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The Influence of Structure Heterogeneity on Resilience in Regional Innovation Networks

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ABSTRACT

The presence of structure heterogeneity in regional innovation networks reflects the complexity and diversity of knowledge diffusion and collaborative R& D relationships. This article introduces a network model based on the multiple systems generating functions mathematical algorithm to analyze the resilience of interacting networks under different link patterns. The percolation threshold is illustrated at two different levels: the subcritical and supercritical states. The algorithm is then tested on both simulated networks and real-world networks. The results of the simulation study highlight the crucial role of linking between sub-networks and emphasize the effectiveness of a moderate degree protection strategy.

KEYWORDS

Innovation Networks, Percolation, Resilience, Structure Heterogeneity

INTRODUCTION

Regional innovation networks, as a significant component of the national innovation systems, play a crucial role in promoting economic development. Classical works in the field of innovation networks, emphasizing satisfactory performance among innovators, underscore the importance of a dense network structure with small-world properties (Gay & Dousset, 2005). This topology, quantified by the average shortest distance, increases the probability of collaboration between groups of innovators (Amaral et al., 2000; Caloghirou et al., 2021). However, collaboration within these networks often introduces competitive issues such as income inequality, moral hazard, information asymmetry, and technical barriers (Uzzi & Spiro, 2005). Consequently, the links between stakeholders in partnerships are unstable (Bassett et al., 2014). These dynamic structural changes offer new insights for studying the functionality of innovation networks (Fleming et al., 2007).

Increased interest in the relationship between connection patterns and the function of innovation networks has led to various new developments in both empirical and analytical studies (Schilling &

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Phelps, 2007; Phelps, 2010; Zhang et al., 2016; Bertotti et al., 2016; Casablanca et al., 2023). However, the literature has primarily focused on a single network-based view, limited to exploring interactions among various innovators, such as scientists and their teams, enterprise technicians and engineers, universities and research institutes, and government departments. With a growing emphasis on the resilience and function of networks, there is an urgent need to broaden our understanding of strong interfirm networks with dynamic partnerships, taking a new perspective on structural heterogeneity, which determines the endogenous architecture of the network (Briscoe & Rogan, 2016; Bernard et al., 2022). Consequently, scholars are increasingly shifting their research perspectives toward the diversity of connections and network functions across multiple networks, as evidenced by recent research (Peres, 2014; Li & Zhang, 2015; Bin & Sun, 2022).

The structural heterogeneity of regional innovation networks reflects the dynamic linking process, directly influenced by innovators' behavior and innovative uncertainty (Mazzola et al., 2015). Factors such as knowledge spillover and research and development (R&D) collaboration may increase links within the innovation networks, while credit risk, technical failure, and partnership failure may decrease them (Gay & Dousset, 2005; Wu & Wu, 2014; Vivona et al., 2023). Drawing from the network embeddedness perspective, each innovator should optimize the technological distance between partners and secure a strategic position within the alliance network to absorb knowledge and information from external sources (Phelps, 2010; Han et al., 2020). Trust, influenced by changes in network configuration, plays a dominant role in establishing strong links (Shazi et al., 2015). Additionally, the absorptive capacity of external knowledge also has positive impacts on innovative partnerships and the overall network density (Tortoriello, 2015).

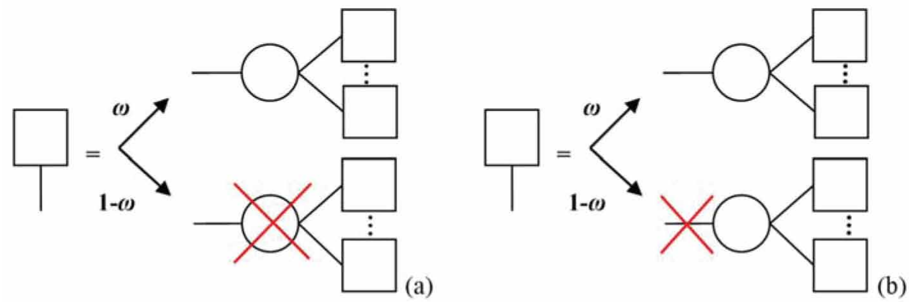
The utilization of generating functions with connected probability allows for the exploration of the structural heterogeneity of regional innovation networks, providing insights into the process of randomly choosing partners among innovators (Li & Zhang, 2015). The percolation threshold of the giant linked group varies significantly based on probability (Morone & Makse, 2015; Ziff et al., 2020). This threshold holds crucial importance in setting policies aimed at achieving the highest performance to facilitate the spread of technology within regional innovation networks (Zhao et al., 2023; Tabassum et al., 2022).

