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Article

The Impact of Ego-Network Stability on Firm Innovation Efficiency From the Perspective of Multilevel Network

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Abstract

Firm innovation is typically embedded within multilevel networks, where dynamic changes at various levels of the network can significantly influence firm innovation. Previous research has often overlooked the dynamics of these networks and failed to consider the differential impacts that distinct network levels have on firm innovation. Drawing on social network theory, this study develops a theoretical model that explores the relationship between ego-network stability and innovation efficiency from a multilevel network perspective. We analyze patent data in the domains of artificial intelligence and intelligent manufacturing equipment in China, covering the period from 2012 to 2022, and test our hypotheses using a Data Envelopment Analysis-Tobit Regression (DEA-Tobit) model. The results reveal that organizational ego-network stability exhibits an inverted U-shaped effect on innovation efficiency. Additionally, urban ego-network stability and knowledge ego-network stability enhance the influence of organizational ego-network stability on innovation efficiency. This paper contributes to the theory of multilevel network embeddedness by introducing organizational collaboration networks, urban collaboration networks, and knowledge networks as external contexts that affect firm innovation and by examining their relationships with innovation efficiency from a dynamic perspective.

Keywords: collaboration network; knowledge network; stability; innovation efficiency; multilevel network
JEL: O31, O32, O33

1. Introduction

Innovation activities are becoming increasingly complex, requiring firms to access interdisciplinary knowledge that often exceeds their internal capabilities (Xu et al., 2025). In response to these challenges, firms increasingly embed themselves in collaboration networks to access complementary resources and enhance innovation outcomes (Zhang and Luo, 2020). While previous research has established that collaboration networks serve as important channels for promoting innovation (Wang et al., 2023), significant gaps remain in our understanding of how multiple network levels interact dynamically to influence firm innovation.

Three critical limitations characterize the current literature. First, extant research has predominantly adopted a single-level network perspective, despite compelling evidence that firm innovation is simultaneously embedded in multiple interconnected networks (Huang and Hsueh, 2024). As Wang et al. (2014) and Guan and Liu (2016) argued, firm innovation is embedded in both organizational collaboration networks and knowledge networks. Additionally, urban collaboration networks formed through inter-city partnerships create important spatial contexts that influence firms' access to innovation resources (Yao et al., 2020b). The failure to integrate these multiple levels represents a significant theoretical limitation, as Guan et al. (2015) noted that different level networks are interconnected yet operate through distinct innovation mechanisms.

Second, existing research has largely treated networks as static structures (Huang and Hsueh, 2024; Wen et al., 2021), overlooking their dynamic evolution in response to changing innovation needs (Kumar and Zaheer, 2019). Firms continuously reconfigure their ego-networks by establishing new beneficial partnerships and terminating old unhelpful ones, creating dynamic network structures that existing cross-sectional approaches cannot adequately capture (Yan and Guan, 2018). While the resource-based view (RBV) suggests that firms access heterogeneous resources through collaboration networks (Burt and Soda, 2021), we know little about how stability in these dynamically evolving networks affects innovation outcomes.

Third, the literature has predominantly focused on innovation output rather than innovation efficiency (Wang et al., 2023; Huang and Hsueh, 2024; Wen et al., 2021). This focus on outputs alone provides an incomplete picture of innovation performance, as it fails to account for the resource inputs required to generate these outputs (Wan et al., 2023). Innovation efficiency, which captures the relationship between innovation inputs and outputs, offers a more comprehensive measure of firms' actual innovation capabilities. It is important to distinguish innovation efficiency from related constructs such as innovation performance and innovation capability. While innovation performance typically refers to the output side of innovation activities (e.g., patent counts, new products), and innovation capability denotes a firm's potential to generate innovations, innovation efficiency specifically captures the effectiveness with which firms transform innovation inputs into valuable outputs (Wan et al., 2023; Wang and Yu, 2025). This focus on the input-output transformation process is particularly relevant in network contexts, where the central challenge involves efficiently converting accessed network resources into innovation outcomes. By examining innovation efficiency rather than mere output, we can better understand how firms leverage their network positions to optimize resource utilization in innovation activities.

To address these gaps, this study establishes a theoretical model examining how ego-network stability across multiple levels influences firm innovation efficiency. Drawing on social network theory, organizational collaboration networks emphasize the importance of searching for resources based on inter-organizational partnerships (Yan and Guan, 2018; Guan and Liu, 2016). Knowledge networks emphasize the importance of searching for resources based on knowledge elements (Wang et al., 2014; Yayavaram and Ahuja, 2008). Urban collaboration networks emphasize the importance of searching for resources based on inter-city partnerships (Yao et al., 2020b). To fill the research gap on the relationship between multilevel networks and firm innovation from a dynamic perspective, we supplement the traditional focus on innovation efficiency by considering ego-network stability in different level networks as antecedents at the firm level. So the research question is twofold:

1. How do different levels of networks contribute to the firm's innovation efficiency?

2. How do multilevel networks play a joint role in innovation efficiency from a dynamic perspective?

By addressing these questions, our study makes several important contributions. First, we advance multilevel network embeddedness theory by simultaneously examining organizational, urban, and knowledge networks as interconnected contexts for firm innovation. Second, we contribute to the emerging literature on network dynamics by examining how ego-network stability across these multiple levels jointly influences innovation outcomes. Third, we shift the focus from innovation output to innovation efficiency, providing a more nuanced understanding of how networks affect the translation of innovation resources into outcomes.

In the sections that follow, we develop our theoretical framework and hypotheses, describe our methodology using patent data from China's artificial intelligence (AI) and intelligent manufacturing equipment sectors (2012–2022), present our empirical results, and discuss the theoretical and practical implications of our findings.

2. Theory and Hypotheses Development

This study establishes an integrated multilevel network framework that conceptualizes organizational collaboration networks, urban collaboration networks, and knowledge networks as three analytically distinct yet functionally interdependent levels shaping firm innovation (Guan et al., 2015; Wang et al., 2014). Organizational collaboration networks operate at the meso-level, forming the relational infrastructure through which firms access complementary resources and capabilities via inter-organizational partnerships, grounded in resource-based view principles (Burt and Soda, 2021). Urban collaboration networks function at the macro-level as spatial infrastructure, concentrating innovation resources within geographic boundaries and facilitating inter-city knowledge flows through agglomeration economies and regional innovation systems (Yao et al., 2020b), as emphasized in economic geography theories. Knowledge networks constitute the micro-level cognitive infrastructure that structures technological search and recombination processes through knowledge element combinations (Wang et al., 2014; Yayavaram and Ahuja, 2008), aligned with knowledge-based view perspectives. While each network level operates through different mechanisms, they collectively create the embedded context where organizational relationships enable resource access, urban environments determine resource availability, and knowledge structures guide resource recombination. This theoretical integration addresses the simultaneous embeddedness of firms across multiple network levels and enables examination of how ego-network stability across these interrelated dimensions jointly influences innovation efficiency, providing a more comprehensive understanding of innovation in complex, multilayered environments.

Innovation efficiency, a relative concept, refers to the ability to maximize innovation output given specific levels of innovation resource input, or alternatively, to minimize innovation resource input while maintaining certain levels of innovation output (Wang and Yu, 2025). It is a critical component of a firm's capacity to enhance innovation within the framework of open innovation. Building on resource-based and knowledge-based views, we conceptualize innovation efficiency as a firm's capacity to transform innovation inputs into valuable innovation outputs with minimal resource waste (Dimakopoulou et al., 2023). This conceptualization differs fundamentally from innovation performance and innovation capability, as it specifically addresses the transformation process between inputs and outputs.

In network contexts, innovation efficiency becomes particularly salient for several theoretical reasons. First, networks provide access to external resources, but firms vary significantly in their ability to efficiently convert these accessed resources into innovation outcomes (Wang et al., 2023). Second, the costs of maintaining network relationships represent important inputs that must be justified by the innovation outputs generated (Kumar and Zaheer, 2019). Third, different network configurations may either enhance or diminish the marginal returns on innovation investments, making efficiency considerations crucial for understanding optimal network strategies (Guan et al., 2015).

The multilevel network perspective further enriches our understanding of innovation efficiency. By examining how ego-network stability across different levels affects innovation efficiency, we address the fundamental question of how firms can optimally configure their multilevel network embeddedness to maximize returns on their innovation investments.

2.1 Ego-Network Stability in Organizational Collaboration Networks and Firm Innovation Efficiency

Organizational collaboration networks, characterized by collaborative relationships among various types of organizations, aggregate a diverse array of resources and establish a stable network structure. This structure facilitates firms in identifying potential innovation opportunities (Shi and Zhang, 2020). While the structural properties of the network can be evaluated from an overall perspective, this stable configuration does not adequately reflect the changes occurring within the ego-network (Yan and Guan, 2018). In the context of collaborative innovation, firms often modify their relationships with different partners based on their specific innovation needs. By reconfiguring partnerships, firms can access and integrate heterogeneous resources, resulting in dynamic transformations within their ego-networks. Research by Lin et al. (2022) and Kumar and Zaheer (2019) has demonstrated the dynamic nature of the ego-network. Although previous studies have primarily focused on the structural configurations of ego-networks, such structural features hinder the effective capture of network changes (Huang and Hsueh, 2024; Yao et al., 2020a). This limitation arises because, while the composition of ego-networks evolves over time, their underlying structure often remains unchanged. Consequently, shifts in a firm's partners within an ego-network influence the range of resources available to the firm (Aggarwal, 2020). Therefore, it is essential to analyze changes in ego-networks from a dynamic perspective to elucidate their impact on firm innovation efficiency.

Ego-network stability in organizational collaboration networks reflects the extent to which the composition of the ego-network in which the firm is located remains constant from one period to the next (Kumar and Zaheer, 2019). While previous research has established that ego-network stability influences innovation outcomes (Yan and Guan, 2018; Kumar and Zaheer, 2019), important theoretical questions remain regarding its effect on innovation efficiency, particularly whether this relationship follows a non-linear pattern. Yan and Guan (2018) examined ego-network stability as a mediator between social capital and inventors' innovation performance, demonstrating its positive role in knowledge processes. Conversely, Kumar and Zaheer (2019) identified a negative effect of ego-network stability on firm innovation in alliance networks, highlighting the potential downsides of network rigidity. These contradictory findings suggest that the relationship may be more complex than previously theorized, potentially following a non-linear pattern that reconciles these opposing perspectives.

