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The Impact of Shareholder and Director Networks on Corporate Technological Innovation: A Multilayer Networks Analysis

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Abstract: We adopt a multilayer networks approach to assess how network structural embeddedness affects corporate technological innovation. Our findings indicate an annual increase in both single-layer and multilayer networks, although adoption of the latter by Chinese listed companies is comparatively low. We found that structural embeddedness of multilayer networks positively impacts corporate technological innovation. By reducing uncertainty within the internal environment, these networks bolster technological innovation. Moreover, such embeddedness notably spurs innovation in non-state-owned companies and those with greater internal transparency and robust external oversight. Our analysis reveals an intermediate effect where structural embeddedness in multilayer networks influences innovation. Our work provides new insights into enhancing innovation capacity via network embeddedness and supplies empirical data on utilizing network resources for innovation. We also offer actionable guidance and policy advice for managers, investors, and policymakers, especially relevant amidst economic transformation and pursuit of technological self-reliance of China.

Keywords: multilayer networks; director network; shareholder network; technological innovation; embeddedness

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1. Introduction

Facing the impacts of a technological revolution, trade tensions, and the COVID-19 outbreak, China is building a new development pattern focused on bolstering domestic circulation, complemented by synergistic domestic and international dual circulations. Accelerating technological innovation and self-reliance is key to facilitating the domestic circulation and shaping the proactive position of China in the global circulation. From a macroeconomic perspective, companies, as the primary agents of innovation, play a crucial role in economic development, necessitating continuous self-improvement and innovation. From a micro perspective, technological innovation is crucial for enhancing company core competitiveness [1], improving company performance [2], and sustaining business viability [3].

In listed companies, ownership is shared among various shareholders, with governance provided by a board of directors. Shareholders with stakes in multiple companies, known as interlocking shareholders [4], create crucial economic links among firms [5]. A shareholder network is based on equity links among interlocking shareholders. If two shareholders co-own a listed company, a connection is established between them [6]. Interlocking shareholders in the shareholder network can influence corporate innovation decisions through enhanced monitoring and control over management [7,8]. Interlocking directors, serving on the boards of multiple companies, provide a reliable, low-cost connection between companies. The director network, based on these overlapping board positions [9–11], facilitates resource and information sharing through its structure and centrality [12–14].

Technological innovation is vital for both micro-level business development and macroeconomic growth. Numerous existing studies have confirmed the significant role of networks in corporate innovation. Network relationships [15,16] and network structures [17–19] are progressively infiltrating the domains of corporate strategic positioning and the dynamics of interactions between businesses. Interlocking shareholders and directors serve as crucial links between different businesses, facilitating the flow of information and resources in the market. Companies embedded in both shareholder networks [20] and director networks [18] display complex, multilayered network characteristics. According to the embeddedness hypothesis of Granovetter [21], economic actions are deeply rooted in social networks, suggesting that corporate technological innovation is influenced by both networks. However, existing literature lacks clarity on the combined impact of shareholders and directors on corporate innovation.

Granovetter [21,22] first introduced the concept of network embeddedness, highlighting how social relations affect individual behavior and decision making. This perspective was further developed by Uzzi [23], who emphasized the impact of network structure on individual behavior and resource acquisition. Deep embeddedness in both shareholder and director networks provides businesses with diverse resource acquisition avenues [24], intertwining these networks significantly [25].

Regarding the economic impact of these networks on corporate technological innovation, existing studies have primarily focused on single-layer networks with homogeneous nodes. As the field evolves, the importance of both shareholder and director networks in affecting businesses is recognized [14,26], but the specific impact and mechanisms of interlocking shareholders and directors remain unclear. With the development of complex network theory, it has been found that the relationship between subjects is difficult to be described by a single metric method [27,28]. In this context, the research approach of multilayer networks has emerged [29,30] and gradually become a novel analytical framework for studying the interconnected and interactive behaviors among numerous entities in complex systems [25,31–33]. Therefore, studying how multilayer networks with heterogeneous nodes influence corporate technological innovation is essential. For investors and managers, multilayer networks feedback provides valuable insights for innovation decision making, ensuring a healthy internal innovation environment. For policymakers and regulators, understanding the characteristics of these interconnected networks enables precise regulation and macroeconomic control, fostering a favorable external innovation environment for businesses, thus supporting the quest of China for technological self-innovation. Figure 1 shows the research framework diagram of this paper.

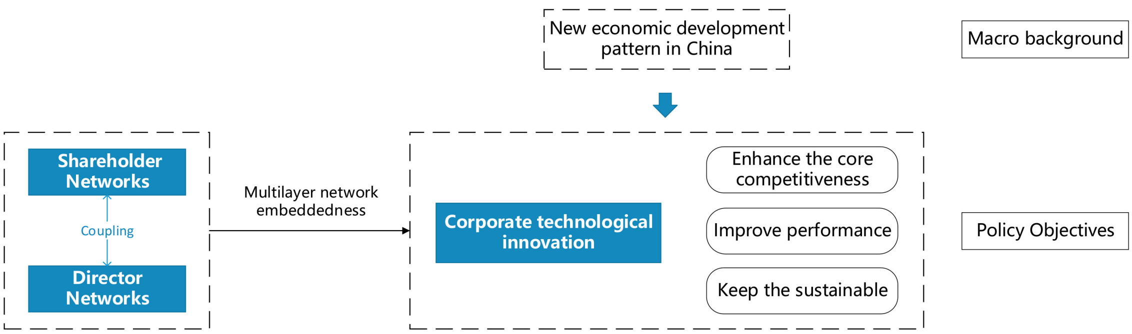

Figure 1. Research framework diagram.

We considered the limitations of single-layer network analyses in capturing how businesses are embedded in various governance bodies and adopted a multilayer networks perspective to analyze the impact of shareholder and director networks on corporate technological innovation. Firstly, shareholder and director adjacency matrices are constructed based on interlocking relationships, and their information is filtered to align the shareholders and directors with the same set of companies, resulting in a multilayer network.

Secondly, the structure of this network is analyzed, and indices for network structural embeddedness are measured. Thirdly, a panel data regression model is designed to examine the correlation between corporate technological innovation and structural embeddedness of multilayer networks. Fourthly, endogeneity tests, robustness checks, mediation effect tests, and heterogeneity tests are conducted on the main effects. We contribute to corporate governance research by introducing a multilayer networks analysis with heterogeneous nodes, expanding existing literature perspectives, and providing new evidence supporting previously discussed viewpoints. Furthermore, we elucidate the dominant mechanisms by which the positional advantages of heterogeneous nodes in multilayer networks influence corporate technological innovation, offering insights for promoting such innovation.

2. Literature Review

2.1. Shareholder Networks

Current research on shareholder networks typically focuses on individual shareholder functions and the overall characteristics of the network.

The analysis of shareholder functions considered aspects like co-ownership concentration [5], multi-sector holdings [8,34], institutional cross-holdings [4,7,35,36], joint control [20], and beneficial ownership [37]. These studies explore the behavioral logic and pathways of shareholders in corporate governance, recognizing shareholders as not isolated entities but influenced by the actions of other shareholders and the company. However, this approach has limitations. Firstly, it treats each interlocking relationship as independent, overlooking the complex interdependencies within the network. Shareholder behavior is influenced not only by other nodes in the network but also by their positions within it. Secondly, this perspective focuses more on the allocation of shareholder resources, emphasizing mechanisms like equity concentration and balance of power, while overlooking the differences in behavior logic among shareholders influenced by the distribution of information resources and social capital.

From a network perspective, multiple studies have shown that multiple holdings can provide shareholders with information advantages and governance experience, leading to better corporate governance. For instance, Ma and Du [6] distinguished shareholder heterogeneity and found that the network centrality of non-controlling shareholders significantly curbs the self-serving actions of controlling shareholders, with institutional investors enhancing this effect. Huang and Jiang [26] differentiated networks into strong and weak ties, discovering that shareholder networks, as weak tie networks, positively impact corporate technological innovation through information advantage mechanisms. Bi et al. [38] suggested that co-control by multiple major shareholders brings about an equity balance, curbing financial redundancies and boosting innovation efficiency. Ma and Du [39] built a shareholder rights network based on direct economic and administrative relationships, clarifying the strategies for diverse shareholders to participate in decision making and acquire decision rights. Wan [40] established corporate shareholder networks based on informal common shareholder relationships, finding that network centrality and structural holes positively affect corporate performance. Chen [41] developed an institutional investor network based on mutual funds holding the same stocks, suggesting that these institutions utilize their information networks to enhance management's understanding of external information.

However, some studies indicate that shareholders within networks can exploit these connections to harm corporate interests. Pan et al. [42] supported the "competitive collusion" view, finding that interlocking shareholders not only fail to improve investment efficiency but also cause investment insufficiencies by forming interest alliances within the industry. Djankov et al. [35] observed that cross-holding institutional investors might balance interests between companies to maximize their investment portfolio returns. Luo and Shi [43] argued that as network distance increases, the authenticity of information diminishes. Companies at the core of the network are likely to receive redundant information, leading to higher information processing costs, reduced decision-making efficiency, and decreased R&D expenditure in an effort to avoid risks. Guo et al. [44] found that tightly connected network groups within institutional investor networks increase corporate agency costs and exacerbate inefficient investment phenomena.

The network structure approach addresses limitations in analyzing shareholder functions by recognizing that behavior and decision making are influenced by social network structures. Access to information and social capital within networks plays a critical role in shaping corporate technological innovation, especially for interlocking shareholders embedded in these structures. This approach highlights the influence of the network position of a shareholder on their access to resources and subsequent decision-making behavior.

2.2. Director Networks

The research on director networks is primarily conducted from individual and organizational perspectives. The individual perspective focuses on interpersonal networks, defining the director network as a collection of relationships among individual board members, established through concurrent service on at least one board [45]. The organizational perspective, on the other hand, considers organizational relationship networks, viewing the director network as a collection of relationships between boards (companies) formed due to directors holding multiple positions [46–49]. Research at the individual level examines the impact of the network position of a director on corporate technological innovation [13,45,50], the influence of network relationships on corporate behavior [10], and the effect of personal attributes of directors on the distribution of network capital [51]. Organizational-level studies focus on how the position in the director network impacts corporate technological innovation [52,53], corporate performance [48,54,55], and the effects of information dissemination [56] and efficiency of information flow [57] in the director network.

Reviewing the literature reveals that existing research, from various network construction perspectives, has explored the impact of director networks on corporate governance. However, regardless of the research perspective, there is no consensus on the innovative effects of director networks. Current studies on the relationship between director networks and corporate technological innovation present three conclusions: promotion, inhibition, and threshold theories. The promotion theory posits that director networks provide information and resources to foster innovation, drawing on the principles of resource dependency and social network theory. According to resource dependency theory, companies need external resources for survival, and director networks offer vital channels for resource exchange, promoting technological innovation through access to financing opportunities [13], emerging technologies [13,58], etc. Social network theory suggests that different network positions offer varying capacities for information and resource acquisition. Companies in advantageous network positions typically have a better reputation and more network power, leading to increased efficiency in inter-organizational information flow and resource access [45,50,57]. This, in turn, enhances corporate technological innovation.

