concentration. As shown in Table 1, from 2000 to 2022, in-degree centralisation fluctuated but generally increased from 0.0144 to 0.0230, while out-degree centralisation fluctuated but generally decreased from 0.0410 to 0.0116. This narrowing gap between in-degree and out-degree centralisation highlights a growing trend of import centralisation and export decentralisation in the soybean trade network. It also suggests that soybean importers are becoming more concentrated while exporters are becoming more dispersed.

The substitutability of soybean trade has increased, reducing trade risks. The trade dependency value reflects the “irreplaceability” of the soybean trade. By introducing this metric, the degree of “irreplaceability” between trading partners can be further analysed, revealing the overall dependency level of the network. The average trade dependency value shows a slight downward trend, decreasing from 0.1721 in 2000 to 0.1588 in 2022. This indicates that, with the deepening of globalisation, economies have more soybean trade partners, enhancing the substitutability of soybean trade. For example, Country A can import soybeans not only from Country B but also from Countries C or D. This reduces the dependency between economies and lowers the risks associated with soybean trade.

3.2. Analysis of the Core–Periphery Structure Characteristics of the Network

The soybean trade network exhibits a relatively stable “core–periphery” hierarchical structure with spatiotemporal variations. Using the Ucinet (The version number is 6.204) software, the core coefficients from 2000 to 2022 were calculated, and core and peripheral countries were identified, revealing a distinct “core–periphery” structure in the global soybean trade network. This section selects 2000 and 2022 as the start and end years of this study. To visually observe the evolution of the “core–periphery” structure, the soybean trade networks for the start and end years (2000 and 2022), as well as two critical transition years (2009 and 2018), are visualised. Additionally, the top 10 countries in terms of network core coefficients for these four key periods are calculated using Ucinet software, allowing for a comprehensive exploration of the changes in the network’s core structure before and after critical events.

3.2.1. Visualisation Analysis

Under the previous conditions, first, visualise the weighted directed network constructed previously with trade dependence values as weights to more intuitively demonstrate the “core–periphery” structural characteristics of the soybean trade network. Here, nodes represent sample economies, and the size of the node’s shadow reflects the average degree of the node; that is, the more trade-related edges an economy has, the larger the node’s shadow; economies with close trade relations are close to each other, while those with weak trade relations repel each other; the connecting lines represent the existence of trade-related edges, and the thickness of the edges represents the magnitude of trade dependence, with thicker edges indicating a higher degree of dependence. The visualisation results are shown in Figures 3–6.

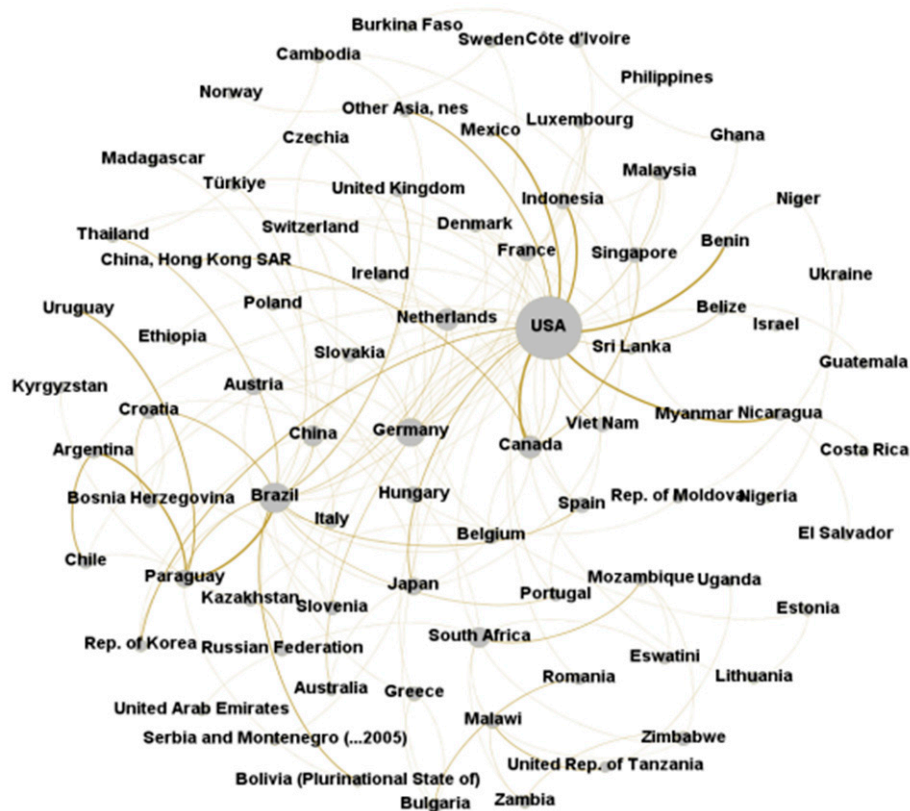


Figure 3. The soybean trade network in 2000.

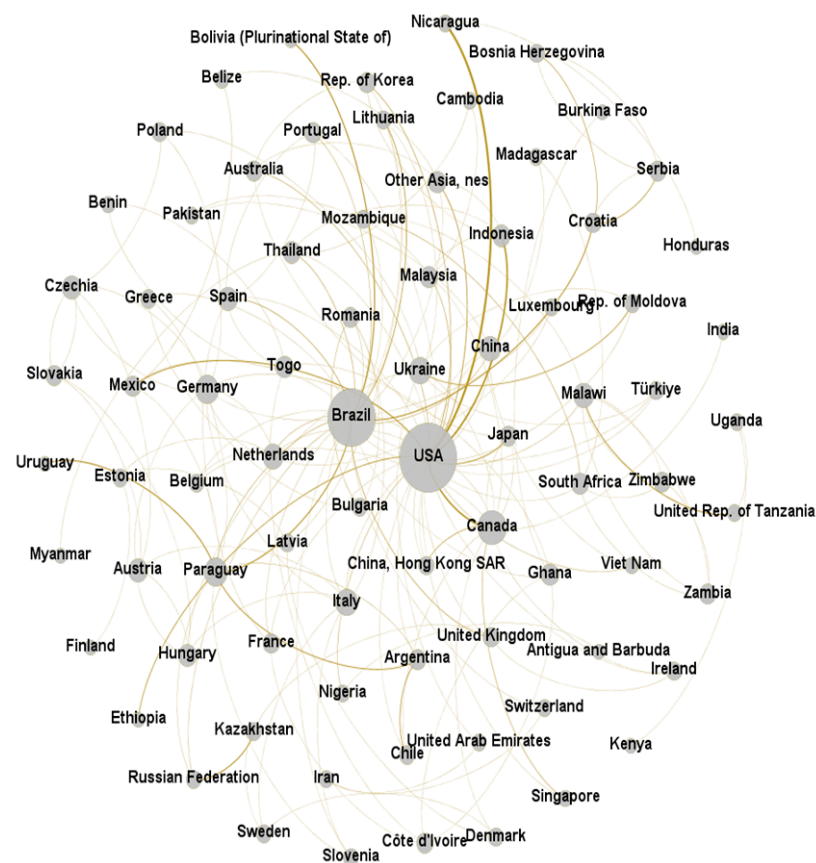


Figure 4. The soybean trade network in 2009.

