Analysis of ERGM Evolutionary Dynamics from a Multi-layer Network Perspective: Based on New Energy Vehicle Industry Data

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Abstract: In the context of environment and energy bundle, the development of the economy has gradually entered into a new state, and more and more countries have started to pay attention to the environment and ecological development issues, and have made strategic deployment at the national macro level. In order to optimize the green innovation network and promote the development of green innovation, this study, from the perspective of a multi-layer network, uses the data of new energy vehicle patent citation, paper co-publication data, and production supply relationship data from 2009 to 2020, constructs a multi-layer network including paper knowledge network, innovation R&D network and production supply network to explore the evolution of structural characteristics of new energy vehicle innovation network, and uses principal component analysis to obtain knowledge capability and production capacity variables, and constructs ERGM model to analyze the evolutionary dynamics of the multilayer network. The results show that the innovation level of the new energy vehicle industry is closely related to the network structure; at the level of evolutionary dynamics, the number of partners, the degree of similarity in production level is positively related to partnership formation, the number of shared partners is negatively related to partnership formation, and the difference in knowledge level has no significant determining effect on relationship formation.

1 INTRODUCTION

Under the background of resource environment and energy constraint, more and more countries are implementing the guiding measures of "innovation-driven, quality-first, green development and structural optimization". As a perfect combination of green, innovation, and economic development, the new energy vehicle industry, which belongs to the manufacturing industry, has become an important object of research for scholars. However, the current new energy vehicle industry faces problems such as imperfect innovation deployment, unbalanced industrial layout, and insufficient innovation efficiency. Therefore, it is important to explore the evolution and layout of collaborative innovation and industrial chain network of new energy vehicles and identify the key factors affecting innovation performance.

For the evolution of green innovation networks, studies mainly focus on two perspectives: the evolution of network structure and the dynamics of network evolution. From the perspective of network structure characteristics, at the level of evaluation of influencing factors, Xu used the method of cluster analysis to divide the development stages of new energy vehicle technology innovation and dynamically analyzed its network evolution in three aspects: the overall network characteristics, the location characteristics of innovation subjects, and the distribution of the depth and breadth of cooperation of innovation subjects (Xu 2020). In the spatial and temporal dimensions, Cao et al. used the social networks to analyze the network structure and the evolution pattern of spatial distribution of the new energy vehicle patent cooperation network during 1989-2015 (Cao 2019). Lee analyzed the evolution of the network structure of collaborative inventions in

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urban areas in the United States during 1979-2009 and found that the complexity of intercity networks expanded and deepened, and technical collaborative inventions were closely linked to core urban areas (Lee 2016).

In the perspective of the evolutionary dynamic, Ruan clarified the dynamics of technological innovation network evolution and used ERGM to analyze the evolutionary dynamics of OLED technology innovation networks from five different proximities: geographic, social, technological, organizational, and institutional (Ruan 2018). CSternitzke et al. found that collaborative relationships among inventors can facilitate knowledge interaction processes among inventor collaborative network organizations (Csternitzke 2016).

Comprehensive domestic and international literature reveals that existing system theories have studied the structure, innovation dynamics, innovation process, and innovation performance of green innovation systems in traditional manufacturing industries in a relatively detailed manner, but the current research on innovation networks often focuses only on a certain level of R&D or industry, lacking the overall exploration of the integration of innovation and industry chains. In addition, in terms of perspective, it is more from the perspective of a single-layer network and lacks the analysis of the inter-layer linkage between innovation and industrial multi-layer networks to achieve multi-layer interaction among academia, innovation, and industry.

Based on this, this study constructs a multilayer network from the perspective of multilayer networks, using the data of new energy vehicle thesis, patent data, and supply relationship data to build a multilayer network for the fusion of the three layers of networks in the manufacturing industry, analyze the structure and evolution trend of the multilayer network, and use ERGM to explore the influence of knowledge and production capacity on the evolution of the innovation network. In order to analyze the innovation ecological network of new energy vehicles with the help of the multilayer network theory, and to provide references for the construction and optimization of the green innovation ecological network of the national manufacturing industry.

2 DATA SOURCES AND RESEARCH METHODS

2.1 Data Source and Processing

New energy vehicles, as the leading industry of green innovation, exploring the technological innovation network of it is representative and relevant. And among many innovation achievements, patents are the most widely used data in the field of innovation, which are advanced and innovative (Zhao 2009), so this paper selects the field of new energy vehicles as the empirical object and uses patent R&D as a measure of innovation performance.