The inhibition theory argues that innovation activities, requiring long-term investment and carrying significant risk, can impact short-term performance [59], and director networks exacerbate agency conflicts, thus inhibiting technological innovation. According to agency theory, network connections can lead to redundant information, which distracts directors and diminishes their monitoring abilities. Extensive network connections might foster interest groups among directors, promoting short-sighted behaviors and crowding out innovation resources [53]. From the perspective of network dynamics, earnings manipulation behavior can spread through director networks [60], adversely affecting technological innovation. The threshold theory suggests that the resource effect of networks has a threshold. Based on resource-based theory, the quantity of information and resources brought by the network can create a "lock-in effect" when it exceeds a critical value, leading to information redundancy, exacerbating "free-riding" behavior, and involuntary knowledge spillovers [61].

In summary, research on the impact of director networks on corporate technological innovation is abundant, while studies on the influence of shareholder networks are less frequent. Most research primarily uses director networks to represent internal corporate networks, thus neglecting other network types. Given that both shareholder and director governance are integral to internal corporate mechanisms, a comprehensive analysis of internal corporate networks should include both. We integrated the structural characteristics of shareholder and director networks to investigate how the position of a company in multilayer networks affects its technological innovation.

3. Theoretical Analysis and Research Hypothesis

Corporate technological innovation relies on both internal and external resources. The prospects and changes in industry technology determine the direction of innovation, while the ability to absorb resources and information is closely related to the network position of a company [62]. Social network theory indicates that trust from close business interactions significantly influences corporate behavior [63], and social capital theory suggests central network members access more social capital [64]. This indicates that central positions in networks facilitate corporate technological innovation investments through status and resource advantages: (1) Companies in central network positions enhance trust and dependency through frequent interactions with other members, improving their ability to broaden financing channels, increase debt financing, reduce financing costs, and ease financing constraints [65,66]. This provides stable, long-term funding for innovation activities and favorable investment decisions. (2) Companies in central positions enjoy a good reputation, making them more attractive as partners and providing more opportunities to select advantageous partnerships. This facilitates the flow of resources and knowledge between companies [67], providing a solid informational foundation for technological innovation. (3) Harmonious and close partnerships can mitigate conflicts of opinion in innovation activities, preventing directors from wasting unnecessary time and energy, which benefits increased innovation investments [68]. Long-standing close direct contacts enhance homogeneity between companies, which is conducive to sharing management systems, experiential knowledge, and accelerating the integration and management of existing knowledge [69]. This homogeneity fosters innovative thinking and the realization of innovation investment activities.

However, such innovation typically targets relatively low-risk projects, such as upgrading products and services [70]. This is because companies at the core of the network often show over-specialization and information homogenization, which limits their ability to explore new markets and solutions in new product development [71,72]. When a single-layer network exhibits such deficiencies, another type of network can counteract these through higher network positions, enhancing the effectiveness of information acquisition [73]. In multilayer networks where companies collaborate across shareholder and director networks, non-isomorphic coupling relationships exist [74,75]. Both types of networks, based on social network theory and social capital theory, transmit information and resources to companies: the network structure facilitates the flow of social capital among network subjects, and social capital promotes the pursuit of core network positions by network subjects. Both networks influence corporate innovation activities, but the mechanisms differ due to the logic of network relationship construction and the composition of the two types of network subjects.

For shareholder networks: (1) Shareholder networks are sparse. The characteristic that allows a shareholder to hold shares in any company enables them to connect with an unlimited number of companies [76], thus providing unrestricted access to information resources. Major shareholders usually have diverse investment portfolios, and shareholders in core positions can provide heterogeneous information and resources, distinct from directors. (2) The information sources of shareholders differ from directors. Shareholders generally do not participate directly in day-to-day company operations but delegate management to directors [77]. Therefore, shareholders offer advice and guidance from a different perspective than directors, focusing more on long-term value and investment returns.

However, the shareholder network based on the joint shareholding relationship has the following defects: (1) Sparse networks can limit in-depth information exchange and collaboration, potentially affecting the depth and efficiency of innovation cooperation. (2) The long-term perspectives of shareholders might also be misaligned with current operations and market needs, creating a gap between strategic planning and execution.

For director networks: (1) Director networks are denser. Independent directors, in principle, can serve on up to five company boards simultaneously [76], which limits the scale but increases the density of the director network. This structure promotes rapid information and resource circulation, enhancing the speed at which companies learn new knowledge. (2) Directors are directly involved in company operations and governance. Interlocking directors bring firsthand information and experiences from different companies into their roles, providing rich tacit knowledge and resources [78], thereby enhancing innovation capabilities.

However, director networks also have limitations: (1) Their limited scale restricts the diversity of information and resources obtained. (2) High-density networks can lead to information overload, increasing the pressure on directors and potentially diverting their attention from focusing on and investing in innovation activities within their company [53].

In summary, shareholder networks, with their unique information resources, long-term focus, and market insights, can effectively supplement the limitations of director networks in terms of information breadth and decision-making balance. Conversely, director networks, with their rapid information exchange, managerial expertise, and internal governance strengths, can address the gaps in shareholder networks, particularly in terms of weak connections and strategic misalignment. The synergistic interaction between these networks mitigates the shortcomings of a single-layer network, collaboratively enhancing overall corporate governance and technological innovation. Figure 2 shows the theoretical analysis framework of this paper.

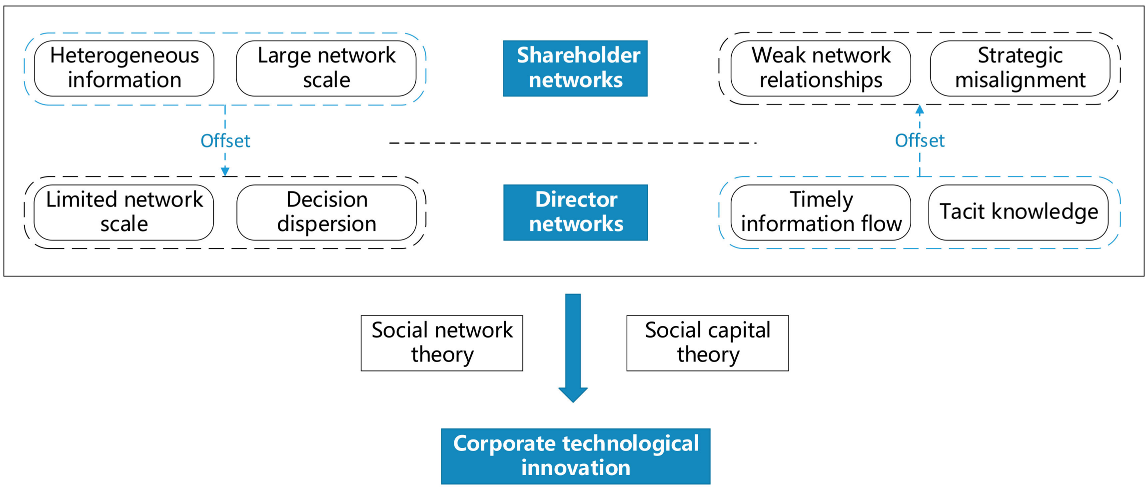

Figure 2. Theoretical analysis framework.

The structural embeddedness of multilayer networks not only brings diversity in resources and information for the innovating entity but also enables the avoidance of the costs associated with filtering redundant information through multiple channels of information acquisition. This further promotes the flow of useful information between companies. The accumulation of knowledge provided by advantageous network positions facilitates knowledge learning, reorganization, and integration within companies, leading to high-quality innovative outputs. Based on these considerations, the hypothesis is proposed:

H1: *The structural embeddedness of multilayer networks promotes corporate technological innovation.*

4. Research Methodology

4.1. Data

This research paper selects A-share listed companies from 2007 to 2019 as the initial study sample, and the sample selection is conducted as follows: first, data acquisition. The first step involves gathering data from the CSMAR and WIND databases. These data encompass the characteristics of directors and shareholders of the listed companies and their respective financial data. Second, data organization and network construction: The second step entails manual organization and verification of the data related to directors and shareholders. Each director or shareholder is assigned a unique ID. Multilayer networks are then constructed using R language. The centrality indices for directors and shareholders are calculated using UCINET 6.212 and Pajck 5.16 software. Third, cluster calculation and data refinement: In the third step, cluster calculations at the company level are performed. This includes data comparison, supplementation, and the removal of samples with significant missing or unreasonable data. The process results in a final set of 16,938 company-year observation samples with data from 3025 companies.

Additionally, this paper classifies industries based on the 2012 China Securities Regulatory Commission (CSRC) industry standards, with a detailed subdivision in manufacturing. To mitigate the impact of outliers, tail-trimming is applied to the top and bottom 1% of the main continuous variables. The financial data of the listed companies used in this study, including data on innovation investments and related corporate governance, are sourced from the Wind database and the CSMAR database.

4.2. Research Method

4.2.1. Main Effect Model

To test the core hypothesis, this paper constructs the fixed effect model. Model 1 is structured as follows:

$$innovation_{i,t} = \alpha_0 + \alpha_1 ddegree_{i,t} \times gdegree_{i,t} + \alpha_2 \sum controls_{i,t} + \sum industry_j + \sum year_t + \varepsilon_{i,t} \quad (1)$$

(1) Dependent Variable: The dependent variable, denoted as $innovation_{i,t}$, represents the innovation level of company i in year t. The innovation level is measured by the number of invention patent applications filed by the company. The choice of using patent applications as a measure is because they accurately reflect current innovation activities and provide quick feedback to external shocks. Additionally, patent approvals undergo a lengthy review process, making it difficult to accurately depict the effect of external influences within the same year [79]. Invention patents are chosen for their high value, representing a more reliable indicator of corporate technological innovation.

(2) Independent Variable: The independent variable, $ddegree_{i,t} \times gdegree_{i,t}$, represents the multilayer networks position centrality of company i in year t, defined as the interaction between the degree centrality of the director network and the shareholder network for that company in the given year. In the robustness test section, this paper also uses the interaction of multilayer networks closeness centrality and betweenness centrality as supplementary tests.

(3) Control Variables: The model incorporates several control variables based on existing research, including Company Size (*Size*), Leverage (*Lev*), Return on Assets (*ROA*), Revenue Growth Rate (*Growth*), Board Size (*Board*), Board Independence (*Indep*), CEO-Chairman Duality (*Dual*), Book-to-Market Ratio (*BM*), Property Nature (*SOE*), Company Age (*Company Age*), and the Shareholding Percentage of the Largest Shareholder (*Top1*). To control for industry and annual effects, the model includes year and industry dummy variables, where j and t represent specific classifications for industries and years, respectively. In empirical analysis, industry classification codes and years from the dataset are typically used to create fixed effect variables. These classification codes are usually established during the data collection or organization phase and are reflected in the corresponding variables within the dataset.