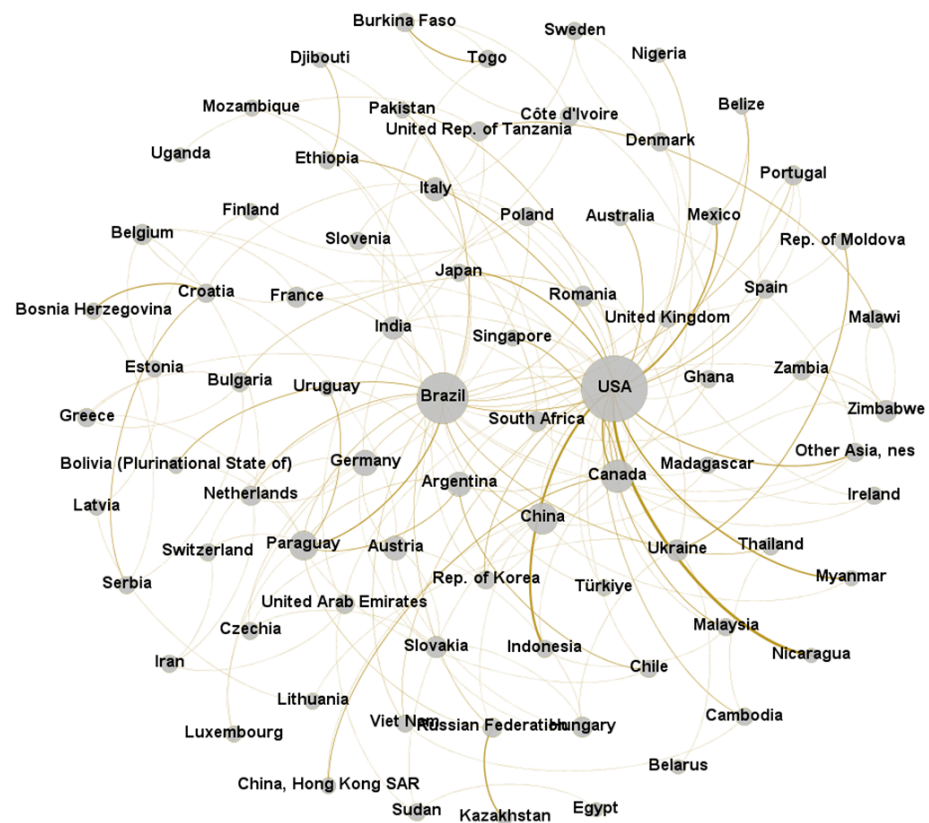


Figure 5. The soybean trade network in 2018.

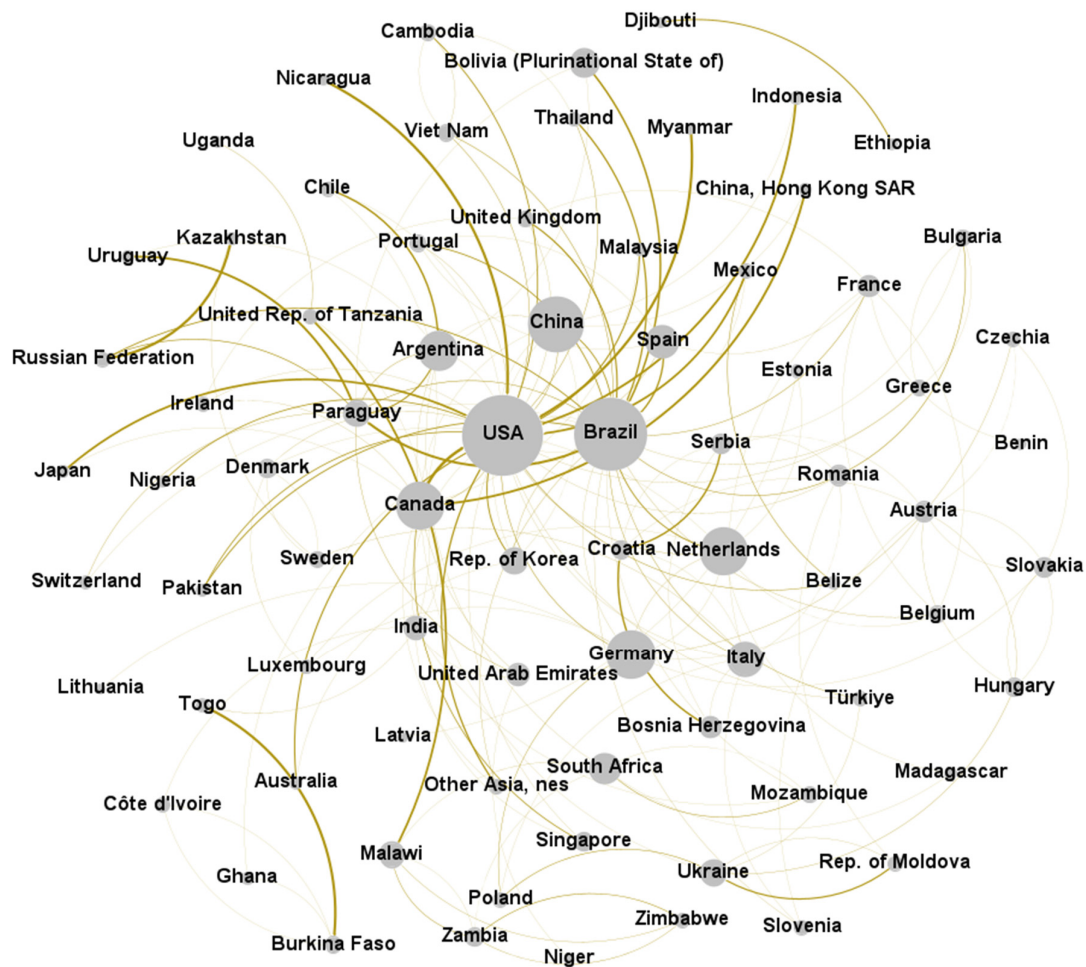


Figure 6. The soybean trade network in 2022.

