Journal of Engineering and Technology Management 77 (2025) 101894

Contents lists available at ScienceDirect

Journal of Engineering and Technology Management

journal homepage: www.elsevier.com/locate/jengtecman

Elite community dynamics, knowledge search, and innovation output –Evidence from energy-saving techniques in China

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A R T I C L E I N F O

JEL classification in this article:
O32 O36 Q55

Keywords:
Elite community
Community dynamics
Knowledge search
Innovation output
Energy-saving techniques

A B S T R A C T

This paper constructs a conceptual framework combining social network theory, knowledge base view, and absorptive capacity theory to investigate how elite community dynamics interact with internal/external knowledge search strategies in shaping community-level innovation outputs. Employing longitudinal patent data from China’s energy-saving sector, we empirically demonstrate the nonlinear relationship between community dynamic and overall innovation outputs. Internal knowledge search moderates this nonlinear effect, whereas external cross-community search fails to produce multiplicative innovation gains. By highlighting the dualistic nature of knowledge boundaries , this work advances theoretical understanding community-based innovation mechanisms and offer practical guidelines for optimizing elite community governance through balanced dynamics.

1. Introduction

In the early 21st century, the Chinese government launched policies to establish innovation alliances led by flagship enterprises or research institutions, aiming to address critical technological challenges through cross-sector collaboration. These alliances epitomize innovation networks, where nodes represent entities (e.g., firms, universities, governments) and ties reflect knowledge-sharing or collaborative innovation activities. A representative case is the Biomass Gas Industry Innovation Alliance initiated by Tsinghua University in 2010. This alliance initially aggregated 22 industry leaders, forming an elite-centric network anchored by Tsinghua. Through strict admission and exit mechanisms governed by the Tsinghua-led council, membership expanded to 47 entities by 2014, accompanied by a surge in cumulative patents to 227. This evolution highlights the necessity of strategic innovation network regulation and underscores the imperative to explore how such networks can be systematically governed to drive overall innovation (Chuluun et al., 2017; Inkpen and Tsang, 2005).

Prior studies on innovation network regulation have primarily focused on macro-network (overall structure) or ego-network (individual-centric ties) levels. Position-based research reveals that elite actors occupying central nodes leverage regulatory capabilities—such as network design, relational governance, and structural advantage exploitation—to optimize innovation outcomes (Sovacool and Brisbois, 2019; Yi et al., 2023). Structural analyses further demonstrate the dual role of network density: dense networks enhance knowledge accumulation, while sparse networks utilize structural holes to foster novel ideas (Alguezaui and Filieri, 2010; Mao et al., 2020).

However, Sytch and Tatarynowicz (2014) proposed a paradigm shift toward community-level regulation—tightly-knit subgroups

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https://doi.org/10.1016/j.jengtecman.2025.101894
Received 15 March 2024; Received in revised form 18 April 2025; Accepted 9 June 2025
Available online 12 June 2025

with sparse external connectivity. Community-level performance hinges on balancing innovation quantity (rapid ideation via external bridging) and innovation quality (deep expertise via internal cohesion). Excessive closure stifles diversity (e.g., homogeneous knowledge pools), whereas excessive openness disrupts knowledge coherence (e.g., fragmented R&D). Building on this, Wei and Dang (2017) emphasized that regulating community networks requires attention to their dynamic nature, particularly moderate member mobility under asymmetric network positions. Elite members, acting as "architects," must orchestrate member mobility and relational adjustments under asymmetric power distributions to sustain community vitality. Consequently, unraveling the dynamic evolution of elite communities and how structural forces within these subgroups drive or constrain innovation processes is essential for understanding how community architectures shape knowledge renewal and innovation activities. These insights provide both theoretical foundations and practical guidance for optimizing innovation network governance.

While a few pieces of literature have explored the relationship between dynamics in elite community members and community-level innovation output, research on knowledge search update strategies remains an underexplored area (Liu et al., 2021; Wei and Dang, 2017). Previous studies have validated that moderate dynamics among elite community members are beneficial for innovation output and have treated cross-community external heterogeneous knowledge search as the core strategy for knowledge updating, showing that cross-community knowledge search indeed promotes an increase in innovation output (Liu et al., 2021; Wei and Dang, 2017). However, a fraction of studies have delved into how to optimize knowledge search strategies within the community itself. Zhang et al. (2022) suggested that internal expansion within communities can reduce knowledge search and transfer costs, thereby promoting innovation performance. Yet, the interplay between internal and external knowledge search strategies under dynamic member changes remains unclear.

The nature of knowledge itself further amplifies the complexity of knowledge search strategies. The knowledge-based view argues that the core capabilities of innovation subjects stem from their tacit knowledge, which is highly sticky and typically carried by individuals (Katila and Ahuja, 2002; Zhang et al., 2023). As a result, innovation subjects face two key tasks: integrating and innovating their internal personal knowledge to create new specialized knowledge, and effectively acquiring the external knowledge needed for innovation(Alguezaui and Filieri, 2010; Zakaryan, 2023). For elite communities with shared goals, this duality manifests as dual boundaries: the organizational boundary demanding tacit knowledge integration, and the community boundary requiring external knowledge acquisition to fuel innovation. As the members of an elite community undergo dynamic changes, the knowledge needs of the community are constantly updated, prompting members to balance knowledge search between "known directions" and "new directions" (Clark, 1967). However, how to optimize knowledge search strategies in the context of dynamic changes in elite community members, balancing the process of internal and external knowledge acquisition and integration to promote community-level innovation output, has yet to be explored.

The purpose of this paper is to comprehensively understand the relationship between the dynamics of elite network communities, knowledge search, and innovation output: (1) What is the structure and dynamic change of elite network communities? How do the dynamics of elite groups affect their innovation output? (2) How does knowledge search affect the relationship between elite group dynamics and innovation output? To answer these questions, we draw on social network theory, the knowledge-based view, and absorptive capacity theory to develop a comprehensive conceptual framework. Using patent data from China’s energy-saving technologies, we empirically test the relationship between the dynamics of elite communities and innovation output. Additionally, this paper proposes that the boundaries of knowledge search are dual in nature, consisting of both organizational boundaries within the community and inter-community boundaries, which contrasts with previous studies that have mainly focused on inter-community boundaries. By exploring the decision-making process of knowledge search directions, we further reveal how the choice of knowledge search direction influences the relationship between elite community dynamics and innovation output.

This paper contributes to the literature in three ways. First, by incorporating social network theory, the knowledge-based view, and absorptive capacity theory, we construct a comprehensive theoretical framework that provides new insights into the regulation and optimization of elite network communities. Second, this paper introduces the duality of knowledge search boundaries of elite communities, offering a new theoretical perspective for studying knowledge flow and community interactions. Third, by formally examining the relationship between elite community dynamics and innovation output, this paper validates the central proposition in the literature regarding the nonlinear impact of community dynamics on innovation output (Wang et al., 2019) and provides empirical evidence on how knowledge search direction decisions influence the relationship between elite community dynamics and innovation output. This offers practical implications for the regulation of elite communities.

The rest of the paper is organized as follows. In 2, we introduce the theoretical framework, elaborate on the argument for a nonlinear effect of elite community dynamics on innovation output and provide a moderating model for the role of knowledge search on nonlinear effects. We discuss our data and outline our empirical model in 3. In 4, we empirically test our hypotheses using patent data from China’s energy-saving technologies and discuss our main findings, and finally, we provide our conclusions and suggestions for future research in 5.

2. Theory and hypotheses development

2.1. *Definition of elite innovation community dynamics*

The concept of "innovation community" originates from innovation networks. Freeman (1991) defined "innovation networks" as institutional connections formed through collaborative innovation between individuals or organizations. With the rise of collaborative innovation, the scale of innovation networks has gradually expanded, forming multiple clusters with tight internal connections, which are referred to as "innovation communities" (Gulati et al., 2012). Compared to the overall level and the individual level, the community structure provides insights into the characteristics of innovation networks at the meso level. Essentially, a community consists of a set of nodes that are tightly connected internally, while the connections between different communities are relatively sparse (Newman and Girvan, 2004). This phenomenon of "community grouping" and "sparse connections" reveals the boundaries and heterogeneity between communities (TIMOTHY et al., 2005; Wang & Lu, 2021).

Previous research, based on the resource-based view, has demonstrated that innovation communities evolve dynamically based on the continuous development of resource relationships, with the aim of solving shared cognitive challenges within the network's entities (Hargadon and Bechky, 2006). However, these studies on community dynamics often overlook the resource endowments of individual actors. Modern technological innovation requires inventors to possess deep expertise and accumulated knowledge in their specific fields. Therefore, the connections within innovation networks are a deliberate process characterized by preference; nodes tend to establish links with those possessing stronger capabilities, better social reputations, and more advanced technologies (Snijders, 2001; Wang et al., 2019). These capable, influential, and reputable nodes attract numerous connections and become key figures within the community, often referred to as focal inventors or star inventors. This phenomenon leads to the evolution of innovation communities centered around star members. Hence, we define an elite community as follows: (1) a community in which star members occupy central positions; (2) a community where members are tightly connected, forming a highly interactive network structure; (3) a community that has distinct boundaries and differences with other communities.

In elite communities, elites (i.e., star members occupying core positions) are typically niche experts recognized as highly innovative due to their ability to identify opportunities and translate them into outputs (Jones, 2009). Their structural embeddedness within innovation networks grants them significant structural capital, enabling broad knowledge exchange channels and accumulation of cognitive resources (e.g., skills, experience) over time (Ansari et al., 2012). As primary beneficiaries, star members exhibit strong retention incentives and rarely exit the community.

In contrast, non-core members demonstrate higher mobility. Network proximity to stars critically determines resource access: nodes distant from stars face reduced resource acquisition likelihood (Kang, 2014; Schilling and Phelps, 2007; Wang et al., 2020). Consequently, new members strategically position themselves near stars to leverage knowledge spillovers, while older members may exit due to diminishing returns or passive exclusion for failing to contribute novel perspectives (Liu et al., 2021; Wei and Dang, 2017; Zhang et al., 2022). This asymmetric network structure—stable star cores versus dynamic peripheries—enhances both sustainability (prolonged star dominance) and dynamism (peripheral member turnover), distinguishing elite communities from other innovation networks.

2.2. Theoretical framework

This paper draws upon Social Network Theory, the Knowledge-Based View, and Absorptive Capacity Theory to propose a comprehensive theoretical framework, aiming to provide a theoretical foundation for exploring the relationship between elite community dynamics, knowledge search, and innovation output.