More importantly, existing research has focused predominantly on innovation outputs rather than innovation efficiency. The distinction is theoretically significant because innovation efficiency captures the relationship between resource inputs and innovation outputs, reflecting firms' ability to transform network resources into performance outcomes (Wan et al., 2023). A focus on efficiency rather than output alone allows us to examine whether stable networks enhance resource utilization or instead lead to diminishing returns as networks become overly rigid.

When the stability of a firm's ego-network increases, the cohesion between the firm and its network partners also tends to strengthen (Guo et al., 2021). This mutual trust among partners facilitates resource sharing and knowledge transfer within the network (Majuri, 2022). Through stable network relationships, firms can effectively integrate and leverage the innovative resources provided by various partners. This efficient allocation of resources can lead to increased innovation outputs, thereby enhancing the overall innovation efficiency of the firms. According to social network theory, network stability serves as a significant source of value (Yan and Guan, 2018). Stable ego-networks minimize friction between partners and reduce the likelihood of opportunistic behaviors among network members (Lin et al., 2022). In such stable environments, the transfer of tacit knowledge becomes more feasible, enabling firms to update and reorganize their knowledge bases, ultimately enhancing their innovation efficiency (Xu et al., 2023).

However, as the stability of ego-networks improves, excessively stable networks can adversely impact a firm's innovation efficiency. While inter-organizational collaboration may remain relatively stable for a certain period and help mitigate the uncertainties associated with innovation activities, overly stable network relationships can lead to the homogenization of network members. This phenomenon tends to render firms path-dependent (Zhang et al., 2023). In such over-stabilized networks, firms encounter challenges in accessing novel innovation resources (Lin et al., 2022). Prolonged fixed collaboration results in the uniformity of resources among organizations, and the accumulation of these homogenized resources seldom yields increased innovation outputs, ultimately hindering innovation efficiency. Moreover, an over-stabilized ego-network constrains the scope of collaboration, preventing firms from pursuing new partners and exploring new knowledge (Guan et al., 2022). Simultaneously, excessively stable ego-networks intensify inter-organizational relationships, potentially leading to technological lock-in. This lock-in effect complicates firms' ability to respond swiftly to the dynamically changing external environment, thereby inhibiting the enhancement of innovation efficiency (Zhao et al., 2021). Kumar and Zaheer (2019) assert that overly stable ego-networks fail to provide firms with diverse knowledge resources, which can ultimately detrimentally affect innovation outcomes. Therefore, we expect the following hypothesis:

Hypothesis 1. Ego-network stability in organizational collaboration networks has an inverted U-shaped effect on firm innovation efficiency.

2.2 The Moderating Effect of Ego-Network Stability in Urban Collaboration Networks

Cities, as the gathering place of all kinds of innovation factors, are the spatial carriers of firms' innovation activities. Firms' innovation activities are embedded in cities, and firms and cities are an integrated system. A firm's innovative behavior is driven by the link between the innovation environment provided by the city and the firm's innovative traits (Lee and Rodríguez-Pose, 2014). Inter-city collaboration facilitates the flow of innovation resources between different cities and brings together a large number of heterogeneous resources for firms within cities (Guan et al., 2015).

Ego-network stability in urban collaboration networks is the composition and reorganization of inter-city partnerships presenting a stable network state over time (Kumar and Zaheer, 2019). Ego-network stability in urban collaboration networks reflects the degree of persistence of inter-city partnerships in ego-networks. A stable urban ego-network can maximize the resource effect, and the optimization of urban resource allocation can help firms efficiently transform resource inputs into innovation outputs (Fan et al., 2023). As the organizational ego-network stability increases, the interactions between firms and partners become stronger (Lin et al., 2022). Different organizations can work together to exploit the rich innovation resources provided by a stable urban ego-network. However, while a stable urban ego-network can reduce the cost of searching for resources between cities, the flow of the same resources between cities does not change over time, resulting in mostly homogenized resources owned by different cities (Sheng et al., 2019). When the organizational ego-network stability is too high, the scope of collaboration of firms is limited to fixed partners, and it is difficult for firms to obtain novel external resources (Kumar and Zaheer, 2019). Stable urban ego-networks are equally difficult to provide firms with diversified access to external resources. According to the RBV, the accumulation of homogenized resources cannot promote firm innovation (Burt and Soda, 2021). Overly stable organizational ego-networks and urban ego-networks bring more repetitive and redundant information to firms, which undermines innovation efficiency. That is, urban ego-network stability reinforces the inverted U-shaped effect of organizational ego-network stability on firm innovation efficiency. Thus, we propose the following hypotheses:

Hypothesis 2. The ego-network stability of the city where the firm is located has a positive moderating effect on the relationship between organizational ego-network stability and innovation efficiency.

2.3 The Moderating Effect of Ego-Network Stability in Knowledge Networks

The knowledge-based view (KBV) posits that knowledge is a fundamental resource for firms seeking to achieve a competitive advantage (Zámborsky et al., 2023). Knowledge networks capture the combinations and affiliations of knowledge elements derived from existing innovation experiences, serving as channels for the migration and recombination of these elements (Yayavaram and Ahuja, 2008). Prior research has established that organizational collaboration networks and knowledge networks operate independently (Wang et al., 2014; Guan and Liu, 2016). Knowledge networks influence firm innovation through a distinctive mechanism centered on knowledge search. These networks are dynamic, with different organizations possessing varying knowledge elements (Wang et al., 2018). As inter-organizational partnerships evolve, the knowledge elements within the network also change. Additionally, organizations can learn to acquire new knowledge elements, further contributing to transformations within the knowledge network.

Ego-network stability in knowledge networks reflects the extent to which the knowledge domain formed by the focal knowledge elements and their combinatorial relationships remains unchanged (Lin et al., 2022). The more stable the knowledge ego-network is, the fewer new knowledge elements enter the network. Firms can focus on the knowledge domain of their current innovation activities and build a strong knowledge base for their innovation activities (Xie et al., 2016). Stable knowledge ego-networks can maintain knowledge elements with high innovation value, thus bringing higher certainty as well as lower risk to inter-organizational collaborative innovation activities (Capaldo et al., 2017). As the stability of organizational ego-networks increases, there is more and more information sharing and mutual learning between network partners. Members of an organizational ego-network who have established stable collaborative relationships can explore the depth of knowledge in a stable knowledge ego-network (Xiong and Sun, 2023). Through a deeper understanding of stable knowledge networks, firms reinforce the value of innovation created by the organizational ego-network stability, which in turn enhances innovation efficiency (Guan and Liu, 2016). However, when the organizational ego-network stability is too high, it is difficult for the firm to reach out to new partners to supplement the firm with novel knowledge resources (Kumar and Zaheer, 2019). Meanwhile, the stable knowledge network lacks the recombination of knowledge elements to provide heterogeneous knowledge to the firm (Lin et al., 2022). New combination patterns of knowledge elements in a stable knowledge ego-network tend to dry up and make it difficult to drive innovation, which can exacerbate the negative effects when the stability of the organizational ego-network is too high and impair innovation efficiency. That is, knowledge ego-network stability reinforces the inverted U-shaped effect of organizational ego-network stability on firm innovation efficiency. Hence, we make the following hypotheses:

Hypothesis 3. The ego-network stability of knowledge elements owned by the firm has a positive moderating effect on the relationship between organizational ego-network stability and innovation efficiency.

2.4 Interaction of Multilevel Ego-Network Stability

Building on our theoretical framework that positions urban collaboration networks as spatial infrastructure and knowledge networks as cognitive infrastructure, we propose that these two network levels interact synergistically to jointly moderate the relationship between organizational ego-network stability and innovation efficiency. This synergistic interaction arises because urban and knowledge networks operate through complementary but interdependent mechanisms that collectively shape how firms transform network resources into innovation outcomes (Shi and Zhang, 2020; Lyu et al., 2020). The interaction between the organizational collaboration network, the urban collaboration network, and the knowledge network is shown in Fig. 1.

The synergistic mechanism operates through three interconnected pathways. Stable urban ego-networks create predictable spatial contexts that enhance the reliability of knowledge flows (Yao et al., 2020b), while stable knowledge ego-networks provide coherent cognitive structures that facilitate the absorption and application of these spatially-embedded knowledge resources (Guan and Liu, 2016). When both networks are stable, they create a mutually reinforcing environment where the spatial reliability of resource access complements the cognitive coherence of knowledge integration (Choi and Zo, 2022), thereby amplifying the benefits of organizational ego-network stability for innovation efficiency.

The interaction between urban and knowledge networks creates emergent properties that transcend their individual effects. A stable urban ego-network ensures consistent access to geographically-embedded knowledge resources, while a stable knowledge ego-network enables deeper exploitation of these resources through specialized expertise (Lin et al., 2022). Together, they create a condition where the geographic distribution of knowledge resources aligns with firms' cognitive structures for processing these resources (Hamidi et al., 2019; Tang et al., 2023). This alignment enhances the efficiency with which firms in stable organizational networks can leverage both their relational partnerships and their internal knowledge bases.

However, this synergistic reinforcement also amplifies the negative effects when organizational ego-network stability becomes excessive. Overly stable urban networks tend to circulate homogenized resources between cities (Sheng et al., 2019; Hu et al., 2020), while overly stable knowledge networks constrain novel knowledge recombination (Lin et al., 2022). When combined with overly stable organizational networks that limit partnership diversity, this triple stability creates a rigid configuration where spatial, cognitive, and relational constraints mutually reinforce each other, severely diminishing innovation efficiency (Cui and O'Connor, 2012).

This synergistic perspective explains why the joint effect of urban and knowledge ego-network stability is not merely additive but interactive. The urban network provides the spatial context that determines which knowledge resources are accessible, while the knowledge network provides the cognitive framework that determines how these accessible resources can be utilized. Their interaction creates emergent effects that fundamentally reshape how organizational ego-network stability influences innovation efficiency. Thus, we posit that:

Hypothesis 4. The joint moderating effect of urban ego-network stability and knowledge ego-network stability strengthens the inverted U-shaped relationship between organizational ego-network stability and innovation efficiency, such that the relationship is steepest when both urban and knowledge ego-network stability are high.

Based on the preceding analysis, the theoretical framework is illustrated in Fig. 2.