In terms of data selection, this study selected 60 new energy vehicle innovation subjects including BYD, Xiaopeng Automobile, Chery Automobile, and other vehicle enterprises as research objects. Because new energy vehicles formally entered the preparation stage of R&D industrialization around 2008, before that it was mostly the strategic layout stage with fewer invention patents, and the patent data in 2021 is incomplete, so the data period chosen in this paper is 2009-2020, and a three-tier network of academia, research, and industry is established to analyze the evolutionary characteristics and formation mechanism of the innovation network of new energy vehicles.

2.1.1 Knowledge Learning Layer

The knowledge layer network was based on the publication of papers, and the paper data were exported on CNKI, Google Scholar based on the advanced search mode of vehicle enterprise + time. Duplicates were excluded and 15033 papers were obtained. With the vehicle enterprise as the node and the university institution as the intermediary, a cooperative relationship was established based on the joint publication of author units, and 3963 connections were obtained by screening out non-intermediated institutions and isolated nodes.

2.1.2 Patent R&D Layer

The R&D layer is based on patent data, and on the website of incopat (https://www.incopat.com/), input (AP=(vehicle enterprise)) AND (AD=[20090101 TO 20211004]), export data according to the vehicle enterprise as a unit, and after screening out invalid data, get 86,839 patents, and use patent citation After filtering out the invalid data, we got 86,839 patents, and using the citation and cited relationship to establish a connection, we got 19,063 times of patent citation frequency.

2.1.3 Supply Production Layer

The supply chain layer is based on the supply relationship of new energy vehicle battery, drive motor, battery control, and motor control, and the data is exported from the "MARK LINES Global Automotive Information Platform" website (https://www.marklines.com/cn/cn) according to the classification of each segment to obtain a total of We filtered out 1,435 data of vehicle enterprises in the scope of our study, and established connections by supplying parts to vehicle enterprises with the vehicle as a unit, and obtained supply relationships 740 times.

2.2 Research Methods and Models

Based on the network data, we use python to read the data to establish a three-layer network of learning, research, and production, and analyze the laws and trends of network evolution over time from the perspective of the multi-layer network, and select two extrinsic variables, knowledge learning, and supply production, as well as patent R&D itself as an intrinsic variable, to investigate the impact of multi-layer network structure on enterprise innovation performance. The multi-layer network structure is shown in Figure 1.

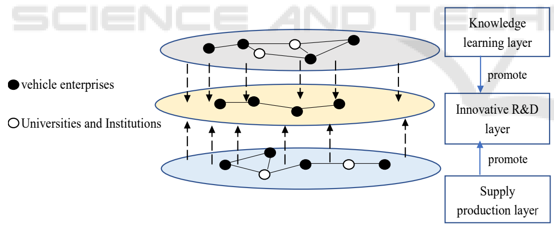


Figure 1: Schematic diagram of the network structure.

2.2.1 Structural Feature Analysis

The evolutionary characteristics of the innovation network are described at two levels: overall network and individual. Since cooperation and innovation performance has a lag effect (Liu 2021), based on a lag period of three years, the data from 2009-2020 are divided into 2009-2011, 2010-2012, 2011-2013, 2012-2014, 2013-2015, 2014-2016, 2015-2017, 2016- 2018, 2017-2019 nine stages to analyze the evolutionary characteristics of the innovation network structure.

2.2.2 Evolutionary Dynamics Analysis

In order to study the impact of multi-chain integration on innovation networks, this paper uses principal component analysis to measure the knowledge and production levels of nodes with the help of knowledge layer and industry layer indicators as exogenous variables, and the degree, degree-sharing, and edge-sharing of nodes in the innovation network as endogenous variables to establish hypotheses to build a model. Finally, the ERGM model is fitted to diagnose the impact of the variables on the evolution of the innovation layer network.

The general form of the ERGM is as follows:

$$P(Y = y) = \frac{exp(\theta' g(y))}{k(\theta)} \quad (1)$$

where k is a constant ensuring that the probability of a new network structure ranges from 0 to 1 and θ' is a coefficient of the network structure statistic g(y). Based on the above assumptions, an analytical framework containing endogenous structural variables and exogenous node attributes is constructed, and the model architecture is schematically shown in Figure 2:

3 ANALYSIS OF THE EVOLUTION OF MULTI-LAYER INNOVATION NETWORKS

Using the Gephi import network matrix, the stage network indicators and the Pearson correlation coefficients between each indicator and innovation performance were obtained as shown in Figure 2, and the influence of network structure on innovation performance was analyzed by observing the changes of each network indicator selected to integrate innovation performance.