4.2.2. Measures of Core Variables

We used network centrality indices, referencing the approaches of AlKuaik et al. [80] and Arranz et al. [64], to measure network structure embeddedness. The specific measurement methods are as follows:

(1) Director Network Degree Centrality:

Freeman [81] proposed that "centrality" depicts whether an actor is closer to the center or the periphery of a social network. Degree centrality is particularly effective in measuring the connectivity between various nodes in a network. It quantifies the number of companies that have direct contact with those embedded in the director network. Companies with higher degree centrality are more active in the network and receive more homogeneous information. As Haunschild and Beckman [82] noted, degree centrality captures the quantity of information sources available to a company.

The calculation method involves first computing the network indicators for directors.

$$ddegree_{i,t} = \frac{\sum_j X_{i,j}}{g-1}, i \neq j \tag{2}$$

For director i, if i and another director j are employed by the same company, $X_{i,j}$ is assigned a value of 1; otherwise, it is 0. The variable g represents the total number of directors in listed companies for that year. The difference in the number of directors each year is normalized by using $g-1$.

At the company level, the network position indices of all directors are aggregated. The company is considered a node in the network, and the average degree centrality of all directors is used as the network characteristic indicator for the company, denoted as *ddegree*. The higher this indicator, the greater the embeddedness of the company in the network. To reduce the influence of dimensionality, the *ddegree* indicator is standardized.

This paper measures network structure embeddedness using the following network centrality indices:

(2) Closeness Centrality of Director Network:

Closeness centrality of a node, as defined by Freeman [81], is a measure based on the "distance" between nodes in a network. A node with shorter distances to all other nodes in the network has higher closeness centrality. We indirectly measured the closeness centrality of a company through the network relationships between its directors. The calculation of "relative closeness centrality" is necessary to compare closeness centrality from different graphs.

$$dcloseness_{i,t} = \frac{g-1}{\left[\sum_{j=1}^{g} d(i,j)\right]}, i \neq j \tag{3}$$

The formula includes $d(i,j)$, representing the distance from director i to director j and signifies the control capability within the network.

Company-level closeness centrality is calculated by aggregating the network position indices of all directors. The average closeness centrality of all directors is taken as the network feature indicator for the company, *dcloseness*. To mitigate dimensionality effects, this indicator is standardized.

(3) Betweenness Centrality of Director Network:

Freeman [81,83] suggests that a person who must be passed through by others to establish connections is in a critical position, as they can influence the group by controlling or distorting the transmission of information. Betweenness centrality measures the extent to which a node controls the interactions between other nodes. A node with a betweenness centrality of 0 implies no control over any other nodes in the network, indicating a peripheral position. Conversely, a centrality of 1 means complete control over other nodes, indicating a central, powerful position.

$$dbetween_{i,t} = \frac{2\sum_j^g \sum_k^g b_{jk}(i)}{g^2-3g+2}, j \neq k \neq i, j < k \tag{4}$$

The calculation involves $b_{jk}(i)$, indicating the ability of node *i* to control the interactions between nodes *j* and *k*, which is equal to the probability that node *i* lies on the shortest path between nodes *j* and *k*. The value of this formula ranges from 0 to 1.

Company-level betweenness centrality is also calculated by aggregating the network position indices of all directors. The average betweenness centrality of all directors is taken as the network feature indicator for the company, *dbetween*. To reduce the influence of dimensionality, this indicator is standardized.

(4) Degree Centrality of Shareholder Network:

Initially, the sample company data are organized into a company–common shareholder–company bipartite relationship link using the QT-Creator programming platform, forming an undirected binary shareholder connection network graph. Based on this, the RStudio 2022.07.2 is used to calculate the network centrality indicators, representing different positions within the shareholder network.

Degree centrality reflects the total number of direct contacts each entity has with others. It not only shows the connectivity of each individual with others but also relates to the scale of the shareholder connection network. As the size of the shareholder network increases, the value of degree centrality correspondingly rises. To neutralize the effect of network size on degree centrality, a standardized measurement formula is utilized.

$$gdegree_{i,t} = \frac{\sum_j X_{i,j}}{g-1}, i \neq j \tag{5}$$

(5) Closeness Centrality of Shareholder Network:

Closeness centrality indicates the proximity of a shareholder to other shareholders in the network, reflecting the closeness of contacts with others. The calculation method is similar to that used for the director network.

$$gcloseness_{i,t} = \frac{g-1}{\left[\sum_{j=1}^{g} d(i,j)\right]}, i \neq j \tag{6}$$

(6) Betweenness Centrality of Shareholder Network:

Betweenness centrality focuses on the control exerted by individual shareholders within the shareholder network. The calculation method follows the same principles as outlined for the director network.

$$gbetween_{i,t} = \frac{2\sum_j^g \sum_k^g b_{jk}(i)}{g^2 - 3g\_2}, j \neq k \neq i, j < k \tag{7}$$

Subsequently, the company-level degree centrality, closeness centrality, and betweenness centrality indicators for the shareholder network are computed using similar methods to those employed for the director network.

Table 1 lists the variable definitions for this paper.

Table 1. Description and measurement of variables.

Variable Type	Variable Symbol	Variable Name	Variable Measurement
Dependent variable: Technological innovation	*innovation*	Number of invention patent applications	*ln* (1 + number of invention patent applications in year *t* of company *i*).
	Rdperson	Proportion of R&D personnel (for robustness test)	The proportion of R&D personnel in the total number of employees in year *t* of company *i*.
	rd	R&D expenditure (for robustness test)	The proportion of the R&D expenditure to its operating income in year t of the company *i*.

Table 1. *Cont.*

Variable Type	Variable Symbol	Variable Name	Variable Measurement
Independent variable: Director network centrality	*ddegree*	Director network degree centrality	$ddegree_{i,t} = \frac{\sum_j X_{i,j}}{g-1}, i \neq j$
	dcloseness	Director network closeness centrality (for robustness test)	$dcloseness_{i,t} = \frac{g-1}{\left[\sum_{j=1}^{g} d(i,j)\right]}, i \neq j$
	dbetween	Director network betweenness centrality (for robustness test)	$dbetween_{i,t} = \frac{2\sum_j^g \sum_k^g b_{jk}(i)}{g^2-3g\_2}, j \neq k \neq i, j < k$
Independent variable: Shareholder network centrality	*gdegree*	Shareholder network degree centrality	$gdegree_{i,t} = \frac{\sum_j X_{i,j}}{g-1}, i \neq j$
	gcloseness	Shareholder network closeness centrality (for robustness test)	$gcloseness_{i,t} = \frac{g-1}{\left[\sum_{j=1}^{g} d(N_i,N_j)\right]}(i \neq j)$
	gbetween	Shareholder network betweenness centrality (for robustness test)	$gbetween_{i,t} = \frac{2\sum_j^g \sum_k^g b_{jk}(i)}{g^2-3g\_2}, j \neq k \neq i, j < k$
Control variable	*Size*	Company size	The natural logarithm of total assets of the company for the year.
	Lev	Asset–liability ratio	The ratio of total liabilities to total assets of the company for the year.
	ROA	Return on total assets	(Total profit + Interest expense)/Average total assets
	Growth	Revenue growth rate	(Current operating income for the year–Operating income for the previous year)/Operating income for the previous year.
	Board	Board size	*ln* (Number of directors).
	Indep	Board independence	Number of independent directors/Number of board members.
	Dual	Dual function	1 if the chairman is also the CEO, otherwise 0.
	BM	Book-to-market ratio	The ratio of total assets to market value, where market value = book value of liabilities + market value of tradable shares + number of non-tradable shares × net asset value per share.
	SOE	Property right nature	1 for state-owned companies and 0 for non-state-owned companies.
	Companyage	Company age	*ln* (up to current year of incorporation).
	Top1	Proportion of the largest shareholder	Shares held by the largest shareholder/Total shares of the company.

5. Empirical Results and Analysis

5.1. Data Feature Analysis

We categorized companies based on the annual median values of their director network degree centrality and shareholder network degree centrality. They were divided into three groups: (1) Lower Multilayer Networks Degree Centrality Group: Companies where both the director network degree centrality and shareholder network degree centrality are below the median. (2) Single Network Higher Degree Centrality Group: Companies where either the director network degree centrality or the shareholder network degree centrality is above the median. (3) Higher Multilayer Networks Degree Centrality Group: Companies where both the director network degree centrality and shareholder network degree centrality are above the median.

Table 2 presents the annual distribution of the number of samples with varying degrees of centrality in multilayer networks. From 2007 to 2019, there is an upward trend in the number of samples across all three groups. The lower multilayer networks degree centrality group grew from 53 samples in 2007 to 757 in 2019, demonstrating a steady upward trend. Particularly after 2012, the growth rate of this group accelerated. The number of samples in the single network higher degree centrality group peaked in 2019. In contrast, the higher multilayer networks degree centrality group saw the most significant growth throughout the period, especially from 2017 to 2019.

Table 2. Temporal distribution of degree centrality of companies in multilayer networks.

Year	Lower Multilayer Networks Degree Centrality Group	Single Network Higher Degree Centrality Group	Higher Multilayer Networks Degree Centrality Group	Total
2007	53	100	51	204
2008	75	135	74	284
2009	99	166	92	357
2010	169	344	167	680
2011	232	362	218	812
2012	333	600	326	1259
2013	362	596	361	1319
2014	368	696	361	1425
2015	435	769	431	1635
2016	479	865	476	1820
2017	596	1000	590	2186
2018	641	1030	631	2302
2019	757	1149	749	2655
Total	4599	7812	4527	16,938

Furthermore, Figure 3 presents the trends in the number of companies within three distinct network degree centrality groups from 2007 to 2019. The lower multilayer networks degree centrality group (blue line) shows moderate growth in the number of companies in this group from 2007 to 2011. Post-2011, the growth rate accelerated, particularly from 2013 onwards, culminating in a notable increase by 2019. The single network higher degree centrality group (red line) exhibits a consistently faster growth in company numbers from the outset in 2007, maintaining a steady rise through to 2019. It had the most rapid and stable growth trajectory among the three groups. The higher multilayer networks degree centrality group (black line) shows the growth in company numbers in this group was slow from 2007 to 2012 but began to accelerate in 2013, with a significant uptick between 2014 and 2015. After 2016, the growth pace decelerated yet continued to show an overall upward trend.