3. Methodology

3.1 Setting and Data Collection

Our study examines China's high-tech listed firms operating in AI and intelligent manufacturing equipment. These fields are characterized by their inherent interdisciplinarity, requiring firms to integrate diverse knowledge domains and engage extensively with heterogeneous partners, making them empirically suitable for analyzing multilevel network dynamics. Focusing on publicly listed firms ensures data consistency and reliability due to mandatory disclosure requirements, while their regulated status enhances comparability and reduces noise from irregular innovators. Methodologically, this sample enables a clear examination of how organizational, urban, and knowledge networks interact under conditions of complex innovation. Moreover, China's distinctive hybrid innovation system offers a compelling context to study how multilevel ego-network stability shapes innovation efficiency within an environment where institutional and market logics coexist. While findings from this setting may reflect unique aspects of

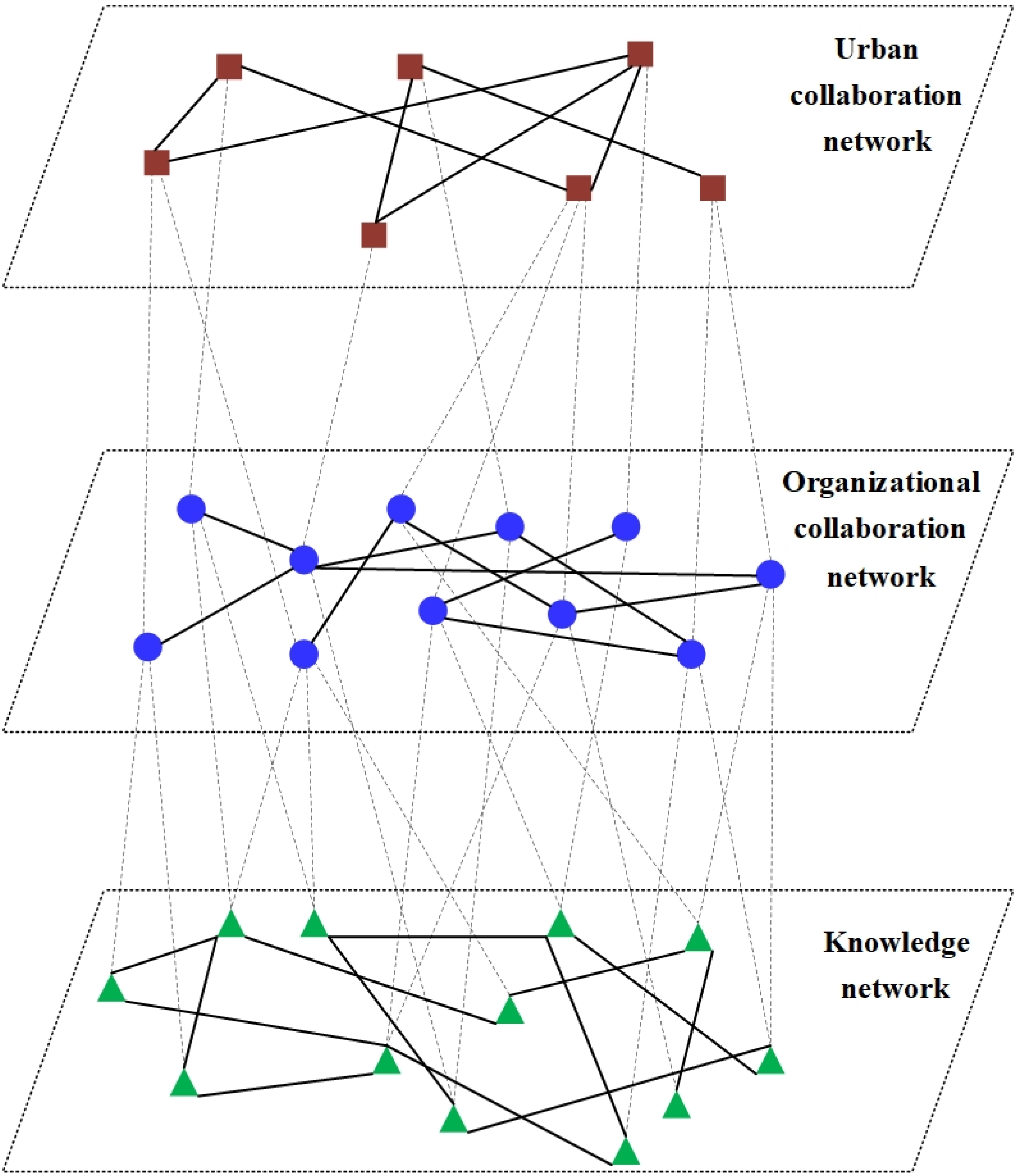

Fig. 1. The interaction of multilevel networks.

China's innovation governance and sectoral targeting, the core mechanisms explored represent general theoretical relationships applicable across varied institutional environments, albeit with contextually specific manifestations.

Following established practice in innovation network research (Yan and Guan, 2018; Lin et al., 2022), we used jointly authorized invention patents to construct multilevel networks. We selected authorized patents rather than applications for several methodological reasons. First, authorized patents represent completed innovations that have passed substantive examination, ensuring that we capture collaborative relationships that actually produced successful outcomes. Second, the authorization process validates both the collaborative relationship and the technological

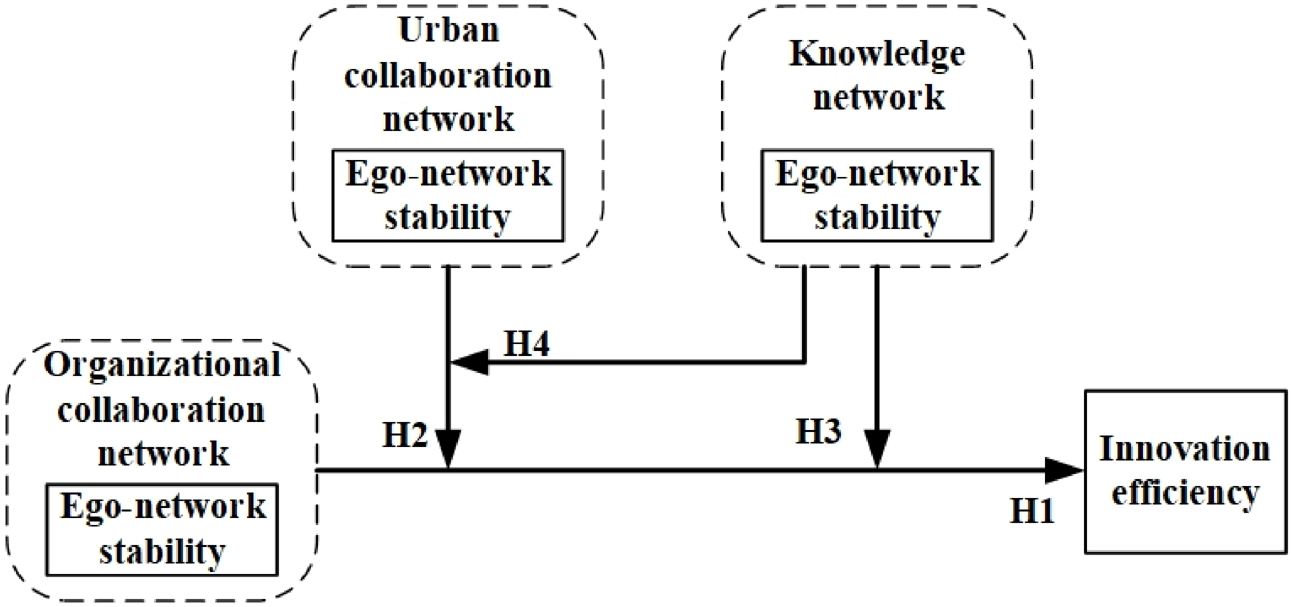

Fig. 2. Theoretical framework.

content, providing greater reliability for identifying knowledge elements through International Patent Classification (IPC) codes. Third, authorization helps filter out strategic patent applications that may not reflect genuine collaborative innovation. We downloaded data on jointly authorized invention patents in the field of AI and intelligent manufacturing equipment in China from the PATSNAP database. For the search, we set the number of patentees greater than or equal to 2 and excluded patent data where the patentee was an individual. We set the patent grant period from 2012–2022 and we collected 9692 patents. Drawing on existing studies (Wang et al., 2023; Shi and Zhang, 2020), we constructed organizational collaboration networks with the information of joint patentees in jointly authorized invention patents. We used TianYanCha to query the registration places of joint patentees and constructed urban collaboration networks based on the information of the cities where different patentees in the same patent are located (Guan et al., 2015). Wang et al. (2014) and Guan and Liu (2016) proposed that IPC code can be used as a categorization criterion for knowledge elements, and we used different IPC codes appearing in the same patent to indicate the combinatorial relationship of knowledge elements and used it to construct knowledge networks.

Because network ties may change, longer observation periods do not reveal changes in communication among network members, and shorter observation periods make it difficult to present a full picture of network member interactions. Therefore, consistent with previous studies (Yan and Guan, 2018; Lin et al., 2022), we used a 3-year rolling time window to ensure a rich longitudinal dataset. In this study, the period 2012–2022 was divided into nine time windows, i.e., 2012–2014, 2013–2015, ..., 2020–2022. The organizational collaboration network for 2020–2022 is shown in Fig. 3, the urban collaboration network is shown in Fig. 4, and the knowledge network is shown in Fig. 5. When examining ego-network stability, we need to compare changes in network composition over time. The baseline periods (Period T-1) were 2012–2014, 2013–2015, ..., 2019–2021, and the observation periods (Period T) were 2013–2015, 2014–2016, ..., 2020–2022. Among all the members of the organizational collaboration network, we selected listed firms as the research sample. Data for listed firms were obtained from the CSMAR database. We obtained unbalanced panel data for a total of 777 sample points over the entire observation period (2013–2022).