1) The number of nodes, which indicates the number of subjects involved in knowledge citation in the patent citation network, can be used to measure the scale of the knowledge innovation network of new energy vehicles. The nodes of vehicle enterprises in each time window from 2009 to 2020 grew from 15 to 58, and the scale of the network continuously expanded and stabilized. The larger the network and the richer the network resources, the more it facilitates knowledge integration and exchange and innovation (Jin 2020), which has a positive effect on innovation performance positively.

2) The weighted average degree indicates the average number of citations of patents in the current window of each subject in the patent citation network, which can be used to measure the closeness and frequency of node connections in the knowledge innovation network. As can be seen from the table, the average degree shows a rising trend year by year and the growth rate is steadily climbing, indicating that the knowledge exchange among enterprises is gradually frequent and close, which plays a role in promoting knowledge innovation.

3) The agglomeration coefficient reflects the formation and aggregation of community groups in the network. It is also obvious from the table that with the change of time, the clustering coefficient of the patent citation network increases continuously and stabilizes at about 0.8. It indicates that with the passage of time, the knowledge cooperation among enterprises in the new energy vehicle industry tends to be more and more clustered and stable, forming a joint development pattern centered on a small number of strong enterprises.

Time Stage	Average degree	Weighted average degree	Density	Number of citations	Innovation Performance	Agglomeration coefficient
2009-2011	15	18.933	0.295	142	48700	0.436
2010-2012	19	57.895	0.203	550	65150	0.716
2011-2013	24	117.333	0.286	1408	65199	0.797
2012-2014	31	192.129	0.245	2978	77395	0.824
2013-2015	38	258.211	0.213	4906	83882	0.817
2014-2016	46	319.652	0.207	7352	117080	0.819
2015-2017	50	409.92	0.242	10248	139189	0.833
2016-2018	51	539.451	0.296	13756	181821	0.821
2017-2019	58	650.966	0.294	18837	203193	0.803
Correlation coefficient	0.930	0.985	0.327	0.991	-----	0.491

Figure 2: Innovation Network Indicators.

4 STUDY OF THE EVOLUTIONARY DYNAMICS OF INNOVATION NETWORKS

4.1 Hypothesis Building

4.1.1 Endogenous Structural Variables

Network connections for technological innovation have a certain preference, objects with high degree nodes can be considered to have gained the recognition of more companies and are more likely to establish connections with other nodes in the choice of companies, presenting as the basic side structure in the network. However, network relationships are established in long-term interactions between subjects, after a long period of examination, learning, and selection, and there are costs to be paid for accumulating and maintaining network relationships, requiring long-term and continuous investment in relationship building, and when existing partners can meet their own innovation needs, subjects are reluctant to spend high costs to establish new partnerships.

Therefore, the hypothesis is established that:

H1a: During the evolution of innovation networks, nodes with a high degree tend to establish new collaborations.

H1b: During the evolution of innovation networks, nodes with a high degree tend to avoid establishing new collaborations.

In the context of business innovation, sociologists have coined the term 'transmissibility' to describe the triadic sharing partnerships that are established between firms. If both firm A and firm B are linked to C, then firm C acts as a kind of intermediary, a witness, and it is easier to build trust between A and B, forming links that are presented as side and degree sharing in the network.

Therefore, the hypothesis is established that:

H2a: Nodes with shared edges are more inclined to establish new collaborations during the evolution of innovation networks.

H3a: Degree sharing nodes are more inclined to establish new collaborations during the evolution of innovation networks.

4.1.2 Exogenous Attribute Variables

In addition to the characteristics of the location structure of the nodes that affect the establishment of network relationships, there are also attributes that are inherent to the enterprises themselves that are detached from the network structure. In order to study the impact of chain integration of industry-academia-research on enterprise innovation, this paper selects two variables, knowledge level, and production level, to explore their evolutionary dynamics.

In terms of knowledge level, the more similar the knowledge level is, the more knowledge crossover there is in the exchange process, the less costly it is to transfer information and therefore the easier it is to establish connections and the more efficient the exchange of innovation is, which is explained by the term 'homogeneity' in social networks. At the same time, however, from another point of view, the purpose of knowledge exchange is to complement each other's strengths, and the closer the knowledge of two companies is, the less benefit they can gain from working with each other, and therefore the similarity of knowledge levels may have the opposite effect on the establishment of a partnership.