Research based on Social Network Theory has widely confirmed the phenomenon of "clustering" in innovation networks (Wei and Dang, 2017). These studies not only focus on the positive effects of community aggregation and similarity on innovation output but also emphasize the limitations brought about by excessive embedding (Liu et al., 2021). Specifically, when innovation actors frequently collaborate within a community, excessive similarity may lead to a lack of new ideas, thereby triggering the risk of innovation lock-in.

To avoid the risks of excessive embedding, a moderately dynamic community structure is considered an effective strategy for mitigating the negative effects of member similarity (Wei and Dang, 2017). Community stability is a relative state, typically characterized by fewer new members entering and fewer original members leaving. Stable communities are more likely to establish network norms and trust, which helps facilitate communication among members, reduce conflicts, and support knowledge transfer and absorption, ultimately driving innovation (Pinto et al., 2015). However, the stable development of a community can also lead to a trend of homogenization and lock-in risks. At this point, the entry and exit of members can help alleviate this trend. Introducing new members brings new knowledge and information, while interaction with them can reduce the network peer pressure caused by similarity (Sovacool and Brisbois, 2019). Meanwhile, the exit of original members may disrupt the community's entrenched state and stimulate the innovation vitality of existing members. While elite communities possess stronger dynamics and persistence compared to other innovation networks, theoretically, a moderately dynamic strategy is effective in mitigating innovation lock-in caused by similarity.

With the development of the Knowledge-Based View, the academic community has increasingly recognized the role of knowledge in innovation (Mickeler et al., 2023). Searching for external knowledge is crucial for overcoming lock-in effects and updating local knowledge bases (Liu et al., 2021). To avoid the risks of excessive embedding, the search for external knowledge can introduce potential diversity and non-redundant ideas and technologies into the community, which is key to breaking through innovation bottlenecks. For elite communities, there are two boundaries involved in acquiring external knowledge: one is the organizational boundary within the community, and the other is the boundary between dense communities and external communities.

According to Absorptive Capacity Theory, the ability to identify, assimilate, and apply external knowledge is considered a key determinant of innovation output (Cohen and Levinthal, 1990). On the one hand, within the elite community, although collaboration between organizations facilitates the flow of knowledge across organizational boundaries, knowledge flow relies more on the individuals who create and produce knowledge rather than on the organizations themselves (Fotopoulos, 2023). Therefore, inventors within the community are the main source of knowledge contributions, playing an indispensable role in knowledge flow and innovation. On the other hand, the process of assimilating, transferring, and combining external knowledge with the community's local knowledge requires individuals who act as "brokers" (Liu et al., 2021). These "brokers" are typically located at the periphery of the community and also act as gatekeepers. They possess the ability to cross community boundaries and play a crucial role in transforming external knowledge into information that can be absorbed by the community's internal members.

Through a moderately dynamic community structure, elite communities can maintain stability while absorbing new members and perspectives, thereby reducing the risks of homogenization and innovation lock-in. Meanwhile, promoting bidirectional knowledge search—both internal and external—enhances knowledge flow and absorption, stimulating innovative ideas. The combination of a moderately dynamic community structure and bidirectional knowledge search provides an effective pathway for enhancing innovation output and overcoming the lock-in problem.

2.3. The impact of elite community dynamics on innovation output

Previous studies have emphasized that social networks are dynamic, manifested by relatively few new members entering and relatively few existing members exiting (Wang et al., 2020). At the community level, the inflow and outflow of members introduces heterogeneous knowledge and promotes innovation. The innovation output at the community level determines the competitive position and long-term viability of the community in the knowledge ecosystem. As a sign of healthy development, community influence is manifested in two aspects: the quantity of innovation and the quality of innovation. The quantity of innovation output refers to the number of inventions, which has the characteristics of short-term and high resource input. The quality of innovation output includes the technical and economic value of the invention, and has the characteristics of long-term, specialized and high risk. Therefore, the mechanisms by which elite community dynamics affect the quantity and quality of innovation output at the community level need to be discussed separately.

The increase in innovation quantities requires a significant investment of resources to get more innovation outputs in a short period. Within the elite community, focal firms which as core actors, leverage their expertise and influence to attract new members (Sovacool and Brisbois, 2019), thereby expanding the community's collective resource base. Transient partnerships form rapidly, enabling efficient resource utilization to boost the total number of inventions produced by the community. However, excessive member turnover—whether through entry or exit—disrupts this equilibrium. High entry rates create resource redundancy, while excessive exits erode trust (Zhang and Hu, 2017). Both scenarios hinder short-term collaboration, reducing the community's overall innovation output count.

Improving the quality of innovation depends on deepening expertise and stable resource allocation (Aghion et al., 2009). Focus companies attract professional entrants and enhance the collective expertise of the community (Sovacool and Brisbois, 2019). However, high-quality innovation requires long-term, high-risk research and development, which requires stability. If the mobility of elite community members is too high, it will exacerbate the crisis of trust and knowledge gap among elite community members. On the one hand, the more professional members stay because they are more competitive, while the other less professional members withdraw from the original community, resulting in a crisis of trust. On the other hand, knowledge gaps increase barriers to collaboration and hinder long-term knowledge integration and transfer. As a result, the overall quality of innovation in the community decreases. This leads to our hypothesis.

H1a. There is a quadratic (inverted U-shaped) relationship between elite community dynamics and community-level innovation quantity.

H1b. There is a quadratic (inverted U-shaped) relationship between elite community dynamics and community-level innovation quality.

2.4. The moderating role of knowledge search inside the community

Similar to organizational innovation, the innovative development of elite communities also relies on both internal and external knowledge resources (Roper and Hewitt-Dundas, 2015). Considering the dual boundaries of elite groups, we propose the existence of a duality in knowledge search within these groups. Specifically, knowledge search can occur both within the elite group itself and between elite groups. Current research indicates that knowledge search strategies aimed at acquiring external knowledge can stimulate innovation output (Shi et al., 2020; Zhao and Shen, 2024).

In situations with low mobility, the stability of the elite community is higher, as it has already established network conventions and trust, which facilitates communication among members, thereby supporting knowledge transfer and absorption to foster community-levell innovation (Lyytinen et al., 2016). However, excessive stability within the community can accelerate the trends of homogenization and innovation lock-in (Du, 2021; Fleming, 2001; Rosenkopf and Nerkar, 2001). At this point, while a few new members may enter or old members may leave, bringing new knowledge or eliminating outdated knowledge, the stable community members are more reliant on prior knowledge. They tend to consult, learn, and collaborate with others who are similar to themselves (Zhang and Hu, 2017). If knowledge search occurs solely within the community, it may exacerbate the risk of innovation lock-in, further diminishing the motivational effects of low mobility on community-level innovation (Zhang et al., 2019). Furthermore, the quality of innovation places higher demands on knowledge specialization. In a low mobility environment, those pursuing innovation quality tend to engage in frequent internal knowledge search to secure a stable knowledge base, which increases the risk of knowledge lock-in due to over-specialization (Giuliani, 2011). Moreover, when an elite community is characterized by a homogeneous knowledge base and intensifying competition, members are more likely to compete rather than collaborate (Dyba et al., 2020). Therefore, in low mobility situations, repeated collaborations within homogeneous organizations can lead to a greater risk of local search and incremental learning among innovation participants, making it harder to generate new innovative ideas, thus reducing community-level innovation output. In other words, internal knowledge search within the community can weaken the positive effects of low mobility on community-level innovation output.

In cases of high mobility, the stability of the elite community is lower. At this point, a large influx of new members or the significant departure of existing participants can disrupt established network conventions and trust, damaging the original cognitive structures and cooperation paths of internal inventors, and making it difficult to form reliable partnerships (Call et al., 2015; Li et al., 2019). In such cases, actively engaging in internal knowledge search strategies within the community can help acquire new, specialized knowledge, mitigate friction between new and old members, rebuild network conventions and trust, and promote knowledge absorption among members. Therefore, internal knowledge search within the community can alleviate the negative impact of high mobility on community-level innovation output.

To summarize, we expect that the impact of elite community dynamics on community-level innovation output, which we proposed in Hypothesis 1, will be negatively affected by intra-community-based knowledge search. Specifically, our theory is that intra-community-based knowledge search will moderate the relationship between elite community dynamics and innovation output. Further, this moderating effect is curvilinear. Thus, we have proposed the following hypotheses:

H2a. Intra-community knowledge search will negatively moderate the curvilinear relationship between elite community dynamics and community-level innovation quantity.

H2b. Intra-community knowledge search will negatively moderate the curvilinear relationship between elite community dynamics and community-level innovation quality.

2.5. The moderating role of knowledge search cross communities

The previous discussion highlighted how intra-community knowledge search strategies may weaken the relationship between elite community dynamics and community-level innovation output. Here, we further explore how inter-community knowledge search strategies affect the relationship between elite community dynamics and community-level innovation output. Some studies have confirmed that external knowledge search is a powerful means for innovators to update their local knowledge base (Liu et al., 2021). Initially, external knowledge search was understood as activities conducted by organizations beyond their boundaries, involving the creation and recombination of knowledge from a wide range of external sources, where the boundary often pertains to the individual or regional level (Fotopoulos, 2023). In this context, the boundary of inter-community knowledge search refers to the process through which an elite community seeks knowledge from other communities by crossing its own boundaries. What is considered common knowledge in one community may be considered marginal but highly valuable knowledge in another (Ehls et al., 2020). For example, Dyba et al. (2020) noted that members of the same community need to seek knowledge resources outside their community to establish a competitive advantage. Therefore, even well-defined elite communities may need to engage in external searches to acquire new knowledge. After all, nearly all communities need external search to avoid knowledge lock-in (Liu et al., 2021).

The absorption, transfer, and recombination of external knowledge is a complex task. When elite communities implement inter-community knowledge search strategies, they often require actors with cross-community operational capabilities, known as "gatekeepers" (Breschi and Lenzi, 2014). Gatekeepers create bridges across communities through sparse connections, occupying structural holes and playing a key role in the acquisition, dissemination, absorption, and integration of knowledge. As a result, gatekeepers are considered crucial for innovation (Fleming and Waguespack, 2007). The inter-community knowledge search facilitated by gatekeepers can provide advantages in collective creativity. First, gatekeepers can explore non-local information and knowledge, helping other local participants access new information and knowledge earlier. These uncommon yet necessary external resources are introduced in a timely manner to help members of the elite community stay on top of emerging innovation trends. Second, gatekeepers can translate information and knowledge to enable communication between elite communities. Therefore, gatekeepers undoubtedly promote the absorption of new information and knowledge by themselves and other local participants, making significant contributions to collective innovation output (Castaldi et al., 2015; Miguelez and Moreno, 2018).