3.2 Measurement

3.2.1 Dependent Variable

Innovation efficiency (IE). Most of the studies that have been conducted to measure innovation efficiency have used Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) models (Wang and Yu, 2025). The SFA model needs to set specific functions, and its assumptions are stricter. The DEA model can avoid the estimation bias caused by parameter setting, can objectively calculate different indicators, and is widely used in innovation efficiency measurement (Jovanović, 2022). We use the Banker-Charnes-Cooper (BCC) model proposed by Banker et al. (1984) to measure firm innovation efficiency. Table 1 reports the system of indicators of innovation efficiency. To establish temporal precedence and mitigate reverse causality concerns, we implement a comprehensive lag structure in our analysis. First, in measuring innovation efficiency via DEA, we recognize that innovation resources require time to yield measurable results. Therefore, we use output variables lagged by one year relative to input vari-

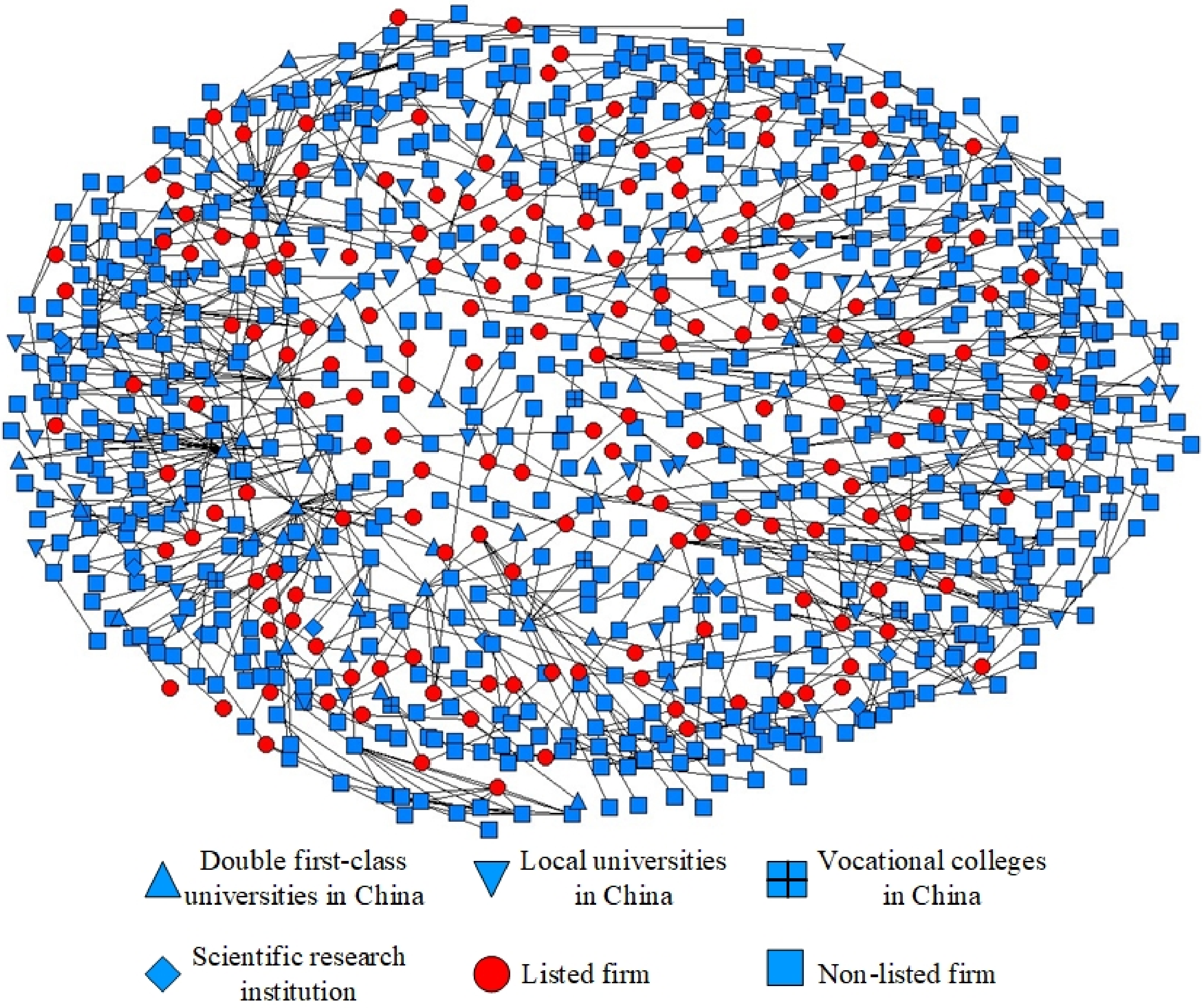

Fig. 3. Organizational collaboration network of Period 2020–2022. Note: The red circular nodes are the sample firms for this study.

ables, as shown in Table 1. More importantly, in our main regression analysis examining the effect of ego-network stability on innovation efficiency, we ensure clear temporal ordering between independent and dependent variables. Specifically, we measure all independent variables and control variables in period T, while measuring innovation efficiency in period T+1. This design ensures that network stability measures temporally precede the innovation efficiency outcomes they are hypothesized to affect, thereby addressing endogeneity concerns related to reverse causality. This approach is consistent with established practices in innovation studies examining causal relationships between network characteristics and innovation outcomes (Wang et al., 2023; Guan et al., 2015). The data collection period for the innovation efficiency is 2013–2023. The formula for calculating innovation efficiency is as follows:

$$\text{Efficiency} = \text{Max}_{1\le i\le n}\frac{a_1Y_{1i}+a_2Y_{2i}}{b_1X_{1i}+b_2X_{2i}+b_3X_{3i}}$$
$$\begin{cases} a_1Y_1 + a_2Y_2 - b_1X_1 - b_2X_2 - b_3X_3 \le 0 \\ a \ge \varepsilon, b \ge \varepsilon \end{cases} \qquad (1)$$

where a_1, a_2 are the weights of the output indicators. b_1, b_2, b_3 are the weights of the input indicators. *n* is the number of decision-making units. Y_{1i}, Y_{2i} are the innovation outputs of the unit *i*. X_{1i}, X_{2i}, X_{3i} are the innovation inputs of the unit *i*. Efficiency is the calculated value of innovation efficiency.

3.2.2 Independent Variable

Ego-network stability in organizational collaboration networks (ESO). Ego-network stability emphasizes the extent to which the composition of the ego-network in which a firm is located remains constant from one period to the next. When measuring the ego-network stability, we need

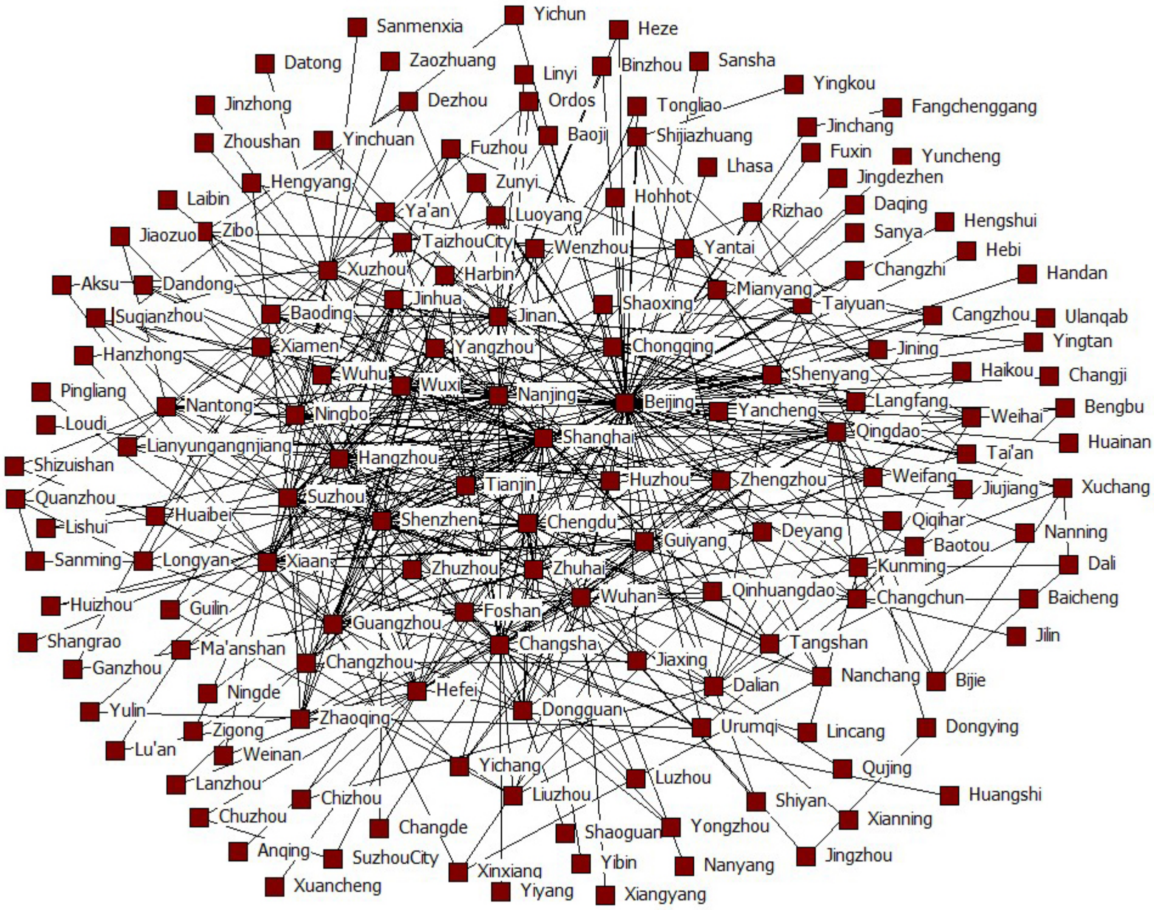

Fig. 4. Urban collaboration network of Period 2020–2022.

Table 1. Input and output indicators of innovation efficiency.

Type	Name	Explanation	Data period
Output variable	Technological innovation output	Number of new patent applications	t+1 year
	Economic benefit output	Operation revenue	t+1 year
Input variable	Capital investment	Research and Development (R&D) expenditure	t year
	Human resource input	Number of R&D personnel	t year
	Investment in fixed assets	Net value of fixed assets	t year

to compare the network composition of ego-networks in the period T-1 with that of the period T. Kumar and Zaheer (2019), Lin et al. (2022) reflect ego-network stability by calculating network churn. Drawing on previous literature (Yan and Guan, 2018; Kumar and Zaheer, 2019), we use the following formula to calculate ego-network stability:

$$\text{Stability} = \frac{C_T \cap C_{T-1}}{C_T \cup C_{T-1}} \tag{2}$$

where C_T denotes the ego-network composition of the focal node in period T. C_{T-1} denotes the ego-network composition of the focal node in period T-1.