From the four visualisations, it is evident that the soybean trade network exhibits a distinct core–periphery structure. Over time, the network’s structural characteristics have evolved from a single-core periphery model to a multi-core periphery model. This shift indicates that the network is no longer driven by a “few cores”; more economies are playing a “multi-core driving” role in the trade network. This evolution has, to some extent, weakened the central market dominance of a few developed economies. Therefore, Hypothesis 2 is supported.

The specific factors driving this transition from a single-core to a multi-core structure are multifaceted. First, from a temporal perspective, the deepening globalisation process and increasing regional trade agreements have likely promoted greater participation by diverse economies and diversification of trade networks. For instance, China, as the world’s second-largest economy, has played a pivotal role in reshaping the soybean trade landscape through its rapidly growing demand and expanding international trade network. Second, geopolitically, adjustments in international trade relations and strengthened regional cooperation may have also facilitated the formation of a multi-core structure. Examples include initiatives such as the Belt and Road Initiative and the Regional Comprehensive Economic Partnership (RCEP), which have fostered deeper integration of Asian countries in soybean trade. Finally, from technological and trade policy perspectives, improved logistics efficiency and reduced trade barriers have enabled more countries to engage more deeply in the global soybean trade network.

3.2.2. Analysis of the Evolution of the Core–Periphery Structure

To refine the classification and highlight structural changes, this section categorises the top 2% of countries as core countries, the next 10% (excluding core countries) as semi-peripheral countries, and the remaining countries as peripheral countries. The classification is presented in the order of core countries, semi-peripheral countries, and peripheral countries. Furthermore, by focusing on four critical events—T1: The Big Four Grain Merchants Shorting Chinese Soybeans (2003), T2: The Global Financial Crisis (2008), T3: The US-China Trade War (2018), and T4: The COVID-19 Pandemic (2020)—the evolution characteristics of the core–periphery structure are extracted. The core coefficient rankings for these events are summarised in Table 2.

Table 2. Core coefficient table.

Type	T1				T2			
		2002		2003		2007		2009
Core Country	USA	0.789	USA	0.803	USA	0.657	USA	0.743
	BRA	0.224	BRA	0.224	BRA	0.375	BRA	0.288
Semi-peripheral Country	FRA	0.200	CAN	0.123	NLD	0.170	CAN	0.153
	CAN	0.191	NLD	0.119	JPN	0.161	ITA	0.146
	NLD	0.110	ITA	0.115	CAN	0.158	CHN	0.139
	CHN	0.108	ARG	0.113	ITA	0.145	NLD	0.133
	JPN	0.108	JPN	0.113	ESP	0.143	SVN	0.122
	ARG	0.106	FRA	0.111	CHN	0.136	AUS	0.120
	DEU	0.100	THA	0.111	KOR	0.134	GBR	0.119
	KOR	0.097	CHN	0.107	FRA	0.130	FRA	0.116
Type	T3				T4			
		2017		2018		2019		2022
Core Country	USA	0.714	USA	0.743	USA	0.777	USA	0.743
	BRA	0.340	BRA	0.307	BRA	0.302	BRA	0.324
Semi-peripheral Country	CHN	0.237	CAN	0.215	CHN	0.215	CHN	0.199
	CAN	0.219	CHN	0.214	CAN	0.161	CAN	0.178
	KOR	0.113	KOR	0.119	ARG	0.097	NLD	0.126
	ARG	0.103	IND	0.108	MEX	0.096	ARG	0.121
	VNM	0.103	ARG	0.104	PRT	0.096	ESP	0.110
	FRA	0.102	JPN	0.102	GBR	0.096	DEU	0.106
	DEU	0.102	PRT	0.100	ITA	0.095	ITA	0.105
	PRT	0.102	ESP	0.100	THA	0.095	VNM	0.102

- T1: The Big Four Grain Traders Short Sell Chinese Soybeans

In 2003, the four major international grain traders launched a siege on Chinese soybeans, an action that caused heavy losses to China's soybean industry.

The core position of the United States was further consolidated, while China's trade status declined. The top ten countries in terms of core coefficient ranking were the United States, Brazil, France, Canada, the Netherlands, China, Japan, Argentina, Germany, and South Korea. From the perspective of countries related to this event, international grain traders' short selling of Chinese soybeans led to a drop in China's core coefficient, ranging

from 6th to 10th. Among them, the core position of the United States was further strengthened, and the positions of Canada and the Netherlands were both enhanced. Italy rose from 12th to 5th.

- T2: The 2008 Global Financial Crisis

In 2008, the financial crisis swept the world, and the agricultural product market faced a joint crisis in both supply and demand. The soybean trade was significantly impacted.

The overall core coefficient of the network decreased, but that of the United States increased instead, further strengthening its position and demonstrating a significant “Matthew Effect”. The positions of Italy, China, and Canada gradually became prominent. The soybean trade network was severely hit, and the soybean trade market faced a crisis. From the perspective of individual nodes, except for the United States, the core coefficients of other core countries decreased, facing an influence crisis, which reflects a relatively strong “Matthew Effect” in the soybean market.

- T3: The China–US Trade War

The United States enhanced its trade position by exporting soybean crises to its original trading partners. In addition, the positions of South Korea, India, Canada, and other soybean trading partners of the United States were strengthened.

From a macro-perspective on the soybean trade market, the United States is the largest exporter. According to the BACI database, in 2022, the United States exported 57.33 million tons of soybeans, accounting for 36.8% of the world’s total soybean exports. In the same period, China is the largest importer. In 2022, China imported 91.08 million tons of soybeans, accounting for 58.3% of the world’s total soybean exports. The influence of the two countries on the trade network is self-evident. From a micro-perspective, China is the largest soybean export market in the United States, and the United States is the second-largest soybean import market in China. The bilateral trade dependence is relatively close. In fact, since 19 August 2017, when the Office of the United States Trade Representative (USTR) launched a Section 301 investigation against China, there have been continuous trade frictions between China and the United States, bringing many impacts on the trade between the two countries and also bringing uncertainties as to the stability of the soybean trade network. In April 2018, the United States announced the proposed tariffs on China under the Section 301 investigation. In response, China imposed a 25% tariff on 106 commodities, including soybeans, originating from the United States.

Affected by China’s tariff countermeasures, the total amount of US soybean exports to the world in 2018 decreased by 16.2% compared with 2017, among which the amount of soybeans exported to China decreased by 72.7%. Although China’s tariff increases on US soybeans led to a 16.2% decline in the total US exports compared with 2017, it did not change the core position of the United States in the soybean market. Instead, it strengthened its position. In fact, in response to the economic sanctions, the United States tried to expand its soybean export market to digest its domestic soybeans. It sold some of the soybeans that could not be exported to China to its original trading partners. The export volume to countries such as Egypt, the Netherlands, Germany, and Mexico increased significantly. The import volume of Egypt from the United States doubled compared with 2017. Moreover, the United States actively expanded new trading partners, further deepening its connections with trading countries and thus enhancing its position. At the same time, the positions of South Korea, India, Canada, and other soybean trading partners of the United States were strengthened as a result, indicating obvious reciprocity in the soybean trade network.