Excessive stability within an elite community leads to the risks of homogenization and innovation lock-in. In low-mobility environments, the small turnover of members cannot alleviate the trend of homogenization within the elite community because most of the original members, conditioned by existing network practices and trust, are reluctant to establish new relationships with new members, thus failing to improve the risk of innovation lock-in. The literature on innovation geography suggests that overcoming the knowledge barriers of local networks requires combining dense local networks with external networks to acquire heterogeneous knowledge (Bathelt et al., 2002; Powell, 2004). In this context, compared to existing knowledge bases, only searching for new knowledge beyond community boundaries can accelerate problem-solving speed (Jeppesen and Lakhani, 2010). Through gatekeepers, elite communities can establish sparse collaborations with other communities, transforming the elite community from a closed network environment. Gatekeepers, with their rich knowledge reservoirs and collaborative experiences, can facilitate the transfer of heterogeneous knowledge resources between communities, thus mitigating the negative effects of excessive embedding and knowledge homogenization within the elite community. Therefore, inter-community knowledge search can bring heterogeneous resources that stimulate innovation, enriching the specialized knowledge base of the elite community (Eggers et al., 2012). As a result, inter-community knowledge search amplifies the contribution of elite community dynamics to community-level innovation output.

However, excessive mobility within an elite community also poses risks of trust collapse and increased collaboration costs. In high-mobility environments, the existing network practices and trust foundations of the elite community are disrupted, and friction between new and old members hinders cooperation, increasing collaboration costs and risks (Li et al., 2019). In such cases, although gatekeepers can bring new innovation information and knowledge encoding services to the elite community, the difficulty of absorbing and integrating heterogeneous resources increases, making it harder to effectively stimulate innovation. Under these circumstances, rational participants tend to avoid the risks of inter-community knowledge search. Therefore, inter-community knowledge search exacerbates the hindering effect of high mobility on innovation quantity in elite communities. Furthermore, in high-mobility environments, elite communities may struggle to maintain the stable specialized knowledge base required for technological innovation. Since gatekeepers, by operating across community boundaries, provide fast-evolving and highly heterogeneous information and knowledge (Fleming and Waguespack, 2007), they are unlikely to offer the long-term stable expertise needed for the sustained quality enhancement of technological innovation activities. In fact, this may further exacerbate the negative impact of high mobility on innovation quality within elite communities.

In summary, we expect that the impact of elite community dynamics on community-level innovation output (Hypothesis 1) will be positively influenced by inter-community knowledge search. Specifically, our theory posits that inter-community knowledge search will strengthen the relationship between elite community dynamics and community-level innovation output. Therefore, we propose the following hypothesis:

H3a. Knowledge search across communities will positively moderate the curvilinear relationship between elite community dynamics and community-level innovation quantity.

H3b. Knowledge search across communities will positively moderate the curvilinear relationship between elite community dynamics and community-level innovation quality.

3. Methodology

3.1. Data and sample

This study employs patent data to test hypotheses, as patents serve as a widely accepted proxy for innovation output. Innovation, defined as the creation of novel and impactful improvements in products, methods, or services, inherently involves resource-intensive processes and knowledge spillovers, necessitating intellectual property protection (De Rassenfosse, 2013). Co-invented patents, particularly invention patents (which reflect higher innovativeness than design or utility models), encapsulate scientific and technical knowledge, making them a viable measure for analyzing community dynamics and knowledge search through social network analysis (Bercovitz and Feldman, 2011; Ponomariov, 2013). While patent counts and values are imperfect proxies, they remain a critical open-source indicator for evaluating technological innovation trajectories.

We, therefore, use a social network analysis based on co-invented patent data to investigate the community dynamics and knowledge search. In the sample selection, we focused on the Energy-saving field in Environmentally Conscious Manufacturing, the reasons are as follows: (1) From the United Nations Framework Convention on climate change to the Paris Agreement, the basic framework for the global response to climate change has been established. The Chinese government work report of the national two sessions and the outline of the 14th Five-Year Plan, "peak carbon dioxide emissions" and "carbon neutrality" were written for the first time. They call for the reduction of energy consumption through energy-saving and material-saving measures in industries, consumption, and other fields, to indirectly achieve the purpose of reducing carbon emissions. (2) In the data collection, the patent cooperation data in the energy-saving field appeared earlier, and the amount of patent cooperation shows a growing trend. (3) In China, energy-saving is focused on a wide range of clearly differentiated areas, including industry, transportation, buildings, commercial, residential and agricultural use. Thus, community structure is more common in technical cooperation networks in the Energy-saving field.

In the data collection part, we obtained those co-invented patents granted data in China Energy-saving filed from the Patsnap Scientific and Technological Innovation Information Platform, which deeply integrates more than 161 million patent data from 126 countries or regions worldwide from 1790 to the present, and is updated on time. Since the examination period of invention patents in China is 2–3 years, this study selects the data set of co-invention patents from 2006 to 2021. To ensure the accuracy of data, we carefully checked the patentee of each patent to eliminate the patent data where the patent owner includes individuals. After filtering out patent families and domestic and foreign patents cooperation, this study selects 1060 patent holders (including companies, universities, and research institutes),8867 valid granted invention patents, and 1084 valid granted cooperative invention patents, which provided the guarantee of patent quantity and quality for this study of patent cooperation network.

3.2. R&D network construction and elite community detection

To construct the energy-saving technical cooperation network, we followed the analytical procedures established in previous studies(Yan and Guan, 2018). Herein, elite communities' detection is based on how densely focal and other actors are connected in an inter- or intra-community (Wang and Lu, 2021). First, we adopted the Girvan-Newman (GN) algorithm for community detection (Gu and Liu, 2019), avoiding subjective biases common in data-scarce contexts(Luo, 2005). From the network, individual structural metrics can be derived (e.g. in-degree or out-degree centrality, which describes the number of unique individuals each actor has received information from, or delivered information to, respectively). Degree centrality in social network metrics can be divided into, absolute degree centrality, relative degree centrality, and eigenvector centrality. Comparatively, Elite identification relies on eigenvector centrality—a metric prioritizing both a node's direct connections and the influence of its neighbors—as it outperforms degree centrality in capturing individual importance (Novak et al., 2021).

We limited the duration of partnerships to five years because shorter windows could result in insufficient specification of network effects(Wang and Lu, 2021; Zang and Jinjuan, 2018). With the year 2006 as the first year, we captured 16 snapshots of the network, which resulted in 12 observation periods. Further, we filtered and cleaned the data. Communities that last less would result in many zeros of independent variables, which would lead to a significantly skewed distribution of variables and significant bias for estimations. Hence, we only focus on communities that have been consistently present for more than 7 years. We select two networks (2011–2015;2017–2021) in Fig. 1.

3.3. Measurement

3.3.1. Independent variables

Elite community dynamics-We viewed the movement of members within the elite community as Elite community dynamics. The movement of members within the elite community refers to the degree of change in the number of elite community members in the year t compared to the previous year (J. Wang et al., 2020; Wei and Dang, 2017). The specific formula is as follows:

$$A_{\mathrm{i,t}} = 1 - \frac{C_{i,t-1} \cap C_{i,t}}{C_{i,t-1} \cup C_{i,t}} \tag{1}$$

where $C_{i,t}$ refers to the set of innovation participants in the elite community i which at time t.

3.3.2. Dependent variable

Innovation output– Both the quantity and quality of innovation need to be emphasized to achieve the goal of high-quality development. As mentioned earlier, we chose invention patent data to measure innovation output. Patent quantity represents the total number of patents granted by members of the elite community in the current period t. As the most common measure of innovation performance(Wang et al., 2020), we use Patent quantity to refer to the number of innovations. Patent quality represents the total number of patents cited by other organizations for each member of the elite community during the period t. This indicator represents the degree of innovation diffusion of technology to other industries or innovation agents(Chien, 2018). Therefore, we use it to refer to the quality of innovation. It is important to note that in measuring both patent quantity and quality, this study includes all patents attributed to the elite community, rather than focusing solely on collaborative patents. While collaborative patents reflect joint innovation and synergies among elite group members, exclusive attention to them may overlook innovations independently achieved by individual members. These independently generated innovations may result from members' embedding within the elite community and are facilitated by the dynamic nature of the community. Therefore, a comprehensive consideration of all patents offers a more accurate representation of the overall innovation capacity and output of the elite group.

3.3.3. Moderating variables

(1) Knowledge search within the community

Knowledge search within the community is defined as the scope of participants' knowledge activities within the community. It mainly reflects the ability to acquire and broaden technical knowledge resources and channels within the community. Inventors as a subjective source of advanced knowledge, the number of inventors is considered as a strong indicator to characterize the extensive level of knowledge(Reitzig, 2007). Therefore, it can be described by the number of inventors within the community after the weighting process. The formula is shown as follows:

$$KSW_{i,t} = \frac{I_{i,t}}{n_{i,t}} \tag{2}$$

$KSW_{i,t}$ refers to the degree of knowledge search within community i in year t, $I_{i,t}$ means the total number of inventors of patents for the elite community i in year t, and n means the total number of patentees within the elite community i in year t.

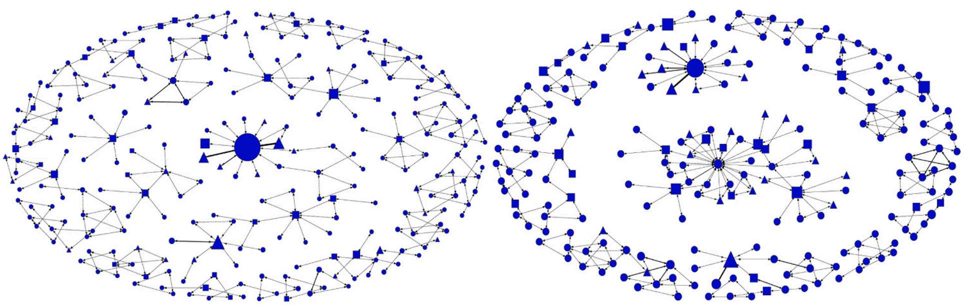

Fig. 1. Network structure: 2011–2015 and 2017–2021. notes: firm (Circle); university (Square); institution (Upper triangle).

