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Degree assortativity in collaboration networks and breakthrough innovation: the moderating role of knowledge networks

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Abstract

Collaboration networks are widely recognized as essential channels for accessing innovation resources and facilitating creative activities by enabling the exchange of knowledge and information. However, there is little known about whether and how the similarities and dissimilarities between actors forming ties in a collaboration network can either stimulate or inhibit firms' breakthrough innovation. This study explores the relationship between degree assortativity in collaboration networks and breakthrough innovation performance, considering the moderating role of knowledge network characteristics. Using a sample of 80,129 semiconductor patents from the United States Patent and Trademark Office database spanning the years 1975 to 2007, we constructed both the internal collaboration network and the knowledge network of firms. To test our hypotheses, we employed a negative binomial regression model. Our findings demonstrate that firms with lower degree assortativity in their collaboration networks tend to exhibit higher levels of breakthrough innovation performance compared to those with higher degree assortativity. Moreover, the number of direct ties in the knowledge network strengthens the negative relationship between collaboration network degree assortativity and breakthrough innovation. Conversely, the number of non-redundant ties in the knowledge network mitigates the negative relationship between collaboration network degree assortativity and breakthrough innovation. This study provides practical guidance for firms aiming to enhance their innovation capabilities by simultaneously developing internal collaboration networks and knowledge networks.

Keywords Degree assortativity · Breakthrough innovation · Collaboration network · Knowledge network

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Introduction

Innovation activities are embedded in multilevel networks (Brennecke & Rank, 2017; Guan et al., 2015, 2017; Luo & Zhang, 2021), especially knowledge networks and collaboration networks (Guan & Liu, 2016; Wang et al., 2014). Both collaboration networks and knowledge networks have a significant impact on innovation and jointly influencing innovation performance (Wang & Yang, 2019; Wang et al., 2020; Xu et al., 2017). Collaboration networks are recognized as an important channel for accessing innovation resources, providing the knowledge and information needed for creative activities (Fleming, 2001; Rodan & Galunic, 2004; Singh, 2005). Within an organization, researchers frequently engage in innovative activities that lead to the development of a collaboration network (Nerkar & Paruchuri, 2005). This network is decoupled from the firm's knowledge network. Firm knowledge represents a collection of links between knowledge elements (Dibiaggio et al., 2014). Knowledge networks are consisted of connections between the core domains of scientific and technical knowledge (Carnabuci & Bruggeman, 2009; Yayavaram & Ahuja, 2008). In knowledge networks, nodes represent knowledge domains, and the ties between them capture past combinatorial relationships (Carnabuci & Bruggeman, 2009; Phelps et al., 2012). Previous research has indicated that certain structural characteristics of collaboration networks and knowledge networks are associated with exploratory and exploitative innovations (Guan & Liu, 2016; Wang et al., 2014), the quantity and quality of invention outputs (Ahuja, 2000; Yan & Guan, 2018), and breakthrough innovation (Vestal & Danneels, 2022), such as structural holes (Guan & Liu, 2016; Wang et al., 2014), centrality (Dong & Yang, 2016; Wang et al., 2014), and network cohesion (Wang & Yang, 2019; Wang et al., 2020). Consequently, recognizing the significant roles played by collaboration networks and knowledge networks in enhancing innovation performance at the firm level and driving economic development, scholars have called for additional studies to explore the diverse dimensions of these networks and their effects on innovation outcomes (Yan & Guan, 2018).

In their seminal study of the pharmaceutical industry, Khanna and Guler (2021) investigated degree assortativity as a structural attribute that characterizes patterns of collaborative relationships in a collaboration network. They discovered that higher degree assortativity in the collaboration network, indicating a stronger tendency for similar nodes to connect with each other, is associated with increased innovation output but lower average novelty and impact. Degree assortativity measures the similarity in node degrees between connected nodes (Watts, 2004). In a collaboration network, a high degree assortative structure implies that inventors with similar degree centrality ranks tend to form connections, such as highly central members connecting with other highly central members. These network characteristics influence access to knowledge and resource mobilization and are associated with firm-level innovation outcomes (Khanna & Guler, 2021), which are also crucial for breakthrough innovation generation. A large number of studies have shown that breakthrough innovation requires an extensive search for information (Fleming, 2001; Romer, 1994; Schumpeter, 1939), the integration and recombination of different types of knowledge or previously unrelated knowledge elements (Ahuja & Lampert, 2001). Therefore, our objective is to investigate the relationship between collaboration network degree assortativity and breakthrough innovations in firms.

Moreover, this study emphasizes the importance of knowledge network structural attributes for organizational knowledge creation and the inclination towards generating new knowledge. A firm's internal knowledge network is an important factor in the effective use of external knowledge resources. Intra-firm knowledge networks are critical for acquiring new knowledge and generating useful and impactful new combinations. The structural characteristics of knowledge networks indicate the potential for combining existing knowledge elements with other knowledge elements within a firm's technological domain as well as knowledge search tendencies (Guan & Liu, 2016; Yayavaram & Chen, 2015). Following Wang et al. (2014), we test the conceptual model using a dataset of patents from U.S. semiconductor firms. In this study, we focus on two specific organizational knowledge network characteristics, direct ties and non-redundant ties. The number of direct ties in a knowledge network represents the average level of direct connections that nodes possess (Guan & Liu, 2016). Another characteristic is the number of non-redundant ties in the knowledge network, which describes the extent to which focal organization's knowledge elements are interconnected, i.e., the degree of non-redundancy in the relationships. Following Guan and Liu (2016), we measure it using network efficiency, the ratio of non-redundant connections to the total connections in the ego network, to describe the structural hole position of knowledge elements. Since the degree of assortativity of the collaboration network affects the firm's acquisition of new knowledge as well as the generation of useful and impactful knowledge combinations, the direct and non-redundant links in its knowledge network show motivation for new knowledge acquisition and learning. This is crucial for understanding the impact of the degree assortativity of a collaboration network on a firm's breakthrough innovation. Therefore, we argue that the number of direct ties and non-redundant ties in a firm's knowledge network can moderate the influence of degree assortativity on breakthrough innovation.

Based on the studies of Ahuja et al. (2012) and Khanna and Guler (2021), this study complements and enriches previous studies of multilevel networks for innovation and further extend the discussion on the relationship between the degree assortativity of a collaboration network and breakthrough innovation. The composition level of collaboration between similar individuals within a firm affects not only differences in the quantity, novelty, and impact of innovation (as in Khanna & Guler, 2021), but also differences between firms' breakthrough innovation performance. This paper focuses on the question of how degree assortativity of a collaboration network influences a firm's breakthrough innovation outcomes, especially how different knowledge bases and knowledge network structures affect this relationship. We argued that this network structure influences breakthroughs, as degree assortativity impacts the transfer and acquisition of new knowledge, as well as the creation of useful and influential novel combinations, thereby causing systematic differences in breakthrough outcomes. And the number of direct ties in a knowledge network and non-redundancy among ties in a knowledge network can affect a firm's motivation to explore new knowledge (Guan & Liu, 2016; Wang et al., 2014), which may moderate the impact of degree assortativity within the collaboration network on breakthroughs. This study further confirms that innovation outcomes of organizations are influenced by multilevel networks. And in order to enhance breakthrough innovation performance, organizations should also consider their internal knowledge base as well as knowledge network structure when designing collaborative teams to achieve their innovation strategy goals.

Theoretical background and hypotheses

Collaboration networks, knowledge networks, and innovation

Networks serve as the foundation for systematic innovation (Lin & Li, 2006). Innovation activities within firms are embedded in multiple networks (Brennecke & Rank, 2017; Guan et al., 2015, 2017; Luo & Zhang, 2021), especially collaboration networks and knowledge networks (Guan & Liu, 2016; Wang et al., 2014). According to social network theory, internal collaboration within organizations exhibits a network structure, with researchers as nodes and their collaborations forming the connections. Distinct from collaboration networks, knowledge networks consist of connections between scientific and technological knowledge elements (Carnabuci & Bruggeman, 2009; Yayavaram & Ahuja, 2008). The structural characteristics of collaboration networks and knowledge networks significantly influence innovation outcomes, jointly affecting innovation performance (Wang & Yang, 2019; Wang et al., 2020; Xu et al., 2019). In the modern business environment, a firm's competitiveness increasingly relies on its knowledge resources. The firm's innovation capability depends on how it transforms knowledge resources into internal knowledge assets within its internal networks, thereby driving innovation development (Carnabuci & Operti, 2013; Funk, 2014; Grigoriou & Rothaermel, 2017; Zahra & George, 2002).