- T4: The COVID-19 Pandemic

It had a limited impact on the overall core structure. Among them, the core position of the United States declined, while the position of Brazil was strengthened, and the trade positions of China and Canada were further consolidated.

At the end of 2019, the COVID-19 pandemic quietly emerged, profoundly impacting the world economy. This global crisis has not only affected South American ports, such as the Port of Rosario in Argentina and the Port of Santos in Brazil, but also the entire logistics and port loading system. The uncertainty in soybean supply is a shared concern across the globe.

In 2020, the top five economies in terms of the network core coefficient ranking were the United States, Brazil, China, Canada, and the Netherlands. Compared with 2019, the top four countries in the 2020 ranking remained unchanged, and the fifth place changed from Argentina to the Netherlands. Compared with the T1 period, China was basically in third place during the T3 and T4 periods, indicating that its position has been improved, and its trade position is becoming increasingly prominent, moving towards a core country. It is worth noting that Argentina was squeezed out of the top five. According to the report of the Buenos Aires Grain Exchange, Argentina suffered from a drought in 2020, with a 7% reduction in soybean production and a 33% decrease in soybean exports compared with 2019. Secondly, the core coefficient of the United States decreased, while that of Brazil increased, and Brazil's say in the market was enhanced. Affected by factors such as a bumper soybean harvest and local currency depreciation, Brazil had a strong impetus for soybean exports, with an 8.8% increase in exports in 2020 compared with 2019.

Overall, looking at the four periods, the impact of external events on the network structure tends to be stable, but the impact on the peripheral structure is heterogeneous. That is, when the soybean trade network structure is affected by external shocks, the core structure is stable, but the peripheral structure differentiates, proving that Hypothesis 3 holds.

4. Analysis of Influencing Factors of the Soybean Trade Network

After analysing the evolutionary characteristics of the soybean trade network structure, the next step is to investigate the factors that determine the formation of new trade relationships and the dissolution of existing ones in the global soybean trade. Clarifying this issue is crucial for formulating effective soybean trade policies. This section proposes hypotheses regarding the factors influencing the evolution of soybean trade network relationships and conducts empirical tests using the Temporal Exponential Random Graph Model (TERGM).

4.1. Theoretical Analysis

According to the existing complex network theory, the evolution of a network is influenced by both endogenous and exogenous factors [34–36]. Finally, the variable meanings for constructing the Temporal Exponential Random Graph Model and their hypothesis tests are selected.

(1) Endogenous Mechanism Variables

The emergence of some relationships in a network often determines the probability of the emergence of other relationships. The formation of such relationships does not involve factors such as the attributes of economies or the political, economic, and cultural differences between economies. It only depends on the self-organising process of the network system. This is often referred to as the endogenous structural effect.

Real-world networks often exhibit the characteristic of reciprocity. Reciprocity is an important way to observe and reveal the formation mechanism of network structures. Similar to the peer effect, there is also this phenomenon of nodes in the network mutually achieving and enhancing each other [37]. In this paper, reciprocity is incorporated into the

TERGM model to describe the tendency of forming reciprocal relationships among various economies. Its root may lie in two mechanisms. One is the information mechanism. The trade flow between two connected economies in the network drives the flow of information, improves the trust level between the two sides, and thus reduces trade costs. The other is the trade balance mechanism. Each economy has different comparative advantages in soybean production. Through trade, the exchange and integration of resources and factors are completed, thereby establishing a mutually beneficial soybean trade relationship. In fact, in the above-mentioned analysis of the evolutionary characteristics of the soybean trade network, it has been observed that this network conforms to the basic characteristics of reciprocity. Therefore, a positive reciprocity effect is expected.

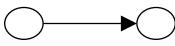
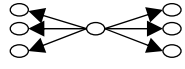
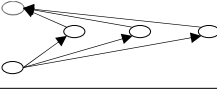
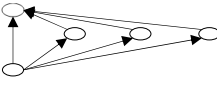
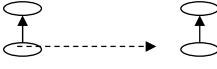
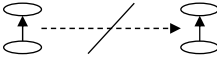
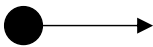
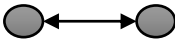
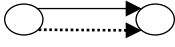
Secondly, the empirical evidence of the soybean trade network shows that this network has a noticeable “core–periphery” hierarchical structure. Therefore, the formation of new relationships is likely to be driven by the status effect. The status effect is the root of asymmetric relationships and hierarchical network structures. In this paper, an expansion index is used to test whether there is a status effect in the network that promotes the formation of new relationships. Considering that in soybean trade, the economies at the export end have more advantages, this paper focuses on the out-degree-based preferential attachment. Economies at the edge of the network cannot obtain effective information about other economies. In contrast, the star nodes in the network that initiate more trade relationships, due to their production and information advantages, will attract new economies to trade with them, gradually strengthening the central position of the central economies. Therefore, the coefficient of the expansion variable is expected to be negative, indicating that there are a small number of economies with high out-degrees in the network, and economies with prominent status will form more connections over time.

In addition, over time, the soybean trade network has a strong cohesion effect. This paper believes that this may be due to the inertia mechanism of reciprocal relationships and the opportunity conditions that lead to a higher degree of closure of network relationships between different economies (such as transitive closure). The trade network is the spatial organisation and relationship state formed by the trade between economies. Transitive closure can more easily monitor relationships, prevent opportunistic behaviour, and promote valuable and implicit information exchange [38,39]. The test of the transitive closure effect can be explained by a negative multiple connectivity (Multiple2_paths) and a positive triadic closure (Triadic_closure) coefficient, indicating that the connected trade relationships in the network tend to be closed, and, macroscopically, it shows a tendency for economies to connect in small groups. In a network diagram, multiple connectivity means that the transmission of the relationship between two nodes requires one or more other nodes as a bridge, which is a basic parameter and prerequisite for ensuring the existence of the transitive closure effect in the network structure [40–42]. Adding a connection relationship on the basis of multiple connectivity forms a triadic closure, referring to the formation of a division-of-labour closed-loop in the network relationship among three economies. The more division-of-labour closed loops there are, the more obvious the characteristics of the small-group division of labour are. The soybean trade network has the characteristics of a “small-world”; over time, the regional clustering characteristics of the soybean trade network become more prominent. Therefore, the multiple connectivity coefficient is expected to be negative, and the triadic closure is expected to be positive.