(2) Cross-community knowledge search

Cross-community knowledge search. This is defined as the number of members (gatekeepers) shared between an elite-based community and other communities. It was primarily embodied the ability of elite communities to build "bridges" that allow their members to draw heterogeneous resources from other communities(Wang et al., 2020). It can also be described as the number of gatekeepers within the elite community. Gatekeepers are individuals who can span multiple communities, meaning they are members of at least two different communities simultaneously. The formula is as follows:

$$KSA_{i,t} = |G_{i,t}| = |\{m \in M_{i,t} | \exists C_k (k \neq i), m \in M_{k,t}\}| \tag{3}$$

$|G_{i,t}|$ represents the number of elements in set$G_{i,t}$, that is, the number of gatekeepers in community i at time$t$.$M_{i,t}$refers to the collection of members of community i at time t, and $M_{k,t}$ refers to the collection of members of community k at time t. C_k refers to the community k. m refers to a member of Community C_k.

To further elucidate Eq. (3), we present an illustrative example. Consider three distinct communities: A, B, and C, each comprising five members. Within these communities, one member is shared between A and B, and another member is shared between B and C. Based on Eq. (3), both community A and community C possess one gatekeeper each, resulting in a cross-community knowledge search degree of 1 for both. In contrast, community B has two gatekeepers (one shared with A and one shared with C), yielding a cross-community knowledge search degree of 2. This demonstrates that community B exhibits stronger inter-community connectivity, enabling it to access a greater volume of external resources through its gatekeepers, whereas communities A and C maintain relatively weaker connections.

3.3.4. Control variables

(1) Technology novelty of patent - Technology novelty of patent is the number of nonpatent references cited by the patents of members of the elite community. Scientific papers are more representative of the latest technological developments than patents. The community cites more non-proprietary literature, such as scientific papers, which reflect the novelty of the knowledge and are more conducive to developing patents.

(2) Technology breadth of patent - Technology breadth of patent is the number of claims claimed by the patent of members in the elite community. More claims mean broader protection of rights and interests, which is conducive to stimulating innovation.

(3) Generality of technology patent - Generality of technology patent is the number of countries connected with an elite community through forwarding citation. The more countries a patent is cited by, the more power it holds. Thus, elite communities with these patents may have stronger innovation ability.

(4) Density - The density of an elite community measures how closely connected its members are. Drawing on the concept of network density from graph theory, the density of an elite community is defined as the ratio of the actual number of edges to the maximum possible number of edges within the community.

$$Density_{i,t} = \frac{2n_{i,t}}{N_{i,t} * (N_{i,t} - 1)} \tag{4}$$

N represents the total number of nodes in the elite community i at time t , and n represents the actual number of edges in the elite community i at time t .

(5) Type - As mentioned earlier, this paper distinguishes between science-based and technology-based communities based on the nature of elite organizations. Therefore, the constructed *Type* variable is a binary dummy variable with a value of 0 for the science-based community and 1 for the technology-based community.

(6) IPCs - IPCs (International Patent Classification codes) are used to represent the breadth of technical knowledge within an elite community. Different technical fields correspond to distinct areas of knowledge. Therefore, the four-digit IPC classification code serves as a proxy for the technical field, while the number of unique four-digit IPC codes associated with the elite community is used to represent the diversity of technical fields involved within the community, or the scope of its technical knowledge.

The definition of each variable is shown in Table 1.

Table 1
Variable definitions.

Variable type	Variable name	Variable definition
Dependent variables	NP	Number of patent outputs
	QP	Quality of patent outputs
Independent variables	MMC	Movement of members within the elite-centered community(elite community dynamics)
Moderating variables	KSW	Knowledge search within the community
	KSA	Knowledge search across communities
Control variables	NTP	Technology novelty patent
	WTP	Technology breadth of patent
	GTP	The generality of technology patent
	Density	The density of the elit community
	IPCs	Number of unique four-digit IPC codes
	Type	The nature of the elite-centered community

3.4. Statistical method

In this study, the innovation output of the elite community is treated as the dependent variable, with two proxy variables—number of patents (NP) and patent quality (QP)—both being count variables with characteristics of overdispersion. Using linear regression models in this context would lead to inconsistent, inefficient, and biased coefficient estimates. Therefore, the study employs count data models, specifically the Poisson regression model and the negative binomial regression model. The Poisson model assumes that the mean is equal to the variance of the data. However, the negative binomial regression model allows for a difference between the mean and variance. According to empirical studies on innovation, the conditional variance of innovation performance is typically greater than the conditional mean (Wang et al., 2020). As such, the negative binomial model is more appropriate for handling the over-dispersed nature of the data, providing more accurate and reliable estimates , which is used in the following form:

$$p\left(Y_i = y_i\right) = \frac{\Gamma(y_i + (1/\alpha))}{\Gamma(1/\alpha)\Gamma(y_i+1)}\left(\frac{1}{1+\alpha\lambda_i}\right)^{\frac{1}{\alpha}}\left(\frac{\alpha\lambda_i}{1+\alpha\lambda_i}\right)^{y_i} y_i = 0,1,2\ldots n \tag{5}$$

where $E(y_i) = \lambda_i$, $Var(Y_i) = \lambda_i + \alpha\lambda_i{}^2, for\ \alpha > 0$

Our data is organized as a panel containing elite communities (i) and time (t). In addtion, to address potential endogeneity arising from reverse causality, this study employs a standard longitudinal design approach, incorporating a time lag between the independent and dependent variables. Specifically, all explanatory variables were lagged by 1 year. The negative binomial regression equation in this paper is as follows:

$$\log(Y_{i,t}) = \beta_0 + \beta_1 * MMC_{i,t-1} + \beta_2 * MMC_{i,t-1}^2 + \text{control}_{i,t-1} \tag{6}$$

$$log(Y_{i,t}) = \beta_0 + \beta_1 * MMC_{i,t-1} + \beta_2 * MMC_{i,t-1}^2 + \beta_3 * M_{i,t-1} + \beta_4 * MMC_{i,t-1} * M_{i,t-1} + \beta_5 * MMC_{i,t-1}^2 * M_{i,t-1} + control_{i,t-1} \tag{7}$$

Where $Y_{i,t}$ refers to the dependent variable, the quantity of innovation *NP* or the quality of innovation *QP*. $M_{i,t-1}$ refers to the moderating variable*, KSW* or *KSA*.

4. Results

4.1. Identification of elite-centric communities

To identify elite communities and present the dynamic changes in community cooperation networks, we drew a cooperation network relationship map based on patent data in the field of energy-saving. In a rolling window of 5 years, we calculated the eigenvector centrality of each participant, and members with larger centrality indices were treated as elite members. Then, we filter network communities based on the principles of network nodes greater than 3, network density higher than 0.1, and emergence time higher than 7 years. Finally, we determine and calculate the number of gatekeepers in the community based on the principle of whether the community boundary is crossed or not.

Finally, we select 44 elite communities with a "focal actor" as the core. Further, we divide elite communities into two categories: Science-based communities and Technology-based communities. This classification is based on the type of focal actors, as universities focus on basic science research, firms are more interested in technology application research. Table 2 lists the name of universities in the Science-based elite community. While the focal actors of the remaining elite communities are firms, called Technology-based elite communities (Table 3).

We calculated 44 elite community dynamic indices for 12-period windows. Since the elite community dynamics are calculated by the change of members in the current period relative to the previous period, the dynamic index was obtained for only 11 periods for the 12-period windows. Also, we used 2006–2010 as the base period, denoted as T0. In this period, the dynamic index of all elite

Table 2
University-centric elite communities.

No.	Elite name(University)	No.	Elite name(University)
1	Tsinghua University	11	Shandong University
2	East China University of Science and Technology	12	Central South University
3	Qingdao University of Science and Technology	13	Dalian University of Technology
4	South China University of Technology	14	Donghua University
5	Institute of process engineering, Chinese Academy of Sciences	15	State Grid Shandong Electric Power Company Electric Power Research Institute
6	Shanghai Institute of Materia Medicine, Chinese Academy of Sciences	16	South China Agricultural University
7	Zhejiang University of Technology	17	Sun Yat-sen University
8	Xi'an Jiaotong University	18	Jiangnan University
9	Zhejiang University	19	Xiamen University
10	Shanghai Jiao Tong University	20	Southeast University

communities was zero. Most elite communities have a dynamic index below 0.5, indicating that elite community members have a low turnover rate.

Fig. 2 presents the dynamic indices of elite communities across three time periods: T = 1 (2007–2011), T = 6 (2012–2016), and T = 11 (2017–2021). For instance, the elite community with ID 30 (Xuzhou Woniushan Advanced Waterproof Materials Co., Ltd) consistently exhibits a dynamic index of 0 throughout all three time windows, indicating no membership turnover (i.e., neither inflow nor outflow of members) during these periods. In contrast, the elite community with ID 15 (Southeast University) demonstrates a dynamic index of 0 in T = 1, suggesting complete stability in membership. However, its dynamic index rises to 0.6 in T = 6 and further increases to 0.67 in T = 11, reflecting significant membership changes during these later periods.

We take two elite communities with "Tsinghua University" and "State Grid" as core respectively, as examples to show a typical snapshot of the dynamic evolution of elite communities in a 5-year rolling window. Fig. 3 shows that the two elite communities are small and unrelated between 2006 and 2010. As time goes on, both communities experience a flow of members (flow encompasses both inflow and outflow of members), although this flow does not occur at every stage. The connections between members within the communities have increased significantly. Then, two elite communities interacted through gatekeepers that crossed community boundaries during 2014–2018.

Further, we analyze the community dynamics of the technology field to which the elite community belongs. Our dataset comprised 44 distinct elite communities collectively holding patents across 23 primary IPC classifications. we groups these technologies into six principal categories based on functional relationships and thematic similarities: (A) Organic Chemistry and Catalytic Technologies (C07C, C07D, C07F, C07H, B01J, C01B); (B) Polymer Materials and Low-Pollution Coating Technologies (C08F, C08L, C09D, C09B); (C) Heat Exchange and Energy Transfer Technologies (F28D, F28F, H02J, F23C); (D) Metallurgy and Resource Recycling Technologies (C22B, C21B, B29B); (E) Lubrication and Fuel Technologies (C10M, C10G, C11B); and (F) Textile and Fiber Processing Technologies (D04H, D06M, D04B).

To assess technological evolution, patent data from 1986 to 2023 for each domain were collected from the Patsnap Scientific and Technological Innovation Information Platform. Technology lifecycles were quantified using Loglet Lab 5 software (Fig. 4). The results revealed heterogeneous developmental trajectories: most domains (A, C, D) exhibited similar evolutionary rates, while Category B and E advanced slightly faster, and Category F progressed at a marginally slower pace.

