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Collaboration networks and radical innovation: Two faces of tie strength and structural holes

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ABSTRACT

This paper studies how tie strength and structural holes collectively affect innovation radicalness at a location within an innovating firm. We identified 16,011 inventors' locations of the 93 most innovative U.S. pharmaceuticals and biotechnology companies on the EU Industrial R&D Investment Scoreboard. We tracked their patents from 2001 to 2013 and constructed a panel dataset for analysis. Using firm-location fixed effect models, we found that the average tie strength of a location's egocentric network has a negative effect on innovation radicalness, and this negative effect is stronger when the location's egocentric network is cohesive. This suggests that weak ties have informational advantages for radical innovation, which are more pronounced when there is network cohesion to mitigate the relational disadvantages of weak ties. We also found a negative effect of structural holes on innovation radicalness when tie strength is weak but a positive effect when tie strength is strong. This indicates that strong ties are needed for mobilizing the informational advantages associated with structural holes.

1. Introduction

Joseph Schumpeter's concept of "creative destruction" (1942) underscores the destructive impact of innovation, but innovations can range from incremental improvements to radical changes that disrupt existing technologies, cognitive frameworks, and organizational structures (Anderson & Tushman, 1990; Chang et al., 2012; Delgado-Verde et al., 2016; Dosi, 1982; Henderson, 1993; Henderson & Clark, 1990; Kobarg et al., 2019; Tushman & Anderson, 1986; Utterback, 1996; Verhoeven et al., 2016). Radical innovation, in particular, has been the subject of extensive research focusing on its technological origins and economic implications (Capponi et al., 2022; Schoenmakers & Duysters, 2010; Wang et al., 2023). Building on this literature, our study aims to enhance understanding of the social determinants influencing radical innovation, specifically through the lens of firm-location networks.

The significance of network structure for fostering creativity and innovation has been well documented (Amabile, 1983; Drazin et al., 1999; Ford, 1996; Sosa, 2011; Woodman et al., 1993). Previous research highlights the benefits of weak ties and structural holes

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in accessing diverse information crucial for innovation (Burt, 1992; Fleming et al., 2007; Granovetter, 1973), while also noting the advantages of strong ties and network cohesion (Coleman, 1988; Nahapiet & Ghoshal, 1998; Rost, 2011; Tortoriello & Krackhardt, 2010). This paper investigates the dual nature of weak ties and structural holes, distinguishing their informational benefits from their relational drawbacks. We argue that the informational advantages of structural holes are best mobilized when complemented by strong ties that mitigate their relational disadvantages. Similarly, network cohesion plays a crucial role in leveraging the benefits of weak ties.

Focusing on the internal R&D collaboration networks of multinational corporations, this study explores how the egocentric network of individual R&D locations influences radical innovation. Multinational R&D efforts are often geographically dispersed, and a firm's competitiveness hinges on effective coordination of these global activities (Alcácer & Zhao, 2012; Almeida & Phene, 2004; Belderbos et al., 2021; Du et al., 2022; Kuemmerle, 1997). While existing research has examined drivers of R&D location decisions and coordination strategies, it has yet to address how the specific network of a single R&D location affects its innovative output.

We focus on the 93 most innovative U.S. pharmaceuticals and biotechnology firms listed in the EU Industrial R&D Investment Scoreboard, tracking their patenting activities from 2001 to 2013. Utilizing a panel dataset of 19,343 firm-location-year observations, we construct egocentric collaboration networks and apply fixed-effects models to analyze how tie strength and structural holes interactively affect innovation radicalness within these networks.

This study makes three contributions: First, it contributes to the social network literature by proposing a dual perspective on egocentric networks, distinguishing between informational and relational aspects. This approach offers a useful lens for reconciling competing theories on network effects and understanding the complex interplay between different network properties. Second, it contributes to the radical innovation literature by exploring how social and structural network properties influence radical innovation, moving beyond traditional technological and economic perspectives. Third, it enhances the understanding of multinational R&D by illustrating how the structure of firm-location networks impacts the creation of radical innovation.