Previous studies considered collaboration networks and knowledge networks are not isomorphic, but decoupled (Guan & Liu, 2016; Wang et al., 2014), as depicted in Fig. 1. The top section illustrates a partial view of an organization's internal collaboration network, where nodes represent researchers, and links denote past collaborations in inventions. The example covers 12 researchers as nodes, with an average degree centrality of 4.333 for researchers within the internal collaboration network. Additionally, the average network efficiency of researchers in the internal collaboration network is 0.598. On the other hand, knowledge networks differ from social networks as they consist of connections

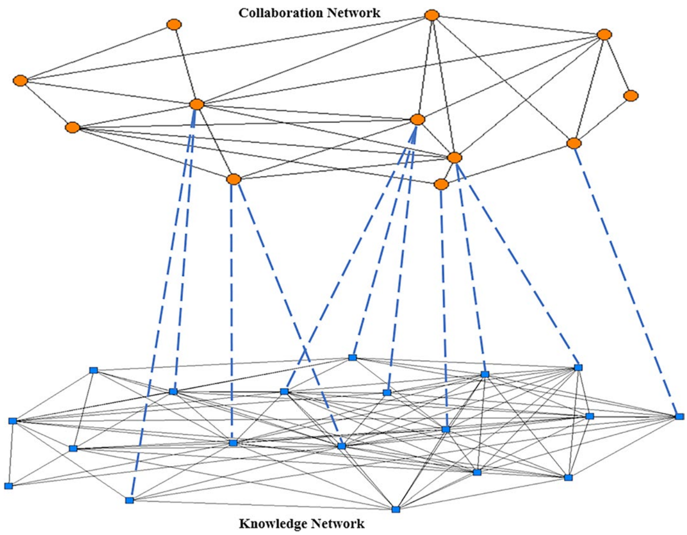

Fig. 1 An example for the decoupling of collaboration and knowledge networks (referring to Guan & Liu, 2016; Wang et al., 2014)

between elements of scientific and technical knowledge (Carnabuci & Bruggeman, 2009; Yayavaram & Ahuja, 2008). The bottom section presents the firm's knowledge network, where nodes represent knowledge elements, and links represent connections between two knowledge elements. The average degree centrality of knowledge elements in the internal knowledge network is 9.789. Moreover, the average network efficiency of knowledge elements in the internal knowledge network is 0.455.

Degree assortativity and breakthrough innovation

Degree assortativity in collaboration networks

Degree assortativity, or degree correlation, is defined as the Pearson correlation of the degree of connected network members, and measures the extent of connectivity and clustering between nodes with similar numbers of ties of a network (Ahuja et al., 2012; Muller & Peres, 2019; Newman, 2003). In social networks, the structure shows assortative matching or assortative mixing, if actors prefer to connect with those who are similar or dissimilar to themselves (Newman, 2002, 2003). In a collaboration network, the high degree assortative structure implies inventors connect with similar degree centrality ranks members, such as highly central members connect with other highly central members. Moreover, a collaboration network with similar levels of degree centrality, average degree, and density may have different levels of degree assortativity. Figure 2a, b are respectively collaboration networks of Microsemi Corporation and Sirenza Microdevices Inc. in 2000–2004, and

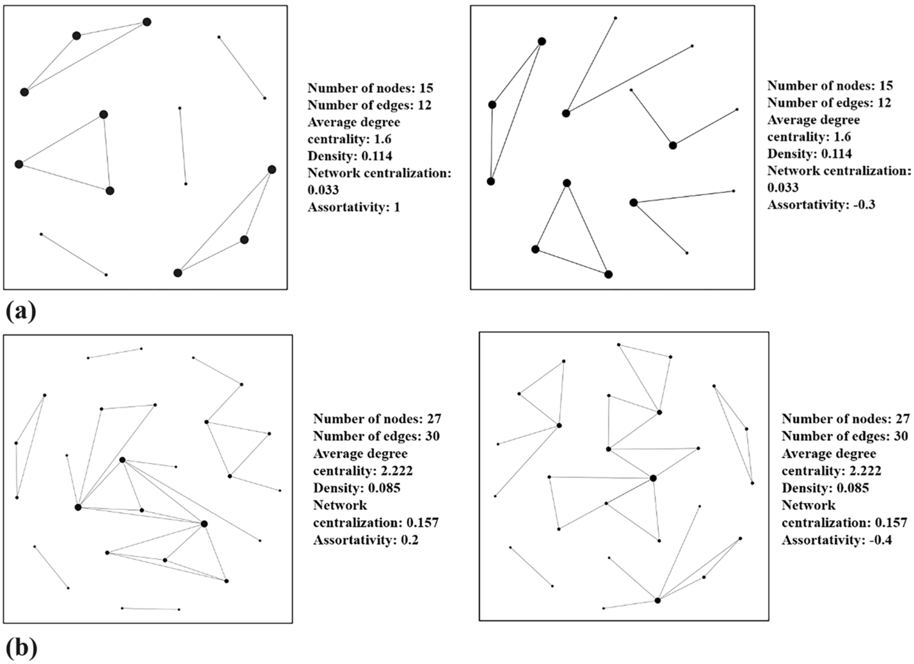

Fig. 2 **a** are collaboration networks of Microsemi Corporation and Sirenza Microdevices Inc. (2000–2004); **b** are collaboration networks of Centillium Communications Inc. and Semtech Corporation (1999–2003)

collaboration networks of Centillium Communications Inc. and Semtech Corporation in 1999–2003. As shown in Fig. 2, two networks have similar typical characteristics in collaboration networks, but the levels of degree assortativity are different. Therefore, degree assortativity of a firm's collaboration network probably relates to their benefits and constraints on breakthrough innovation outcomes.

Breakthrough innovation is a subset of innovation that serves as the foundation for numerous technological advancements, enabling firms to create new value and explore new markets (Ahuja & Lampert, 2001; Cho & Kim, 2017; Rosenberg, 1994). In "The Structure of Scientific Revolutions" (1962), Kuhn proposed that new ideas are initially disregarded but gradually accumulate and trigger a paradigm shift, leading to the replacement of old viewpoints with new perspectives. The theory of scientific change posits that whether focusing on large-scale and rare revolutionary changes or more frequent and gradual evolutionary changes, they revolve around two key concepts: novelty and significance. Highly assortative network structures, characterized by collaborations between inventors with similar degrees, there exists a potential drawback.

In highly assortative network, nodes with similar degrees are connected to each other. High assortativity may increase network redundancy, deepening the homogeneity of knowledge among highly connected nodes, much like clustering (Muller & Peres, 2019). Within this structure, inventors within highly connected clusters of similarity possess abundant information and resource flow, yet information flow between clusters is limited (Fang et al., 2010). Establishing trust and knowledge sharing among members of different levels in highly assortative networks might pose challenges. The clustered network structure could reduce openness to information and diverse approaches, leading to collective blindness at times, resulting in catastrophic consequences (Nahapiet & Ghoshal, 1998). Higher knowledge similarity among members may lead to entrenched thinking patterns, favoring similar methods and perspectives when addressing problems and seeking opportunities (Mangelsdorf, 2018). This homogeneity might inhibit breakthrough innovation output, as breakthrough innovations often require diversity in backgrounds and perspectives (Glover & Kim, 2021). Overreliance on existing knowledge domains may lead organizations into a 'maturity trap', reducing their acceptance and exploration of new knowledge, while these knowledge domains gradually become outdated and lose competitiveness, thereby depriving firms of breakthrough innovation opportunities.

In intra-firm collaboration networks, assortative mixing frequently results in the emergence of core-periphery structures. In such configurations, the core is composed of densely interconnected central inventors, whereas inventors with lower centrality make up the periphery (Ahuja et al., 2012; Borgatti & Everett, 2000). Core/periphery structures might exhibit highly uneven and hierarchical link distributions (Goyal et al., 2006). However, Xu et al. (2022) found that flat structures are more effective in driving innovation. In contrast to flat, egalitarian teams, highly hierarchical teams generate less novelty and tend to iterate on existing ideas more frequently. While these hierarchical teams may enhance productivity for individuals at the top, they often decrease productivity for those at the bottom. Moreover, they may receive more short-term citations but experience a decline in long-term influence or impact.