Further analysis of elite community dynamics (Table 4) showed an overall mean dynamic index of 0.254. Categories A (Organic Chemistry) and E (Lubrication/Fuel) closely aligned with this mean value. In contrast, Categories B (Polymer Materials) and C (Energy Transmission) displayed lower dynamic indices (<0.254), whereas Categories D (Metallurgy) and F (Textile) exceeded the mean value, with fluctuations within approximately ± 0.05 of the central value.

4.2. Regression analysis and result

To verify the hypotheses presented above, this study uses stata15.0 for data analysis. Descriptive statistics are performed on all variables. The statistical results are shown in Table 5. In addition, Pearson correlation analysis was carried out between the variables in this study. Correlation matrixes are provided in Table 6. We find that our results are slightly noisier without any control variables. Elite community dynamics (MMC) weakly positively correlated with the number of innovations (NP) . However, there is no significant correlation between elite community dynamics (MMC) and the quality of innovations (QP). Even so, our hypothesis of nonlinear effects is not affected and requires further testing. According to Table 6, the correlation coefficient between explanatory variables is less than 0.8, preliminarily indicating no obvious multicollinearity. Further, this paper carries out the VIF test, and the VIF of each variable is lower than 5, indicating that the multicollinearity problem between variables is effectively controlled.

Since both the number of patents (NP) and the number of patent citations (QP) are non-negative integers, and their ratio of the standard deviation to the mean are significantly greater than 1, a negative binomial regression model is more suitable for analysis. Finally, we use the negative binomial regression model to estimate the marginal effects of changes in community membership on the innovation output of elite communities. Given the duality of the patent output, we report the estimated coefficients separately.

Table 7 shows the results of the relationship between the number of patent outputs and the mobility of elite community members.

Table 3
Firm-centric elite communities.

No.	Elite name(Firm)	No.	Elite name(Firm)
1	China Petroleum & Chemical Corporation	13	Shanghai Oriental Yuhong Waterproof Technology Co.Ltd.
2	National Energy Investment Group Co., Ltd.	14	Xuzhou Woniushan Advanced Waterproof Materials Co., Ltd.
3	State Grid Corporation of China	15	SINOPEC Engineering (Group) Co., Ltd.
4	China National Offshore Oil Corporation	16	Shenyang Research Institute of Chemical Industry Co., Ltd.
5	China Tianchen Engineering Corporation	17	Tianjin Tianchen Green Energy Engineering Technology Development Limited Company
6	Shanghai Lanbin Petrochemical Equipment Co., Ltd	18	Shanghai Three Guns (Group) Co., Ltd.
7	China Shenhua Coal to Liquid and Chemical Co., Ltd.	19	SHANGHAI TEXTILE RESEARCH INSTITUTE
8	Hefei Ketian Waterborne Technologies Co., Ltd.	20	Shanghai Mingjie Garmeng Manufacture Co., Ltd.
9	Lanzhou Ketian Waterborne Technologies Co., Ltd.	21	Lufeng Weaving & Dyeing Company Ltd.
10	Peking University Founder Group Corp.	22	Rianlon Corporation(Zhejiang)
11	PKU HealthCare Industry Group Co., Ltd.	23	State Grid Tianjin Electric Power Company
12	Lanpec Technologies Limited	24	Apeloa Pharmaceutical Co., Ltd

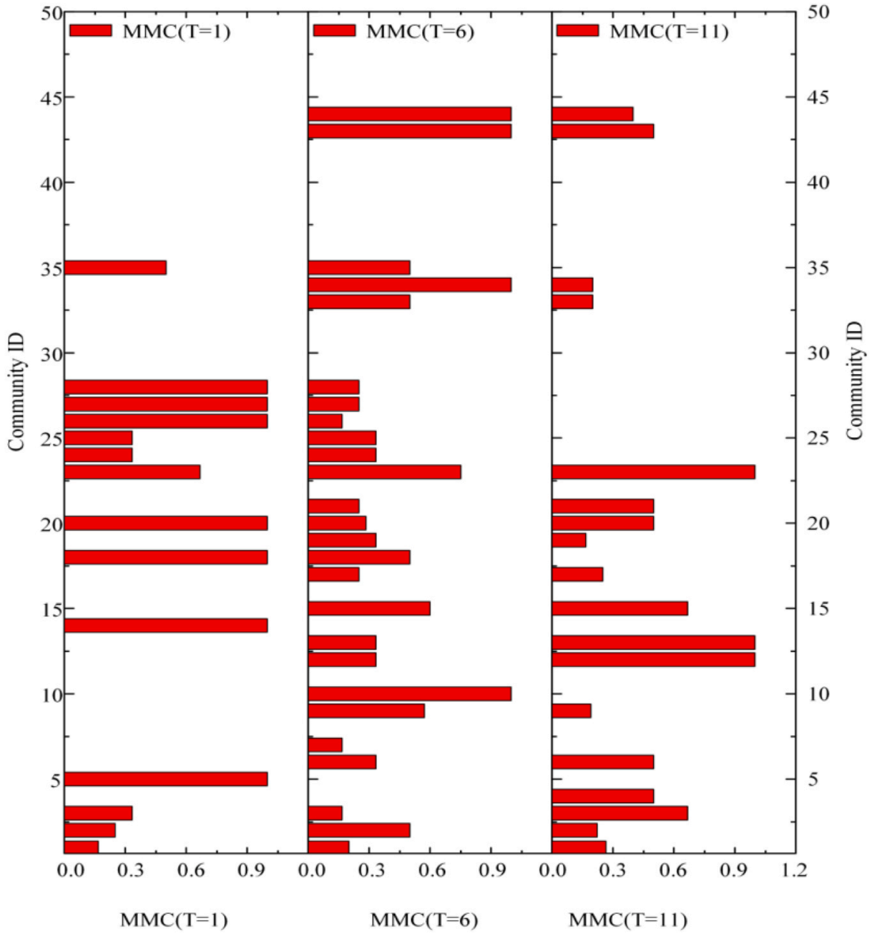

Fig. 2. Elite community dynamics index. Note: the Y-axis represents the ID of elite communities, with a total of 44. The X-axis displays the dynamic index of the elite community (MMC), which ranges from 0 to 1.

For models 1–2, we tested Hypothesis 1a and there was a significant positive correlation between elite community dynamics and an elite community's innovation quantity. As expected the elite community dynamic squared was negatively related to an elite community's innovation performance (β= 0.667, $p < 0.1$; β= −0.963, $p < 0.01$, respectively). Thus, our test supported Hypothesis 1a that elite community dynamics have an inverted-U-shaped relationship with an elite community's innovation quantity, which was supported by Haans et al. (2016). Furthermore, the inflection point of the nonlinear effect is 0.35(see Fig. 5., left side), and 29.3 percent of the observations in our sample fall above this inflection point.

Furthermore, in models 3–6, we tested Hypothesis 2a and 3a. The results of model 4 supported Hypothesis 2a, which indicates that *Knowledge search within the community* can affect the relationship between elite community dynamics and an elite community's innovation quantity. And this moderating effect was negative (β= −0.353, $p < 0.01$; β= 0.541, $p < 0.01$, respectively). Hypothesis 3a, seemingly logical, is nonetheless not supported by our results. The results of model 6 indicated that *Cross-community knowledge search* could affect the relationship between elite community dynamics and an elite community's innovation quantity. Regrettably, the effect of the moderating variable is not in the expected direction (β= −0. 537, $p < 0.1$; β= 0.815, $p < 0.1$, respectively). The reason for this phenomenon may be that cross-community knowledge search leads to a fragmentation of resources in the elite community, with part of the effort being spent on cross-community exchange and learning, thus reducing the time and effort spent on innovation and patenting outputs within their own community. There is also the possibility that cross-community knowledge search leads to a more fragmented knowledge structure in elite communities, which reduces the efficiency of innovation and the quality of patent output. This is because the integration and application of knowledge within the community is compromised.

Table 8 shows the results of the relationship between the quality of patent outputs and elite community dynamics. For models 1–2, we tested Hypothesis 1b and there was a significant positive correlation between elite community dynamics and an elite community's patent citations. The elite community dynamics squared was negatively related to an elite community's patent citations as expected (β= 1.801, $p < 0.01$; β= −2.602, $p < 0.05$, respectively). Thus, our test supported Hypothesis 1b that elite community dynamics have an inverted-U-shaped relationship with an elite community's patent citations. In addition, the inflection point of the nonlinear effect is 0.34 (see Fig5., right side), and 29.55 percent of the observations in our sample fall above this inflection point.