Thus the hypothesis is established that:

H3a: During the evolution of an innovation network, individuals with widely varying levels of knowledge are more likely to form collaborative relationships.

H3b: During the evolution of innovation networks, individuals with similar levels of knowledge are more likely to form collaborative relationships.

In terms of production levels, as a business enterprise, profit always comes first and a company's production capacity determines to a certain extent the ability to translate knowledge into real value, the better the production capacity and production conditions, the easier it is to attract companies to establish connections.

Thus establishing the hypothesis that:

H4a: During the evolution of innovation networks, cooperation is more likely to be established between individuals with large differences in production capacity.

H4b: During the evolution of innovation networks, individuals with similar levels of production are more likely to establish collaborative relationships.

4.1.3 Calculation of Indicators of Production Capacity and Knowledge Level

There are two main types of indicators for an enterprise's knowledge and production capacity.

The first category is its own attributes, for example, the number of published papers can represent its knowledge reserve, and the annual output of an enterprise can measure its production capacity. The second category is resource attributes, which can be measured by their position in the network.

In order to make a comprehensive measurement of the knowledge level and production level of an enterprise, this paper adopts the principal component analysis method and uses SPSS to do principal component analysis on the above variables, so as to obtain a comprehensive score of knowledge level.

4.2 Study of the Evolutionary Dynamics of ERGM Networks

4.2.1 Model Building

Based on the above hypothesis building, an analytical framework containing endogenous structural variables and exogenous node attributes is constructed and the ERGM model is established as follows.

$$P(X = x) = \frac{1}{k}\left[exp\left(\theta_1 \text{Edges} + \theta_2 \text{Gwdsp} + \theta_3 \text{Gwesp} + \theta_4 nodmatch(\text{Knowledge}) + \theta_5 nodecov(\text{Output})\right)\right] \quad (2)$$

The specific variables and associated explanations are shown in Figure 3 below:

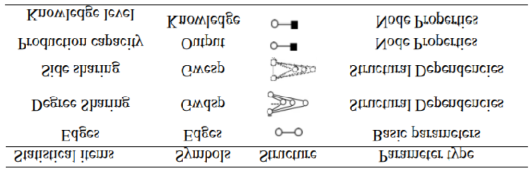


Figure 3: Explanation of indicators.

4.2.2 ERGM Analysis Results

The ERGM model was calculated using the Statenet program package in the R environment, and the model parameters were estimated using Markovian Monte Carlo maximum likelihood estimation (MCMC), and the model fit was assessed. The patent citation cooperation network of new energy vehicle enterprises from 2009 to 2020 was introduced as the observation network. Model architecture as in Figure 4.

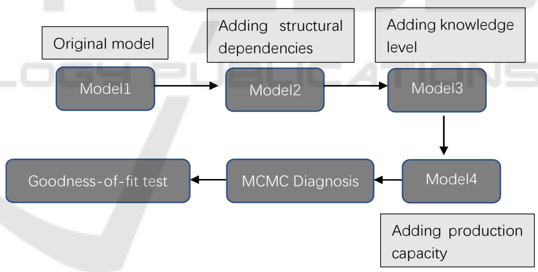


Figure 4: Model architecture.

From the results, it can be seen in Figure 6 that after adding the statistical terms in turn, Model4 has the smallest AIC and BIC coefficients, indicating that the model fits the observation network most closely.

From the specific fitting details, Figure 5 and Figure 6 show the gap between each statistical term of the model and the observation network. On the whole, most of the indicators are concentrated near the observation network, and as shown in Figure 7 the deviation curve basically conforms to the normal distribution characteristics and is concentrated near 0, and each indicator fits better. From the degree statistics results, the relationship between the number of nodes of the simulated network and the corresponding degree of the observed network can be seen in Figure 3, and it can be found that the number of nodes of the observed network for each degree is roughly contained between the maximum and minimum values of the simulated network, fluctuating in a small range above and below the mean value. So it can be seen that the integrated model of Model4 is closer to the observed network than the more advanced model, and it is reasonable to assume that the other model is more accurate than the other models in terms of estimation results.