Conversely, networks with lower assortativity might provide opportunities for new knowledge combinations through information flow between central and peripheral clusters (Ahuja & Lampert, 2001; Hargadon & Sutton, 1997). It fosters more knowledge transfer among members. Comparatively, peripheral roles are more likely to offer fresh perspectives to the system. Being peripheral enables exploration of ideas and information not widely shared yet, while the core effectively organizes support around these ideas and information

(Cattani & Ferriani, 2008). Collaboration among members with mixed hierarchies promotes more new knowledge transmission, offering organizational members more exposure to new knowledge, increasing the likelihood of generating novel knowledge combinations. Additionally, members with higher degree centrality often possess a conventional knowledge base and higher influence. Collaboration among members with mixed hierarchies provides opportunities to combine existing and new knowledge, not only enhancing the novelty of innovation but especially fostering useful and impactful novelty. Not all forms of novelty are conducive to breakthrough innovation (Leahey, 2023; Hofstra et al., 2020), where useful and impactful novelty is more conducive to breakthrough innovation. Therefore, we propose the following baseline hypothesis:

Baseline hypothesis Degree assortativity of a firm's collaboration network is negatively associated with the likelihood of generating breakthrough innovation.

Knowledge and knowledge networks

Innovation is considered a knowledge-intensive activity (Kanter, 1988), and knowledge plays a significant role as an organizational attribute in facilitating innovation (Dougherty, 1992). Many studies suggest that the knowledge base is essentially comprised of knowledge elements (Carnabuci & Bruggeman, 2009; Wang et al., 2014; Yayavaram & Ahuja, 2008). Specifically, the knowledge base can be broken down into numerous independent cores, each belonging to different scientific and technological fields, which are defined as knowledge elements (Carnabuci & Bruggeman, 2009; Wang et al., 2014; Yayavaram & Ahuja, 2008). From the perspective of knowledge stock, previous research has covered the breadth/diversity of knowledge (Zhou & Li, 2012; Tortoriello et al., 2015; Moreira et al., 2018), the knowledge recombinant process (Gruber et al., 2013; Moaniba et al., 2018; Schillebeeckx et al., 2021), and knowledge distance (Capaldo et al., 2017; Rosenkopf & Nerkar, 2001; Stuart & Podolny, 1996). In fact, what organizations and individuals possess is not just an accumulation of knowledge elements but rather a collection of connections between knowledge elements (Dibiaggio et al., 2014). In which knowledge elements are regarded as nodes, and the combination of two knowledge elements in previous patents is regarded as ties, forming the knowledge network of an enterprise (Carnabuci & Bruggeman, 2009; Guan & Liu, 2016; Wang et al., 2014). The structural features of knowledge networks indicate the extent of opportunities for combinations within the technological domain of the enterprise and the potential combinations with other knowledge elements (Yayavaram & Chen, 2015). Figure 3 illustrates the knowledge networks of Vitesse Semiconductor Corporation (up to 2002) and Kopin Corporation (up to 2002).

The moderating role of direct ties in knowledge network

Previous research considered that the specific characteristics of intra-firm knowledge networks have an impact on the likelihood of firms generating new knowledge (Grigoriou & Rothaermel, 2017; Guan & Liu, 2016; Wang et al., 2014; Yan & Guan, 2018; Zakaryan, 2023). Direct ties in knowledge networks represent the topological relationships between knowledge domains (Zhao et al., 2019). The number of direct ties between knowledge elements in a knowledge network is the count of other knowledge elements with which a particular knowledge element has been combined in previous technological inventions (Wang et al., 2014). This indicator not only reflects the degree of involvement of knowledge

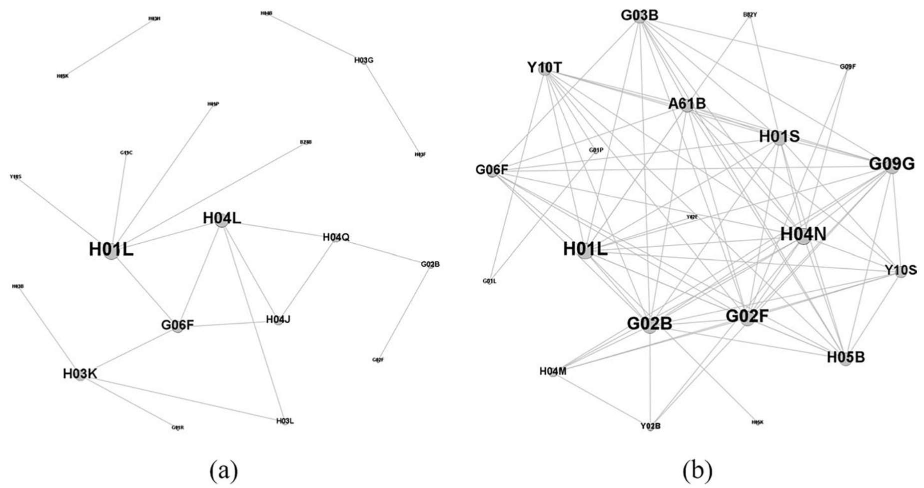

Fig. 3 **a** Knowledge network of Vitesse Semiconductor Corporation (up to 2002) with mean direct ties (1.9) and non-redundancy among ties (0.93); **b** knowledge network of Kopin Corporation (up to 2002) with mean direct ties (7.27) and non-redundancy among ties (0.51)

elements in past technological innovations but also indicates the potential for forming new knowledge combinations in innovation activities. Wang et al. (2014) argued that organizations are likely to search for subject-related knowledge elements through their own existing knowledge elements (Katila & Ahuja, 2002), because knowledge elements possess a natural degree of association with other knowledge elements (Quatraro, 2010). The educational psychologist Ausubel (1968) states that the construction of new knowledge needs to be based on existing knowledge. The direct linkages of a firm's knowledge network play a vital role in accepting new knowledge, making connections with existing knowledge, and realizing the potential of the knowledge combination.

In assortative networks, nodes with higher similarity are more likely to connect with each other. The similarity among collaborators may lead to higher levels of trust, common cognitive frameworks, and motivation to share knowledge. However, this structural or status-based homophily also inhibits knowledge sharing among collaborators with status asymmetry, as differences in status may affect their willingness to share (Bunderson & Reagans, 2011; Tzabbar & Vestal, 2015). Additionally, the similarity among collaborators can result in them possessing more consensual knowledge, thereby reducing their ability to explore diverse knowledge. In networks with higher degree assortativity, it is easier to form a core-periphery structure, where collaborators with higher centrality are connected to each other, while those with lower centrality are connected at the periphery. However, the connections between these two types of clusters are very limited, leading to fragmented knowledge formation within the organization, where knowledge sharing occurs mainly within clusters and is limited between clusters (Fang et al., 2010).

When direct ties of knowledge networks increase, the negative effect between collaboration network degree assortativity and breakthrough innovation will be enhanced. Although leveraging familiar knowledge elements for knowledge combinations can enhance invention efficiency by establishing conventions, standards, and modules (Levitt & March, 1988), it may also heighten dependence on previous work, leading to the 'knowledge echo chamber' predicament. The allocation of enterprise resources tends to lean towards this relevant theme (Guan & Liu, 2016), further reinforcing the focus of members on developing existing knowledge. As existing knowledge becomes reinforced, the likelihood of integrating external new ideas and perspectives decreases. Consequently, the production of innovative combinations within assortative collaboration networks diminishes. In such circumstances, obtaining diverse knowledge sources might become challenging, thereby increasing the homogeneity of knowledge within the organization. Similar groups are more inclined to establish cooperation, potentially resulting in unequal hierarchical structures (Rubí-Barceló, 2012). This further reinforce the negative impact of assortativity in collaboration networks on breakthrough innovation.

Therefore, we put forward the hypotheses as follows:

Hypothesis 1 The direct ties of a firm's knowledge elements in a knowledge network reinforce the negative effect between the degree assortativity of a firm's collaboration network and the likelihood of generating breakthrough innovation.