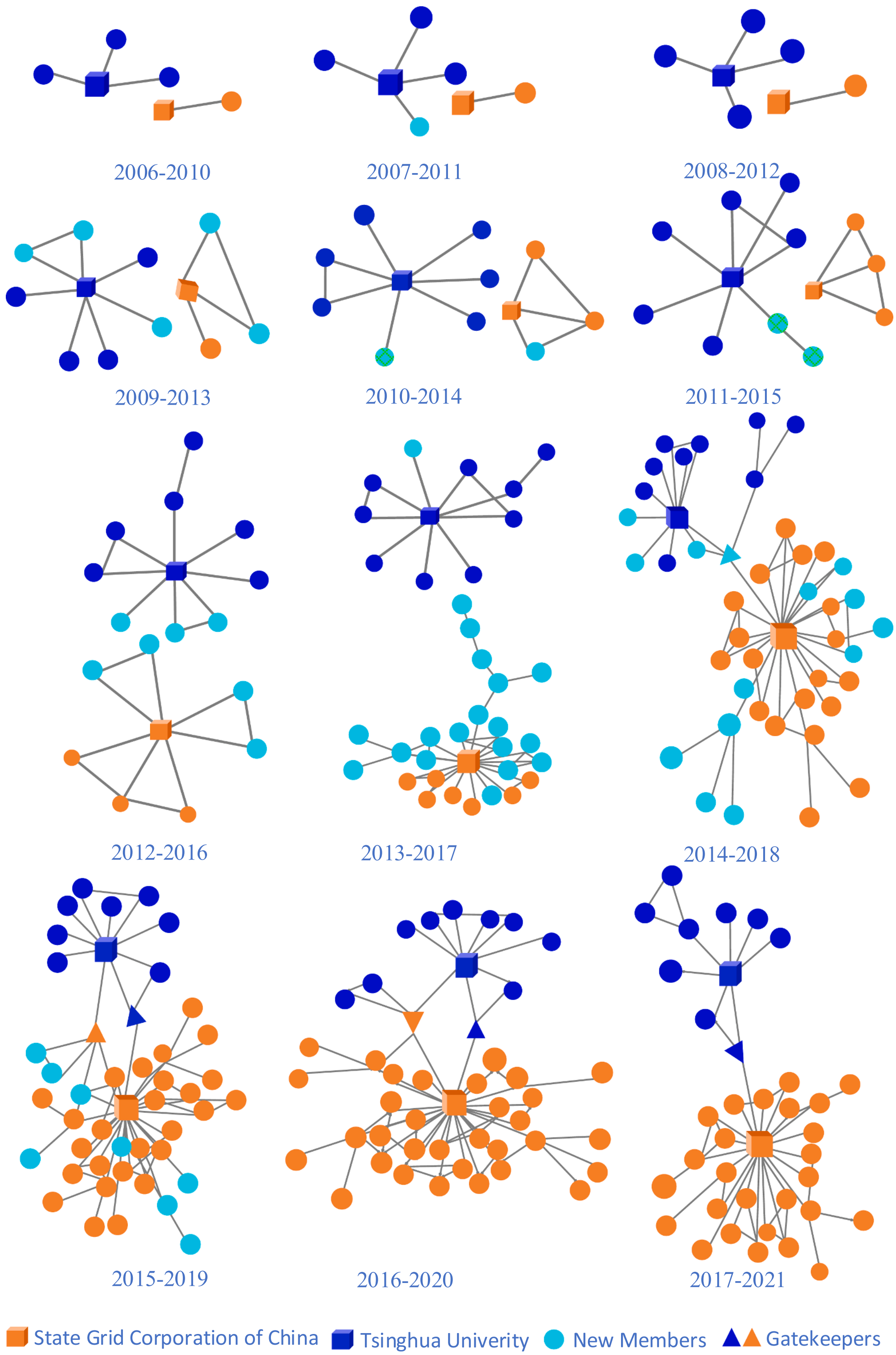

Fig. 3. Evolution of elite-centered innovation network communities.

Furthermore, in models 3–6, we tested Hypotheses 2b and 3b. The results of model 4 supported Hypothesis 2b, which indicates that *Knowledge search within the community* can affect the relationship between elite community dynamics and an elite community's innovation quality. However, the results didn't support Hypothesis 3b, which indicates that *Cross-community knowledge search* does not significantly affect the relationship between elite community dynamics and an elite community's patent citations. This may be due to

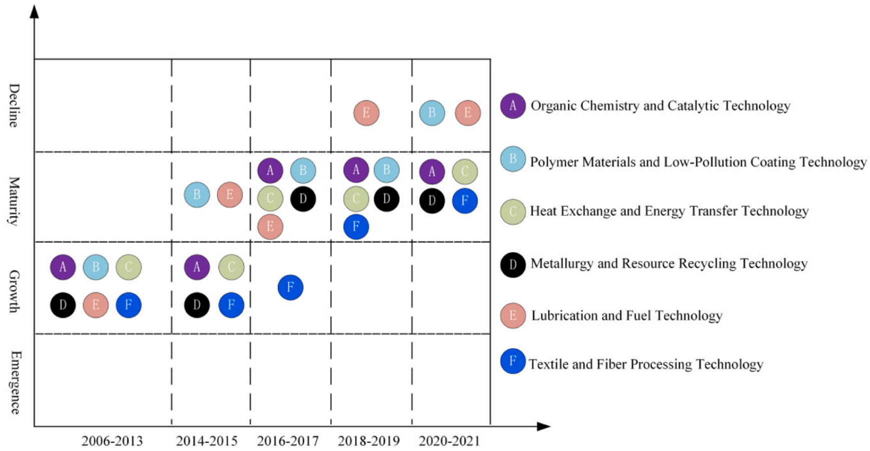

Fig. 4. Evolutionary stage distribution of six technological domains in elite communities.

Table 4
Technical field distribution of elite communities and the mean value of MMC.

Category	Elite Community ID	MMC Mean
A	1, 3, 4, 5, 6, 14, 20, 23, 24, 25, 28, 32, 33, 35, 36, 38	0.258
B	8, 10, 11, 17, 18, 21, 29, 30	0.219
C	9, 12, 13, 31, 34, 37, 43, 44	0.191
D	7, 15, 27	0.302
E	2, 16, 22	0.243
F	19, 26, 39, 40, 41, 42	0.308

Table 5
Descriptive statistics.

Variables	Obs	Mean	Std. Dev.	Min	Max
QP	528	64.305	212.139	0	2055
NP	528	14.4	27.983	0	216
MMC	528	0.217	0.323	0	1
KSW	528	3.108	2.012	0	7.098
KSA	528	0.648	1.159	0	6
NTP	528	7.67	17.803	0	146
WTP	528	165.348	475.307	0	4727
GTP	528	1.384	3.052	0	25
Density	528	0.276	0.162	0	0.833
IPCs	528	3.343	4.293	0	30
Type	528	0.545	0.498	0	1

Note: *KSW* is treated logarithmically.

Table 6
Correlation matrix.

Variables	MMC	NTP	WTP	GTP	KSW	KSA	Density	IPCs	Type
NP	0.094**	0.610***	0.566***	0.543***	0.116***	0.384***	0.353***	−0.032	0.117***
QP	−0.010	0.455***	0.349***	0.670***	0.490***	0.194***	0.384***	−0.046	0.005
MMC		0.017	0.006	0.025	0.138***	−0.036	0.149***	0.012	0.082
NTP			0.780***	0.468***	0.501***	−0.009	0.279***	−0.011	0.017
WTP				0.332***	0.455***	0.004	0.245***	−0.062	−0.083
GTP					0.468***	0.096**	0.378***	−0.043	0.046
KSW						0.387***	0.495***	−0.048	0.165***
KSA							0.433***	0.133***	−0.319***
Density								−0.030	0.172***
IPCs									−0.148***
VIF	1.04	1.99	3.75	1.41	4.51	1.69	2.01	1.07	1.38

Table 7
Reported estimated coefficient. A negative binomial regression model. Dependent variables: the quantity of granted invented patents. The dependent variable lags one phase.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
NTP	0.014**	0.015**	0.007	0.004	0.013**	0.013**
	(0.007)	(0.006)	(0.008)	(0.006)	(0.006)	(0.006)
WTP	0.001**	0.001**	−0.000	0.000	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GTP	0.070	0.077	0.092	0.023	0.106*	0.107*
	(0.065)	(0.065)	(0.067)	(0.059)	(0.064)	(0.063)
Density	6.333***	6.407***	5.928***	2.067***	5.550***	5.758***
	(0.451)	(0.456)	(0.475)	(0.738)	(0.503)	(0.515)
IPCs	−0.006	−0.003	−0.001***	0.020	−0.002	−0.006
	(0.050)	(0.050)	(0.000)	(0.045)	(0.050)	(0.046)
Type	−0.133	−0.183	−0.178	0.198	−0.365	−0.326
	(0.225)	(0.226)	(0.251)	(0.236)	(0.230)	(0.230)
MMC		0.677*	0.481*	0.532	0.386*	0.448
		(0.358)	(0.251)	(0.422)	(0.204)	(0.358)
MMC^2		−0.963**	−0.781**	−0.728*	−0.692*	−0.757**
		(0.387)	(0.391)	(0.411)	(0.389)	(0.382)
KSW			0.002***	0.001		
			(0.000)	(0.001)		
KSW* MMC				−0.353***		
				(0.052)		
KSW* MMC^2				0.541***		
				(0.117)		
KSA					0.407***	1.033***
					(0.109)	(0.362)
KSA* MMC						−0.537*
						(0.300)
KSA* MMC^2						0.815*
						(0.471)
Constant	−1.503***	−1.494***	−1.352***	0.007	−1.214***	−1.484***
	(0.242)	0.241	0.251	0.350	0.246	0.289
Observations	484	484	484	484	484	484
Number of ID	44	44	44	44	44	44
ID FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

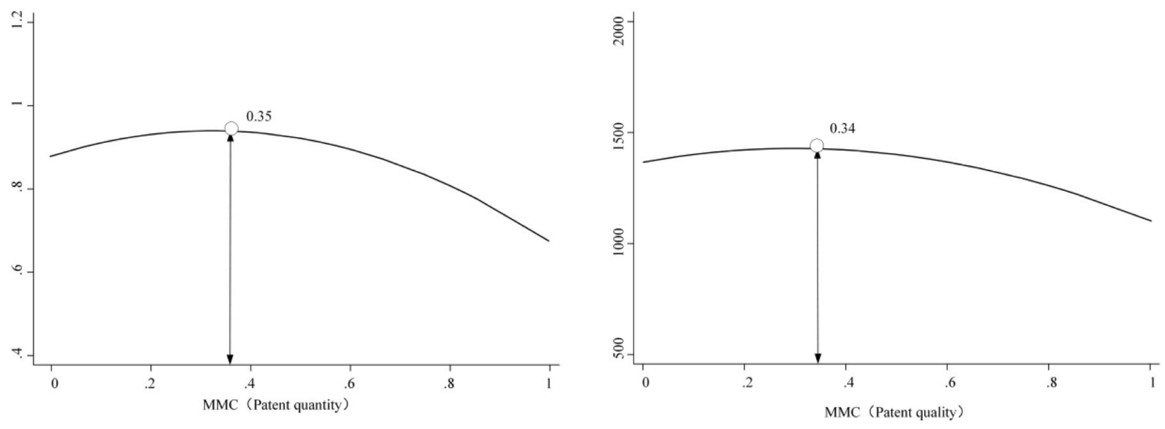

Fig. 5. The inflection points of the U-shaped relationship.

the stability of the internal mechanisms of elite communities. The mechanism and process within the elite community may have a certain stability and self-regulation ability, so that the impact of member flow rate on the quality of patent output is regulated and balanced by the internal mechanism. The degree of cross-community knowledge search is not enough to affect the innovation process of the elite community. In other words, the stability and self-regulation mechanism within the elite community can still maintain the relationship between member flow and patent quality.