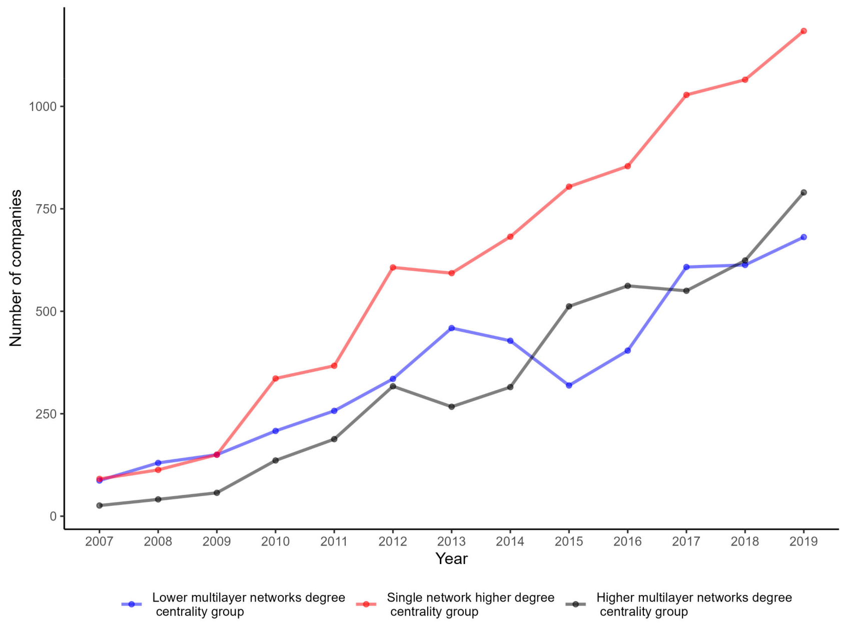

Figure 3. Temporal distribution of degree centrality of companies in multilayer networks.

Overall, all three groups demonstrate an increasing trend in company numbers, yet they differ in growth rate and timing. This may reflect an industry-wide increase in network connections and the dynamic changes in the number of companies at different levels of network centrality. The steady growth in the red line signifies that companies with high centrality in a single network maintain their numerical dominance despite overall market shifts. The divergent growth in the black and blue lines could point to internal industry structural dynamics, possibly driven by technological advancements, market strategy shifts, or industry policy changes. These trends underscore the importance of considering a company's position within both single and multilayer networks when examining the impact of network location on business performance.

Figure 4 illustrates the trends in the average number of patent applications for three different groups of companies, categorized by network centrality, from 2007 to 2019. The lower multilayer networks degree centrality group (blue line) exhibits a relatively stable trend, with minor fluctuations from 2007 to 2011, but then shows a year-by-year increase starting in 2011, despite some fluctuations in the growth rate. The single network higher degree centrality group (red line) shows an overall upward trend in the average number of patent applications but experiences a significant drop in 2019. The higher multilayer networks degree centrality group (black line) trend is the most pronounced, gradually ascending from 2007 and rapidly growing after 2016, especially in 2018 and 2019, indicating the strongest growth momentum. The relationship between the three lines suggests that there is a clear disparity in the number of patent applications among companies with different degrees of network centrality. Companies with higher multilayer network centrality are evidently outpacing the other two groups in growth rate, possibly because they are better able to leverage their network positions to foster innovation.

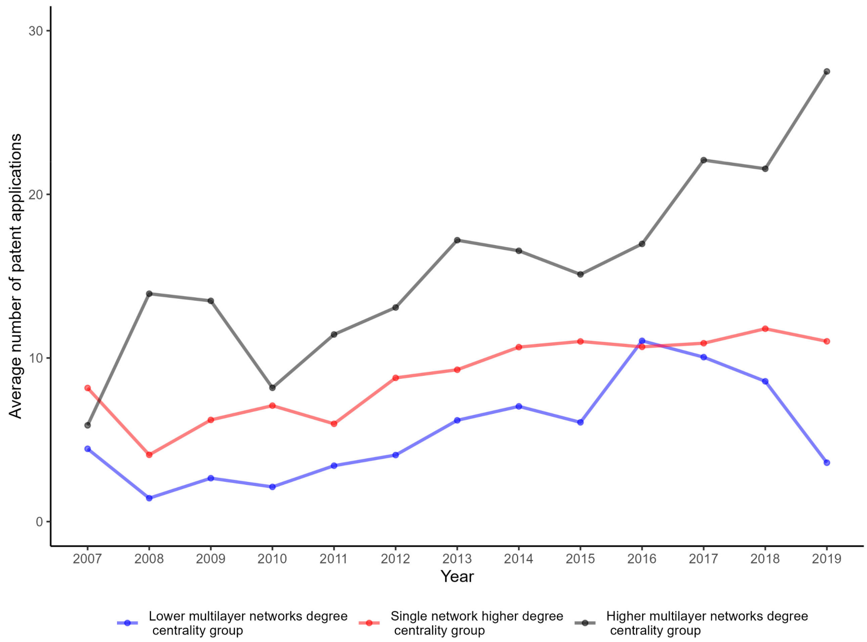

Figure 4. Trends in differences in total patent applications for companies in different network positions.

The analysis indicates that the degree of a company's centrality within networks may play a role in its innovative output, as measured by patent applications. The most significant finding is the robust growth in patent applications for companies in the higher multilayer networks degree centrality group, suggesting that a prominent network position may be advantageous for innovation.

To examine the differences in innovation levels indicated by single-layer network degree centrality, we further divided the group with higher single-layer network degree centrality into two subgroups based on the annual median: companies with higher shareholder network degree centrality and those with higher director network degree centrality.

Figure 5 displays the trends in the average number of patent applications for two groups of companies from 2007 to 2019. The higher director network degree centrality group (blue line) shows the average number of patent applications fluctuated minimally from 2007 to 2011, began to trend upward in 2012, and exhibited significant growth from 2016 to 2019. The higher shareholder network degree centrality group (red line) shows the companies represented by this line had relatively lower numbers of patent applications starting in 2007 but showed a rapid increase in trend from 2013 onwards, particularly with marked growth in 2018 and 2019. The relationship between the two lines indicates that the centrality of the director network has a slower impact on the number of patent applications compared to the shareholder network centrality, but both have been on the rise since 2013.

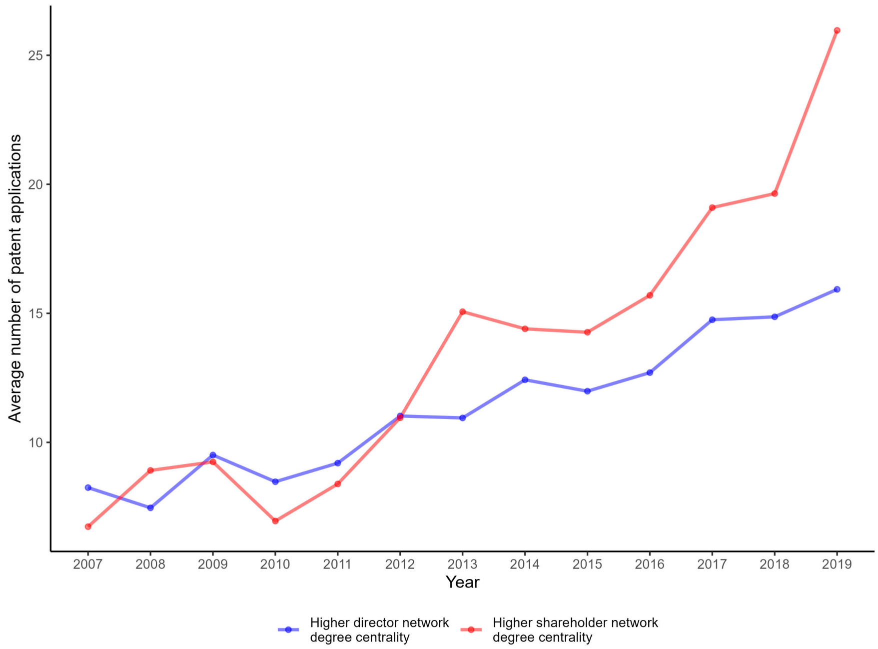

Figure 5. Trend in patent application volume based on degree centrality in single-layer network.

This analysis reflects the differing impacts that director and shareholder network centralities may have on corporate patent application activities, with shareholder centrality showing a more pronounced effect in recent years.

5.2. Descriptive Statistics

Table 3 provides the descriptive statistics of the variables. The data show that in terms of R&D investment by companies, the proportion of R&D personnel ranges from a minimum of 0% to a maximum of 94.490%, with a median of 5.665% and an average of 9.797%. This distribution is right-skewed, indicating an uneven distribution across the sample. The minimum R&D expenditure is 0%, with a maximum of 37.400%, a median of 3.340%, and an average of 4.235%, also showing a right-skewed distribution. Regarding the innovation output of companies, the number of patent applications (*innovation*) has an average of 1.119 but a median of only 0.693, suggesting that most companies in the sample have lower volumes of patent applications. In terms of director and shareholder network centrality, the minimum and maximum values for director network degree centrality are 0 and 4.898, respectively; for closeness centrality, the minimum is 0 and the maximum is 1.000; and for betweenness centrality, the range is from 0 to 0.098. For shareholder network degree centrality, the minimum is 0 and the maximum is 0.682, with closeness centrality ranging from 0.132 to 1.000, and betweenness centrality from 0 to 0.015. In summary, these descriptive statistics reveal significant disparities among the sampled companies in terms of R&D investment, innovation outcomes, organizational size, and network structure.

Table 3. Descriptive statistics.

Variables	N	Mean	sd	Min	p25	p50	p75	Max
rdperson	16,938	9.797	13.180	0.000	0.000	5.665	14.450	94.490
rd	16,938	4.235	5.136	0.000	1.130	3.340	5.120	37.400
innovation	16,938	1.119	1.357	0.000	0.000	0.693	1.946	8.460
ddegree	16,938	1.041	0.558	0.126	0.628	1.005	1.381	4.898
dcloseness	16,938	0.102	0.227	0.000	0.000	0.000	0.091	1.000
dbetween	16,938	0.001	0.001	0.000	0.001	0.028	0.041	0.098
gdegree	16,938	0.094	0.151	0.000	0.003	0.017	0.090	0.682
gcloseness	16,938	0.406	0.105	0.132	0.343	0.387	0.452	1.000
gbetween	16,938	0.001	0.001	0.000	0.000	0.000	0.001	0.015
Size	16,938	22.100	1.296	19.320	21.160	21.900	22.820	26.390
Lev	16,938	0.402	0.198	0.027	0.242	0.395	0.550	0.908
ROA	16,938	0.046	0.059	−0.373	0.019	0.046	0.072	0.257
Growth	16,938	0.169	0.377	−0.645	0.000	0.101	0.259	4.024
Board	16,938	2.138	0.195	0.000	1.946	2.197	2.197	2.708
Indep	16,938	0.374	0.053	0.000	0.333	0.333	0.430	0.600
Dual	16,938	0.291	0.454	0.000	0.000	0.000	1.000	1.000
BM	16,938	0.612	0.234	0.064	0.435	0.612	0.785	1.225
SOE	16,938	0.335	0.472	0.000	0.000	0.000	1.000	1.000
CompanyAge	16,938	2.787	0.375	0.693	2.565	2.833	3.045	3.555
Top1	16,938	0.353	0.147	0.083	0.236	0.336	0.452	0.758

Table 4 presents the results of the *t*-test for the mean values of the sample. Specifically, based on the annual median of director/shareholder network degree centrality, the sample is divided into two groups: "Group G1 (0) with both director and shareholder network degree centralities below the median" and "Group G2 (1) with either director or shareholder network degree centrality above the median". The *t*-test conducted on the volume of patent applications reveals that the innovation level of Group G2 (1) is significantly higher than that of Group G1 (0). This indicates that the innovation level of companies not falling into the category of both director and shareholder network degree centralities being below the median is significantly higher than those that do, preliminarily validating our core hypothesis.