The moderating role of non-redundancy among ties in knowledge networks

Non-redundant ties ae also an important dimension of knowledge network configuration. When a knowledge element has been combined with other knowledge elements in previous inventions, and these elements themselves are unrelated to each other (Carnabuci & Bruggeman, 2009; Wang et al., 2014), the egocentric network of that knowledge element becomes a non-redundant or sparse structure. An organization that possesses numerous non-redundant knowledge network structures faces minimal constraints when exploring new ideas because it is less susceptible to knowledge inertia, which is a common phenomenon in redundant network structures (Cheon et al., 2015).

According to Guan and Liu (2016), organizations exhibit a preference for local search within the ego-networks of their knowledge elements. However, in redundant knowledge network structures, organizations are more likely to be influenced by inertial tendencies and inclined towards exploit existing knowledge. Considering the costs associated with searching and learning new ideas, organizations locked within redundant knowledge structures may be reluctant to invest time and financial resources in exploring new knowledge structures. A redundant knowledge network structure enhances an organization's tendency to focus on and utilize existing knowledge elements and hinders the exploration of new knowledge and ideas. In redundant knowledge structures, organizations may prefer to focus on the utilization of existing knowledge elements rather than exploring new ideas. Conversely, in knowledge network structures with non-redundant connections, enterprises face fewer limitations when exploring new knowledge, as such structures exhibit less knowledge inertia (Cheon et al., 2015). On one hand, this structure is more conducive to accepting and acquiring new knowledge; on the other hand, having fewer redundant connections implies a greater potential for new combinations of existing knowledge within the network. For instance, if knowledge elements A and B, as well as A and C, have been combined previously, but there hasn't been a combination between B and C, the combination of B and C represents a new combination of existing elements. Such knowledge combinations, built upon a conventional knowledge base, are more likely to generate useful novelty, thereby fostering breakthrough innovation. Therefore, having a higher level of non-redundant connections in the knowledge network can mitigate the negative impact of degree assortativity in collaboration networks on breakthrough innovation.

Therefore, we put forward the hypotheses as follows:

Hypothesis 2 Non-redundancy among ties of a firm's knowledge elements in a knowledge network mitigates the negative effect between the degree assortativity of a firm's collaboration network and the likelihood of generating breakthrough innovation.

Figure 4 summarizes all the hypotheses of the study.

Methodology

Data collection and samples

Our focal sample consists of inventions made by semiconductor firms from 1975 to 2007. We investigated our hypotheses by examining semiconductor patents held by U.S. firms used with all other U.S. semiconductor firms that are available via COMPUSTAT (SIC code = 3674). Next, we compiled a list of 164 U.S. semiconductor firms, which have a COMPUSTAT record and at least granted one USPTO patent during the time period 1975–2007. We obtained enterprise patent data from the database "DISCERN: Duke Innovation & SCientific Enterprises Research Network," linking patent data to Compustat firms. Our sample consisted of firms that filed patents during the observation period from 1996 to 2007 and submitted at least one patent application within the 5 years preceding the focal year. After handling missing values, our primary sample spanned from 1975 to 2007, comprising 80,129 patents assigned to 124 firms.

We constructed firms' collaboration networks and knowledge networks, using patents data of semiconductor firms. The collaboration network was based on co-application in patents for the t to t + 2 years prior to the observation period. We then filtered different firms' patent data for the years t to t + 2. By matching this data with "The careers and co-authorship networks of U.S. patent-holders, since 1975" database, we obtained information about the inventors. For example, in patent US6829240B1, inventors 57,682,750,031 and 57,682,750,011 (data sourced from "The careers and co-authorship networks of U.S. patent-holders, since 1975", https://doi.org/10.7910/DVN/YJUNUN, Harvard Dataverse) are considered as two nodes in the collaboration network, establishing a collaborative relationship between them due to their joint involvement in the patent. Because this paper only studies the intra-firm collaboration

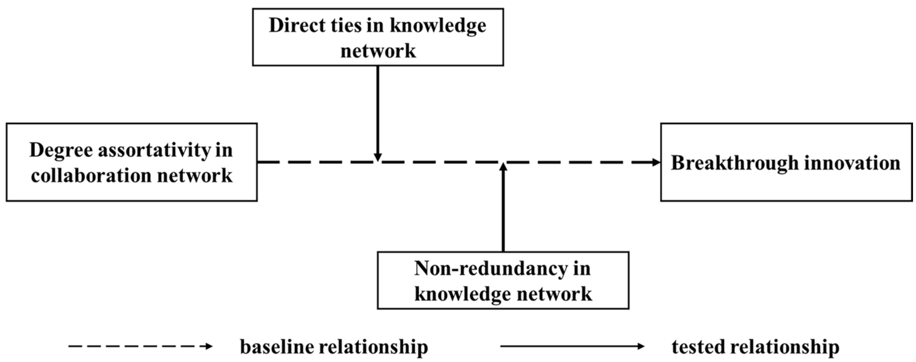

Fig. 4 The conceptual model

network and innovation relationship, the patent data of inter-firm collaboration (of which there are 93 patents of inter-firm collaboration from 1975 to 2005) are excluded.

Then we constructed a knowledge network of knowledge elements based on the co-application of four-digit CPC (Cooperative Patent Classification) codes in each patent before t-1 years (i.e., during 1975 to t-1 year). The knowledge network represents the network expression of the knowledge possessed by a firm from its previous research activities and the combinations of this knowledge. In this network, the elements of knowledge serve as nodes, while the combinations of these knowledge elements serve as connections or edges between the nodes.

For instance, consider a patent such as US6175880, with a CPC classification code where the first four segments are G06F; G06F; Y02B; Y02D. In this case, the three knowledge elements (G06F; Y02B; Y02D) would establish pairwise connections between each other within the knowledge network (refer to Wang et al., 2014). Because patents need enough time to accumulate forward citations, our focal sample is limited to the 1996–2007 periods, reducing the concern for right censoring.

Variables and measures

Dependent variable

Breakthrough innovation We defined breakthroughs as fundamental inventions that have a great impact on subsequent technological advances (Rosenberg, 1994). Breakthrough innovation is usually measured by the number of forward citations, that is, a higher number of citations indicates that the patent is a breakthrough innovation (Kaplan & Vakili, 2015; Trajtenberg, 1990; Vestal & Danneels, 2022). Following recent research (Ahuja & Lampert, 2001; Vestal & Danneels, 2022), we identify breakthrough inventions based on the top 5% of future citations received (up to 2015) compared with patents (from 1996 to 2005) filed in the same year. Initially, for each year (t, t + 1, and t + 2), we identify patents within the top 5% of industry patent citations, coding them as ‘1’, while the remaining patents are labeled ‘0’. Subsequently, for the focal firm, we calculate the count of patents ranked in the top 5% of citations obtained during the periods of t, t + 1, and t + 2. This count serves as a measure of the firm’s breakthrough innovation from t to t + 2. And for sensitivity we also repeated the analyses using top 3 percent.

Independent variables

Degree assortativity The independent variable is the degree assortativity of a firm’s collaboration network. Following Newman (2003), we defined assortative mixing characteristics as e_{ij}, the fraction of edges in a network that connect a vertex of degree type i to one of degree type j, that is,

$$e_{ij} = \text{probability that an edge links node of degree type} i \text{with a node of degree type} j \tag{1}$$

In an undirected network, this quantity is symmetric in its indices e_{ij}=e_{ji}. It satisfies the sum rules:

$$\sum_{ij} e_{ij} = 1, \sum_{j} e_{ij} = a_i, \sum_{i} e_{ij} = b_j \tag{2}$$

where a_i is the fraction of each degree type of end of an edge that is attached to vertices of degree type i, same as for b_j. And in a perfectly assortative network, the probability e_{ij} that an edge joins nodes of degree types i and j would be 0; in a perfectly disassortative network, the probability e_{ij} that an edge joins nodes of degree types i and j would be 1, since no two nodes in the network that are connected are of the same degree type.