The resilience of regional or geographic innovation networks refers to the systems' ability to withstand random or targeted deletions of network nodes (Callaway et al., 2002; Newman et al., 2002; Gao et al., 2016; Buldyrev et al., 2010). These deletions signify cooperative innovation risk, which can be detrimental to economic growth by disrupting R&D and technology spread (Adams, 2012). Percolation models based on these networks can be instrumental in identifying the best connection pattern, ensuring an appropriate selection and a moderate number of links between innovators. This helps to ensure that contacts capable of efficiently transmitting techniques are maintained at lower costs (Freitas, 2013). In recent years, scholars focusing on algorithms and simulations of various subclasses of multilayer networks have emerged. Their works reveal the expected size of the giant linked group with complex structure and multiple percolation phase transitions, playing a crucial role in the resilience or robustness of the network of networks (Leicht et al., 2009; Buldyrev et al., 2010; Hackett et al., 2016; Casablanca et al., 2023).

In this paper, we modeled the influence of structural heterogeneity on resilience in regional innovation networks based on percolation theory. Our specific focus is on structural changes in multi-networks, where one subnet is composed of enterprises and the other consists of universities and institutes. Rigorously applying generating functions, we calculate different connection probabilities and percolation thresholds. Additionally, we use this approach to generate a classical regional innovation network, testing the efficiency and stability of multiple coupled networks within the context of collaboration between universities, institutes, and enterprises. We conduct numerical simulations of resilience in networks, examining both random failure and intentional attacks.

The remainder of this paper is organized as follows: Section 2 provides a description of the construction basis and derivation process of the model. The discussion of simulation results is

Figure 1. A network generation model based random graph



presented in Section 3. Resilience protection strategies are outlined in Section 4. Finally, Section 5 offers our concise conclusion and discussion.

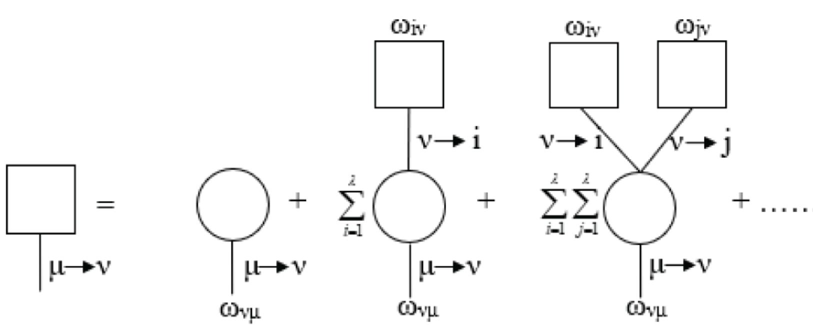
THE MODEL

It is an essential aspect of the study to generate different types of networks with various connected probabilities under investigation and test how heterogeneous architecture influences resilience in regional innovation networks. Utilizing classic random graph theory, we have constructed a model of network generating functions. The application of this model allows us to randomly generate various networks with any probability for a randomly chosen node (Figure 1a) and edge (Figure 1b).

Assume a regional network has λ different industries sub networks, and connection presents uniform characteristics, i.e., if node x_i is connected to x_j, meanwhile x_j is linked with x_i. Additionally, consider the connected probability ω, representing the likelihood of success in cooperative innovation between innovators. Figure 2 illustrates the probabilities that one node from subnet μ links to a node from subnet ν, nodes from separate subnets μ and ν are $\omega_{\nu\mu}$, ω_{μ} and ω_{ν}, respectively. It can be inferred that this network is a standard random graph if all probabilities of subnets are the same.

The distribution of group sizes can be obtained by the multi-degree distribution which is $\{ p^{\mu}_{k_1 k_2 \& k_\lambda} \}$ (λ>2) in each individual network μ in regional innovation networks, where $p^{\mu}_{k_1 k_2 \& k_\lambda}$ indicates that there are k_1 edges connected to the nodes of network 1 in the nodes of the network μ, and k_λ edges are connected to the nodes of network λ. We also use ω_{μ}, ω_{ν} and $\omega_{\mu\nu}$ to describe the connection threshold of nodes within and between networks, separately.

Figure 2. The generating function with connection probability



The multi-degree distribution for network μ is given by the following expression:

$$G_{\mu}(\omega_{\mu}x_1,\ldots,\omega_{\mu}x_{\lambda}) = \sum_{k_1=0,\ldots,k_{\lambda}=0}^{\infty} p^{\mu}_{k_1\ldots k_{\lambda}} (\omega_{\mu}x_1)^{k_1} \cdots (\omega_{\mu}x_{\lambda})^{k_{\lambda}} \tag{1}$$