To visualize the ego-network stability at different levels, Fig. 6 reports the ego-network stability with 2019–2021 as period T-1 and 2020–2022 as period T. In the case of Firm-A, for example, the ego-network has 2 exiting nodes in period T-1 and 3 new nodes in period T. There are 3 persistent nodes in the two periods. $C_T \cap C_{T-1}$ is 3 and $C_T \cup C_{T-1}$ is 8, the ego-network stability of Firm-A is 0.375.

3.2.3 Moderator Variables

Ego-network stability in urban collaboration networks (ESU). We also use Eqn. 2 to calculate the ego-network stability of the city where the firm is located. In Fig. 6, taking Chongqing as an example, the ego-network has 7 exiting

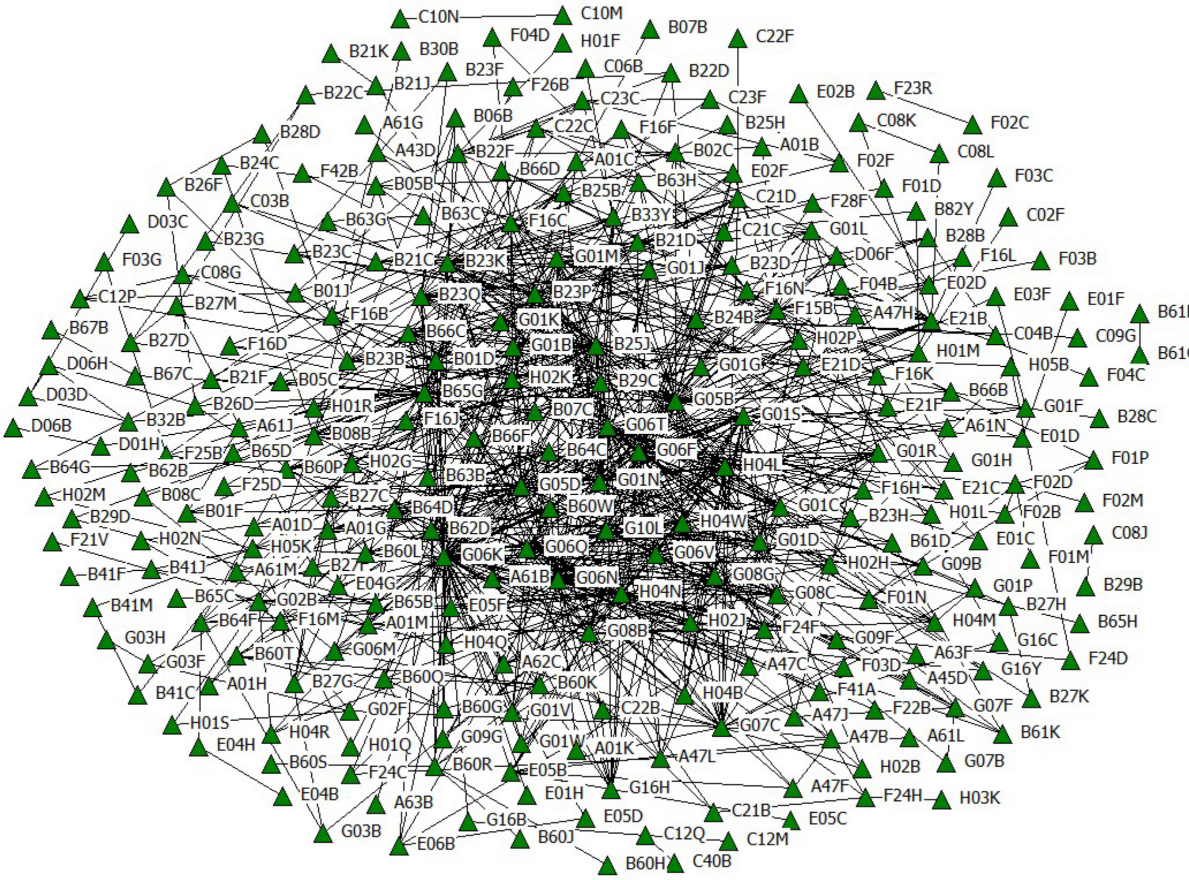

Fig. 5. Knowledge network of Period 2020–2022.

nodes in period T-1 and 2 new nodes in period T. There are 6 persistent nodes in the two periods. $C_T \cap C_{T-1}$ is 6 and $C_T \cup C_{T-1}$ is 15, the ego-network stability of Chongqing is 0.4.

Ego-network stability in knowledge networks (ESK). We also use Eqn. 2 to calculate the ego-network stability of knowledge elements owned by firms. In Fig. 6, using H04M as an example, the ego-network has 8 exiting nodes in period T-1 and 1 new node in period T. There are 7 persistent nodes in the two periods. $C_T \cap C_{T-1}$ is 7 and $C_T \cup C_{T-1}$ is 16, the ego-network stability of H04M is 0.4375. Firms typically possess multiple knowledge elements; therefore, it is essential to aggregate the characteristics of these elements at the firm level. In accordance with Wang et al. (2014), we employ arithmetic averaging to consolidate the knowledge elements of a firm. For instance, if a firm has three knowledge elements, and the ego-network stability of the three knowledge elements is Z_1, Z_2, Z_3 respectively, then the knowledge ego-network stability of the firm after aggregation to the firm level is $(Z_1 + Z_2 + Z_3)/3$.

3.2.4 Control Variables

First, we control for the overall characteristics of networks at different levels, including organizational collaboration network density (OND), urban collaboration network density (UND), and knowledge network density (KND). Second, we control for the structural characteristics of the firms at different levels of the network, including the degree centrality of the firm in the organizational collaboration network (DCO), the degree centrality of the city where the firm is located in the urban collaboration network (DCU), and the degree centrality of the knowledge elements owned by the firm in the knowledge network (DCK). Third, we control for the operating characteristics of the listed firms. We measure firm scale (SCA) as the natural logarithm of the total number of employees. The difference between the year of observation and the year of establishment is used to measure the firm age (AGE). We measure the debt-to-asset ratio (DAR) as the ratio of total liabilities to total assets. We measure the intensity of intangible assets (IIA) as the ratio of year-end net intangible assets to year-end total assets. The aggregate shareholding of the top ten shareholders is used to calculate the ownership concentration (OC). We also control for the proportion of R&D personnel in the total number of employees (PRD) and the proportion of employees with a bachelor's degree or above in the total number of employees (PBD). Finally, we control for the effect of the year.

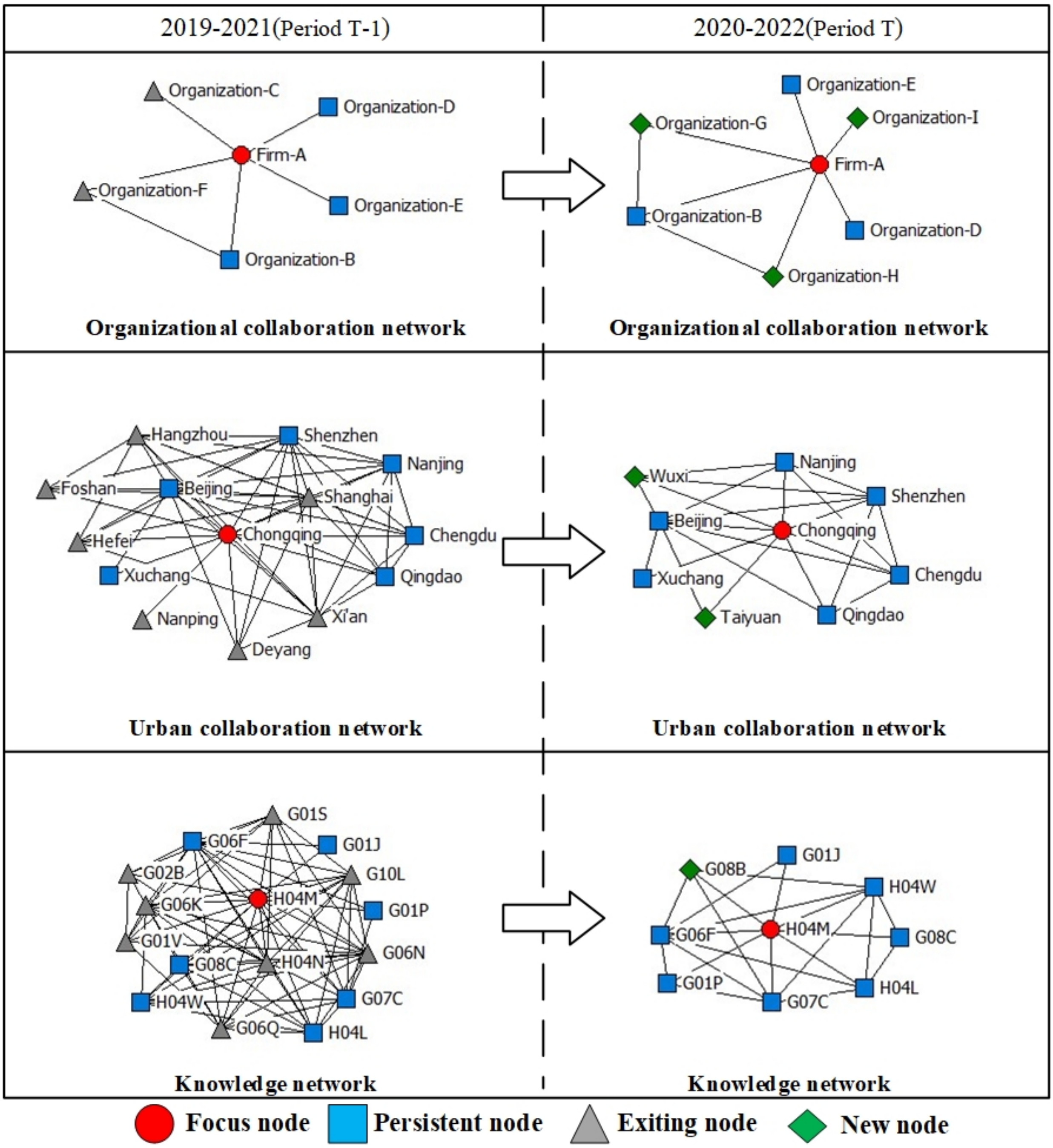

Fig. 6. Multilevel ego-network stability.