Table 4. Mean *t*-Test.

Variable	G1(0)	Mean1	G2(1)	Mean2	MeanDiff
innovation	4527	1.019	12411	1.391	−0.372 ***

Note: *** indicates statistical significance at the 1% level. Robust standard errors clustered at the company level are used in this paper, with t-values shown in parentheses, and the same applies to the table below.

5.3. Baseline Regression

Table 5 describes the regression results examining the impact of multilayer networks on technological innovation. This table reveals that centrality in multilayer networks positions significantly enhances corporate technological innovation. Specifically, column (1) does not control for industry and year, while column (2) does. The regression results show that the coefficients for the interaction term of multilayer networks structure are significantly positive, confirming our core hypothesis: the structural embeddedness of multilayer networks promotes the corporate technological innovation.

Table 5. Baseline regression of the impact of multilayer networks on technological innovation.

	(1)	**(2)**
	innovation	***innovation***
ddegree × *gdegree*	0.0204 ***	0.0254 ***
	(3.968)	(6.464)
Size	0.282 ***	0.329 ***
	(20.103)	(26.032)
Lev	−0.319 ***	−0.281 ***
	(−4.918)	(−4.182)
ROA	1.601 ***	1.908 ***
	(8.396)	(9.863)
Growth	−0.138 ***	−0.177 ***
	(−5.717)	(−6.665)
Board	−0.0728	0.101
	(−1.012)	(1.605)
Indep	−0.00138	0.000750
	(−0.549)	(0.348)
Dual	0.0507 **	0.0270
	(2.218)	(1.217)
BM	−0.389 ***	−0.282 ***
	(−7.425)	(−4.689)
SOE	0.0110	0.142 ***
	(0.429)	(5.664)
CompanyAge	−0.154 ***	−0.152 ***
	(−5.554)	(−4.898)
Top1	−0.00169 **	−0.000559
	(−2.237)	(−0.792)
Year/Industry	NO	YES
_cons	−4.147 ***	−5.812 ***
	(−12.412)	(−19.498)
N	16,938	16,938
r2	0.0613	0.198
r2_a	0.0606	0.193
F	64.64	14.6

Note: ***, ** indicate statistical significance at the 1% and 5% levels respectively. Robust standard errors clustered at the company level are used in this paper, with t-values shown in parentheses, and the same applies to the table below.

5.4. Endogeneity Tests

5.4.1. Instrumental Variable Method

- The lagged term of the independent variable

There might be reverse causality, an endogeneity issue, between network centrality and corporate innovation levels. That is, the higher the level of corporate innovation, the more likely it is to attract more capital shareholders, leading to varying degrees of connections with other invested companies [20]. We used the lagged interaction term of the multilayer networks structure (IV1) as an instrumental variable for testing. Table 6 reports the results of the instrumental variable test, indicating that our conclusions are largely supported by the instrumental variable test.

- The network scale

We use network scale as our second instrumental variable. Network scale refers to the total number of nodes within a network. While network scale directly correlates with network centrality, it does not have a direct impact on a firm's level of innovation. Larger networks, with more nodes, provide increased opportunities for nodes to establish connections with others, potentially enhancing their centrality in the network. However, the following reasons account for the lack of a direct correlation between network scale and firm innovation levels: (1) Independence of network scale and innovation quality. Network scale primarily involves the number of nodes, reflecting the extent of a company's connections with other entities. This mirrors the breadth rather than the depth of connections. Innovation levels, however, relate more to the quality of knowledge, research and development inputs, and technological innovativeness, factors not necessarily enhanced by an expanding network scale. (2) Diversity and complexity of innovation. The innovation process is often complex and multifaceted, influenced by a variety of factors such as a company's R&D capabilities, organizational culture, market positioning, and industry characteristics, which may not directly link to network scale. (3) Heterogeneity of the network. Even in large networks, there can be significant differences in the innovation capabilities of nodes (i.e., other companies or entities). Some nodes in a network may not possess high innovation capabilities, meaning that an expansion in network scale does not necessarily enhance the overall network's level of innovation. (4) Quality of connections and relationship strength. Innovation often requires in-depth collaboration and knowledge exchange, relying on strong network relationships and high-quality interactions. Large-scale networks might predominantly consist of weak relationships, which may have limited effects on promoting deep collaboration and knowledge sharing. In summary, the size of a network does not directly impact the innovation level of individual firms. Table 7 reports the results of the instrumental variable test, indicating that our conclusions are largely supported by the instrumental variable test.

Table 6. IV test—the lagged interaction term of the multilayer networks structure.

	(1) **First Stage** ***ddegree* × *gdegree***	**(2)** **Second Stage** ***innovation***
IV1	0.879 ***	
	(12.01)	
ddegree × *gdegree*		0.032 ***
		(5.29)
Size	0.553 ***	0.279 ***
	(27.94)	(17.72)
Lev	−0.743 ***	−0.280 ***
	(−6.59)	(−3.41)
ROA	0.053	1.596 ***
	(0.17)	(6.90)
Growth	−0.382 ***	−0.067 *
	(−7.99)	(−1.92)
Board	0.202*	−0.063
	(1.84)	(−0.79)
Indep	0.002	−0.001
	(0.41)	(−0.36)
Dual	0.007	0.037
	(0.17)	(1.33)
BM	−1.286 ***	−0.369 ***
	(−15.19)	(−5.93)
SOE	−0.109 ***	0.046
	(−2.67)	(1.57)
CompanyAge	0.227 ***	−0.245 ***
	(4.56)	(−6.78)
Top1	0.003 **	−0.002 **
	(2.22)	(−2.35)
Constant	−11.733 ***	−3.872 ***
	(−24.34)	(−10.25)
Observations	12,886	12,886
R−squared	0.639	0.650

Note: ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered at the company level are used in this paper, with t-values shown in parentheses, and the same applies to the table below.

Table 7. IV test—the network scale.

	(1) First Stage *ddegree × gdegree*	(1) Second Stage *innovation*
IV2	0.0003 ***	
	(31.03)	
ddegree × gdegree		0.059 ***
		(3.43)
Size	1.071 ***	0.235 ***
	(49.46)	(9.83)
Lev	−1.558 ***	−0.235 ***
	(−12.21)	(−3.03)
ROA	0.438	1.617 ***
	(1.17)	(8.02)
Growth	−0.537 ***	−0.118 ***
	(−10.22)	(−3.99)
Board	1.179 ***	−0.098
	(9.50)	(−1.47)
Indep	0.021***	−0.002
	(4.83)	(−0.88)
Dual	−0.043	0.049 **
	(−0.98)	(2.08)
BM	−2.058 ***	−0.316 ***
	(−20.98)	(−5.10)
SOE	0.315 ***	0.009
	(6.57)	(0.34)
CompanyAge	−0.027	−0.186 ***
	(−0.45)	(−5.86)
Top1	0.004 ***	−0.002 **
	(3.27)	(−2.46)
Constant	−26.582 ***	−3.067 ***
	(−52.30)	(−5.56)
Observations	16,938	16,938
R−squared	0.270	0.056

Note: ***, ** indicate statistical significance at the 1% and 5% levels, respectively. Robust standard errors clustered at the company level are used in this paper, with t-values shown in parentheses, and the same applies to the table below.

5.4.2. Higher-Order Joint Fixed Effects

To further address issues of endogeneity and considering the interrelationships between companies in different cities and years, we employed a higher-order fixed effects method. This involves fixing industry-year and city-year level fixed effects and clustering at the city-year level to mitigate heteroscedasticity. The regression results, as shown in Table 8, demonstrate that the conclusions are fundamentally robust.

Table 8. Higher-order joint fixed effects.

	(1) *innovation*	(2) *innovation*
ddegree × gdegree	0.0790 ***	0.0227 ***
	(15.181)	(5.343)
Size		0.342 ***
		(17.291)
Lev		−0.280 ***
		(−3.760)
ROA		1.943 ***
		(7.944)
Growth		−0.176 ***
		(−6.613)

Table 8. *Cont.*

	(1) *innovation*	(2) *innovation*
Board		0.0185
		(0.224)
Indep		0.000513
		(0.166)
Dual		−0.000315
		(−0.013)
BM		−0.351 ***
		(−5.252)
SOE		0.163 ***
		(5.512)
CompanyAge		−0.144 ***
		(−3.628)
Top1		−0.00120
		(−1.395)
Industry×Year	YES	YES
City×Year	YES	YES
City−time level clustering	YES	YES
_cons	1.008 ***	−5.870 ***
	(138.044)	(−12.868)
N	16,938	16,937
r2	0.328	0.377
r2_a	0.135	0.198
F	230.5	68.65

Note: *** indicates statistical significance at the 1% level. Robust standard errors clustered at the company level are used in this paper, with t-values shown in parentheses, and the same applies to the table below.

5.5. Robustness Tests

5.5.1. Variable Replacement

- Dependent variable replacement

We conducted a robustness test by utilizing variable replacement. Specifically, the proportions of research personnel (*rsperson*), research expenditure (*rd*), innovation quality (*LnCit*), total patent applications (*Patent_sum*), and innovation efficiency (*InnoEff*) were employed as proxy variables for the level of innovation to re-run regression on Model 1. Innovation quality is measured using the natural logarithm of one plus the total number of citations received by the firm's patent applications in the following year. The total number of patent applications is calculated using the natural logarithm of one plus the combined quantity of applications for invention patents, utility model patents, and design patents. Innovation efficiency, defined as the number of patent applications per unit of research and development investment, is calculated using the formula $Patent\_sum/ln(1 + R\&D\ expenditure)$.

According to the regression results in Table 9, columns (1), (2), (3), (4), (5), the conclusions remain unchanged.

Table 9. Robustness test for dependent variable replacement.