In the following formula, ν-μ edge represents the connection in a node from subnet μ and another node from subnet ν. This is certainly a random selection process. The remaining connectivity of each single subnet node to nodes in other subnets is also explained by the excessive degree. Thus, $p^{\mu\nu}_{k_1\cdots k_{\nu}\cdots k_{\lambda}}$ is used to describe the probability of randomly selecting an ν-μ edge and connecting to a node has ν degrees excessive, while local subnet ν has $k_{\nu}+1$ degree. The generating function under the { $p^{\mu\nu}_{k_1\cdots k_{\nu}\cdots k_{\lambda}}$ } distribution is:

$$\begin{aligned}
G_{\mu v}\left(\omega x\right) &= \sum_{k_1,\ldots,k_{\lambda}=0}^{\infty} p^{\mu v}_{k_1\ldots k_{\lambda}} \left(\omega_{\mu 1}x_1\right)^{k_1} \ldots \left(\omega_{\mu\lambda}x_{\lambda}\right)^{k_{\lambda}} \\
&= \sum_{k_1=0,k_2=0}^{\infty} \frac{p^{\mu}_{k_1\ldots(k_v+1)\ldots k_{\lambda}}\left(k_v+1\right)}{\Sigma^{\infty}_{j_1=0,\ldots j_{\lambda}=0} p^{\mu}_{j_1\ldots(j_v+1)\ldots j_{\lambda}}\left(j_v+1\right)} \left(\omega_{\mu 1}x_1\right)^{k_1} \ldots \left(\omega_{\mu\lambda}x_{\lambda}\right)^{k_{\lambda}} \\
&= \left(\sum_{j_1=0,\ldots,j_{\lambda}=0}^{\infty} j_v p^{\mu}_{j_1\ldots j_{\lambda}}\right)^{-1} \frac{\partial}{\partial x_v} \sum_{k_1,\ldots,k_{\lambda}=0}^{\infty} p^{\mu}_{j_1\ldots j_{\lambda}} \left(\omega_{\mu 1}x_1\right)^{k_1} \ldots \left(\omega_{\mu\lambda}x_{\lambda}\right)^{k_{\lambda}} \\
&= \frac{G'^{\,v}_{\mu}\left(\omega x\right)}{G'^{\,v}_{\mu}\left(1\right)}
\end{aligned} \tag{2}$$

where $G'^{\nu}_{\mu}\left(1\right) \equiv \bar{k}^{\nu}_{\mu}$ can help to calculate average degree of a node in subnet μ connected to subnet ν. As cooperative innovation begins, all the component sizes, initially limited, grow larger as a giant connected component, gradually appears. The function can be used to calculate the average component size and the probability that a randomly selected node in a supercritical state is a giant group, when the group size is too large to tolerate the closed loop in networks. The distribution function $H_{\nu\mu}$ can be applied to calculate the size of group consisting of randomly selected edges connecting nodes between subnet ν and subnet μ. Therefore, all the types of probabilities for the associated generating function are given by the following expression:

$$\begin{aligned}
H_{\mu\nu}\left(\omega x\right) = x_{\mu} p^{\mu\nu}_{0\cdots 0} & \\
&+ x_{\mu} \sum_{k_1\ldots k_{\lambda}=0}^{1} \delta_1, \sum\nolimits_{\phi=1}^{\lambda} k_{\phi} p^{\mu\nu}_{k_1\cdots k_{\lambda}} \prod_{\gamma=1}^{\lambda} H_{\gamma\mu}\left(\omega x\right)^{k_{\gamma}} \\
&+ x_{\mu} \sum_{k_1\ldots k_{\lambda}=0}^{2} \delta_2, \sum\nolimits_{j=1}^{\lambda} k_{\phi} p^{\mu\nu}_{k_1\cdots k_l} \prod_{\gamma=1}^{\lambda} H_{\gamma\mu}\left(\omega x\right)^{k_{\gamma}} + \cdots
\end{aligned} \tag{3}$$

To simplify the formula, we introduce the Kronecker delta δ_i used to explain all edges connected from subnet μ to the specified node with excessive degree i. From Eq. 3 we get:

$$\mathrm{H}_{\mu\nu}(\omega x) = x_{\mu} \sum_{k_1,\cdots,k_{\lambda}=0}^{\infty} q^{\mu\nu}_{k_1\cdots k_{\lambda}} H_{1\mu}(\omega_{1\mu}x)^{k_1} \cdots H_{\lambda\mu}(\omega_{\lambda\mu}x)^{k_{\lambda}} \tag{4}$$

Thus, put Eq. 2 into Eq. 4 could be derived as $H_{\mu\nu}(\omega x) = x_{\mu} G_{\mu\nu}\left[H_{1\mu}(\omega_{1\mu} x)\cdots H_{\lambda\mu}(\omega_{\lambda\mu} x)\right]$. Only if consider nodes chosen at random from subnet μ, the distribution function can be written as:

$$H_{\mu}(\omega x) = x_{\mu} G_{\mu}\left[H_{1\mu}(\omega_{1\mu} x)\cdots H_{\lambda\mu}(\omega_{\lambda\mu} x)\right] \tag{5}$$