To quantify degree assortativity of a network, r, we estimate it as the Pearson correlation coefficient:

$$r = \frac{\sum_i e_{ii} - \sum_i a_i b_i}{1 - \sum_i a_i b_i} = \frac{\mathrm{Tr}\mathbf{e} - ||\mathbf{e}^2||}{1 - ||\mathbf{e}^2||} \tag{3}$$

where e is the element of the matrix is e_{ij} and $||\mathbf{e}^2||$ is the sum of all elements of the matrix e. When the mixing is random, the value of r is 0, because in this case $e_{ij} = a_i b_j$. In the case of perfect assortativity, r=1 and e_{ij}=1; in the case of perfect disassortativity, r=-1 and e_{ij}= 0. Therefore, the value of r ranges between -1 and 1, with a negative value representing a disassortative structure and a positive value representing an assortative structure.

Moderating variables

Mean knowledge network direct ties This variable represents the average direct ties of the focal firm's knowledge elements. The value is calculated by the following two steps. First, we calculated direct ties of each knowledge element in the focal firm's knowledge network for the period 1975 to t-1. Second, for each firm, we averaged the direct ties values for all knowledge elements it possessed. We calculated these variables using UCINET 6.186.

Mean knowledge network non-redundancy Following Guan and Liu (2016), we selected network efficiency as a metric to assess the level of non-redundancy in knowledge networks. This variable indicates the average extent to which knowledge elements tied to the focal firm's knowledge elements are disconnected, without being combined in previous inventions. The value of this variable is calculated by averaging the network efficiency scores of each knowledge element of a firm. Following Burt's (1992), we used the efficiency measure, which calculates the ratio of nonredundant contacts to total contacts to total contacts for the focal firm i:

$$Networkefficiency_i = \left[\sum_j \left(1 - \sum_q p_{iq} p_{jq} \right) \right] / C_i \tag{4}$$

where p_{iq} is the proportion of relations that the knowledge element i invested in the connection with the knowledge element q. The meaning of p_{jq} is similar to it. And C_i expresses the total number of its direct connecters. This formula yields a value in the range of 0 to 1, where higher values indicate a lower presence of redundant ties.

Control variables

Certain firm-level attributes can influence breakthrough innovation in the focal firm. First, we controlled for *collaboration network direct ties*, measured as the average degree of inventors in a firm's collaboration network. And we control for *collaboration network* *non-redundancy*, measured as the ratio of non-redundant ties to a firm's collaboration network (Burt, 1992). We also controlled for other properties that may influence creativity, such as *coordination costs*, using a five-year rolling window procedure in which we divided the total number of partnerships used to develop patents from year t-4 to year t by the same five-year window of participation in the total number of inventors involved in the knowledge production process (i.e., network size) (Grigoriou & Rothaermel, 2017). We controlled for *knowledge network local cohesion* as the weighted overall clustering coefficient of the focal firm, and *knowledge network global cohesion* as the density of the overall network (Guler & Nerkar, 2012). There are some knowledge-related control variables. At the firm level, we controlled for *Technological diversity* measures as a Herfindhal index of concentration (see also Ahuja & Katila, 2001; Fleming, 2001). R&D intensity(asset) was measured as the mean level of R&D expenditures scaled by lagged total assets (Miller, 2006). Then, at the patent level, we controlled for *firm patents lagged*, measured as the number of successful patent applications of the firm in the prior year (ln) (Paruchuri & Awate, 2017). We measure *firm age* of the focal firm by calculating the difference between its first patent application year and the focus year (ln) (e.g., Sørensen & Stuart, 2000).

Model specification

The dependent variable of the study, breakthrough innovation performance, is a count variable and takes only nonnegative integer values. The Poisson model strictly assumes that the mean and variance of the dependent variables should be equal. Since the variance of explanatory variable is greater than its mean, the negative binomial model (NB) is more appropriate (Gulati et al., 2012). And according to the Hausman test ($p < 0.01$), we adopted negative binomial regression models with fixed effects for the panel data. We used STATA 14. to estimate the models.

Results

Table 1 presents the descriptive statistics of variables and their correlations. To deal with the problem of multicollinearity, we calculated variable inflation factors (VIFs) for each variable. The maximum VIF score is 3.29 less than 5, and the average VIF is 1.81, indicating that the estimated results of this study are insignificantly affected by the potential bias of the multicollinearity problem (Belsley, 1991). We summarized our theoretical framework in Fig. 1 and the predicted directions of the coefficients in order to facilitate the discussion of our findings.

Table 2 presents the results of the negative binomial regressions. Model 1 is the baseline model that only includes the control variables. Model 2 adds the independent variable of collaboration network degree assortativity to Model 1. In model 2, the results show that the degree assortativity of an intra-firm network negatively and significantly associated with breakthrough innovation performance. The coefficient of assortativity is-0.608 at a p-value of 0.002. Model 3 extends upon Model 2 by introducing Mean knowledge direct ties and the interaction term with assortativity. The results of Model 3 show that the interaction term between the degree assortativity of a collaboration network and direct ties of a knowledge network was negative and significant for breakthrough innovation performance. This means that when the number of direct ties in a knowledge network is high, it can intensify the negative impact between the degree assortativity of a collaboration network and

Table 1 Descriptive statistics and correlations for all variables

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Breakthrough Innovation performance	1												
2	Collaboration network degree assortativity	− 0.012	1											
3	Mean knowledge network direct ties	0.405***	0.03	1										
4	Mean knowledge network non-redundancy	− 0.076*	0.123**	− 0.456***	1									
5	Knowledge network local cohesion	0.259***	− 0.01	0.585***	− 0.329***	1								
6	Knowledge network global cohesion	− 0.044	− 0.074	0.283***	− 0.303***	0.772***	1							
7	Collaboration network direct ties	− 0.234***	− 0.219***	− 0.263***	− 0.002	− 0.063	0.200***	1						
8	Coordination costs	0.244***	− 0.033	0.486***	− 0.243***	0.569***	0.390***	− 0.085*	1					
9	Collaboration network non-redundancy	0.03	− 0.032	− 0.153***	0.107**	− 0.218***	− 0.275***	− 0.211***	− 0.431***	1				
10	Firm patents lagged(ln)	0.560***	0.074	0.639***	− 0.084*	0.311***	− 0.104**	− 0.586***	0.355***	0.032	1			
11	Technological diversity	0.110**	0.237***	0.363***	− 0.06	0.149***	− 0.125**	− 0.258***	0.025	0.087*	0.355***	1		
12	R&D intensity(asset)	− 0.157***	− 0.015	− 0.062	− 0.065	− 0.073	0.036	0.138***	− 0.019	− 0.06	− 0.161***	− 0.064	1	
13	Firm age(ln)	0.235***	0.094*	0.459***	− 0.019	0.273***	− 0.084*	− 0.293***	0.256***	− 0.026	0.480***	0.420***	− 0.260***	1
	Mean	12.167	0.24	3.493	0.715	2.019	0.577	0.125	1.818	0.575	2.914	0.716	0.156	2.174
	S.D	37.259	0.36	2.234	0.128	2.803	0.914	0.144	0.8	0.127	1.65	0.185	0.122	0.732

Table 1 (continued)

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13
Min	0	− 0.806	0	0	0	0	0.001	0.579	0.186	0	0	0	0
Max	300	1	13.407	1	20.299	8.162	0.933	5.081	1	7.542	0.943	0.883	3.401

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 2 The results of the hypotheses test

Variables/model	Model 1 Breakthrough Innovation	Model2 Breakthrough Innovation	Model 3 Breakthrough Innovation	Model 4 Break-through Innovation
Control variables				
Knowledge network local cohesion	– 0.215*** (– 5.16)	– 0.217*** (– 5.27)	– 0.119*** (– 3.24)	– 0.211*** (– 5.14)
Knowledge network global cohesion	0.400*** (3.21)	0.412*** (3.35)	0.470*** (4.02)	0.354*** (2.87)
Collaboration network direct ties	– 4.540*** (– 4.33)	– 5.240*** (– 4.67)	– 4.780*** (– 4.45)	– 5.422*** (– 4.79)
Coordination costs	– 0.104 (– 1.20)	– 0.093 (– 1.06)	– 0.206** (– 2.34)	– 0.114 (– 1.31)
Collaboration network non-redundancy	– 0.751 (– 1.26)	– 1.104* (– 1.81)	– 0.936 (– 1.51)	– 0.781 (– 1.27)
Firm patents lagged(ln)	0.283*** (6.23)	0.258*** (5.56)	0.409*** (7.52)	0.256*** (5.54)
Technological diversity	– 0.037 (– 0.08)	– 0.166 (– 0.36)	0.126 (0.27)	– 0.026 (– 0.06)
R&D intensity(asset)	– 0.695 (-1.48)	– 0.691 (– 1.47)	– 0.723 (– 1.56)	– 0.753 (– 1.63)
Firm age(ln)	– 0.913*** (– 6.80)	– 0.851*** (– 6.19)	– 0.667*** (– 4.78)	– 0.896*** (– 6.45)
Moderating variables				
Mean knowledge network direct ties			– 0.156*** (– 3.32)	
Mean knowledge network non-redundancy				– 1.369*** (– 2.96)
Direct effect				
Collaboration network degree assortativity		– 0.608*** (– 3.07)	0.176 (0.49)	– 2.952*** (– 3.15)
Moderating effects				
Collaboration network degree assortativity × Mean knowledge network direct ties			– 0.258*** (– 2.66)	
Collaboration network degree assortativity × Mean knowledge network non-redundancy				3.266*** (2.61)
Constant	3.646*** (6.69)	4.069*** (7.07)	3.550*** (6.02)	4.959*** (7.77)
Wald χ^2	180.85	185.87	234.87	195.42
Log likelihood	– 1106.13	– 1101.28	– 1084.39	– 1095.87
Observations	572	572	572	572