2. Theoretical framework and hypotheses

2.1. Radical innovation

Schumpeter highlighted the destructive nature of innovation, while innovations may vary in the intensity of destruction that they bring. Subsequent studies have further separated radical innovation from incremental or run-of-the-mill innovation. For example, Henderson and Clark (1990) defined radical innovation as innovation that disrupts both existing components and architecture. Henderson (1993) viewed radical innovation as innovation that obsoletes a company's existing information filters and organizational procedures. Dahlin and Behrens (2005) emphasized three defining features of radical innovation: novel, unique, and having a major impact on future technology. Funk and Owen-Smith (2017) and Chen et al. (2021) viewed radical innovations as those that destabilize existing technology trajectories or reshape the network of technology interlinkages by diverting the focus of future inventors from the knowledge upon which the focal patent is based. Following this line of literature, we view radical innovation as innovation which brings intensive destruction and changes technology trajectories.

Prior studies of radical innovation have extensively investigated its economic impact (Hsieh et al., 2018; Rosenkopf & Nerkar, 2001), technological origins (Capponi et al., 2022; Schoenmakers & Duysters, 2010), response strategies (Matthews et al., 2022), and methods for adjusting business models after disruption (Bourreau et al., 2012; Simms et al., 2021). These studies have contributed many insights for understanding radical innovation. In this research, we contribute to the social determinants of radical innovation in the organizational and social environment. In particular, we study how the properties of egocentric collaboration network affect the likelihood of producing radical innovations in the context of corporate R&D networks. Answers to this question will help us to explain why radical innovation emerges in some places but not others, as well as informing innovation strategy about how to create a favorable collaboration network for radical innovation. This research pays attention to two network properties: tie strength and structural hole.

2.2. Informational advantage of weak tie for radical innovation

Mark Granovetter (1973) defined tie strength as: "a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie". Since Granovetter's seminal work, tie strength has attracted a lot of attention. Scholars have investigated its effects on various outcomes such as career advancement (Bian, 1997; Granovetter, 1995; Montgomery, 1992; Yakubovich, 2005), knowledge transfer (Messeni Petruzzelli et al., 2010; Reagans & McEvily, 2003; Tortoriello et al., 2012; Wang et al., 2017), and knowledge creation (Levin et al., 2011; McFadyen et al., 2009; Smith et al., 2005; Sosa, 2011; Tortoriello & Krackhardt, 2010; Tu, 2020; Wang, 2016). Building on this line of research, we develop theory and hypotheses about how tie strength affects the creation of radical innovation.

The central argument in favor of weak ties pertains to its advantage over strong ties in accessing non-redundant information (Granovetter, 1982; Granovetter, 1973; Uzzi & Spiro, 2005). Similar actors tend to be interconnected with one another by strong ties, and therefore an actor is likely to acquire similar information from others through strong ties (Festinger et al., 1950; Granovetter, 1973; Katz & Lazarsfeld, 2017). In other words, information circulated across a network through strong ties is prone to be redundant since actors inside this social circle tend to recycle ideas. In contrast, weak ties usually serve as information bridges between unconnected communities. Therefore, such ties provide channels for accessing diverse knowledge which originates from outside actors' direct social circle.

Furthermore, access to diverse knowledge is an important condition for generating creative ideas. The creativity literature highlights one important source of novelty as new combinations of pre-existing knowledge components (Mednick, 1962; Schumpeter, 1939). Accordingly, having access to diverse information provides opportunities for identifying new connections and generating novel ideas. This has the potential to destabilize existing technology trajectories. In addition, diverse knowledge enables more thorough search through problem- and solution- spaces, leading to better solutions and inventions (Page, 2007; Simonton, 1999, 2003).

Prior studies on tie strength and creativity have shown that actors with more weak ties are more adept at generating novel ideas (Baer, 2010; Perry-Smith & Shalley, 2003; Zhou et al., 2009). For instance, Perry-Smith and Shalley (2014) argued that weak ties foster creativity by providing access to disconnected actors and enhance the domain- or creativity-relevant knowledge. We expect that access to non-redundant knowledge is of critical importance for developing radical innovations, because non-redundant knowledge provides the foundation for creating new components and connections in a unique way that deviates from existing ways of thinking. Accordingly, weak ties have the potential to make obsolete existing technology trajectories.