Next, a test of the moderating effect is performed. Drawing on Haans et al. (2016), two tests are required: whether the transfer point is displaced and whether the shape of the curve changes. The results of the tests are displayed in the Table 9. In order to visualize the

Table 8
Reported estimated coefficient. A negative binomial regression model. Dependent variables: the quality of granted invented patents.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
NTP	−0.024	−0.015	−0.006	−0.008	−0.016	−0.017
	(0.017)	(0.017)	(0.015)	(0.016)	(0.014)	(0.015)
WTP	0.005***	0.005***	0.003***	0.003***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GTP	−0.705***	−0.482**	−0.341	−0.252	−0.309	−0.406*
	(0.199)	(0.201)	(0.214)	(0.214)	(0.200)	(0.223)
Density	1.983	1.759	−2.841	−3.789	−0.059	0.448
	(1.927)	(1.89)	(2.759)	(3.158)	(1.967)	(1.792)
IPCs	0.100	0.130	0.075	0.086	−0.008	−0.017
	(0.087)	(0.091)	(0.085)	(0.083)	(0.080)	(0.085)
Type	−0.665***	−0.734***	−0.535**	−0.568***	−1.408***	−1.457***
	(0.234)	(0.236)	(0.240)	(0.215)	(0.301)	(0.305)
MMC		1.801***	1.795**	1.613**	1.568*	0.717
		(0.698)	(0.777)	(0.763)	(0.857)	(0.520)
MMC^2		−2.602**	−2.407**	−2.005**	−1.844*	−0.582
		(1.062)	(1.020)	(0.861)	(1.078)	(1.764)
KSW			0.393**	−0.002		
			(0.163)	(0.002)		
KSW* MMC				−0.517		
				(0.562)		
KSW* MMC^2				0.647***		
				(0.186)		
KSA					1.055***	0.178
					(0.283)	(1.047)
KSA* MMC						−0.131
						(1.092)
KSA* MMC^2						0.740
						(0.813)
Constant	−4.064***	−2.196***	−4.615***	−9.600**	−4.697***	−4.872***
	(0.573)	(0.387)	(1.362)	(3.766)	(1.343)	(1.322)
Observations	484	484	484	484	484	484
Number of ID	44	44	44	44	44	44
ID FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

moderating effect more intuitively, the adjustment effect is plotted in Fig. 6. Case (a) indicates that the inverted U-shaped curve turning point is shifted to the right as the intensity of knowledge search within the community increases. Moreover, the curve shape became flatter. Hypothesis 2a is verified, which suggests that the intensity of intra-community knowledge search relaxes the polar requirement between community mobility and the number of patents, but it also moderates the effects on both sides of the community mobility pole. Case (b) indicates that the inverted U-shaped curve turning point shifts to the right as the intensity of cross-community knowledge search increases. Again, the shape of the curve becomes flattened. This suggests that the intensity of knowledge search across communities further relaxes the desired polarity between community mobility and the number of patents. Hypothesis 3a is not tested. Case (c) shows that the inverted U-shaped curve turning point undergoes rightward shift as the intensity of knowledge search within communities increases. The shape of the curve becomes also flattened. Hypothesis 2b is verified.

To summarize, our hypotheses are basically valid, and the results demonstrate that an elite community's innovation output can benefit the most from a moderate rate of elite community dynamics. When the intensity of internal knowledge search in elite communities is high, the negative impact of excessive mobility on innovation output (the "curse effect") is somewhat mitigated. However, compared to patent quality, the relaxation of the appropriate dynamic relationship between community mobility and patent quantity is more pronounced. In contrast, when elite communities engage in stronger cross-community knowledge search, while it can relax the dynamic relationship between community mobility and patent quantity and reduce the negative effects of excessive mobility on innovation quantity, it does not have a significant impact on innovation quality.

In addition, to ensure the robustness of the results, we performed additional tests. First, we change the lag periods to 3 to further test the sensitivity of the results to time. The regression results are shown in Tables 10 and 11. Secondly, we chose data during 2010–2017 to test the robustness of the previous empirical results. The regression results are shown in Table 12. Thirdly, we substituted the negative binomial regression model with ordinary least squares and applied a fixed effects model to assess the robustness of the model

Table 9
Test of the moderating role.

Test	(a)	(b)	(c)
Testing for the shift in the turning point occurs	Shift right	Shift right	Shift right
Testing for flattening or steepening of the inverted U-curve	flatter	flatter	flatter

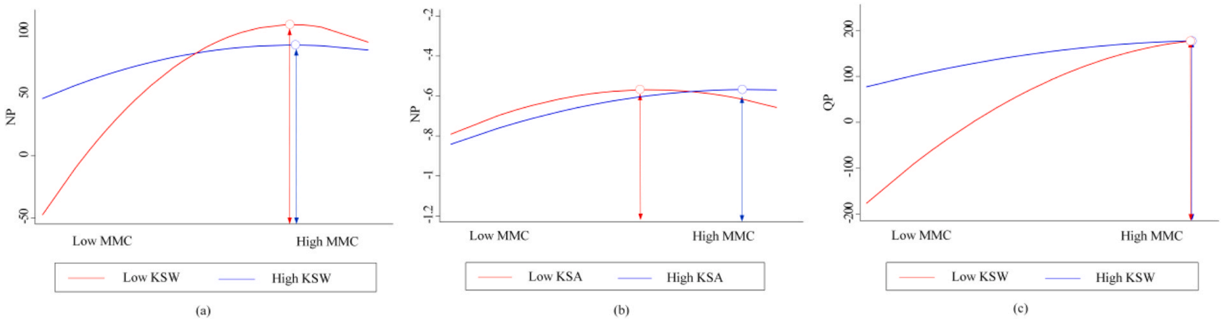

Fig. 6. Illustration of the moderating role.

outcomes. The findings presented in Table 12 are largely aligned with our initial results. In addition, we conducted further robustness tests utilizing a random effects model. The results displayed in Table 13 exhibit general consistency with our prior research findings.

5. Discussion and conclusion

Prior literature has argued that innovation network community structures are dynamic in nature and have a significant impact on firms' innovation output. They suggest that moderate member mobility stimulates innovation(J. Wang et al., 2020). The literature on innovation networks also suggests that collaboration provides access to knowledge and that heterogeneous knowledge search is ideal for innovation(Hung, 2015). Unlike individual organizations or global networks, elite communities offer the idea of cluster knowledge boundaries dominated by core participants. Individuals can acquire a wide range of knowledge through collaboration within and outside the community, however, some have warned against the risk of "over-searching" as they question the participants' ability to absorb knowledge(De Rassenfosse, 2013).

This study focuses on the role of elite community dynamics and knowledge search, drawing on social network theory, the knowledge-based view, and absorptive capacity theory. It integrates a conceptual framework that links elite community dynamics, knowledge search, and innovation output. Furthermore, the study operationalizes this framework and conducts econometric testing using rich data sources. We use the patent output as a proxy for innovation output, although it is an imperfect indicator. In this study, we further divide the patent output into two dimensions, i.e., the quantity of patent output and quality of patent output, and develop a model to explain how the dynamics of elite network communities affect the patent output capacity of the communities. In addition, in terms of the bidirectional nature of knowledge search, we further explore whether these relationships are influenced by the direction of knowledge search. The study yields follow main findings, which will be discussed below.

First, we extended Wang et al. (2020)'s study on the impact of community member dynamics on the number of innovations and found that the dynamics of elite community members have an inverted U-shaped effect on innovation output. With moderate membership turnover, elite communities are able to achieve the highest number of patent outputs. This finding is consistent with previous research (Liu et al., 2021; Wang et al., 2020). Furthermore, we analyzed patent output quality data. The results reveal that elite community member dynamics also exhibit an inverted U-shaped effect on innovation quality. Compared to innovation quantity, the quality of innovation has a lower threshold for restricting member mobility. In other words, higher patent quality requires lower mobility among elite community members. There is no direct econometric evidence to compare these findings with. However, a potential indirect exception comes from Jia (2022), who, using patent data on Chinese electronic information materials, found that community stability can positively modulate the inverted U-shaped effect of community heterogeneity on innovation quality, if stability is viewed as the inverse of mobility.

Second, our results support that the inverted U-shaped relationship between elite community membership dynamics and innovation output is moderated by the knowledge search intensity of community members. Within communities, the higher the knowledge search intensity of members, the more likely it is to cut down the innovation output enhancement from member mobility, both patent quantity and patent quality. That is, there is a substitution relationship between the mobility of members and knowledge search within the community given that both are homogeneous knowledge exploration. Because the previous knowledge search related research did not consider the organizational boundaries within the community, there is no basis for comparison. However, this result is consistent with the previous view that homogenizing knowledge search weakens innovation output (Delgado-Márquez et al., 2018; Stevens and Dykes, 2013).

Third, there is a positive relationship between the cross-community knowledge search and innovation output, which is consistent with the view that searching across the boundary may improve innovation performance in R&D innovations(Huang et al., 2021; Melane-Lavado and Alvarez-Herranz, 2020). However, between communities, the higher the knowledge search intensity of members, the more likely it is to cut the gains from member mobility. This finding is somewhat surprising given the results from those studies of Rosenkopf and Almeida (2003), and Song et al. (2003). They pointed out that the mobility of active inventors in alliances can serve as bridges to other alliances and, thus, enable firms to overcome the constraints of localized interaction and search.

Our finding leads to the need to reconsider the hypothesis that cross-community knowledge search positively moderates the relationship between community dynamics and innovation. The results suggest that cross-community heterogeneous knowledge

Table 10
Reported estimated coefficient. A negative binomial regression model. Explanatory variables lag 3 periods.

VARIABLES	NP			QP		
	(2)	(4)	(6)	(2)	(4)	(6)
MMC	0.598*	0.787**	0.786**	1.032*	1.220**	1.655***
	(0.352)	(0.342)	(0.341)	(0.591)	(0.554)	(0.508)
MMC^2	−0.965*	−1.185**	−1.273***	−1.684*	−2.546***	−4.343***
	(0.511)	(0.517)	(0.491)	(0.955)	(0.979)	(1.065)
KSW		−0.151			0.002***	
		(0.142)			(0.000)	
KSA			−0.413			0.626**
			(0.721)			(0.263)
KSW*MMC		−0.016***			−0.002***	
		(0.004)			(0.000)	
KSW*MMC^2		0.198***			0.759***	
		(0.071)			(0.214)	
KSA*MMC			−1.398**			−0.739***
			(0.551)			(0.193)
KSA*MMC^2			3.513*			−1.240
			(2.131)			(0.971)
Constant	−1.067**	3.128***	3.376***	6.133***	5.641***	6.019***
	(0.471)	(0.576)	(0.662)	(0.682)	(0.673)	(0.629)
Observations	396	396	396	396	396	396
Number of ID	44	44	44	44	44	44
Control	YES	YES	YES	YES	YES	YES
ID FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 11
Reported estimated coefficient. A negative binomial regression model. Time window of 8 years from 2010 to 2017. Explanatory variables lag 1 periods.