By taking the derivative of x on both sides of Eq. 5, the mean group size for any $H_{\mu\nu}(\omega x)$ can be calculated. For instance, an average number of nodes from subnet μ in the group of a node randomly selected from subnet ν is:

$$\begin{aligned}\left\langle S_{\nu}\right\rangle_{\mu} &= \frac{\partial}{\partial x_{\mu}} H_{\nu}(\omega\,\mathrm{x})\Big|_{\omega=1,x=1} \\ &= \delta_{\nu\mu} G_{\nu}\left[H_{1\nu}(1),\cdots,H_{\lambda\nu}(1)\right] + \sum_{\phi=1}^{\lambda} G_{\nu}^{\prime\phi}\left[H_{1\nu}(1),\cdots,H_{\lambda\nu}(1)\right] H_{\phi\nu}^{\prime\mu}(1) \\ &= \delta_{\nu\mu} + \sum_{\lambda=1}^{l} G_{\nu}^{\prime\phi}(1) H_{\phi\nu}^{\prime\mu}(1)\end{aligned} \tag{6}$$

Within the group $H_{\gamma\phi}^{\prime\mu}(1)$ is the mean degree of nodes in subnet μ following a ν-γ edge leading a node from subnet γ. And $G_{\nu}^{\prime\gamma}(1)$ represents the expected value of the ν-γ edge incident from a node in the subnet ν.

The above inference accounts for the size of the component that can be maintained in a subcritical state where there is no giant group. When a giant group appears, Eq. 6 shows the properties of components that do not belong to the group. To calculate the giant group size, we need to consider the contribution from each subnet.

The probability that a randomly selected node belongs to the giant group is calculated as follows:

$$u_{\mu\nu} = G_{\mu\nu}\left(u_{1\mu},\ldots u_{\lambda\mu}\right) \tag{7}$$

The $u_{\mu\nu}$ refers to the probability that a randomly selected edge connects a node of the subnet μ from the node of subnet v, and none of them belong to the giant group. Substituting $G_{\mu\nu}$ into Eq. 7, we get $u_{\lambda\mu}$. In the same way, u_{μ} can be obtained.

$$\begin{aligned}S_{\mu} &= 1 - \sum_{k_1,\ldots,k_\lambda=0}^{\infty} p_{k_1,\ldots,k_\lambda}^{u} u_{1\mu}^{k_1}\cdots u_{\lambda\mu}^{k_\lambda} \\ &= G_{\mu}\left(u_{1\mu},\ldots,u_{\lambda\mu}\right)\end{aligned} \tag{8}$$

Finally, as shown in Eq. 8, we can obtain the probability that a randomly selected node of subnet μ and its subgroup belong to the giant component.

SIMULATION AND RESULTS ANALYSIS

To test how structural heterogeneity influences network resilience, we apply the model introduced in Section 2 to generate three typical regional innovation networks. As the left part of Figure 3 shows, there are ER random graph $N = 9999$, mean degree = 5, W-S small world graph $N = 9999$, scale free graph $N = 9999$, $\gamma = 2.1$. Solid lines represent the estimated values of M. E. Newman's algorithm and dotted lines represent our model (Newman et al., 2002).

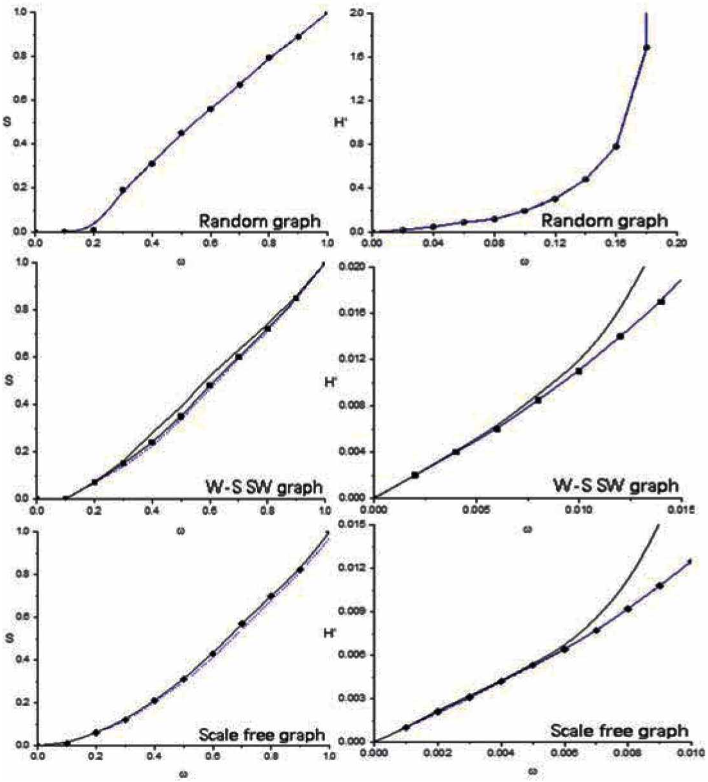
The generating function formalism developed by Newman offers a powerful analytical framework for understanding the complex properties of networks, especially their component size distribution and resilience (Newman et al., 2002). Generating functions are particularly useful in the study of random graphs and their percolation properties, which are relevant for understanding phenomena such as the spread of knowledge innovation or the resilience of communication networks. The generating function offers a powerful analytical framework for understanding the complex properties of networks, especially their component size distribution and resilience. Generating functions is particularly useful in the study of random graphs and their percolation properties, which are relevant for understanding phenomena such as the spread of diseases in populations or the resilience of communication networks (Wu et al., 2023).