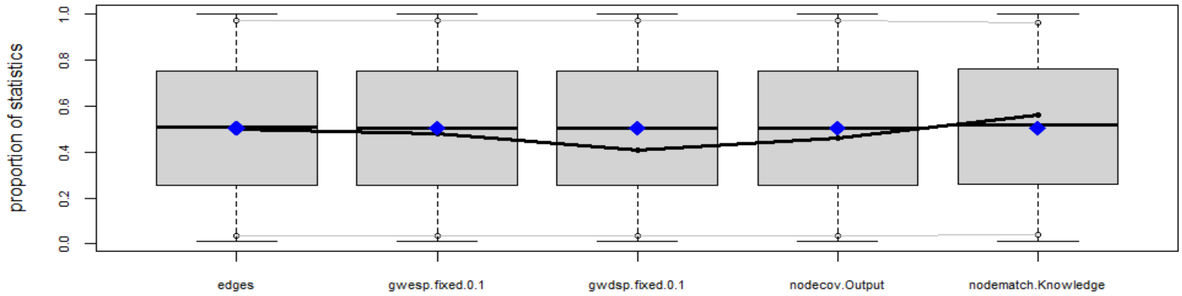


Figure 5: Comparison of indicators.

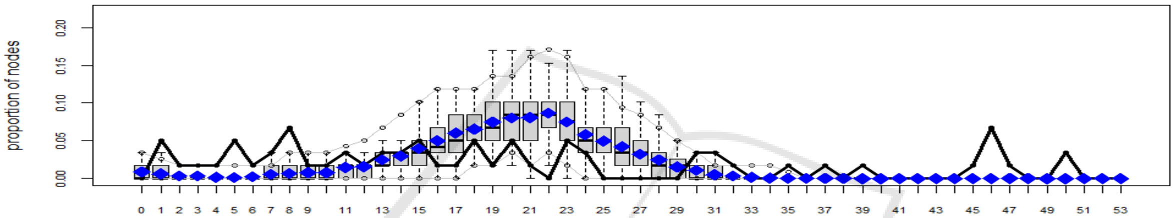
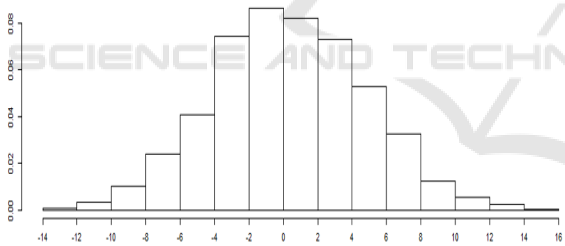
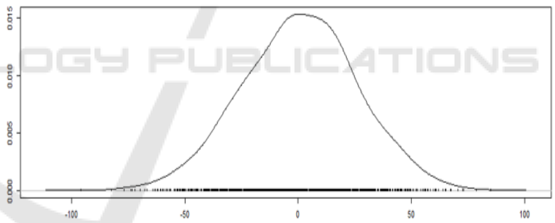
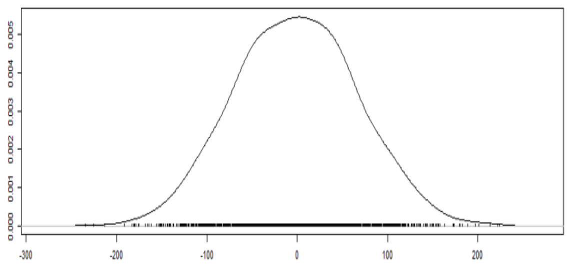


Figure 6: Degree Comparison.







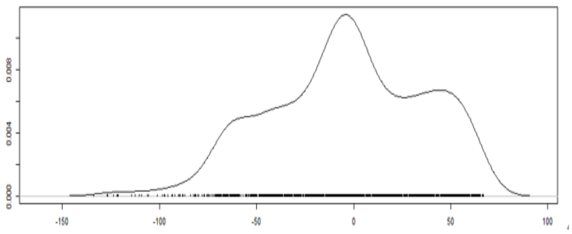


Figure 7: Metrics statistics of the simulation model.

As shown in Figure 8. The endogenous structure of the dependency estimation results show that degree extension edges are positively correlated in relationship formation, thus supporting hypothesis H1a and rejecting hypothesis H1b. Degree-sharing and edge-sharing are significantly negatively correlated in relationship formation, rejecting H2a, H2b, which may be explained by the fact that in the process of network formation, in the early stage of formation, in order to expand the scale and absorb resources, shared partners may have a positive effect on relationship formation. However, in the growth stage and beyond, the innovation network has been gradually improved, the functional overlap of the subjects is very high, and the differences that exist are relatively small, which means that the possibility of substitution is high. Firms choose to avoid sharing their partners in order to safeguard their own interests and to ensure the continued demand for themselves by other subjects (Liu 2020).