VARIABLES	NP			QP		
	(2)	(4)	(6)	(2)	(4)	(6)
MMC	3.130***	2.024**	4.838*	3.001**	4.580*	2.606**
	(0.783)	(0.936)	(2.680)	(1.658)	(2.469)	(1.163)
MMC Square	−3.669***	−2.869 **	−6.217***	−4.133**	−6.067***	−4.006***
	(0.827)	(0.707)	(1.890)	(1.770)	(1.807)	(0.705)
KSW		0.002***			0.000	
		(0.000)			(0.001)	
KSA			0.198			−0.180**
			(0.295)			(0.073)
KSW*MMC		−0.283*			−1.125***	
		(0.152)			(0.400)	
KSW*MMC square		0.352***			1.128***	
		(0.047)			(0.123)	
KSA*MMC			−1.121***			−0.434**
			(0.397)			(0.195)
KSA*MMC Square			1.116***			0.128
			(0.102)			(0.326)
Constant	2.705***	0.488*	−2.596***	4.051***	−2.545***	0.518***
	(0.116)	(0.281)	(0.592)	(0.231)	(0.604)	(0.045)
Observations	308	308	308	308	308	308
Number of ID	44	44	44	44	44	44
Control	YES	YES	YES	YES	YES	YES
ID FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

search does not lead to higher levels of innovation in the presence of member mobility. At least in the field of energy efficiency in China, cross-community knowledge search seems to inhibit innovation output from member mobility rather than stimulate it, or - at best - they only have an effective facilitative effect on the number of innovations. Zhang's (2016) research on community mobility provides an explanation that communities with mobile members will have weaker cooperative relationships than stable communities, and weak relationships cannot provide heterogeneity or core knowledge. Another related previous research evidence may provide another explanation. Liu et al. (2021) found that the stability of community brokers can mitigate the inverted U-shaped relationship between member mobility and innovation output. In other words, in the case of high mobility, although the higher the intensity of

Table 12
Reported estimated coefficient. Fixed model. Explanatory variables lag 1 periods.

VARIABLES	NP			QP		
	(2)	(4)	(6)	(2)	(4)	(6)
MMC	0.734***	1.089***	0.833***	1.606***	2.826**	1.819***
	(0.196)	(0.153)	(0.241)	(0.408)	(1.206)	(0.466)
MMC Square	−1.689***	−1.782***	−1.855***	−2.151***	−4.964**	−2.808***
	(0.330)	(0.309)	(0.413)	(0.640)	(2.024)	(0.724)
KSW		0.001***			1.632***	
		(0.000)			(0.393)	
KSA			0.117			−0.580
			(0.393)			(0.941)
KSW*MMC		−0.463***			−1.439***	
		(0.045)			(0.491)	
KSW*MMC square		0.336***			0.946***	
		(0.017)			(0.295)	
KSA*MMC			−1.718***			−2.770**
			(0.470)			(1.151)
KSA*MMC Square			0.935***			1.075
			(0.295)			(0.741)
Constant	2.855***	1.940***	2.563***	3.303***	−3.741**	3.312***
	(0.242)	(0.188)	(0.303)	(0.540)	(1.633)	(0.613)
Observations	484	484	484	484	484	484
Number of ID	44	44	44	44	44	44
Control	YES	YES	YES	YES	YES	YES
ID FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 13
Reported estimated coefficient. Random model. Explanatory variables lag 1 periods.

VARIABLES	NP			QP		
	(2)	(4)	(6)	(2)	(4)	(6)
MMC	−0.977***	−1.144***	−1.091***	−4.133**	−6.067***	−2.964***
	(0.203)	(0.155)	(0.253)	(1.770)	(1.807)	(1.019)
MMC Square	2.044***	1.753***	2.263***	3.001**	4.580*	2.208**
	(0.354)	(0.314)	(0.432)	(1.658)	(2.469)	(0.958)
KSW		−0.002***			0.000	
		(0.000)			(0.001)	
KSA			−0.146			0.291
			(0.409)			(0.177)
KSW*MMC		−0.432***			−1.125***	
		(0.041)			(0.400)	
KSW*MMC square		0.332***			1.128***	
		(0.014)			(0.123)	
KSA*MMC			−1.926***			−1.663
			(0.497)			(1.714)
KSA*MMC Square			1.059***			0.615
			(0.312)			(1.831)
Constant	3.154***	1.921***	2.916***	4.051***	−2.545***	0.047
	(0.289)	(0.206)	(0.348)	(0.231)	(0.604)	(0.237)
Observations	484	484	484	484	484	484
Number of ID	44	44	44	44	44	44
Control	YES	YES	YES	YES	YES	YES

Notes: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

cross-community knowledge search, the stronger the "bridge" ability of the community, the wider the channels of cooperation and knowledge exchange, it is not conducive to heterogeneous knowledge transmission. In addition, Wang et al. (2024) also found that excessive external knowledge search may not be conducive to efficient reorganization of existing organizational knowledge, providing evidence of the paradox of external knowledge search.

In addition, consistent with argument that community density benefits innovation output by Wang et al. (2019), we found that a higher density of elite communities leads to a stronger promotion of innovation output. Research on the breadth of technology shows that a greater number of patent claims within elite communities strengthens the effect on innovation output. However, excessive involvement in too many technology fields may hinder innovation growth. Righi et al. (2023) support this finding, noting that an increase in patent claims can affect the duration of patent retention by altering patent revenues, thereby having a stronger positive impact on subsequent technological innovation. Regarding the negative effect of technology domain breadth, Lee et al. (2023) offer an explanation based on knowledge distance. They argue that as the number of technology domains increases, the knowledge distance also widens, and there is a negative correlation between knowledge distance and innovation performance. We found that the scientific elite community significantly improved the quality of innovation compared to the technical elite community, which is consistent with the idea that universities and research institutions provide the scientific talent and knowledge necessary for innovation quality (Kafouros et al., 2015).

The generality of technology promotes the quantity of innovation but inhibits the quality of innovation. This is consistent with the view that in the context of cross-industry technology integration and platform innovation. For instance, Zhao et al. (2023) found that digital technologies, as general-purpose technologies, can enhance the innovation of Chinese enterprises. However, Bunjak et al. (2021) cautioned that the overuse of digital technology could lead to digital overload, potentially diminishing creativity. In contrast, technological novelty generally leads to a higher number of innovations. The citation of scientific literature in patents is a key indicator for studying the synergy between science and technology, as explained by Veugelers and Wang (2019). Their study on the impact of scientific citations on technology found that only highly novel scientific publications, which belong to the top 1 % in their field, are significantly more likely to have a direct technological impact than non-novel publications, with the impact being not only significant but also substantially greater.

These findings challenge the prevailing view of the benefits of heterogeneous knowledge for innovation(Ehls et al., 2020). However, they should be considered with caution. First, the analysis focuses only on patent output. Moreover, measuring the quality of innovation in an integrated manner is difficult. While new product output and patent auction prices consider the economic value of innovations to a considerable extent, we do not have information on the quality of these new products or patents for each actor. Therefore, the incentive role of other aspects of innovation quality, such as economic value, cannot be ruled out. Certainly, more complex and advanced innovations may require relatively stable community structures with an active search for heterogeneous knowledge. We also do not understand the optimal balance between elite community member mobility and the number of bridge members.

Taking these caveats into account, the results provide considerable food for thought about the dynamics of innovative collaboration in elite communities. More attention will be needed to confirm or challenge these results. The results provide new ideas about how elites can adjust community membership dynamics to increase community innovation. Fixed partnerships are virtually nonexistent; instead, community member mobility is a fact unless forced. Our results raise questions of general wisdom about what rate of mobility is needed and in what direction and with what intensity of knowledge search to maximize the quantity as well as the quality of elite community innovation. First, elite communities that target numbers of innovations can allow for higher mobility of community members. Elite actors need to design entry and exit mechanisms that are interchangeable and thresholds for internal knowledge search. Second, elite communities that target quality need to maintain a higher degree of stability. Elite actors should design high entry and exit thresholds to reduce the mobility of community members. Similarly, elite actors can design internal cooperation rules coordinated with the entry and exit thresholds to reduce the substitution effects of homogeneous knowledge. Finally, while the findings about cross-community knowledge search are unsatisfactory, the contribution of heterogeneous knowledge to innovation is well documented. Officials and policy makers need to guide elite actors to build clusters that are differentiated and distinct in their knowledge sets, and to design cross-community cooperation thresholds to create more adequate conditions and environments for community innovation.

Despite the valuable insights gained from this study, some limitations should be recognized. First, this study is limited to the field of energy efficiency in China, which may limit the generalizability of the results to other fields. Future studies need a more diverse sample to further validate the results. Second, this study relied solely on members' movements to define the dynamics of elite communities without considering members' network control power. Future research needs to further consider member movements with different levels of control.

CRediT authorship contribution statement

Yonghong Ma: Funding acquisition, Conceptualization. **Huili Ni:** Writing – review & editing, Writing – original draft, Formal analysis. **Enjia Zhu:** Methodology, Data curation. **Yuning Li:** Methodology, Formal analysis.

Consent to participate

Not applicable: This study did not involve direct interaction with human subjects or participants. As a result, obtaining consent to participate was not applicable to this research. The data used in our study were obtained from publicly available sources or pre-existing datasets, and no personal information or identifiable details were included in the analysis. Therefore, ethical approval and consent to participate were not required for this research.

Consent to publish

Not applicable: This study did not involve the collection of any sensitive or personally identifiable information from human subjects. As a result, obtaining consent to publish was not applicable to this research. The data used in our study were sourced from publicly available datasets or sources that do not require specific permission for publication. Therefore, consent to publish was not required for this research.

Ethics

Not applicable: This study utilized publicly available statistical data, which did not involve any human or animal subjects. As a result, ethical approval was not required for this research. We ensured compliance with all relevant data protection and privacy regulations while accessing and analyzing the data. Therefore, this study does not raise any ethical concerns regarding human or animal participants.

Funding

This work was supported by grants from the National Natural Science Foundation of China [Grant numbers 72374053 and 71874040] and the Heilongjiang Provincial Natural Science Fund [Grant No. LH2021G007].

Declaration of Competing Interest

All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

Acknowledgments

The authors sincerely thank the editorial team of the Journal of Engineering and Technology Management for their professional guidance and efficient work, as well as the reviewers for their insightful comments and rigorous perspectives. The authors are grateful to Xiaomeng Yang for constructive suggestions.

Data availability

Data will be made available on request.

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