To validate our model's applicability in real-world scenarios, we conducted extensive tests on data sets derived from actual networks. These data sets span various domains, including social networks, biological networks, and technological networks, providing a comprehensive cross-section of complex network topologies found in nature and human-made systems. For each real-world network analyzed, we carefully curated the data to ensure its relevance and accuracy. This process involved cleaning the data, removing duplicate and self-loop edges, and ensuring the network's consistency. We then characterized each network by its degree distribution, clustering coefficients, average path length, and other relevant metrics that capture its unique structural properties. The model parameters were extracted using statistical methods tailored to each network's specific characteristics. For instance, we used maximum likelihood estimation to fit the degree distribution of the network to the theoretical models. The goodness-of-fit was evaluated using statistical tests such as the Kolmogorov-Smirnov test to ensure that our model accurately represents the underlying distribution. By incorporating these real-world data characteristics into our model, we were able to observe how well our theoretical approach predicts actual network behavior. The comparison between our model's predictions and empirical observations showed a high degree of alignment, reinforcing the model's credibility.

Furthermore, the solid-circle, solid-square, and solid-diamond lines are the average of 100 repeated simulations of direct values on the same network. Initially, we elaborate on the network model construction, detailing the rules for node and edge generation, as well as the selection of network topologies. Subsequently, we describe the various parameters used in the simulation experiments, such as the initial connection probability of the network, the node failure rate, and the mechanisms for network recovery post-failure. Moreover, we explain the rationale behind choosing these parameter values based on theoretical models and empirical cases and provide a sensitivity analysis of the impact of parameter variations on simulation outcomes. Where H' is the abbreviated form of $H_0'(1)$ for illustration, the giant group fraction was simulated here and compared with the numerical values of the classic model and our model in good agreement. These estimates are almost identical with simulation results on the ER random graph. Moreover, the right part describes the average size value of all components under phase change. On these three typical networks, the results of the estimates correspond to the results of numerical simulation when ω values are beyond the percolation threshold interval. As those ω values gradually approach the threshold, by contrast, the results show that the simulated data do not agree well with the estimated data of the classic algorithm. However, on the ER random graph, data fitting is still perfect. Although the model was discussed in dissimilar network structures, this work is rarely used to generate regional innovation systems or networks with the multilayer perspective. This is exactly what we aim to explore.

We apply this procedure to generate a small but closer to a certain industry innovation network in some region. The structure parameter of the network is described in Figure 4. Where the network structure of the regional innovation network ($N = 131$) has a mean degree of 3.41, a W-S clustering coefficient of 0.49, a betweenness centralization of 0.32, and an average distance of 3.59. Figure 4a

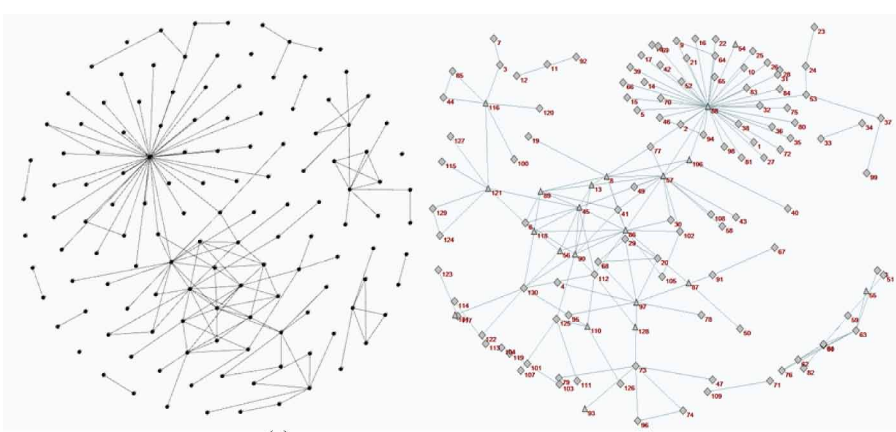
Figure 3. Percolation results for three typical networks



shows the connecting heterogeneity of the network when $\omega = 1$ and $\omega_1 = \omega_2 = 1$, and there are two subnets (diamonds represent enterprises, and triangles represent universities) whose proportion is approximately equal to 0.2. This proportion of dual network is the same as in Li and Zhang (2015).