	(1) *rdperson*	(2) *rd*	(3) *LnCit*	(4) *Patent_sum*	(5) *InnoEff*
ddegree × gdegree	0.351 **	0.0322 **	0.0419 ***	0.0206 ***	0.000818 ***
	(2.217)	(2.411)	(11.126)	(5.185)	(3.729)
Size	0.344 ***	0.266 ***	0.677 ***	0.662 ***	0.0275 ***
	(3.494)	(6.190)	(55.957)	(51.836)	(38.996)
Lev	−4.972 ***	−5.136 ***	−0.345 ***	−0.0731	−0.00195
	(−9.480)	(−22.491)	(−5.351)	(−1.074)	(−0.520)

Table 9. *Cont.*

	(1) *rdperson*	(2) *rd*	(3) *LnCit*	(4) *Patent_sum*	(5) *InnoEff*
ROA	−6.632 ***	−6.853 ***	0.872 ***	1.411 ***	0.0654 ***
	(−4.394)	(−10.426)	(4.706)	(7.210)	(6.054)
Growth	0.193	−0.425 ***	−0.138 ***	−0.0185	−0.000697
	(0.934)	(−4.717)	(−5.431)	(−0.688)	(−0.470)
Board	−1.374 ***	−0.129	0.0617	0.0227	0.00165
	(−2.792)	(−0.600)	(1.011)	(0.352)	(0.465)
Indep	0.0198	0.0118	0.00229	−0.0000282	−0.00000632
	(1.177)	(1.615)	(1.101)	(−0.013)	(−0.052)
Dual	0.485 ***	0.378 ***	0.0627 ***	0.0560 **	0.00255 **
	(2.797)	(5.014)	(2.946)	(2.493)	(2.058)
BM	−6.193 ***	−3.282 ***	−0.623 ***	−0.233 ***	−0.00536
	(−13.178)	(−16.037)	(−10.801)	(−3.818)	(−1.594)
SOE	0.0382	−0.179 **	0.142 ***	0.108 ***	0.00567 ***
	(0.195)	(−2.105)	(5.925)	(4.253)	(4.050)
CompanyAge	−1.335 ***	−1.304 ***	−0.0855 ***	−0.189 ***	−0.00887 ***
	(−5.531)	(−12.403)	(−2.883)	(−6.033)	(−5.132)
Top1	−0.0270 ***	−0.0241 ***	−0.00381 ***	−0.00313 ***	−0.000188 ***
	(−4.903)	(−10.051)	(−5.631)	(−4.376)	(−4.764)
Year/Industry	YES	YES	YES	YES	YES
_cons	15.15 ***	7.049 ***	−11.40 ***	−11.15 ***	−0.423 ***
	(6.516)	(6.961)	(−39.816)	(−36.871)	(−25.348)
N	16,938	16,938	16,938	16,938	16,938
r2	0.482	0.354	0.372	0.429	0.338
r2_a	0.479	0.350	0.368	0.426	0.334
F	43.47	128.7	552.6	496.9	291.5

Note: ***, ** indicate statistical significance at the 1% and 5% levels, respectively. Robust standard errors clustered at the company level are used in this paper, with t-values shown in parentheses, and the same applies to the table below.

- Independent variable replacement

Furthermore, interaction terms between the director network closeness centrality and shareholder network closeness centrality (*dcloseness* × *gcloseness*), as well as between the director network betweenness centrality and shareholder network betweenness centrality (*dbetween* × *gbetween*), were used as proxy variables for multilayer networks position centrality to re-run regression on Model 1. The regression results in Table 10, columns (1) and (2), largely confirm our core hypothesis through the robustness test.

Table 10. Robustness test for independent variable replacement.

	(1) *innovation*	(2) *innovation*
dcloseness × *gcloseness*	0.351 ***	
	(3.429)	
dbetween × *gbetween*		0.00434 **
		(2.438)
Size	0.345 ***	0.353 ***
	(27.869)	(29.436)
Lev	−0.306 ***	−0.316 ***
	(−4.560)	(−4.709)
ROA	1.904 ***	1.907 ***
	(9.831)	(9.847)
Growth	−0.185 ***	−0.187 ***
	(−6.984)	(−7.062)

Table 10. *Cont.*

	(1) *innovation*	(2) *innovation*
Board	0.131 **	0.130 **
	(2.076)	(2.064)
Indep	0.00116	0.00116
	(0.540)	(0.541)
Dual	0.0265	0.0248
	(1.194)	(1.115)
BM	−0.300 ***	−0.321 ***
	(−4.972)	(−5.358)
SOE	0.144 ***	0.149 ***
	(5.740)	(5.940)
CompanyAge	−0.151 ***	−0.152 ***
	(−4.873)	(−4.895)
Top1	−0.000507	−0.000388
	(−0.717)	(−0.550)
Year/Industry	YES	YES
_cons	−6.331 ***	−6.360 ***
	(−22.303)	(−22.391)
N	16,938	16938
r2	0.196	0.196
r2_a	0.191	0.191
F	143.8	143.3

Note: ***, ** indicate statistical significance at the 1% and 5% levels, respectively. Robust standard errors clustered at the company level are used in this paper, with t-values shown in parentheses, and the same applies to the table below.

5.5.2. Lagged Effects of Multilayer Networks Position Advantages

This research also further examined the lagged effects of multilayer networks position advantages to avoid endogeneity issues caused by reverse causality. As shown in Table 11, the multilayer networks position significantly fosters the innovation level of companies in both the following one and two periods. However, the regression coefficients indicate a gradually diminishing trend in these lagged effects. This also, to some extent, validates the robustness of our conclusion.

Table 11. Lagged effects of multilayer networks position advantages.

	(1)	(2)
	F. innovation	***F2. innovation***
degree × gdegree	0.0293 ***	0.0299 ***
	(5.558)	(4.424)
Size	0.361 ***	0.387 ***
	(24.124)	(22.726)
Lev	−0.338 ***	−0.392 ***
	(−4.219)	(−4.351)
ROA	2.528 ***	3.085 ***
	(10.157)	(9.983)
Growth	−0.184 ***	−0.152 ***
	(−6.094)	(−4.561)
Board	0.101	0.161 *
	(1.374)	(1.942)
Indep	−0.00103	−0.00118
	(−0.408)	(−0.417)
Dual	0.0440 *	0.0831 ***
	(1.676)	(2.803)
BM	−0.373 ***	−0.364 ***
	(−5.056)	(−4.296)

Table 11. *Cont.*

	(1)	(2)
	F. innovation	***F2. innovation***
SOE	0.167 ***	0.207 ***
	(5.681)	(6.270)
CompanyAge	−0.151 ***	−0.142 ***
	(−4.205)	(−3.627)
Top1	−0.000768	−0.00140
	(−0.924)	(−1.510)
Year/Industry	YES	YES
_cons	−6.362 ***	−7.054 ***
	(−18.196)	(−17.989)
N	12,886	10,565
r2	0.202	0.203
r2_a	0.196	0.196
F	122.7	108.6

Note: ***, * indicate statistical significance at the 1% and 10% levels, respectively. Robust standard errors clustered at the company level are used in this paper, with t-values shown in parentheses, and the same applies to the table below.

5.5.3. Add Macro Control Variables

To eliminate the influence of macroeconomic factors and market conditions on our model, we have included GNP (*GNP*), GDP (GDP), per capita GDP (*per_GDP*), price-to-earnings ratio (*F100101*), price-to-book ratio (*F100401*), and the industry Herfindahl–Hirschman Index (*HHI*) in our control variables. This approach aids in controlling for the overall economic and market environment impacts on corporate technological innovation.

According to the regression results in Table 12, the conclusions remain unchanged. The absence of coefficients for GNP, GDP, and per capita GDP in the fixed effects is due to the absorption of variable changes by the fixed effects. If the variation of GNP, GDP, and per capita GDP across years or industries is completely absorbed by the fixed effects, it may not appear in the regression results. Our GNP, GDP, and per capita GDP data are a national annual indicator; if GNP, GDP, and per capita GDP is consistent across all industries each year, then the industry and year fixed effects have already captured all the variations of GNP, GDP, and per capita GDP.

Table 12. Control macroeconomic and market factors.

	(1)	(2)
	innovation	***innovation***
ddegree × *gdegree*	0.0174 ***	0.0254 ***
	(3.190)	(6.291)
GNP	0.00000208	0
	(0.320)	(.)
GDP	0.0000295 ***	0
	(3.342)	(.)
per_GDP	0.000465 ***	0
	(7.571)	(.)
F100101	−0.0000141 **	−0.0000132
	(−2.475)	(−1.603)
F100401	0.00831 **	0.00297
	(2.495)	(1.066)
HHI	−0.754 ***	−0.579 ***
	(−15.046)	(−4.389)
Size	0.289 ***	0.333 ***
	(19.376)	(25.223)

Table 12. *Cont.*

	(1)	(2)
	innovation	*innovation*
Lev	−0.201 ***	−0.277 ***
	(−2.852)	(−3.909)
ROA	1.634 ***	1.968 ***
	(7.973)	(9.492)
Growth	−0.143 ***	−0.196 ***
	(−5.682)	(−7.102)
Board	−0.0404	0.0808
	(−0.543)	(1.245)
Indep	−0.000128	0.000664
	(−0.050)	(0.301)
Dual	0.0441 *	0.0295
	(1.903)	(1.303)
BM	−0.332 ***	−0.258 ***
	(−5.511)	(−3.971)
SOE	0.0600 **	0.157 ***
	(2.255)	(6.127)
CompanyAge	−0.224 ***	−0.154 ***
	(−6.962)	(−4.861)
Top1	−0.00183 **	−0.000538
	(−2.391)	(−0.743)
Year/Industry	NO	YES
_cons	−5.591 ***	−5.716 ***
	(−14.795)	(−18.209)
N	16,266	16,266
r2	0.0766	0.197
r2_a	0.0756	0.192
F	58.13	114.4

Note: ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered at the company level are used in this paper, with t-values shown in parentheses, and the same applies to the table below.

5.5.4. External Policy Impact

We utilized the implementation of the "Shanghai-Hong Kong Stock Connect" and "Shenzhen-Hong Kong Stock Connect" policies as external shock factors to examine the stability of the model. The scope of this paper's research sample includes companies listed in China's A-share market. These A-share listed companies are those trading on both the Shanghai and Shenzhen Stock Exchanges, which are the main components of the Chinese stock market. Consequently, the "Shanghai-Hong Kong Stock Connect" and "Shenzhen-Hong Kong Stock Connect" policies are external factors that have a direct impact on the sample. These policies, marking a new phase of high-level openness in China's capital market, have significantly influenced the operational development of real-sector enterprises.