Standard errors are reported in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

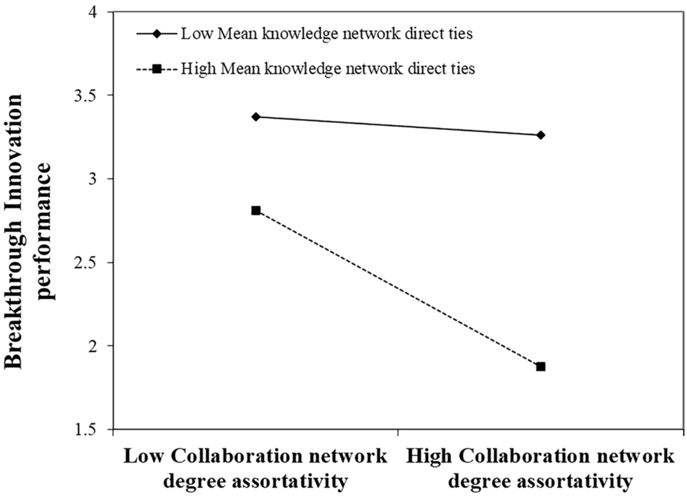

Fig. 5 The moderating role of the number of direct ties in a knowledge network on the relationships between the degree assortativity of a collaboration network and breakthrough innovation performance

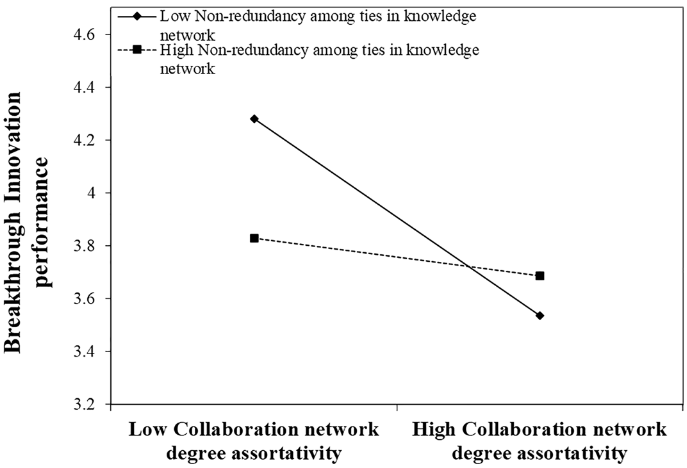

Fig. 6 The moderating role of non-redundancy among ties in a knowledge network on the relationships between the degree assortativity of a collaboration network and breakthrough innovation performance

breakthrough innovation. The coefficient of the interaction term between the degree assortativity of a collaboration network and the number of direct ties in a knowledge network is -0.258 at a p-value of 0.008. Thus, H1 is supported. Furthermore, we tested H2 in Model 4. Model 4 extends upon Model 2 by introducing Mean knowledge network non-redundancy and the interaction term with assortativity. And the results show that non-redundancy among ties in a knowledge network weaken the negative effect between the degree assortativity of a collaboration network and breakthrough innovation performance. The coefficient of the interaction term between degree assortativity of a collaboration network and non-redundancy among ties in a knowledge network is 3.266 at a *p*-value of 0.009. Thus, H2 is supported. The moderating effects are further confirmed by Figs. 5 and 6, showing the difference in the slope effect of the degree assortativity of a collaboration network on breakthrough innovation performance at the two levels of number of direct ties and non-redundancy in a knowledge network.

Robustness check

We conducted a range of additional robustness checks for the results. First, we also re-estimated the model after defining the dependent variable breakthrough inventions as include all patents in the top 3% cited patents (rather than the top 5%), reported in Table 3. Second, we constructed knowledge networks for focal firms based on 3-digit and 6-digit CPC categories to examine the moderating effects of knowledge network structural attributes at different levels of granularity. The results obtained were consistent with those previously reported, and they are presented in Tables 4 and 5. Third, we addressed covariate imbalances between treatment and control groups using coarsened exact matching (CEM) (Iacus et al., 2011). Following Khanna and Guler (2021), we created a binary variable to represent high and low assortativity. Specifically, firms with assortativity greater than 0.5 take the value of 1; firms with assortativity less than 0.5 take the value of 0. To ensure the reliability of the results, we compared the observed outcomes between the treated and untreated groups (Abadie & Imbens, 2002, 2011). R&D intensity (asset) and firm age were selected as matching criteria, and we presented descriptive statistics and mean difference test results for both treatment and control groups before and after Coarsened Exact Matching (CEM) in Table 6. By integrating the weights derived from CEM, we conducted regression analysis on the matched observations using a year fixed-effects negative binomial model and report the results in Table 7. These regressions are generally consistent with previous results, thus confirming the robustness of the results.

Conclusion

Based on the multilevel networks view (Brennecke, 2017; Guan et al., 2015, 2017), we argued that firm-level breakthrough innovation outcomes will be influenced by the structure of intra-firm collaboration networks as well as knowledge networks. And tie formation mechanisms of collaboration networks could lead to differences of innovation outcomes for organizations (Khanna & Guler, 2021). In this paper, we sought to gain insight into how the degree assortativity of a collaboration network affects breakthrough innovation performance and further discuss the moderating role of the number of direct ties and non-redundant ties in a knowledge network. The empirical setting is the semiconductor patents of the USPTO database from 1975 to 2007. Our estimation results confirm that firms with lower degree assortativity in their collaboration networks tend to achieve higher breakthrough innovation performance than those with higher assortativity, indicating a negative relationship between collaboration network degree assortativity and breakthrough innovation.

Furthermore, when the number of direct ties in the knowledge network increases, the negative effect between the degree assortativity of a collaboration network and breakthrough innovation is strengthened. Conversely, an increase in the number of non-redundant ties in the knowledge network mitigates this negative effect. This is because a higher number of direct ties in the knowledge network tends to facilitate local search for firms, whereas non-redundant ties are more conducive to exploring new knowledge. There are several interesting and important implications of our findings for theory and practice.

Theoretical contributions

Our research makes several theoretical contributions. First, we analyze the factors influencing firms' breakthrough innovation performance from the multiple network embedding perspective. Firms' innovation activities are embedded in multiple networks, including collaboration networks and knowledge networks. While there are considerable studies on the relationship between the structure of collaboration networks and innovation (Guan & Liu, 2016; Wang & Yang, 2019; Wang et al., 2014), there are few explorations of the mechanisms of tie formation or collaboration among members (Khanna & Guler, 2021). Our study highlights the importance and influence of the degree assortativity of intra-firm collaboration networks on breakthrough innovation, and further extends the boundary conditions of the relationship between degree assortativity of collaboration networks and breakthrough innovation of firms through knowledge networks architectural attributes. Previous research suggested that knowledge creation depends on factors at the individual, team, and organizational levels (Powell & Grodal, 2005; Wuchty et al., 2007). We find that firms' breakthrough innovation outcomes are influenced not only by the mechanisms of tie formation among collaborators but also by the organizational knowledge environment, such as direct ties and non-redundant ties in the knowledge network. This study extends the existing literature on the relationship of collaboration network assortativity and the interaction between multilevel networks and innovation (Wang & Yang, 2019; Wang et al., 2020; Xu et al., 2017).