As shown in Figure 4a, most of the nodes are linked with each other and, obviously, a giant component exists in this network. But it is, nonetheless, an ideal state for collaborative innovation

Figure 4. An example of a regional innovation network connectivity generated



(a) (b)

and achieving sustainable growth through friendship. Generally speaking, in regional innovation, technology R&D is challenging to succeed, and innovators often change partners for a variety of reasons. So, we should study the resilience with different probabilities. Figure 4b presents the function of dissimilar type innovators. Within the network, universities act as intermediaries between the enterprises. A number of patents were created due to teamwork between enterprises and universities. We also use our model to research the effect of two types of innovators on structural heterogeneity and resilience in the whole network.

We apply the model to calculate if the network has a giant component. Based on Eq. 2, we can get $G_{11}^{'1}(1,1)$ =0.789, $G_{11}^{'2}(1,1)$ =0.684, $G_{12}^{'1}(1,1)$ =0.559, $G_{12}^{'2}(1,1)$ =0.925, $G_{21}^{'1}(1,1)$ =17.312, $G_{21}^{'2}(1,1)$ =2.978, $G_{22}^{'1}(1,1)$ =5.13 and $G_{22}^{'2}(1,1)$ =3.741. And we also can derive the percolation threshold by solving a set of partial differential equations based on Eq. 4. When the results satisfy the following conditions such as:

$$0 \wedge \omega_1 \cdot G_{11}^{'1}(1,1) < 1 \wedge \omega_1 \cdot G_{22}^{'2}(1,1) < 1 \wedge \omega_2{}^2 \cdot G_{12}^{'2}(1,1) \cdot G_{21}^{'1}(1,1) < 1 \tag{9}$$

or:

$$0 \wedge \omega_1 \cdot G_{11}^{'2}(1,1) < 1 \wedge \omega_1 \cdot G_{22}^{'1}(1,1) < 1 \wedge \omega_2{}^2 \cdot G_{12}^{'1}(1,1) \cdot G_{21}^{'2}(1,1) < 1 \tag{10}$$

Thus, we work out $G_{12}^{'1}(1,1) \cdot G_{21}^{'2}(1,1) = 1.665 > 1$ and $G_{12}^{'2}(1,1) \cdot G_{21}^{'1}(1,1) = 16.009 > 1$, so a giant component appears in this network, and the thresholds are $\omega_1 \geq 0.2$ and $\omega_2 \geq 0.25$.

Then, we implement the simulation to test how structural heterogeneity with different connected probabilities influences the network resilience. For each probability of the nodes linked within the network, we calculate 50 times and take an average.

To estimate the impact of structural heterogeneity on network resilience, we examine how the numerical variation of connected probabilities in dual subnet impacts the network resilience. Figure 5 (In this figure, a dashed-circle line describes the giant component fraction of enterprises subnet, and a dashed-square shows the proportion of universities subnet.) presents the percolation station of a regional innovation network, where the proportion of enterprises and universities belonging to a giant component occupies all the innovators, respectively. The giant component fraction in the university subnet descends more slowly, and that fraction rapidly declines in the enterprise subnet. We observe in Figure 5 that the descending curve describes the number of universities belonging to the giant component and, as the connected probability decreases, it fits the logistic curve.

Figure 6 comprises two graphs, illustrating, respectively, the giant component fraction within enterprises and universities. The results show under the threshold that $\omega_2 = 0.25$, the size of the giant component in university subnet, suffers a much larger drop than enterprise subnet, and it rapidly descends when the numerical decrease of ω_1. In addition, under the threshold that $\omega_1 = 0.2$, the giant component fraction in dual subnet comes down fast when ω_2 is in the high level and slowly when ω_2 becomes lower. Thus, the mediate effect of university to regional innovation network is more important.

There are many factors that break the connections within the regional innovation network. Some of them come from outside impacts, and others result from sabotage. Typically, scholars study the resilience of the network under random failure or intentional failure. We use the giant group size as a measure of system damage in the network (Newman et al., 2002).