To promote the internationalization of China's capital market, the Shanghai Stock Exchange officially launched the Shanghai-Hong Kong Stock Connect in November 2014. Subsequently, in December 2016, the Shenzhen Stock Exchange implemented the Shenzhen-Hong Kong Stock Connect, based on the framework of its Shanghai counterpart, with fully corresponding and complementary regulatory systems, settlement, and delivery mechanisms. Compared to the Shanghai-Hong Kong Stock Connect, the Shenzhen-Hong Kong Stock Connect removed the aggregate quota limit, retaining only the daily quota, and expanded the scope of covered securities, further opening the capital market. Overseas investors can trade stocks listed on the Shanghai and Shenzhen exchanges through the Hong Kong Stock Exchange, while mainland investors can trade stocks within the specified range of the Hong Kong Exchange through the Shanghai and Shenzhen exchanges. This expansion of mainland trading channels promotes the free flow of capital and helps improve capital allocation efficiency [84]. As a major reform initiative in the capital market, the implementation of the Shanghai-Hong Kong and Shenzhen-Hong Kong Stock Connects broke the long-standing closed nature of the mainland stock market and, against the backdrop of China's steadily improving economy, helped attract more foreign investors to the A-share market. This development optimizes the investor structure, enhances the operational efficiency of the capital market, and fosters the integrated growth of the mainland and Hong Kong stock markets.

We introduced a dummy variable for enterprises targeted by the "Shanghai-Hong Kong Stock Connect" and "Shenzhen-Hong Kong Stock Connect" (HSGT), defined as follows: if a company was included in the target list of either the Shanghai-Hong Kong or Shenzhen-Hong Kong Stock Connect during the sample period, the variable is assigned a value of 1; otherwise, it is 0. The list of enterprises targeted by the "Shanghai-Hong Kong Stock Connect" and "Shenzhen-Hong Kong Stock Connect" is sourced from the official website of the Hong Kong Exchanges and Clearing Limited. As seen in Table 13, the impact of this external policy did not alter the significance of Model (1), thereby demonstrating the model's stability to a certain extent.

Table 13. The impact of external policy shocks.

	HSGT = 0 ***innovation***	**HSGT = 1** ***innovation***
ddegree × *gdegree*	0.0208 ***	0.0490 ***
	(4.781)	(5.392)
Size	0.369 ***	0.244 ***
	(25.653)	(8.102)
Lev	−0.338 ***	−0.125
	(−4.565)	(−0.759)
ROA	1.565 ***	2.826 ***
	(7.188)	(6.687)
Growth	−0.183 ***	−0.165 **
	(−6.463)	(−2.319)
Board	0.00575	0.260
	(0.084)	(1.638)
Indep	0.00344	−0.00430
	(1.466)	(−0.796)
Dual	0.0135	−0.00461
	(0.543)	(−0.094)
BM	−0.305 ***	−0.272 *
	(−4.521)	(−1.938)
SOE	0.143 ***	0.276 ***
	(5.302)	(3.999)
CompanyAge	−0.367 ***	0.349 ***
	(−9.935)	(5.181)
Top1	−0.000359	−0.00187
	(−0.455)	(−1.169)
Year/Industry	YES	YES
_cons	−5.960 ***	−5.407 ***
	(−18.000)	(−7.588)
N	13,418	3520
r2	0.209	0.225
r2_a	0.203	0.204
F	129.3	28.39

Note: ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered at the company level are used in this paper, with t-values shown in parentheses, and the same applies to the table below.

6. Further Research

6.1. Mechanism Analysis

Existing research indicates that higher environmental uncertainty increases the difficulty for management to accurately assess investment projects, leading to more cautious investment decisions [85]. This caution often results in the rejection of high-risk projects and a tendency towards conservative investments among shareholders [86]. Innovative investment projects, characterized by high risk, long cycles, and significant capital requirements, are adversely affected by high internal environmental uncertainty within a company. However, the information and resource effects brought about by a multilayered network position advantage stabilize the internal environment of a company, reducing performance volatility and thereby enhancing the information and motivation of the management to invest in innovative projects. Building on this, the present study adopts the method of Shen et al. [86], measuring environmental uncertainty as the standard deviation of abnormal earnings for the company over the past five years, adjusted for industry, divided by the average sales revenue of the past five years. We introduced the intermediary variable *EU* (Environmental Uncertainty) to test the mechanism of multilayered network position advantage → reduction in environmental uncertainty → enhancement in corporate technological innovation.

Following the approach of Wen and Ye [87], a mediating effect model is utilized for mechanism testing.

$$EU_{i,t} = \alpha_0 + \alpha_1 ddegree_{i,t} \times gdegree_{i,t} + \alpha_2 \sum controls_{i,t} + \sum industry_j + \sum year_t + \varepsilon_{i,t} \tag{8}$$

$$innovation_{i,t} = \alpha_0 + \alpha_1 ddegree_{i,t} \times gdegree_{i,t} + \alpha_2 EU_{i,t} + \alpha_3 \sum controls_{i,t} + \sum industry_j + \sum year_t + \varepsilon_{i,t} \tag{9}$$

Table 14 reports the results of the channel test for reducing environmental uncertainty. Column (1) indicates that a multilayered network position advantage significantly reduces environmental uncertainty. As seen in Column (2), even after introducing the intermediary variable, the regression coefficient of the core explanatory variable—the interaction term of the multilayered network structure—remains significant. This suggests that the multilayered network position advantage partially enhances corporate innovation levels by reducing environmental uncertainty.

Table 14. Mechanism test: reducing environmental uncertainty.

	(1) *EU*	(2) *innovation*
ddegree × *gdegree*	−0.0311 ***	0.0214 ***
	(−9.058)	(5.411)
EU		−0.0986 ***
		(−11.004)
Size	0.0595 ***	0.339 ***
	(5.336)	(26.479)
Lev	−0.173 ***	−0.312 ***
	(−2.916)	(−4.569)
ROA	−3.596 ***	1.545 ***
	(−21.250)	(7.841)
Growth	1.762 ***	−0.00619
	(76.022)	(−0.200)
Board	−0.154 ***	0.0893
	(−2.776)	(1.399)
Indep	−0.00496 ***	0.000670
	(−2.606)	(0.306)
Dual	−0.00984	0.0225
	(−0.501)	(0.996)
BM	−0.0439	−0.287 ***
	(−0.827)	(−4.710)

Table 14. *Cont.*

	(1) *EU*	(2) *innovation*
SOE	−0.0597 ***	0.135 ***
	(−2.710)	(5.336)
CompanyAge	0.139 ***	−0.167 ***
	(4.960)	(−5.176)
Top1	0.000815	−0.000500
	(1.305)	(−0.698)
Year/Industry	YES	YES
_cons	0.100	−5.831 ***
	(0.380)	(−19.274)
N	16,529	16,529
r2	0.291	0.204
r2_a	0.286	0.200
F	51.84	14.40

Note: *** indicates statistical significance at the 1% level. Robust standard errors clustered at the company level are used in this paper, with t-values shown in parentheses, and the same applies to the table below.

6.2. Heterogeneity Analysis

6.2.1. Property Rights Nature

The sample was divided into two categories based on ownership characteristics: non-state-owned companies and state-owned companies, to examine the impact of multilayered network position advantages on the level of corporate technological innovation in companies with different ownership properties. Table 15 presents the regression results, which indicate a significant positive impact of the interaction term *degree* × *gdegree* on the total number of patent applications and the number of invention patent applications in non-state-owned company samples, while this effect is not significant in state-owned company samples. These results suggest that in privately-owned companies, which are more inclined towards technological breakthroughs, the influence of network position advantages on corporate technological innovation is more pronounced.

Table 15. Test of heterogeneity in property rights.

	Non-State-Owned Companies *innovation*	**State-Owned Companies** *innovation*
ddegree × *gdegree*	0.00846 ***	0.00411
	(4.076)	(1.225)
Size	0.296 ***	0.436 ***
	(20.101)	(19.757)
Lev	−0.0807	−0.645 ***
	(−1.024)	(−5.040)
ROA	1.939 ***	1.991 ***
	(9.228)	(4.618)
Growth	−0.222 ***	−0.115 **
	(−7.203)	(−2.323)
Board	0.123	0.227 **
	(1.539)	(2.165)
Indep	0.00146	0.000200
	(0.541)	(0.053)
Dual	0.0218	0.0692
	(0.947)	(1.150)
BM	−0.399 ***	−0.205 *
	(−5.713)	(−1.760)
CompanyAge	−0.127 ***	−0.264 ***
	(−3.686)	(−4.012)

Table 15. *Cont.*

	Non-State-Owned Companies *innovation*	State-Owned Companies *innovation*
Top1	−0.000705	−0.00134
	(−0.850)	(−0.987)
Year/Industry	YES	YES
_cons	−5.130 ***	−7.999 ***
	(−14.051)	(−15.694)
N	11,270	5668
r2	0.175	0.281
r2_a	0.168	0.269
F	7.02	6.87

Note: ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered at the company level are used in this paper, with t-values shown in parentheses, and the same applies to the table below.

6.2.2. Internal Information Transparency

Using the annual information disclosure assessment ratings of listed companies on the Shenzhen and Shanghai stock exchanges as a proxy for internal information transparency, we examined the impact of multilayered network position advantages on corporate innovation levels in companies with varying degrees of internal information transparency. Specifically, the information disclosure assessment ratings of listed companies are categorized into four grades: A, B, C, and D, with A being excellent, B being good, C being satisfactory, and D being unsatisfactory. Companies rated A or B in a given year are classified as having higher internal information transparency (Opacity = 1), while those rated C or D are classified as having lower transparency (Opacity = 0) for subgroup testing. According to the results in Table 16, in the Opacity = 1 group with higher internal information transparency, the interaction term *ddegree* × *gdegree* shows a significant positive impact on both total patent applications and invention patent applications. Conversely, in the Opacity = 0 group with lower transparency, this interaction term does not significantly influence patent applications. These findings indicate that in companies with higher internal information transparency, where the degree of information asymmetry is lower and the self-interest motives of management and the embezzlement tendencies of major shareholders are weaker, the information and control advantages brought by network position advantages can be fully utilized. This avoids speculative behavior and more significantly enhances the innovation level of listed companies.

Table 16. Test of heterogeneity in internal information transparency.