3.3 Model Estimation

The innovation efficiency scores obtained through DEA modeling are bounded between 0 and 1, creating a limited dependent variable. More importantly, the distribution of innovation efficiency exhibits significant censoring. This pattern of censoring at the boundaries violates the assumptions of ordinary least squares (OLS) regression, which would produce biased and inconsistent estimates. The Tobit model is specifically designed for situations where the dependent variable is censored or cornered at boundary values. It accounts for the fact that the observed zeros (and ones) represent both genuine inefficiency and potential measurement limitations, rather than reflecting a continuous latent variable. By modeling the latent innovation efficiency that underlies the observed censored distribution, the Tobit estimator provides consistent and efficient parameter estimates (Zhan et al., 2025). Given the significant proportion of censored observations in our data, we employ the Tobit regression model to avoid the substantial bias that would result from OLS estimation. All analyses were performed using Stata/MP 17.0 (StataCorp LLC, College Station, TX, USA) with robust standard errors.

4. Analysis and Results

The descriptive statistics and bivariate correlation matrix of all variables in our paper are presented in Table 2. Table 2 shows that the correlation coefficients of the variables are not high and are less than the common threshold of 0.7. The variance inflation factor (VIF) shows that there is no multicollinearity problem.

The regression results of the hypothesis testing are shown in Table 3. Model 1 serves as the base model and contains only control variables. Hypothesis 1 proposes that ego-network stability in organizational collaboration networks has an inverted U-shaped effect on firm innovation efficiency. Following established practice for testing nonlinear relationships (Haans et al., 2016), we first established the significant linear effect of ESO in Model 2 ($\beta = 0.040$, $p < 0.01$). In Model 3, the significantly negative coefficient of ESO^2 ($\beta = –0.025$, $p < 0.05$) provides primary evidence for the concave relationship. Additional analysis confirms significantly positive and negative slopes at low and high ESO values, respectively, with the turning point within data range. Therefore, Hypothesis 1 is supported.

Following established practice for testing moderation of curvilinear relationships (Haans et al., 2016), we focus on the interaction between moderators and ESO^2 as the primary evidence for how moderators affect the inverted U-shaped relationship. In model 4, the coefficient of the product term of ESO^2 and ESU is negative and significant ($\beta = –0.029$, $p < 0.01$). This result supports our second hypothesis that urban ego-network stability strengthens the inverted U-shaped relationship between organizational ego-network stability and innovation efficiency. The visual representation in Fig. 7 confirms this moderating effect, showing steeper curvature at higher levels of ESU.

In model 5, the coefficient of the product term of ESO^2 and ESK is negative and significant ($\beta = –0.032$, $p < 0.01$), indicating that knowledge ego-network stability enhances the inverted U-shaped relationship. While the linear interaction term (ESO×ESK) is non-significant, the key test for the moderation of the curvature lies in the interaction with the square term. Therefore, Hypothesis 3 is supported. Fig. 8 visually confirms that higher knowledge ego-network stability intensifies the inverted U-shaped pattern.

To test the joint moderating effect of urban ego-network stability and knowledge ego-network stability on the relationship between organizational ego-network stability and innovation efficiency, we include ESO, ESU, and ESK in the regression model at the same time. The regression for model 6 shows that the coefficient of the product term of ESO^2, ESU, and ESK is negative and significant ($\beta = –0.028$, $p < 0.05$). This result supports our fourth hypothesis that the combination of high urban ego-network stability and high knowledge ego-network stability strengthens the inverted U-shaped relationship. Fig. 9 provides visual confirmation of this joint moderating effect, showing the steepest curvature when both ESU and ESK are at high levels. Meanwhile, the results of Log Likelihood and chi2 of the improvement of fit comparing the present model with the base model show that all the models have a significant improvement over the base models.

Robustness Checks

To further validate the reliability of our findings, we conducted robustness checks using the following methodology. First, we changed the measurement of innovation efficiency. The super-efficiency DEA model compensates for the inability of the DEA model to rank units with an efficiency of 1 (Fang et al., 2013). Drawing on previous literature (Fang et al., 2013), we utilized the super-efficiency DEA model to calculate innovation efficiency. Second, we changed the control variables. We changed from OND to the average distance of organizational collaboration networks (ADO), from UND to the average distance of urban collaboration networks (ADU), and from KND to the average distance of knowledge networks (ADK). We replaced DCO with the betweenness centrality of the firm in the organizational collaboration network (BCO), DCU with the betweenness centrality of the city in which the firm is located in the urban collaboration network (BCU), and DCK with the betweenness centrality of the knowledge elements owned by the firm in the knowledge network (BCK). Return on total assets (RTA) was used to replace DAR. Inventory density (ID) was used to replace IIA. The percentage of independent directors (PID) was used to replace OC. The natural logarithm of government subsidies (GS) received by the firm was used to replace PBD. Finally, we changed the regression model. We replaced the Tobit regression model with the Feasible Generalized Least Squares (FGLS) regression model. The results of the robustness checks are shown in Table 4. As can be seen from the regression results in Table 4, the robustness check results are consistent with the empirical results in the previous section. Therefore, our findings are reliable.

5. Conclusion and Discussion

5.1 Main Findings

More and more scholars are no longer focusing only on the structural characteristics of the network, but are gradually turning their attention to the dynamic characteristics of the network (Zhang and Luo, 2020; Yan and Guan, 2018; Han et al., 2020). The stability of collaboration networks is a very interesting topic in the literature related to innovation networks. Our empirical analysis reveals several important findings regarding how multilevel ego-network stability influences firm innovation efficiency in China's AI and intelligent manufacturing sectors. The inverted U-shaped relationship between organizational ego-network stability and innovation efficiency suggests that Chinese firms face a delicate balancing act between network stability and flexibility. This finding may be particularly salient in China's rapidly evolving innovation landscape, where policy prior-

Table 2. Descriptive statistics and correlations.

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1.IE	1																
2.ESO	0.168***	1															
3.ESU	0.113***	0.262***	1														
4.ESK	0.475***	0.529***	0.255***	1													
5.OND	0.218***	0.017	0.179***	0.234***	1												
6.UND	–0.243***	–0.001	–0.136***	–0.203***	–0.688***	1											
7.KND	0.165***	0.027	0.187***	0.273***	0.643***	–0.620***	1										
8.DCO	0.173***	0.084**	0.067*	0.114***	0.054	–0.046	0.039	1									
9.DCU	0.047	0.005	0.177***	0.051	0.015	–0.024	0.026	0.010	1								
10.DCK	0.013	0.081**	0.010	0.062*	–0.401***	0.281***	–0.387***	0.159***	0.227***	1							
11.SCA	0.159***	0.016	–0.050	0.077**	0.064*	–0.047	0.089**	0.317***	0.109***	0.147***	1						
12.AGE	0.026	0.001	0.075**	0.069*	0.271***	–0.174***	0.316***	0.147***	–0.149***	–0.111***	0.275***	1					
13.DAR	0.079**	0.050	–0.043	0.042	0.037	–0.030	0.066*	0.171***	–0.196***	–0.069*	0.479***	0.245***	1				
14.IIA	–0.024	0.021	–0.049	–0.049	–0.142***	0.105***	–0.135***	–0.029	0.012	–0.006	0.022	–0.025	0.138***	1			
15.OC	0.211***	–0.013	–0.015	0.034	–0.040	0.012	–0.036	–0.080**	0.156***	–0.063*	0.154***	–0.311***	–0.142***	–0.041	1		
16.PRD	–0.098***	0.049	0.144***	0.121***	0.114***	–0.074**	0.110***	–0.023	0.195***	0.302***	–0.373***	–0.190***	–0.261***	–0.099***	–0.185***	1	
17.PBD	–0.039	0.007	0.074**	0.122***	0.156***	–0.094***	0.184***	–0.012	0.374***	0.279***	–0.152***	–0.184***	–0.198***	–0.045	0.054	0.628***	1
Mean	0.411	0.724	0.799	0.597	0.007	0.138	0.049	0.007	1.164	0.237	8.575	18.741	0.445	0.040	0.609	0.227	0.409
SD	0.269	0.343	0.195	0.220	0.001	0.009	0.014	0.016	1.297	0.324	1.480	6.432	0.177	0.044	0.170	0.162	0.238
VIF		1.48	1.20	1.61	4.28	1.94	3.96	1.17	1.37	1.90	2.15	1.50	1.56	1.06	1.41	2.31	2.07

Note(s): $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Source(s): This table was made by authors.

Table 3. Regression results.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
ESO		0.040***	0.014	–0.005	–0.053***	–0.054***
		(0.009)	(0.015)	(0.017)	(0.014)	(0.016)
ESO^2			–0.025**	–0.038***	–0.046***	–0.051***
			(0.011)	(0.012)	(0.012)	(0.013)
ESU				0.035**		0.022
				(0.016)		(0.016)
ESO×ESU				–0.049***		–0.049***
				(0.016)		(0.015)
ESO^2×ESU				–0.029***		–0.012
				(0.011)		(0.014)
ESK					0.171***	0.191***
					(0.016)	(0.019)
ESO×ESK					–0.011	–0.027
					(0.016)	(0.018)
ESO^2×ESK					–0.032***	–0.044***
					(0.011)	(0.013)
ESU×ESK						0.047***
						(0.017)
ESO×ESU×ESK						–0.056***
						(0.016)
ESO^2×ESU×ESK						–0.028**
						(0.012)
OND	–29.093	–24.657	–21.210	–23.390	35.782	36.528
	(48.972)	(48.406)	(48.208)	(48.105)	(43.404)	(43.339)
UND	–17.398***	–16.736***	–16.386***	–16.247***	–8.776*	–9.003*
	(5.214)	(5.154)	(5.133)	(5.129)	(4.636)	(4.630)
KND	2.139	1.756	1.669	1.554	–2.387	–2.522
	(2.008)	(1.987)	(1.978)	(1.979)	(1.798)	(1.795)
DCO	3.119***	2.894***	2.667***	2.357***	2.134***	1.872***
	(0.716)	(0.702)	(0.698)	(0.695)	(0.631)	(0.630)
DCU	0.009	0.009	0.009	0.008	0.008	0.009
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
DCK	0.180***	0.164***	0.159***	0.156***	0.111***	0.123***
	(0.040)	(0.040)	(0.039)	(0.039)	(0.036)	(0.035)
SCA	–0.014	–0.012	–0.013	–0.012	–0.014*	–0.015*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
AGE	–0.001	–0.001	–0.001	–0.001	–0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
DAR	0.155**	0.138**	0.141**	0.137**	0.121**	0.131**
	(0.066)	(0.066)	(0.065)	(0.065)	(0.059)	(0.058)
IIA	0.094	0.066	0.064	0.078	0.124	0.066
	(0.224)	(0.222)	(0.221)	(0.219)	(0.198)	(0.197)
OC	0.433***	0.425***	0.419***	0.413***	0.358***	0.366***
	(0.066)	(0.065)	(0.065)	(0.064)	(0.058)	(0.058)
PRD	–0.142	–0.155*	–0.140	–0.130	–0.194**	–0.179**
	(0.089)	(0.088)	(0.088)	(0.087)	(0.079)	(0.078)
PBD	–0.134**	–0.120**	–0.132**	–0.128**	–0.128**	–0.135***
	(0.057)	(0.056)	(0.056)	(0.056)	(0.050)	(0.050)
Year	Yes	Yes	Yes	Yes	Yes	Yes
_cons	2.684***	2.581***	2.556***	2.568***	1.424*	1.450*
	(0.937)	(0.926)	(0.922)	(0.920)	(0.830)	(0.829)

Table 3. Continued.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
N	777	777	777	777	777	777
chi2	170.54	188.68	193.56	204.44	357.58	378.75
Log likelihood	–145.609	–136.540	–134.097	–128.658	–52.091	–41.504

Note(s): Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
Source(s): This table was made by authors.