The production capacity indicator Output is significantly negatively correlated as a covariate and positively correlated as a homogeneous indicator, supporting hypothesis H4b and rejecting hypothesis H4a, which implies that high production capacity is not conducive to partnership building. The reason for this may be that for large new energy vehicle enterprises, which are prone to forming independent production lines, they refuse to cooperate with small new energy vehicle enterprises, choosing instead to cooperate with similar enterprises on the basis of other resource requirements for a win-win situation, while for the few disadvantaged new energy enterprises, they also lack the opportunity to cooperate with large enterprises, thus reducing the possibility of cooperation.

On the knowledge level indicator Knowledge, it is significantly positively correlated as a covariate and positively correlated as a homogeneous indicator, but neither correlation is significant and thus for hypothesis H3b, H3a cannot be judged. This suggests that although firms with similar knowledge systems are more likely to establish knowledge exchanges, the crossover of knowledge systems in innovation R&D is less likely to bring more benefits to both parties, and the choice between benefits and exchange costs depends on the needs of the firm.

	Model 1	Model 2	Model 3	Model 4
edges	-0.65 ***	0.32		0.25
	(0.05)	(0.67)		(0.56)
gwesp.fixed.0.25		-0.72		
		(0.48)		
nodecov.Output			-0.13 ***	-0.32 ***
			(0.04)	(0.06)
nodecov.Knowledge			-0.02	0.05
			(0.03)	(0.03)
gwesp.fixed.0.1				-0.20
				(0.50)
gwdsp.fixed.0.1				-0.16 ***
				(0.04)
nodematch.Output				0.13
				(0.17)
nodematch.Knowledge				0.30
				(0.24)
AIC	2203.83	2204.38	2275.63	2112.25
BIC	2209.27	2215.27	2286.52	2150.36
Log Likelihood	-1100.91	-1100.19	-1135.81	-1049.12

*** p < 0.001; ** p < 0.01; * p < 0.05

Figure 8: Fitted coefficients for each model.

On the knowledge level indicator, it is significantly negatively correlated when used as a covariate and positively correlated when used as a homogeneous type indicator, thus supporting hypothesis H3b and rejecting hypothesis H3a, which indicates that enterprises with similar knowledge systems are more likely to establish knowledge exchange, closer knowledge systems in innovation R&D, and more likely to establish cooperation.

5 CONCLUSIONS

5.1 Main Research Conclusions

Based on the multilayer network perspective, this study analyzes the trend of network structure evolution and the evolutionary dynamics of the new energy vehicle innovation network, and mainly draws the following conclusions.

5.1.1 In the Process of Innovation Network Evolution, the Number of Existing Connection Relationships Is Positively Correlated with Relationship Formation

As can be seen in Figure 8, the coefficient on the edges variable is positive, indicating that the number of existing relationships is positively correlated with relationship formation, suggesting a positive feedback effect on the evolution of cooperative relationships in network structures.

5.1.2 In the Evolution of Innovation Networks, Shared Partners Are Not Conducive to the Formation of New Relationships

The analysis of the indicators in Figure 8 shows that the coefficients of degree sharing (gwdsp) and side sharing (gwesp) are negative and the correlation between degree sharing and relationship formation is high, indicating that sharing partners are not conducive to relationship formation.

5.1.3 In the Process of Innovation Network Evolution, the Degree of Similarity in Production Level Is Positively Related to Partnership, and the Level of Knowledge Has No Significant Effect on Relationship Formation.

As can be seen from Figure 8, production capacity (Output) is negative when used as a covariate, while it is positive when used as a covariate, indicating that, the more individuals with similar production levels, the more conducive to relationship formation. The level of knowledge, however, is not significant as a covariate or as a covariate and has no significant effect on relationship formation.

5.2 Recommendations

Multiple factors indicate that due to the gap in the comprehensive capabilities of enterprises and the control of resources caused by shared partners, strong and weak enterprises are not conducive to establishing connections, creating a bifurcation and uneven distribution of resources in a certain perspective, thus the state can introduce policies to promote cooperation among multi-level enterprises and give certain compensation to lead enterprises to promote the balanced development of the industry.

5.3 Practical Implications and Perspectives

This study from the perspective of multi-layer networks, used the data of the new energy vehicle industry to construct a three-layer network of knowledge, innovation, and production. Through principal component analysis to obtain variables, and used the ERGM model to determine the influence of variables on the formation of network relationships.

Due to the long time span of the data used in the construction of the ERGM model, the different stages of network formation are not fully used, and the different evolutionary dynamics can be explored step by step at a later stage by subdividing the network formation stages.

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