Second, we extend the research on the impact of knowledge network structure on innovation outcomes (Grigoriou & Rothaermel, 2017; Guan & Liu, 2016; Wang et al., 2014; Yayavaram & Ahuja, 2008), enriching our understanding of the internal innovation processes within organizations. Phelps et al. (2012) emphasized that knowledge networks exist separately from other networks. In the process of innovation, the structure of knowledge networks will affect the ability to transfer, acquire, and combine knowledge. We analyze at the firm level to identify how certain structural attributes of knowledge network influence innovation. By elucidating the impact of direct and non-redundant ties on breakthrough innovation, we emphasize the importance of considering the structure of the firm's knowledge network to understand the innovation process and outcomes. This study responds to the call for further research on knowledge networks (Phelps et al., 2012). In particular, during the period of rapid development of artificial intelligence, there is a need to supplement prior knowledge and improve the interpretability of models through the exploration of knowledge networks (Sheth et al., 2019). With the growing uncertainty of the task of generalizing to a specific domain, and the incremental improvements that come with large amounts of training data and increased model complexity, concerns have arisen about the features learned by the model. Exploring the logic underpinning innovation from a knowledge network perspective will help drive the development of proprietary AI models that provide clearer and more credible explanations and understandings for organizations. In particular, when utilizing techniques such as deep learning, knowledge networks can provide additional information and constraints to help models better understand and utilize data, improve their performance, enhance their explanatory and interpretable nature, and increase decision credibility.

Managerial implications

This paper is relevant in showing how organizations can enhance the competitive advantage of breakthrough innovations by implementing teamwork mechanisms and knowledge management. First, we found that developing the lower degree assortativity of a collaboration network is necessary for improving a firm's breakthrough innovations. Therefore, firms focusing on breakthrough innovations are advised to alter the level of degree assortativity through teamwork design to a lower one. At the same time, for firms aiming to transform their innovation landscape and strategies, it is critical to design incentive strategies for mixed-rank collaborations.

Second, our findings also suggest that the structure of a firm's knowledge network will influence breakthrough outcomes of collaboration among members. For instance, firms inclined towards exploring new knowledge (i.e., those with more non-redundant ties in their knowledge networks) may choose collaborative patterns among inventors with varying degrees centrality in the collaboration network to foster breakthrough innovation. Conversely, for knowledge-conservative firms that prefer to exploit existing knowledge (i.e., those with more direct ties in their knowledge networks), the adoption of a mixed-rank collaborative pattern to achieve more breakthrough innovation may be weakened. Managers might adjust the structure of their organization's knowledge base to better promote the capability to integrate and apply new ideas and knowledge to firms' existing knowledge repertoire, while also leveraging the structure of the knowledge network. These findings imply that firms with a higher number of breakthrough innovations are those that possess the knowledge and skills to effectively position themselves through strategic innovation design and the coordination of their knowledge networks.

Limitation and future research

While this research advanced our understanding of multilevel networks and breakthrough innovations, our study has a few limitations that may serve as directions for future research.

First, this study selects patent data to construct collaboration networks and knowledge networks. Previous studies suggested that patents may be the most valid and robust indicator of knowledge creation and collaboration research, and many scholars have used patent data to study collaboration innovation activities (Ahmadpoor & Jones, 2017; Guan & Liu, 2016; Maoret et al., 2020; Wang et al., 2014; Wu et al., 2019). However, in addition to working together on patent applications, there are probably other ways of knowledge exchange and sharing within firms, such as friendship networks, project groups (but not co-author patents), work-related advice network, etc. These network connections will influence the willingness to share knowledge and hence breakthrough innovation outcomes as well. Future research could further establish several different networks through various methods such as questionnaires to study this issue.

Secondly, this study focuses on the impact of the degree assortativity of an intra-firm collaboration network on breakthrough innovations. The individual inventor attributes also affect breakthroughs, such as educational background, job title, whether he or she is a specialist or generalist, scientist or engineer, and other demographic traits (Gruber et al., 2013). Future research could further analyze how these individual characteristics influence the relationship between degree assortativity and firms' breakthrough innovation performance.

Finally, this study is a firm-level analysis of the impact of structural attributes of intra-firm collaboration networks and knowledge networks on breakthrough innovation performance. Future research can explore the impact of mixed-rank collaborations on innovation outcomes at the team level, and at the individual level, and further examine how the interaction between individuals produces innovation outcomes at the macro level, providing a new understanding of the generation of breakthrough innovation outcomes.

Appendix

See Tables 3, 4, 5, 6, and 7.

Table 3 Results of robustness analysis (patents in the top 3%)

Variables/model	Model 1 Breakthrough innovation	Model2 Breakthrough innovation	Model 3 Breakthrough innovation	Model 4 Breakthrough innovation
Control variables				
Knowledge network local cohesion	− 0.192***	− 0.193***	− 0.088**	− 0.188***
	(− 4.62)	(− 4.70)	(− 2.49)	(− 4.64)
Knowledge network global cohesion	0.316**	0.325**	0.435***	0.282**
	(2.33)	(2.43)	(3.26)	(2.15)
Collaboration network direct ties	− 4.695***	− 5.267***	− 4.793***	− 5.562***
	(− 3.71)	(− 3.90)	(− 3.77)	(− 4.02)
Coordination costs	0.018	0.023	− 0.126	0.005
	(0.19)	(0.23)	(− 1.26)	(0.05)
Collaboration network non-redundancy	− 0.538	− 0.662	− 0.631	− 0.410
	(− 0.72)	(− 0.88)	(− 0.82)	(− 0.54)
Firm patents lagged(ln)	0.284***	0.261***	0.446***	0.257***
	(5.34)	(4.78)	(6.92)	(4.68)
Technological diversity	− 0.310	− 0.637	− 0.441	− 0.372
	(− 0.53)	(− 1.03)	(− 0.73)	(− 0.60)
R&D intensity(asset)	− 0.944	− 0.897	− 0.880	− 1.079*
	(− 1.53)	(− 1.44)	(− 1.42)	(− 1.74)
Firm age(ln)	− 1.075***	− 0.987***	− 0.677***	− 1.025***
	(− 6.19)	(− 5.51)	(− 3.75)	(− 5.69)
Moderating variables				
Mean knowledge network direct ties			− 0.226***	
			(− 3.92)	
Mean knowledge network non-redundancy				− 1.456**
				(− 2.55)
Direct effect				
Collaboration network degree assortativity		− 0.602**	0.156	− 3.693***
		(− 2.29)	(0.34)	(− 3.02)
Moderating effects				
Collaboration network degree assortativity × Mean knowledge network direct ties			− 0.250**	
			(− 2.11)	
Collaboration network degree assortativity × Mean knowledge network non-redundancy				4.256***
				(2.64)
Constant	4.070***	4.426***	4.022***	5.303***
	(5.83)	(6.09)	(5.28)	(6.78)
Wald χ^2	129.78	132.46	182.20	141.98
Log likelihood	− 852.30	− 849.59	− 832.11	− 845.14
Observations	500	500	500	500

Standard errors are reported in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 4 Results of robustness analysis (three-digit CPC classes)

Variables/model	Model 1 breakthrough innovation	Model2 breakthrough innovation	Model 3 breakthrough innovation	Model 4 breakthrough innovation
Control variables				
Knowledge network local cohesion (CPC-3)	– 0.013	– 0.006	0.441*	0.321
	(– 0.06)	(– 0.02)	(1.89)	(1.03)
Knowledge network global cohesion (CPC-3)	– 0.417***	– 0.452***	– 0.279*	– 0.495***
	(– 2.68)	(– 2.94)	(– 1.83)	(– 3.05)
Collaboration network direct ties	– 4.131***	– 4.799***	– 4.583***	– 5.080***
	(– 4.13)	(– 4.49)	(– 4.30)	(– 4.71)
Coordination costs	– 0.301***	– 0.300***	– 0.251***	– 0.326***
	(– 3.31)	(– 3.27)	(– 2.88)	(– 3.65)
Collaboration network non-redundancy	– 0.836	– 1.210*	– 1.037*	– 1.095*
	(– 1.38)	(– 1.94)	(– 1.69)	(– 1.75)
Firm patents lagged(ln)	0.228***	0.202***	0.344***	0.215***
	(5.02)	(4.36)	(6.73)	(4.58)
Technological diversity	– 0.554	– 0.649	– 0.127	– 0.723
	(– 1.35)	(– 1.53)	(– 0.29)	(– 1.62)
R&D intensity(asset)	– 0.271	– 0.282	– 0.674	– 0.447
	(– 0.59)	(– 0.61)	(– 1.49)	(– 0.97)
Firm age(ln)	– 1.161***	– 1.110***	– 0.760***	– 1.083***
	(– 7.82)	(– 7.39)	(– 4.81)	(– 7.26)
Moderating variables				
Mean knowledge network direct ties (CPC-3)			– 0.251***	
			(– 4.89)	
Mean knowledge network non-redundancy (CPC-3)				0.270
				(0.73)
Direct effect				