Table 4. Results of robustness checks.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
ESO		0.065***	0.020	–0.020	–0.076***	–0.088***
		(0.015)	(0.023)	(0.026)	(0.023)	(0.026)
ESO^2			–0.044**	–0.070***	–0.086***	–0.095***
			(0.017)	(0.019)	(0.019)	(0.021)
ESU				0.073***		0.058**
				(0.024)		(0.025)
ESO×ESU				–0.088***		–0.089***
				(0.025)		(0.024)
ESO^2×ESU				–0.054***		–0.042*
				(0.017)		(0.022)
ESK					0.250***	0.269***
					(0.027)	(0.030)
ESO×ESK					–0.015	–0.030
					(0.025)	(0.029)
ESO^2×ESK					–0.057***	–0.066***
					(0.018)	(0.020)
ESU×ESK						0.073***
						(0.027)
ESO×ESU×ESK						–0.070***
						(0.026)
ESO^2×ESU×ESK						–0.044**
						(0.018)
ADO	–5.472***	–5.273***	–5.163***	–4.997***	–3.276*	–3.369**
	(1.864)	(1.842)	(1.835)	(1.825)	(1.699)	(1.693)
ADU	13.066***	12.647***	12.418***	12.020***	8.593**	8.822**
	(4.228)	(4.176)	(4.160)	(4.135)	(3.850)	(3.832)
ADK	–4.116***	–3.982***	–3.921***	–3.760***	–2.632**	–2.669**
	(1.242)	(1.226)	(1.222)	(1.215)	(1.133)	(1.127)
BCO	0.100	0.085	0.066	0.034	–0.030	–0.067
	(0.103)	(0.102)	(0.102)	(0.101)	(0.094)	(0.093)
BCU	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
BCK	0.034***	0.030***	0.028***	0.026***	0.020***	0.019***
	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
SCA	0.007	0.008	0.008	0.013	0.008	0.010
	(0.020)	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)
AGE	–0.006**	–0.006**	–0.005**	–0.005**	–0.005*	–0.004*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
RTA	1.994***	2.030***	1.997***	1.939***	1.733***	1.706***
	(0.258)	(0.255)	(0.254)	(0.252)	(0.236)	(0.234)
ID	0.636***	0.639***	0.632***	0.626***	0.504***	0.504***
	(0.181)	(0.178)	(0.178)	(0.176)	(0.164)	(0.162)
PID	–0.066	–0.076	–0.108	–0.159	–0.194	–0.231
	(0.193)	(0.190)	(0.190)	(0.189)	(0.175)	(0.174)

Table 4. Continued.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
PRD	-0.315^{***}	-0.322^{***}	-0.300^{**}	-0.265^{**}	-0.354^{***}	-0.324^{***}
	(0.121)	(0.119)	(0.119)	(0.119)	(0.110)	(0.109)
GS	0.001	0.002	–0.001	–0.002	–0.002	–0.002
	(0.015)	(0.015)	(0.015)	(0.014)	(0.013)	(0.013)
Year	Yes	Yes	Yes	Yes	Yes	Yes
_cons	10.132^{***}	9.656^{***}	9.532^{***}	9.174^{***}	4.904	4.954
	(3.482)	(3.440)	(3.426)	(3.415)	(3.185)	(3.180)
N	777	777	777	777	777	777
chi2	144.33	167.75	175.40	194.34	348.43	376.80
Log likelihood	–411.519	–401.770	–398.635	–390.985	–333.781	–324.109

Note(s): Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Source(s): This table was made by authors.

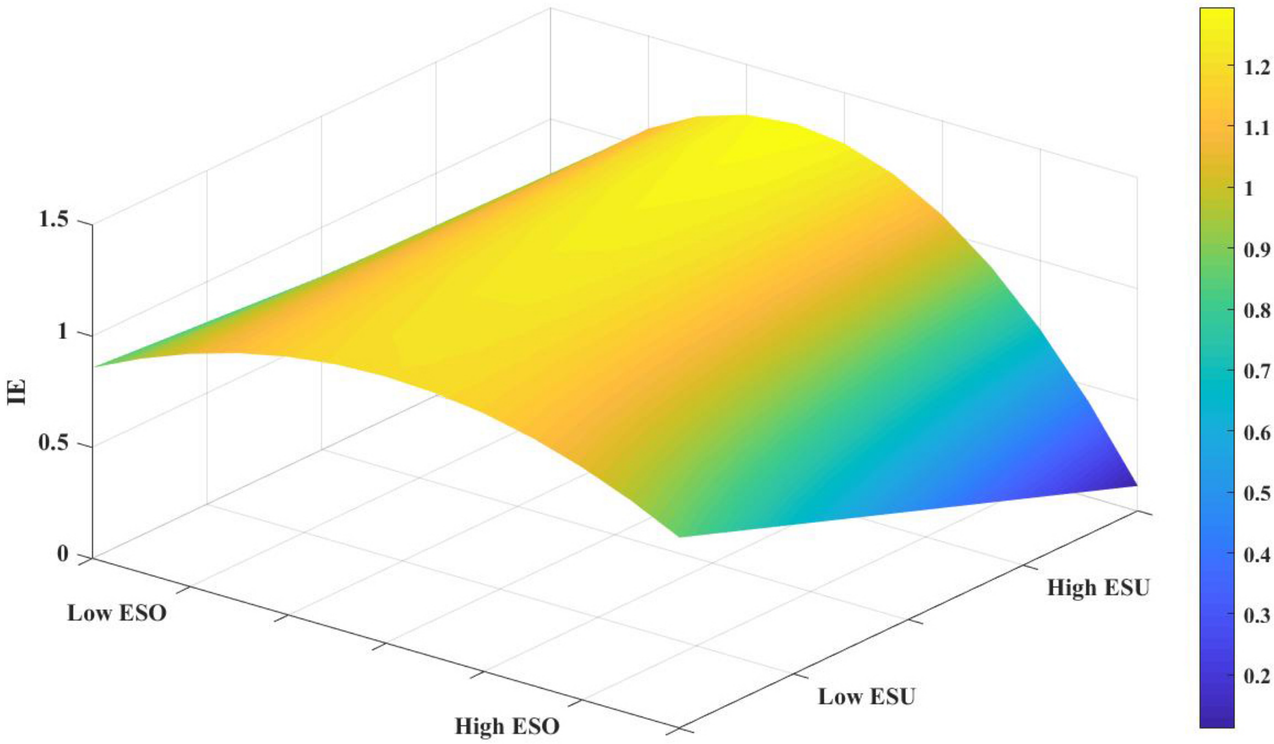

Fig. 7. The moderating effect of ESU.

ities and market conditions shift frequently, requiring firms to maintain both stability for deep collaboration and flexibility for adaptive reconfiguration.

The moderating effects of urban and knowledge ego-network stability likely reflect China's distinctive regional innovation systems and knowledge infrastructure. China's innovation policies often operate through place-based interventions such as national high-tech zones and innovation demonstration cities, which create geographically concentrated innovation ecosystems (Yao et al., 2020b). This spatial patterning of innovation resources may amplify the importance of urban ego-network stability compared to contexts with more decentralized innovation systems.

Furthermore, China's emphasis on technological catch-up and indigenous innovation has shaped distinctive knowledge search and recombination patterns. Chinese firms often engage in combinatorial innovation that reconfigures existing knowledge in novel ways, which may explain why knowledge ego-network stability plays such a crucial moderating role in our findings. The stability of knowledge networks provides the foundation for systematic knowledge accumulation while allowing for strategic recombination within familiar technological domains.