Under different failures, we test the influence of structural heterogeneity by simulation. And 100 times the resilience experiment is run to take the mean value of results. According to Figure 7a, random failure describes random removal of fractions of nodes with probability *q*. We assume that all stochastic processes are defined on a complete probability space (0, 1). The simulation results

Figure 5. Network resilience influenced by structure heterogeneity

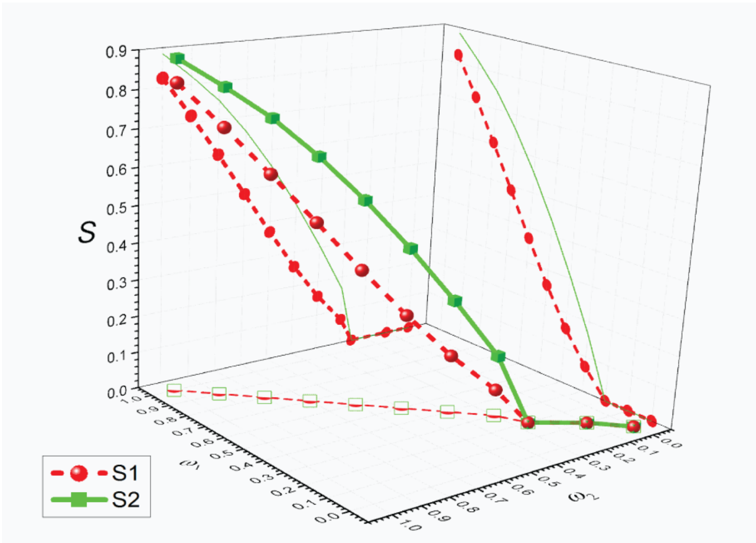
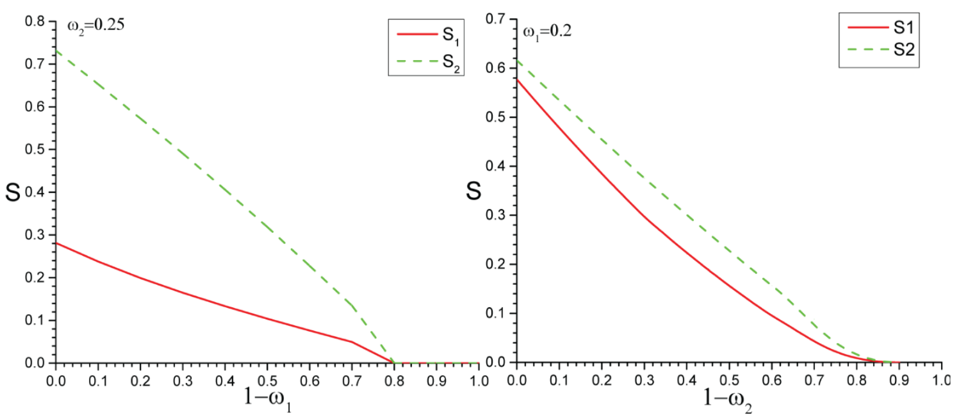


Figure 6. Sub-Network resilience with structural heterogeneity variation



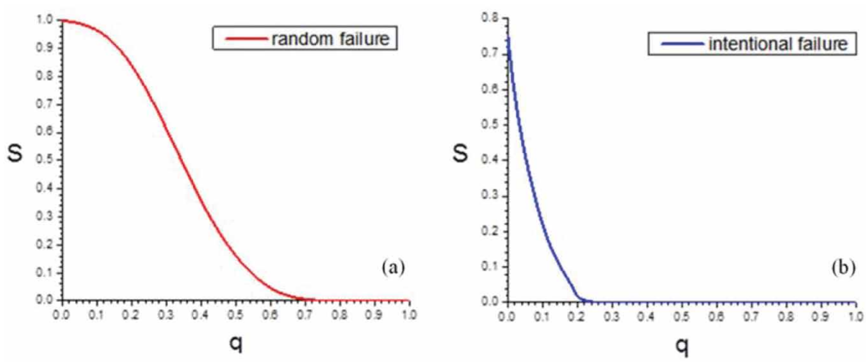
demonstrate the giant component exists until 70% of connections are broken in the network. And Figure 7b illustrates the targeted destruction of certain nodes, which most likely have many partnerships. When 20% of such nodes with the higher degree are removed, the giant component disappears. Therefore, the regional innovation network resists random failure better than intentional failure.

THE RESILIENCE PROTECTION STRATEGIES

We studied the resilience influenced by different connected probability, and the higher degree nodes are significant in terms of maintaining resilience of the network. Hence the protection strategies for network resilience need to be discussed.

To test which strategy is actually having the greatest effect, we simulate the giant component fraction in three protection policies. The first policy protects the nodes that have the highest degree