As can be seen from the previous text, the network structure shows different characteristics in different periods, and the trade relationships among network nodes are constantly evolving. Therefore, when studying the factors influencing the correlation relationships in the soybean trade network, the time-dependence effect needs to be considered, which mainly includes two indicators: stability and variability. Stability describes the trend of

the stable development of the network pattern. After establishing a soybean trade relationship between economies, making hasty changes may bring adverse effects to each other. Therefore, economies usually do not easily change their trade relationships. However, the occurrence of some special events may lead to the breakdown of trade relationships or the emergence of new correlation relationships. The tendency of network relationships to change in different periods is defined as variability. This paper expects that there is a time-dependence effect in the evolution of the correlation relationships in the soybean trade network, with stability being positive and variability being negative. The variable meanings and their hypothesis tests are shown in Table 3.

Table 3. Meanings of TERGM regression variables and their hypothesis tests.

	Variable Name	Meaning	Die Body	Hypothesis Test
endogenous structure	Edges	Side number		Constant terms are generally not explained.
	mutual	Reciprocity		Whether there tend to be mutually beneficial soybean trade relations between economies
	gwodegree	Expansiveness		Whether there are a small number of “soybean trade star” economies
	dgwdsp	Multiple2_paths		Whether to pass on the soybean trade relationship through multiple paths
	dgwesp	Triadic_closure		Whether the soybean trade relationship between economies tends to be of agglomeration and transmission
	Stability	Stability		Whether the soybean trade relationship tends to be consistent between t+1 stage and t stag
	loss	variability		As time goes on, whether there is a tendency to disappear in the soybean trade relations
exogenous mechanism	Nodeofactor (“ln_GDP”)	sender Economic level		Whether an economy with a certain production attribute is more likely to export soybeans
	Nodeifactor (“ln_GDP”)	Receiver Economic level		Whether economies with a certain production attribute are more likely to import soybeans
	Nodeofactor (“ln_pop”)	Sender market scale		Whether an economy with a certain production attribute is more likely to export soybeans
	Nodeifactor (“ln_pop”)	Receiver market scale		Whether economies with a certain production attribute are more likely to import soybeans
	Nodematch (“ln_gdp”)	Assortativity economic level		Whether economies with one of the same attributes are more inclined to trade
	Nodematch (“ln_pop”)	Assortativity market scale		Whether economies with one of the same attributes are more inclined to trade
	Colony Contig distcap	Distance network Proximity network Colonial network		Whether economies with relationships in other networks prefer soybean trade

(2) Exogenous Mechanism Variables

Proxy variables at the node level are incorporated into the network as exogenous attribute variables, and the differences at the economic entity level are regarded as important

driving factors rather than the results of network changes. Most existing studies are based on the gravity model to empirically test the formation of trade relationships [43–45]. In the classical gravity model, the trade flow between two countries is simulated as a function that is proportional to their economic sizes and inversely proportional to the geographical distance between the two countries. With the in-depth development of research, explanatory variables such as whether they belong to the same economic organisation, whether they use the same language, and whether there was a colonial relationship in history have been introduced into the gravity model [46–48], expanding the applicable scope and explanatory power of the gravity model.

Based on the theoretical basis of the gravity model, the exogenous explanatory variables for constructing the Temporal Exponential Random Graph Model are finally selected as follows: ① Level of economic development. Generally speaking, the higher the level of economic development of a country, the better the comprehensive conditions for supporting the division of labour in soybean trade, and the more conducive it is to establishing soybean trade relationships globally. The level of economic development is reflected by the GDP of each economic entity, a traditional macroeconomic characteristic indicator, and is logarithmically transformed and then incorporated into the TERGM. ② Market size. Generally, the larger the soybean consumer market of a country, if the domestic supply cannot meet the domestic demand, the demand for international soybean trade will increase, which is conducive to establishing soybean trade relationships with other economic entities. The market size is reflected by the population data released by the World Bank. ③ Distance. In this paper, the geographical distance in the traditional gravity model is expanded, and language proximity and colonial relationships are incorporated into the TERGM model for estimation. Geographical distance measures the distance between the capitals or core cities of any two economic entities. Language proximity measures the language distance through the language differences between different economic entities, and whether there was a colonial relationship in history is examined to capture the religious and cultural distance between economic entities.

To sum up, the exogenous attribute variables include a total of five variables in the above-mentioned three aspects. In the TERGM model, exogenous mechanism variables can be divided into two categories: First, actor-attribute variables, which explain the impact of the attributes of specific economic entities on the formation of network relationships and can be further subdivided into two effects: the sender effect and the receiver effect. Second, exogenous covariate networks are all other network relationships formed based on a certain proximity or distance between paired participants in the network. Considering the data structure of the variables, the variables measuring the level of economic development and market size are taken as actor-attribute variables, while the variables measuring distance are constructed into exogenous covariate networks. That is, in order to examine the impact of the level of economic development on soybean trade relationships, in the TERGM model, the economic entity that initiates the soybean trade relationship Nodeofactor (“ln_GDP”) and the economic entity that receives the soybean trade relationship Nodeifactor (“ln_GDP”) are added for estimation. To explore the impact of the market-size characteristics of economic entities on the evolution of network relationships, the TERGM respectively estimates Nodeofactor (“ln_pop”) and Nodeifactor (“ln_pop”). Colony, Contig, and distcap, respectively, describe the geographical distance, language proximity, and historical colonial relationship network between economic entities.

4.2. Results of TERGM Benchmark Test

Table 4 reports the TERGM estimation results of the soybean trade network from 2000 to 2022. In Table 4, Model 1 only includes the benchmark regression results of the

number of edges and node attributes. Model 2 is the regression result obtained by adding exogenous network covariates based on Model 1. Model 1 and Model 2 function as intercept terms, and their coefficients are generally not interpreted separately. Model 3 and Model 4 are used for comparative analysis by gradually adding network structure-dependent variables represented by reciprocity, expansiveness, multiple connectivity, and transitive closure, as well as time-dependent variables represented by stability and variability.

Table 4. TERGM estimation results.