	Opacity = 0 *innovation*	Opacity = 1 *innovation*
ddegree × *gdegree*	0.0123	0.0231 ***
	(0.597)	(3.611)
Size	0.295 ***	0.338 ***
	(5.187)	(17.492)
Lev	−0.285	0.0721
	(−1.290)	(0.731)
ROA	0.232	2.274 ***
	(0.550)	(7.793)
Growth	−0.0974	−0.238 ***
	(−1.188)	(−5.788)
Board	0.376	0.0682
	(1.509)	(0.684)
Indep	0.0122	0.000412
	(1.400)	(0.126)

Table 16. *Cont.*

	Opacity = 0 *innovation*	Opacity = 1 *innovation*
Dual	−0.0422	0.0643 **
	(−0.577)	(2.308)
BM	−0.128	−0.494 ***
	(−0.545)	(−5.615)
SOE	0.113	0.332 ***
	(0.851)	(7.259)
CompanyAge	−0.0573	−0.00946
	(−0.511)	(−0.230)
Top1	−0.00162	−0.00107
	(−0.566)	(−1.071)
Year/Industry	YES	YES
_cons	−6.380 ***	−6.177 ***
	(−4.666)	(−12.920)
N	1156	9339
r2	0.207	0.208
r2_a	0.135	0.198
F	4.376	6.35

Note: ***, ** indicate statistical significance at the 1% and 5% levels, respectively. Robust standard errors clustered at the company level are used in this paper, with t-values shown in parentheses, and the same applies to the table below.

6.2.3. External Information Supervision

The number of analysts following a company in a given year was used as a proxy for external information supervision, to investigate the exogenous influence of external information supervision-induced pressure on the ability of network position advantages to foster innovation. This study divided companies based on the median number of analysts following companies in the same industry in the same year. Companies with fewer analysts than the industry median in a given year are considered to have weaker external information supervision (Attention = 0), while those with a number equal to or greater than the median are considered to have stronger supervision (Attention = 1). Table 17 shows the regression results, indicating that the promotion effect of the multilayered network structure interaction term on innovation levels is more significant in the Attention = 1 group and not significant in the Attention = 0 group. This suggests that the innovative promotion effect of network position advantages is more effectively realized under stronger external information supervision. Analysts play a crucial role in corporate governance, possessing professional skills in information searching and processing, and can make predictions and ratings on corporate value based on extensive information. If analysts detect opportunistic behavior such as short-sightedness in management, it can weaken the long-term investment capability of the company [88], thereby constraining opportunistic behaviors of the management. Therefore, under higher analyst scrutiny, short-sighted actions of management are curtailed due to the pressure from external information supervision. Additionally, since the information concealed within the company is more likely to be revealed to external small and medium investors, the motivation of major shareholders to encroach on the interests of minor shareholders is reduced, and to some extent, the collusion effect between management and major shareholders is suppressed. Overall, stronger external information supervision is more conducive to leveraging the positive influence of multilayered network position advantages on innovation levels.

Table 17. Test of heterogeneity in external information supervision.

	Attention = 0 *innovation*	Attention = 1 *innovation*
ddegree × gdegree	0.0347	0.0280 **
	(1.518)	(1.968)
Size	0.233 ***	0.348 ***
	(8.066)	(17.857)
Lev	0.113	−0.129
	(0.853)	(−1.139)
ROA	1.594 ***	2.264 ***
	(4.080)	(7.815)
Growth	−0.170 ***	−0.232 ***
	(−3.120)	(−4.809)
Board	−0.0764	0.0878
	(−0.539)	(0.792)
Indep	−0.0136 ***	0.00132
	(−2.952)	(0.362)
Dual	0.129 ***	−0.00692
	(3.335)	(−0.212)
BM	−0.135	−0.489 ***
	(−1.047)	(−4.954)
SOE	0.262 ***	0.278 ***
	(4.151)	(5.348)
CompanyAge	−0.0101	0.132 ***
	(−0.176)	(2.812)
Top1	−0.000145	−0.000310
	(−0.107)	(−0.273)
Year/Industry	YES	YES
_cons	−3.384 ***	−6.758 ***
	(−4.885)	(−13.685)
N	7622	9316
r2	0.179	0.219
r2_a	0.158	0.208
F	1.10	7.26

Note: ***, ** indicate statistical significance at the 1% and 5% levels, respectively. Robust standard errors clustered at the company level are used in this paper, with t-values shown in parentheses, and the same applies to the table below.

6.2.4. Test of Company Size Threshold Effect

The threshold panel model employs company size (*Size*) as an indicator function to analyze the nonlinear impact of the multilayered network structure interaction term on corporate technological innovation levels as company size varies. As indicated in Table 18, the impact of the multilayered network structure interaction term on corporate technological innovation exhibits a non-significant single threshold effect, while the double threshold effect is significant at the 5% level. This suggests that modeling with company size (*Size*) as the indicator function results in two thresholds and three intervals.

Table 18. Test of company size threshold effect.

	Threshold Value	F-Value	*p*-Value	Number of BS	10% Critical Value	5% Critical Value	1% Critical Value
Single threshold test	25.8406	15.19	0.133	300	17.7249	19.8748	28.4224
Double threshold test	23.822, 23.886	21.21 *	0.0833	300	18.6141	25.9256	53.2581

Note: * indicate statistical significance at the 10% level. Robust standard errors clustered at the company level are used in this paper, with t-values shown in parentheses, and the same applies to the table below.

Further testing for the authenticity of the threshold values, as shown in Table 19, reveals that the likelihood ratio (LR) is below the critical value at the 5% significance level, falling within the acceptance domain of the null hypothesis. This indicates that the double threshold of company size aligns with the real threshold values.

Table 19. Estimation results of company size threshold values.

	Threshold Estimate	95% Confidence Interval
Threshold	23.822	[21.405, 24.461]
Threshold	23.886	[23.000, 24.083]

From Table 20, it can be observed that the coefficients of the multilayered network structure interaction term across different threshold ranges of company size are 0.030, 0.004, and 0.071, respectively. This indicates a typical company size threshold effect on the impact of multilayered network position advantages on corporate technological innovation, with two thresholds—high and low. The threshold values represent structural change points in how the multilayered network structure interaction term affects corporate technological innovation levels. For companies smaller than the lower threshold, which we defined as smaller-scale companies, the impact of the multilayered network structure interaction term on technological innovation is positive and significant at the 1% level. For companies with sizes between the lower and higher thresholds, defined as medium-scale companies, this impact is negative and significant at the 10% level. For companies larger than the higher threshold, defined as larger-scale companies, the impact is again positive and significant at the 1% level. Thus, it is believed that with changes in company size, the influence of multilayered network position advantages on corporate technological innovation levels exhibits interval effects. Specifically, there is a strong head effect, with the innovation promotion role of multilayered networks being more significant for smaller and larger companies. However, for medium-scale companies, where innovation motivation is weaker than in smaller companies and innovation capability is less than in larger companies, the opportunistic governance role played by multilayered networks may suppress improvements in innovation levels.

Table 20. Estimation results of the double threshold model parameters for company size.

	Coefficient	Robust Standard Deviation	t-Statistic	*p*-Value	95% Confidence Interval	
Size	0.342 ***	0.041	8.320	0.000	0.261	0.422
Lev	−0.498 ***	0.150	−3.310	0.001	−0.793	−0.203
ROA	0.020	0.298	0.070	0.947	−0.564	0.603
Growth	−0.014	0.038	−0.360	0.716	−0.089	0.061
Board	−0.146	0.148	−0.990	0.323	−0.435	0.143
Indep	−0.006	0.004	−1.360	0.175	−0.015	0.003
Dual	0.019	0.044	0.420	0.673	−0.068	0.105
BM	−0.134	0.075	−1.790	0.074	−0.281	0.013
SOE	0.025	0.100	0.250	0.804	−0.171	0.220
CompanyAge	0.545 *	0.239	2.280	0.023	0.076	1.014
Top1	0.001	0.002	0.360	0.717	−0.004	0.005
$ddegree \times gdegree\ I$ $(TC < 23.8220)$	0.030 ***	0.006	5.080	0.000	0.019	0.042
$ddegree \times gdegree\ II$ $(23.8220 \leq TC < 23.8864)$	0.004	0.007	0.610	0.545	−0.009	0.018
$ddegree \times gdegree\ III$ $(Cashholding \geq 23.8864)$	0.071 ***	0.013	5.540	0.000	0.046	0.096

Note: ***, * indicate statistical significance at the 1% and 10% levels, respectively. Robust standard errors clustered at the company level are used in this paper, with t-values shown in parentheses, and the same applies to the table below.

7. Conclusions

We explored the impact of network structural embeddedness on corporate technological innovation from a multilayer networks perspective. The main conclusions are as follows:

1. Both single-layer and multilayer networks exhibit an increasing trend over the years. This suggests that the social networks of Chinese listed companies are continuously expanding and strengthening. However, companies with multilayered network relationships, compared to single-layered ones, are still in the minority, indicating the limited prevalence of multilayer networks advantages.
2. Companies with higher centrality in multilayer networks exhibit significantly higher levels of innovation compared to those in single-tier networks. Being in a core position within the network significantly enhances the innovation level of listed companies. This indicates that in the Chinese capital market, the structural embeddedness of multilayer networks can help companies gain more information and resource advantages. Consequently, this secures a dominant position in innovation and stimulates more high-quality innovative outputs.
3. Multilayer networks promote corporate technological innovation by reducing internal environmental uncertainty. More advantageous network positions reduce internal risks and increase the stability of the internal environment, thereby enhancing the motivation and capability for technological innovation.
4. The structural embeddedness of multilayer networks has a greater stimulating effect on innovation in non-state-owned companies, companies with higher internal information transparency, and those with stronger external information supervision.
5. The impact of the structural embeddedness of multilayer networks on corporate technological innovation levels exhibits interval effects, particularly a strong head effect. For smaller and larger companies, the innovation promotion role of multilayered networks is more significant. In contrast, for medium-sized companies, with weaker innovation motivation than smaller companies and lower innovation capability than larger companies, the opportunistic governance role of multilayered networks might suppress improvements in innovation levels.

The significance and value of this study are manifested in several aspects:

1. A deeper understanding of corporate technological innovation: By exploring the impact of shareholder and director networks on corporate technological innovation, we provide a new perspective on how companies can enhance their innovation capacity through network embeddedness. This not only enriches the application of network theory in the field of corporate innovation but also provides empirical evidence for how companies can use network resources for innovation.
2. Innovation in the multilayer networks perspective: We employ a multilayer networks analysis method, breaking through the limitations of traditional single-layer network analysis, and more comprehensively reveal how shareholder and director networks jointly influence corporate innovation. This methodological innovation provides new tools and ideas for studying corporate behavior in complex network systems.
3. Implications for corporate governance and decision making: We indicate that the structural embeddedness of multilayer networks significantly influences corporate innovation, providing practical guidance for managers and shareholders on how to optimize network structures to enhance innovation capabilities. This is especially important for non-state-owned companies and companies with high information transparency.
4. Reference for policy making and regulation: We reveal the impact of multilayer networks structures on corporate innovation, offering references for policymakers and regulatory bodies on how to optimize inter-company network relationships to promote technological innovation and economic growth. This is particularly significant in the context of the economic transformation and independent technological innovation in China.

5. Contributions to theory and practice: We not only provide the academic community with new theoretical perspectives and empirical evidence on the impact of multilayer networks on corporate innovation, but also offer specific strategies and suggestions for practitioners on how to use network relationships to promote corporate innovation.

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