Table 4 (continued)

Variables/model	Model 1 breakthrough innovation	Model2 breakthrough innovation	Model 3 breakthrough innovation	Model 4 breakthrough innovation
Collaboration network degree assortativity		− 0.644***	− 0.114	− 2.245***
		(− 3.22)	(− 0.31)	(− 3.77)
Moderating effects				
Collaboration network degree assortativity × Mean knowledge network direct ties (CPC-3)			− 0.192*	
			(− 1.94)	
Collaboration network degree assortativity × Mean knowledge network non-redundancy (CPC-3)				2.233***
				(2.81)
Constant	4.930***	5.406***	4.582***	5.120***
	(7.96)	(8.41)	(6.96)	(7.05)
Wald χ^2	164.88	171.24	230.41	178.07
Log likelihood	− 1122.90	− 1117.54	− 1092.59	− 1112.41
Observations	578	578	578	578

Standard errors are reported in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 5 Results of robustness analysis (Six-digit CPC groups)

Variables/model	Model 1 Break-through innovation	Model2 Break-through innovation	Model 3 Break-through innovation	Model 4 Break-through innovation
Control variables				
Knowledge network local cohesion (CPC-6)	0.888**	0.899**	1.172***	0.529
	(2.07)	(2.08)	(2.86)	(0.81)
Knowledge network global cohesion (CPC-6)	− 0.400	− 0.518*	− 0.327	− 1.140***
	(− 1.33)	(− 1.70)	(− 1.09)	(− 3.10)
Collaboration network direct ties	− 4.133***	− 4.822***	− 5.272***	− 5.916***
	(− 4.12)	(− 4.47)	(− 4.75)	(− 5.03)
Coordination costs	− 0.298***	− 0.298***	− 0.225***	− 0.316***
	(− 3.22)	(− 3.20)	(− 2.61)	(− 3.43)
Collaboration network non-redundancy	− 0.618	− 1.025	− 0.970	− 0.979
	(− 1.02)	(− 1.63)	(− 1.58)	(− 1.56)
Firm patents lagged(ln)	0.231***	0.202***	0.355***	0.187***
	(5.10)	(4.35)	(7.06)	(4.05)
Technological diversity	− 0.574	− 0.720	− 0.377	− 0.947*
	(− 1.25)	(− 1.51)	(− 0.81)	(− 1.94)
R&D intensity(asset)	− 0.083	− 0.117	− 0.487	− 0.241
	(− 0.18)	(− 0.25)	(− 1.07)	(− 0.51)
Firm age(ln)	− 1.067***	− 1.021***	− 0.924***	− 1.191***
	(− 7.69)	(− 7.23)	(− 6.90)	(− 7.79)
Moderating variables				
Mean knowledge network direct ties (CPC-6)			− 0.087***	
			(− 3.21)	
Mean knowledge network non-redundancy (CPC-6)				− 1.896**
				(− 2.11)
Direct effect				
Collaboration network degree assortativity		− 0.638***	0.569	− 3.302***
		(− 3.15)	(1.50)	(− 4.66)
Moderating effects				
Collaboration network degree assortativity × Mean knowledge network direct ties (CPC-6)			− 0.241***	
			(− 3.63)	
Collaboration network degree assortativity × Mean knowledge network non-redundancy (CPC-6)				4.987***
				(3.95)
Constant	3.808***	4.375***	4.025***	6.484***
	(5.12)	(5.61)	(5.26)	(4.85)
Wald χ^2	161.58	166.42	221.76	171.94
Log likelihood	− 1124.00	− 1118.84	− 1088.98	− 1110.11
Observations	578	578	578	578

Standard errors are reported in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 6 Difference in the means of covariates for high- and low-assortativity samples before and after coarsened exact matching

Variables	Before coarsened exact matching					After coarsened exact matching				
	Low Assortativity Sample		High Assortativity Sample		*p*-value for difference in means	Low Assortativity Sample		High Assortativity Sample		*p*-value for difference in means
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
R&D intensity(asset)	0.13	0.09	0.16	0.11	***0.012***	0.15	0.24	0.16	0.11	***0.96***
Firm age(ln)	2.26	0.65	2.09	0.64	***0.004***	2.09	1.05	2.09	0.64	***0.99***

Table 7 Results of robustness analysis (CEM fixed year effect Negative binomial regression)

Variables/model	Model 1 Breakthrough innovation	Model2 Breakthrough innovation	Model 3 Breakthrough innovation	Model 4 Breakthrough innovation
Control variables				
Knowledge network local cohesion	− 0.036	− 0.060	− 0.079**	− 0.059
	(− 0.94)	(− 1.63)	(− 2.10)	(− 1.59)
Knowledge network global cohesion	0.159	− 0.020	− 0.027	− 0.018
	(1.31)	(− 0.17)	(− 0.23)	(− 0.15)
Collaboration network direct ties	− 1.204***	− 3.482***	− 4.930***	− 4.618***
	(− 2.61)	(− 6.19)	(− 7.62)	(− 6.73)
Coordination costs	0.268***	0.133	0.091	0.143
	(2.88)	(1.53)	(1.06)	(1.63)
Collaboration network non-redundancy	− 2.192***	− 2.360***	− 2.225***	− 2.420***
	(− 4.25)	(− 4.71)	(− 4.46)	(− 4.78)
Firm patents lagged(ln)	0.769***	0.589***	0.556***	0.556***
	(15.06)	(10.64)	(10.10)	(9.87)
Technological diversity	− 0.451	− 0.707**	− 0.804**	− 0.674**
	(− 1.42)	(− 2.18)	(− 2.52)	(− 2.08)
R&D intensity(asset)	− 3.477***	− 3.436***	− 2.841***	− 3.097***
	(− 6.42)	(− 6.56)	(− 5.41)	(− 5.80)
Firm age(ln)	− 0.326***	− 0.310***	− 0.222**	− 0.261***
	(− 3.03)	(− 3.08)	(− 2.21)	(− 2.58)
Moderating variables				
Mean knowledge network direct ties		0.206***	0.352***	0.212***
		(5.12)	(7.34)	(5.23)
Mean knowledge network non-redundancy		− 0.444	− 0.231	− 1.102*
		(− 0.87)	(− 0.47)	(− 1.92)
Direct effect				
Collaboration network degree assortativity		− 1.077***	0.137	− 4.107***
		(− 5.78)	(0.48)	(− 4.49)
Moderating effects				
Collaboration network degree assortativity × mean knowledge network direct ties			− 0.454***	
			(− 5.48)	
Collaboration network degree assortativity × mean knowledge network non-redundancy				4.194***
				(3.40)
Year	Yes	Yes	Yes	Yes
Constant	1.808***	3.116***	2.621***	3.612***
	(3.48)	(4.87)	(4.16)	(5.36)
Pseudo R^2	0.183	0.208	0.217	0.212
LR χ^2	632.08	718.10	748.03	730.49
Log likelihood	− 1408.23	− 1365.22	− 1350.26	− 1359.029
Observations	625	625	625	625

Standard errors are reported in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

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Data availability The data that support the findings of this study are openly available in Harvard Dataverse (The careers and co-authorship networks of U.S. patent-holders, since 1975", https://doi.org/10.7910/DVN/YJUNUN), and Zenodo Dataverse ("Patent citation data for USPTO utility patents granted between 1976–2015 and for patents belonging to 30 technology domains [Data set]" Zenodo. https://doi.org/10.5281/zenodo.3902550).

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