	Model 1	Model 2	Model 3	Model 4
edges	−27.07767 *** (0.20125)	−27.32832 *** (0.21494)	−14.08031 *** (0.22414)	−9.41716 *** (0.24931)
nodeicov.ln_gdp	1.08865 *** (0.01657)	1.07584 *** (0.01735)	0.42967 *** (0.01641)	0.93783 *** (0.02009)
nodeicov.ln_pop	−0.52736 *** (0.01781)	−0.52476 *** (0.01872)	−0.38485 *** (0.01581)	−0.29520 *** (0.02181)
nodeocov.ln_gdp	1.121101 *** (0.01642)	1.22884 *** (0.01720)	0.46690 *** (0.01495)	0.22360 *** (0.01837)
nodeocov.ln_pop	0.36922 *** (0.01792)	0.48125 *** (0.01886)	0.42533 *** (0.01473)	0.30501 *** (0.02069)
colony		0.46980 *** (0.05097)	0.51227 *** (0.05042)	0.34991 *** (0.06197)
contig		2.13160 *** (0.04313)	1.95234 *** (0.04044)	1.17630 *** (0.05391)
distcap		−0.00012 *** (0.00000)	−0.00005 *** (0.00000)	−0.00005 *** (0.00000)
mutual			0.96381 *** (0.03617)	0.63575 *** (0.04151)
gwodegree			−1.09512 *** (0.10964)	−1.84010 *** (0.12466)
dgwdsp			−0.06351 *** (0.00195)	−0.04973 *** (0.00193)
dgwesp			1.21727 *** (0.02608)	1.05722 *** (0.02775)
Stability				1.52725 *** (0.01239)
loss				−0.02239 *** (0.00320)

Note: The figures in parentheses are standard errors. *** represent the significance level of 0.1% respectively in the two-tailed test. The same applies to the following tables.

The soybean trade is characterised by reciprocity. Judging from the estimation results of the most common reciprocity-structured variable among the network endogenous structure variables, the reciprocity (mutual) in Model 3 and Model 4 is significantly positive. This means that, if an economy initiates a soybean trade relationship with Economy *i*, it will increase the probability that Economy *j* will initiate a trade relationship with Economy *i*.

The core–periphery structure is obvious. The coefficient of expansiveness (gwodegree) is significantly negative, indicating that the out-degree distribution of network nodes is significantly discrete. In the soybean trade network, the out-degree distribution of nodes is uneven. Compared with economies with low out-degrees, economies at the centre of the network are more likely to obtain new trade relationships. In contrast, peripheral economies deviating from the network centre are more likely to lose trade relationships. Eventually, at the macro level, it shows a “core–periphery” macro-trade structure, which explains the obvious “core–periphery” structure feature mentioned above.

The soybean trade network has a significant agglomeration and exhibits the characteristics of a “small-world” network. The coefficient of triadic transitive closure (dgwesp) is 1.05722, and the coefficient of multiple connectivity (dgwdsp) is -0.04973 , both passing the 0.1% significance level. This indicates that in the soybean trade network, economies transmit and maintain their trade relationships through diversified paths. However, these connectivity paths gradually show a trend of closure. In fact, in order to reduce the uncertainty brought about by information asymmetry and prevent risks caused by the opportunistic behaviour of potential trading partners, economies are more inclined to establish soybean trade connections with entities that have been verified by other reliable partners. From a macro perspective, this selective cooperation model has led to the agglomeration effect of the trade network and exhibits the characteristics of a “small-world” network; that is, most nodes can be quickly connected through a few intermediate nodes, and, at the same time, there is a high degree of clustering within the network. This also confirms the previous conclusion. This structure not only promotes the accumulation of trust and the reduction of risks but also enhances the stability and efficiency of the global soybean market.

There is an obvious path-dependence characteristic in the soybean trade network. Regarding the time-dependence effect (Stability), the estimated coefficient of stability is 1.52725, passing the 0.1% significance level. This result indicates that there is an obvious path-dependence characteristic in the soybean trade network; that is, the current trade relationships are largely influenced by historical connections. Since establishing and maintaining trade relationships requires certain costs, once a specific trade pattern is formed, economies tend to maintain the status quo to avoid the uncertainties and potential losses that may arise from changing the existing trade relationships. This explains why countries usually do not easily adjust their existing soybean trading partnerships. Variability (loss), as an indicator to measure the structural interruption of network connections, has a negative coefficient, indicating that, *ceteris paribus*, over time, the relationships in the soybean trade network tend to gradually weaken and even disappear. This finding is consistent with the changes in the global trade pattern in recent years, especially in the context of the rise of trade protectionism. For example, during the China–US trade war mentioned above, some traditional trade relationships encountered challenges and were forced to break. This phenomenon not only reflects the impact of the external environment on the stability of the trade network but also reminds us to pay attention to the sustainability of long-term trade relationships and the ability to cope with uncertain risks.

In the soybean trade network, the sender effect refers to whether an economy with a higher value of a given attribute variable is more inclined to initiate soybean trade connections with other economies in soybean trade. The receiver effect refers to whether an economy with a higher value of a given attribute variable is more inclined to receive trade relationships from other economies in soybean trade. The assortative effect refers to whether countries with the same attributes are more inclined to engage in trade relationships. The coefficients of `nodeicov.ln_gdp` and `nodeocov.ln_gdp` are both significantly positive, indicating that, the higher the economic level, the easier it is to receive soybean trade relationships and also to initiate soybean trade relationships. Regions with a larger economic scale are more inclined to establish soybean trade connections with other regions. The coefficient of `nodeicov.ln_pop` is negative, while that of `nodeocov.ln_pop` is positive, passing the 0.1% significance level. This shows that, the larger the market scale based on population size, the less inclined it is to import soybeans and the more inclined it is to export soybeans. In addition, the assortative node attributes `nodematch.ln_gdp` and `nodematch.ln_pop` did not pass the test.

Regarding exogenous network covariates, the coefficient of *edgecov.colony* is positive, indicating that economies with a historical colonial relationship are more inclined to establish relationships in soybean trade. The coefficient of *edgecov.contig* is significantly positive, indicating that two neighbouring countries are more likely to engage in soybean trade. The coefficient of *edgecov.distcap* is negative, which means that geographical distance has an inhibitory effect on soybean trade. The farther the geographical distance between economies, the higher the trade costs, such as transportation and communication, and the less likely it is to form a soybean trade relationship. Based on the above conclusions, Hypothesis 4 is verified.

4.3. Robustness Test

In order to verify the robustness of the empirical results of the TERGM model, this paper reconducts the empirical estimation of TERGM by adjusting the time interval of trade network data, sample selection criteria, and changing the estimation method. The results are shown in Table 5. Specifically, the following steps are included: ① Set the time interval of the dynamic soybean trade network to 3-year intervals, respectively, and the empirical results of TERGM correspond to Model 5. ② Retain the countries ranked in the top 25% in terms of centrality and keep the time interval at 2 years. The empirical results are shown in Model 6. ③ Replace the MCMC MLE estimation method of TERGM with the bootstrap MPLE method. The empirical results are shown in Model 7. By analysing the estimation results in Table 5, it is not difficult to find that Models 5–7 show basically the same empirical results as Model 4, indicating that the TERGM estimation results of this paper are robust. Although the robustness of the existing model has been tested from three different perspectives, which guarantees the reliability of the results, there are still some drawbacks. For example, because the sample size in this paper is too large, the MPLE (Maximum Pseudolikelihood Estimation) method and the MCMC MLE (Markov Chain Monte Carlo Maximum Likelihood Estimation) method are relatively slow when estimating the model, and there is a shortcoming of relatively low estimation efficiency.