Figure 7. Simulation on the network resilience with linking failure



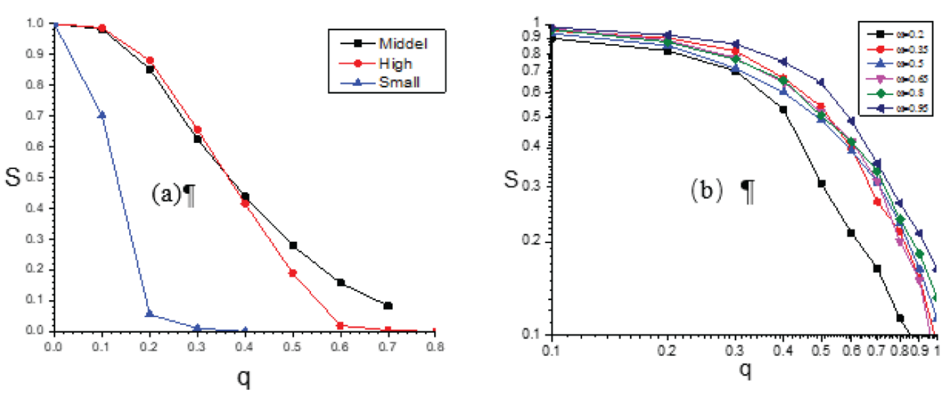
in the network. The second one keeps the nodes with the moderate higher degree out of removal. The third one prevents lower degree nodes from being removed.

As shown in Figure 8a, the protection of highest degree nodes is most effective within minor connected probabilities, but it is not better than the moderately higher degree nodes' policy. The lower degree nodes' protection has poor efficiency in structural heterogeneity. Therefore, if less than 40% of nodes are removed, we should protect the highest degree nodes, because they have more partners in the network. Otherwise, the second strategy is the best choice. The mediation of these nodes with large betweenness is responsible for strong resilience when keeping moderately higher degree nodes out of removal.

Finally, we should explore how structural heterogeneity influences network resilience in the best protection strategy. The simulation analysis results represent the resilience of a network with different connected probabilities under the moderately higher degree nodes' protection. As Figure 8b illustrates, the network has strong resilience when the probability is more than 0.65.

The safeguarding of nodes with a moderate degree of distribution is pivotal for ensuring effective knowledge dissemination, promoting technological iteration, and maintaining the overall vibrancy of the network's innovation. Although these nodes are not the most connected hubs within the network, they play an essential role in linking different innovators, disseminating new knowledge and technology,

Figure 8. The resilience protection strategies



and facilitating cross-disciplinary collaboration. Protecting these nodes ensures that the flow of knowledge is not interrupted due to issues with specific nodes, thereby maintaining the dynamism and adaptive capacity of the innovation network. For instance, in a scientific research cooperation network, these nodes might represent a particular research team or a medium-sized laboratory, transferring knowledge between various research fields and fostering interdisciplinary cooperation and development. If these nodes are protected, the continuity of innovation and the overall health of the network can be safeguarded, even in the face of resource constraints or external shocks. Moreover, these nodes often serve as testing and feedback points for emerging technologies or products, with their security directly linked to the iteration speed of innovative outcomes and market response.

CONCLUSION

Our study delved into the role of connection probability within the overall system and its subnetworks on the resilience of regional innovation networks. By employing a multi-network stochastic probability algorithm grounded in classical generating functions, we simulated the emergence of a dual network that reflects the complexities of an actual innovation network. Our numerical simulations were geared toward evaluating the network's resilience, with a particular focus on the influence of global network properties and the structural heterogeneity present within its subnetworks.

We found that the resilience of regional innovation networks is significantly influenced by structural heterogeneity, particularly within university subnetworks, as compared to the architectural changes in enterprise subnetworks. A notable discovery was that a reduction in connection probability beyond the critical percolation threshold exerts a substantial negative influence on resilience. The strategic removal of nodes with moderately high connectivity incurs a profound impact on network robustness. Therefore, preserving a connection probability above the 65% mark emerges as a pivotal factor for maintaining robust resilience.

These insights contribute to two critical debates within network studies. First, our findings highlight the value of utilizing generating functions for determining percolation thresholds and the sizes of large coherent clusters in various real-world networks. Our probabilistic model is particularly effective in estimating the dynamic consequences of disrupted partnerships on technology diffusion within the innovation network. Second, the vital influence of nodes with moderate degrees of connectivity on network resilience is affirmed. This is particularly salient given that highly connected nodes are susceptible to targeted disruptions, while nodes with fewer connections contribute to network decentralization. This understanding is instrumental for the strategic governance of regional innovation networks.

Given the key findings, it is imperative to consider the practical policy implications of our study. Policymakers and network administrators can leverage our insights by developing targeted strategies to strengthen the resilience of regional innovation networks, particularly by focusing on the critical role of university subnetworks and ensuring the connection probability remains above the identified threshold. By applying our research outcomes, different regions can tailor their innovation policies to enhance network robustness, effectively mitigating the risks of disconnection and fostering a more sustainable innovation ecosystem.

Moving forward, further research can explore the resilience of innovation networks in the face of varied disruption scenarios, such as targeted attacks on nodes of different degrees or sequential failures. Additionally, extending our model to incorporate a broader range of network topologies and connection strategies can unveil new nuances in network resilience dynamics. The challenges for future research lie in understanding the interplay between network structure and the behavior of actors within these networks, especially under different conditions of stress and adaptation.

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