The joint moderating effect of urban and knowledge ego-network stability may reflect the coordinated nature of China's innovation policy implementation, where spa-

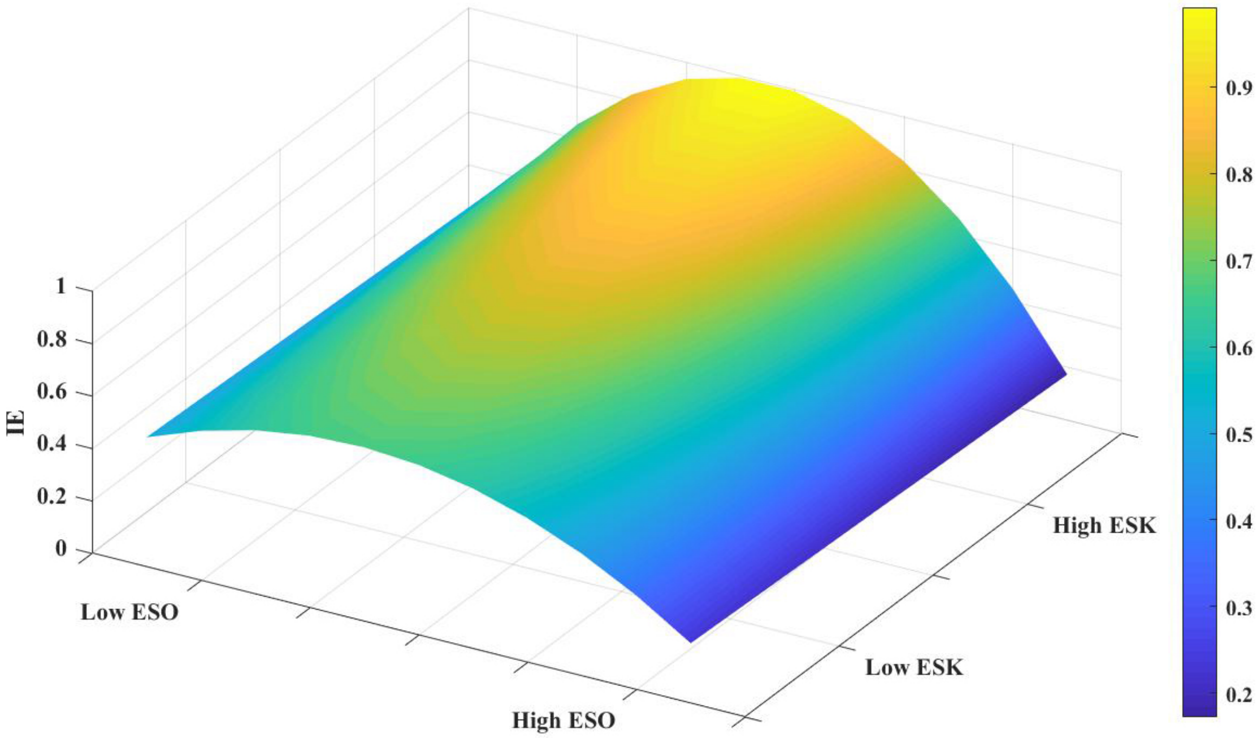

Fig. 8. The moderating effect of ESK.

tial development strategies and technological specialization policies are often aligned. This alignment creates synergistic effects that strengthen the relationship between organizational ego-network stability and innovation efficiency.

While our specific findings emerge from China's unique institutional context, the theoretical mechanisms we identify represent fundamental processes that should operate across different national contexts. However, the specific inflection points and effect sizes may vary depending on institutional arrangements, industrial structures, and technological trajectories.

5.2 Theoretical Implications

First, this study advances the literature on the relationship between innovation networks and firm innovation from a network dynamics perspective. Previous studies have recognized that innovation can be influenced by collaboration networks (Burt and Soda, 2021; Ye and Crispeels, 2022). Notably, such studies have focused mostly on the static characteristics of networks, which are not static and the composition of the network partners changes dynamically (Guo et al., 2021). Existing studies of ego-network stability have mainly emphasized the damaging effects of network stability on innovation (Kumar and Zaheer, 2019; Lin et al., 2022). That is because previous literature focuses on firms' innovation output. This study integrates two aspects of firm innovation, namely resource input and innovation output, and uses innovation efficiency to present the actual situation of firm innovation. By detailing the possible positive and negative effects of ego-network stability on innovation efficiency, we conclude that ego-network stability has a non-monotonic effect on innovation efficiency, contributing to the literature on network dynamics and firm innovation.

Second, our findings elucidate the effects of urban ego-network stability and knowledge ego-network stability on the relationship between organizational ego-network stability and innovation efficiency. Urban collaboration networks underscore the significance of resource acquisition within urban contexts (Yao et al., 2020b), while knowledge networks highlight the importance of resource acquisition based on knowledge (Guan and Liu, 2016; Yayavaram and Ahuja, 2008). Prior research indicates that firm innovation is situated within at least two levels of networks: organizational collaboration networks and knowledge networks (Wang et al., 2014; Guan and Liu, 2016). This study contributes to the literature on multilevel network embeddedness by incorporating urban collaboration networks, building on existing scholarship. From a network dynamics perspective, we examine both the individual moderating effects and the joint moderating effects of urban ego-network stability and knowledge ego-network stability on the relationship between organizational ego-network stability and innovation efficiency. This research broadens the external network context in which firm innovation is situated and substantiates the influence of multilevel ego-network stability on innovation efficiency. Our findings enhance the literature on multilevel network embeddedness from a dy-

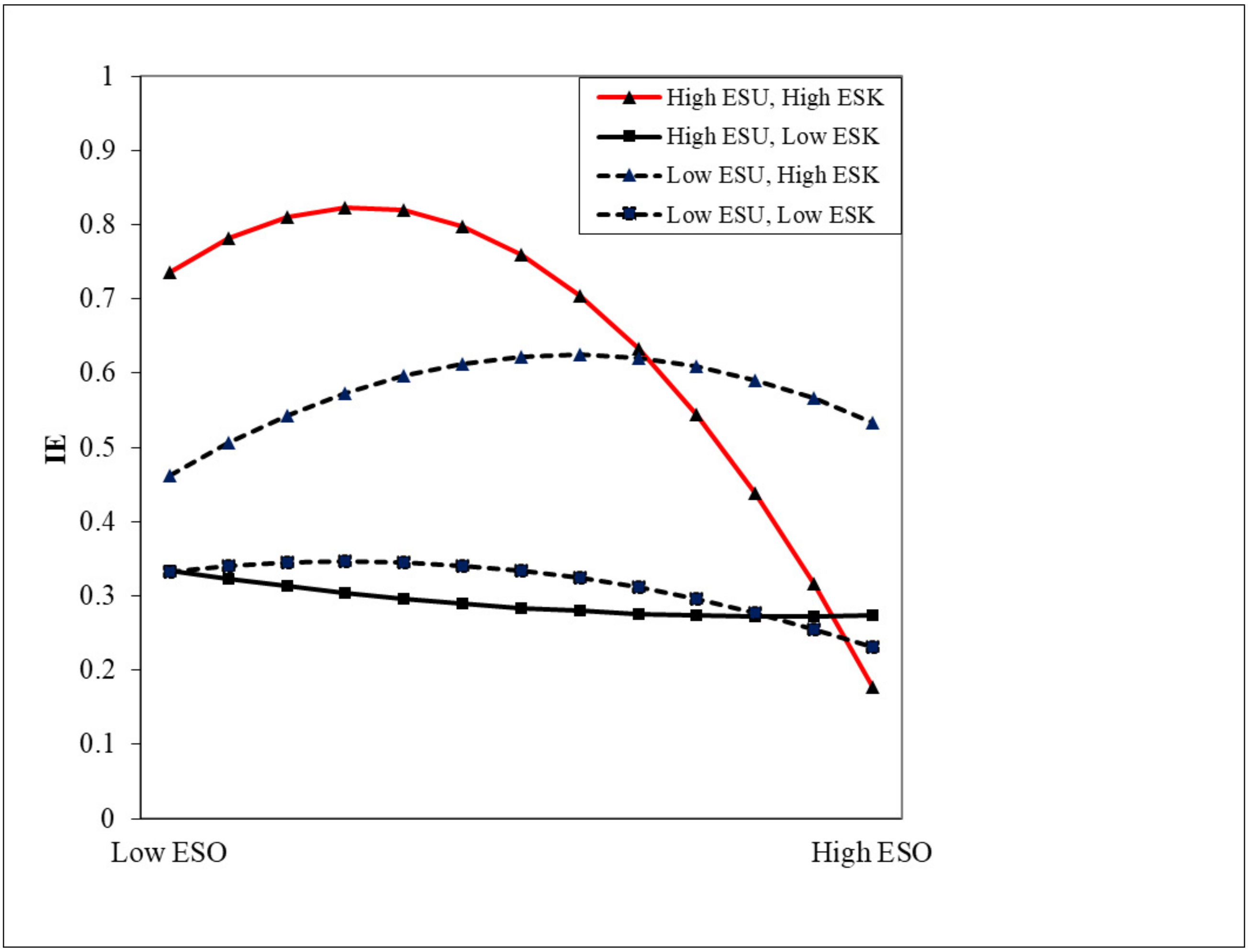

Fig. 9. The joint moderating effect of ESU and ESK.

namic perspective and open new avenues for research regarding the relationship between multilevel network content characteristics and firm innovation.

5.3 Managerial Implications

First, by demonstrating how ego-network stability affects innovation efficiency, we attempt to convey to managers the idea that pursuing an overly stable collaboration network is not conducive to firm innovation and that maintaining a moderately stable ego-network is what promotes innovation. When firms aim to improve innovation efficiency, they should be strategic in deciding how to configure their partnerships with other organizations. Maintaining a moderate degree of ego-network stability can provide firms with reliable channels for external collaboration and maximize the scope of resource acquisition. Second, our findings demonstrate that firm innovation is also affected by the stability of other level networks (i.e., the urban ego-network stability and the knowledge ego-network stability) when it benefits from the organizational ego-network stability. To improve innovation efficiency, firms should innovate in collaboration with other organizations in a moderately stable urban ego-network. A moderately stable urban ego-network ensures the diversity of urban resources while avoiding the accumulation of redundant and repetitive information, which can support firm innovation. At the same time, firm innovation is based on knowledge resources. Firms and partners working together in relatively familiar knowledge domains can effectively enhance innovation efficiency. A moderately stable knowledge ego-network can help firms and their partners tap into the innovation potential of higher-value knowledge elements.

5.4 Limitations and Ideas for Future Research

There are some limitations pertaining to this study. First, we have tested our theory and hypotheses using data on high-tech firms in China's AI and intelligent manufacturing equipment from 2012 to 2022, which may not be generalized to other time periods or fields. Future research could generalize the findings using panel data from other fields or different data sources to improve validity. Second, more and more scholars have called for analyzing firm innovation from a multilevel network embeddedness perspective (Wang et al., 2014; Guan and Liu, 2016; Guan et al., 2015).

While our study considers the different level networks in which firm innovation is embedded as much as possible, there are other level networks that we do not include in our analytical framework, such as individuals' collaboration networks (Lin et al., 2022). Future research could start from different theoretical perspectives, such as the dynamic capabilities view (Guerrero and Siegel, 2024), to analyze the different levels of networks in which firm innovation is embedded. To further investigate the impact of multilevel network embeddedness on firm innovation, future research could employ diverse methodologies, such as case studies, to enhance the understanding of the relationship between multilevel embeddedness and innovation.

Availability of Data and Materials

All data reported in this paper will be shared by the first author upon reasonable request.

Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by JL, BH and WL. The first draft of the manuscript was written by JL and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript. All authors agreed to be accountable for all aspects of the work.

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Conflicts of Interest

The authors declare no conflicts of interest.

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