Table 5. Results of the robustness test.

	Model 5	Model 6	Model 7
edges	−8.95457 *** (−0.46803)	−8.68033 *** (−0.47709)	−12.75974 * [−13.60265; −12.10730]
nodeicov.ln_gdp	0.35368 *** (−0.03737)	0.35878 *** (−0.0367)	0.60186 * [0.53394; 0.69151]
nodeicov.ln_pop	−0.24479 *** (−0.04177)	−0.21820 *** (−0.04038)	−0.34711 * [−0.44474; −0.27274]
nodeocov.ln_gdp	0.19936 *** (−0.0338)	0.17597 *** (−0.03374)	0.42443 * [0.36398; 0.48986]
nodeocov.ln_pop	0.35016 *** (−0.03924)	0.29641 *** (−0.03821)	0.28269 * [0.21398; 0.34542]
colony	0.38307 ** (−0.1315)	0.50797 *** (−0.1223)	0.37477 * [0.28146; 0.46397]
contig	1.29630 *** (−0.10602)	1.29089 *** (−0.10285)	1.12567 * [1.01282; 1.26745]
distcap	−0.00005 *** (−0.00004)	−0.00005 *** (−0.00001)	−0.00006 * [−0.00007; −0.00005]
mutual	0.71290 *** (−0.09101)	0.54929 *** (−0.087)	0.67012 * [0.59583; 0.73729]
gwdegree	−1.75009 *** (−0.22)	−1.97298 *** (−0.22571)	−2.74005 * [−3.19400; −2.39058]
dgwdsp	−0.05673 *** (−0.00423)	−0.06422 *** (−0.00411)	−0.04562 * [−0.05156; −0.03854]
dgwesp	1.58793 *** (−0.04971)	0.96529 *** (−0.04945)	0.73895 * [0.68589; 0.79498]
Stability	1.61264 *** (0.02647)	1.52177 *** (−0.02475)	1.48738 * [1.45852; 1.51794]
loss	−0.10031 *** (−0.02329)	−0.03244 * (−0.02291)	−0.03509 * [−0.05487; −0.01544]

*, **, and *** represent the significance levels of 5%, 1%, and 0.1% respectively in the two-tailed test.

4.4. Goodness-of-Fit Test

Figure 7 shows the gaps between the frequency distribution results of the dyad-wise shared partners, edge-wise shared partners, degree centrality, in-degree centrality, and the key network characteristic parameter—geodesic distance—obtained from simulating the network 500 times based on the estimated parameters of Model 4 and the corresponding observed values of the real network. In the first five figures, the thick black solid line represents the distribution of each characteristic parameter observed in the real network, and the grey lines and box-and-whisker plots represent the 95% confidence intervals of each characteristic parameter of the simulated network. It can be observed that the observed values of the five key network characteristic parameters are all within or close to the 95% confidence intervals of the simulated network, indicating that the benchmark model has a good fitting effect and can better explain the structural characteristics of the real network. In addition, the sixth figure is the ROC curve. Generally, the larger the area under each of the two curves, the better the performance of the model and the higher the degree of fitting. It can be clearly seen that the areas under the two curves in the figure account for a relatively large proportion of the total area, further indicating that the benchmark model has a good fitting effect.

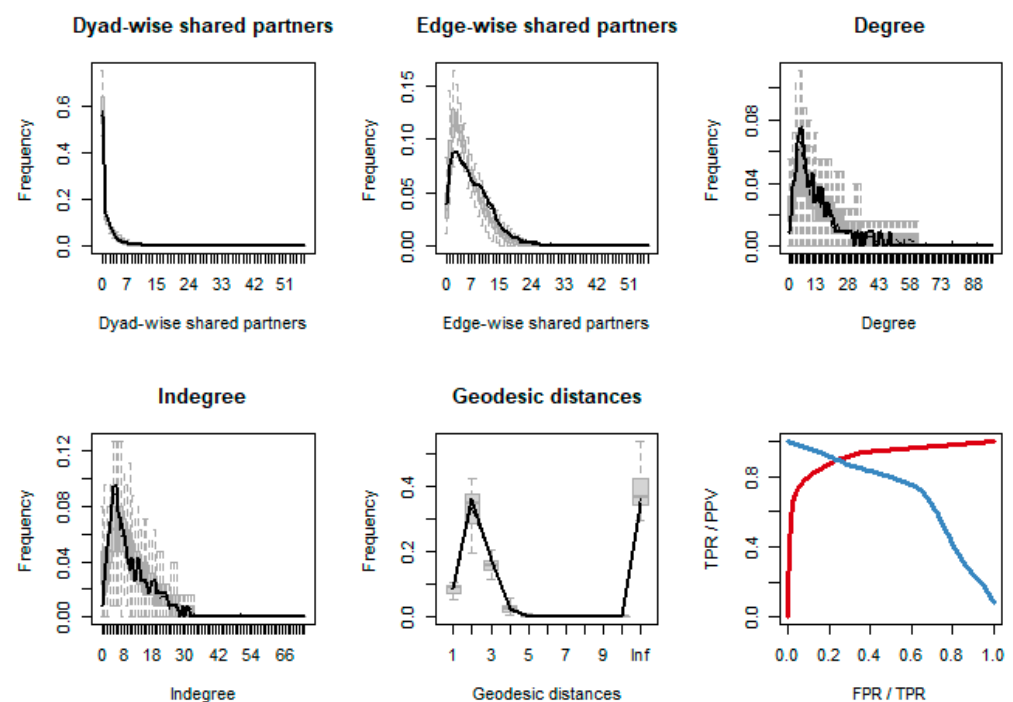


Figure 7. Results of goodness-of-fit test.

5. Conclusions

This paper is based on the original global bilateral soybean trade data from 2000 to 2022. The social network analysis method is used to construct the soybean trade network. A series of network statistical indicators are utilised to explore the dynamic evolution characteristics of the soybean trade network, and the influencing factors of the soybean trade network are explored through the TERGM model. The following conclusions are drawn from the research.

The soybean trade network exhibits obvious dynamic evolution characteristics. In terms of topological structure, the number of nodes and edges in the soybean trade network has increased, indicating a continuous expansion of the network scale. The clustering coefficient has risen, showing the trade agglomeration effect in the soybean trade network.

The average path has shortened, demonstrating the “small-world” feature of the soybean trade network, which reduces the difficulty of soybean trade cooperation among countries. The difference in the centralisation of in-degree and out-degree has narrowed, and the centralisation of the import side and the decentralisation of the export side in the soybean trade network have become more prominent. This indicates that soybean-importing countries are becoming increasingly concentrated, with a few or even a single economy importing a large number of soybeans. The overall dependence average of the trade network has decreased, the substitutability of soybean trade has increased, the selectivity of trade has increased, and the soybean trade risk has decreased. From the perspective of the “core–periphery” structure, the structural characteristics of the soybean trade network have gradually evolved from a single-core–periphery structure to a multi-core–periphery structure. It is no longer “driven by a few cores,” and more economies play a “multi-core driving” role in the trade network. Among the impacts of the four external events on the network structure, the impact on the core structure tends to be stable. For example, the United States and Brazil, which have long been at the core of the network, are less affected. However, the impact on the peripheral structure is heterogeneous. Importing giants like China are vulnerable to the adverse effects of unexpected events.

The evolution of the soybean trade network relationships is influenced by both endogenous and exogenous mechanisms. In terms of the endogenous mechanism, the degree of reciprocity has a significantly positive effect on the formation and development of the network, indicating a high degree of dependence on the trade relationships among countries. The expansion coefficient has a significantly negative effect, indicating that preference-dependence leads to the emergence of “star” nodes in the soybean trade network, reflecting the agglomeration of the network and the obvious “core–periphery” structure from the side. The transitive closure is significantly positive, and the multiple connectivity is significantly negative, indicating a significant agglomeration in the soybean trade network and confirming the “small-world” feature of the network. The stability coefficient is significantly positive, and the variability coefficient is significantly negative, indicating an obvious path-dependence characteristic in the soybean trade network. Moreover, over time, the relationships in the soybean trade network tend to gradually weaken and even disappear. In terms of the exogenous mechanism, the higher the economic level of an economy, the easier it is to both receive and initiate soybean trade relationships. The larger the market scale of an economy, the less inclined it is to import soybeans and the more inclined it is to export soybeans. In addition, economies with a historical colonial relationship and those that share a border are more inclined to establish relationships in soybean trade, while geographical distance has an inhibitory effect on soybean trade. The farther the geographical distance between economies, the higher the trade costs, such as transportation and communication, and the less likely it is to form a soybean trade relationship.

The research of this paper further expands the scope of trade network research, providing experiences from the soybean trade network for other scholars who study agricultural product trade networks. Based on the research findings of this paper, scholars can proceed to study the impact of sudden event shocks on other trade networks and further analyse the influencing factors of the formation and evolution of these networks. In addition, countries around the world can obtain strategically valuable information based on the panoramic view of the soybean network drawn above:

1. Optimise the structure of the trade network: The research in this paper reveals that the soybean trade network is expanding in scale, demonstrating agglomeration effects and exhibiting “small-world” characteristics. In response, countries should actively promote the diversification of trade cooperation, strengthen soybean trade relations with central countries in the network, and leverage the unique position of central countries to establish

soybean trade connections with other trading partners. Specific suggestions are as follows: First, enhance the hub functions of central-node countries. It is proposed that the logistics efficiency and information-sharing capabilities of core-node countries such as the United States, Brazil, and Argentina be improved through technical assistance, infrastructure connectivity, and other means. Relying on their radiation effects, a “core–periphery” coordination mechanism should be established. For example, central countries can be encouraged to carry out cooperation in planting technology with emerging production regions in Africa and Eastern Europe. Regional distribution centres can be established through the port facilities of central countries. Meanwhile, it is necessary to strengthen the financial supervision of domestic soybean production enterprises, enabling them to maintain a sound corporate financial situation, enhance their international competitiveness, and further boost the country’s trade strength [49,50]. By taking advantage of the short-path characteristics in the “small-world” network, peripheral countries can be assisted in accessing the global trade system at a lower cost.

2. The current volatile international situation exposes trade networks to significant impacts from unexpected events. Peripheral countries, often lacking resilience, face challenges in dealing with such situations. Take the 2008 financial crisis as an example. To manage trade risks, countries can strengthen monitoring and early warning of the soybean trade market. Establishing a global soybean trade information-sharing platform enables governments, industry associations, and large trading enterprises from various countries to collaborate on data collection. Applying blockchain technology ensures data integrity while machine-learning algorithms analyse the collected data. By leveraging business-cycle laws [51], the probability, scope, and impact of soybean supply crises can be predicted. Once the early-warning threshold is reached, relevant parties should hold emergency meetings to develop response plans.

3. Coordinate the endogenous mechanism: Based on the positive impact of reciprocity on the trade network, countries should strengthen mutually beneficial cooperation with their trade partners and establish long-term and stable trade relations; guide the rational allocation of trade resources, avoid the excessive concentration of resources in “star” nodes, and promote a more balanced development of the trade network; and consolidate and expand existing trade relations, and at the same time, pay attention to the weakening trend of relations and adjust trade strategies in a timely manner. Countries should also increase investment in the innovation, research, and development of soybean planting technology and, through continuous technological innovation, effectively increase soybean production and then increase the domestic supply of soybeans, reducing the supply risk caused by the impact of sudden events. In terms of technology research and development, the focus can be on key areas such as cultivating excellent varieties, improving planting techniques, enhancing the level of agricultural mechanisation, and using scientific and technological means to promote the sustainable development of the soybean industry.

4. Comply with the exogenous mechanism: Countries that are geographically close can take advantage of their locational advantages to simplify border procedures and establish integrated border management centres where multiple departments such as customs and quarantine work jointly. Through “one-stop” services, the time that goods are detained can be shortened. For example, in the soybean trade between China and Russia, dedicated green channels can be opened at border ports, and soybean transportation vehicles can be given priority in inspection and fast customs clearance. Secondly, for countries with colonial historical connections, they can rely on cultural commonalities such as language and business customs to hold special trade exchange activities (such as soybean processing technology seminars or bilateral trade negotiation meetings) to promote corporate cooperation and mutual trust among the people. Finally, for trading partners that

are far away, it is necessary to improve logistics efficiency through technological innovation: encourage the research and development of energy-efficient large-scale transport vessels, adopt new container designs to increase the loading rate, and use artificial intelligence to optimise route planning, reducing the empty running mileage and the number of transshipments during transportation, so as to reduce the unit logistics cost.

This paper focuses on the soybean trade network and conducts an in-depth analysis centred around the agricultural product trade network system. Taking soybean trade as a starting point, it systematically studies the dynamic evolution characteristics of the trade network and comprehensively explores various influencing factors driving the network's evolution. Currently, there are relatively few studies on the dynamic evolution and influencing factors of the agricultural product trade network. The research findings of this paper effectively fill the gap in this field, providing new research ideas and a unique perspective for subsequent scholars studying the agricultural product trade network. It is expected to help advance the research in this field to a new height.

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