Hypothesis 1. *Tie strength has a negative effect on innovation radicalness.*

2.3. Informational advantage of structural hole for radical innovation

While tie strength investigates dyadic interactions, the concept of structural hole proposed by Burt (1992) focuses on the absence of network ties between actors in a network. More specifically, an egocentric network is rich in structural holes if the ego's contacts are not themselves interconnected. Individuals with networks that have abundant structural holes are at an advantageous position, because structural holes provide "an opportunity to broker the flow of *information* between people, and *control* the projects that bring together people from opposite sides of the hole" (Burt, 2000). In other words, structural holes can be viewed as the information gap between contacts linked to the same ego but mutually unconnected to each other. Actors who stand near a structural hole are positioned to benefit from differences between contacts who have distinct information. Studies have observed benefits of structural holes for career advancement (Burt, 1992; Seibert et al., 2001), generation of novel ideas (Burt, 2004; Lambiotte & Panzarasa, 2009), and project performance (Bordons et al., 2015; Soda et al., 2004). Building on this line of literature, we expect that structural holes are beneficial for developing radical innovations, due to the brokage advantage in gaining broader and earlier access to diverse information.

Even though structural hole is conceptually different from weak tie, it presents informational advantages, same as weak ties. More specifically, structural holes provide broader access to diverse information, which is conducive to radical innovation. Prior studies have shown that information is unevenly spread and tends to be homogenous within communities (Burt, 1992, 2004). Considering the homophily tendency in network formation, that is, actors tend to develop relations with others like themselves (Burt, 1990, 1992; Fischer, 1982; Marsden, 1987; McPherson et al., 2001), information that can be accessed within an interconnected community tends to be redundant. However, information from outside the community can bring diversity (Cohen & Levinthal, 1990; Kleinbaum & Tushman, 2007). Prior studies have shown that creative ideas often emerge when an actor moves information from one community to another or combines information across communities (Burt, 2004; Geroski & Mazzucato, 2002; Menon & Pfeffer, 2003). Therefore, an actor who bridges structural holes can benefit from the difference between his or her contacts who are unconnected and belonging to different communities (Burt, 1992, 2004). This informational advantage of structural hole is beneficial for developing radical innovation, as diverse information offers opportunities for cross-fertilization of ideas and outside-the-box thinking.

In addition, an actor spanning structural holes can have early access to information before the average actor, providing an advantage of acting on the information early and controlling the flow of information across communicates (Burt, 2004). This early access also provides a competitive advantage for developing radical innovation. Taken together, we propose the following hypothesis:

Hypothesis 2. *Structural holes have a positive effect on innovation radicalness.*

2.4. Relational disadvantage of weak tie and structural hole for radical innovation

While both weak ties and structural holes provide informational advantages for fostering radical innovation, they both also present relational disadvantages that can hinder the effective mobilization and integration of diverse information resources. These relational disadvantages arise from a lack of cognitive and relational capital, such as common codes, language narratives, trust, norms, obligations, and identification (Nahapiet & Ghoshal, 1998). Without a common knowledge base between actors, actors may face cognition and communication challenges in exchanging information that is complex or tacit (Hansen, 1999; Uzzi, 1997; Wen et al., 2021). In addition, without mutual trust and shared norms, actors may face a higher level of coordination costs and opportunistic behavior (Krackhardt et al., 2003; Lin & Ensel, 1989; Obstfeld, 2005; Podolny & Baron, 1997). In short, although weak ties and structural holes facilitate access to diverse, non-redundant information, they can create barriers to effectively leveraging this information for radical innovation.

Prior studies of tie strength have underscored the relational advantage of strong ties in fostering shared understandings, trust, and willingness to help (Granovetter, 1973; Krackhardt et al., 2003; Uzzi, 1996, 1997). Empirical evidence has accumulated that strong ties facilitate transferring fine-grained information and in turn generating creative ideas (Rost, 2011; Sosa, 2011; Tortoriello & Krackhardt, 2010). Similarly, social network studies have acknowledged relational disadvantages of structural holes. According to Coleman's (1988) social capital theory, network closure or cohesion (i.e. the absence of structural holes) is conducive to the production of social norms and sanctions, which in turn facilitates trust and cooperative behavior. Empirical evidence has also suggested that structural holes do not translate into organizational advantages without measures to mitigate the relational disadvantages (Rost, 2011; Tortoriello & Krackhardt, 2010). Studies have also attempted to reconcile these competing arguments regarding the effects of tie strength (McFadyen & Cannella Jr, 2004; McFadyen et al., 2009; Wang, 2016) and structural holes (Gargiulo & Benassi, 2000; Obstfeld, 2005;

Rost, 2011; Tortoriello & Krackhardt, 2010), by exploring more complex effect patterns or boundary conditions.

Both tie strength and structural holes exhibit dual roles: they provide informational advantages but also carry relational disadvantages. To better understand how these competing mechanisms interact to influence innovation radicalness, we explore the moderation effect of structural hole and tie strength.

How tie strength moderates the effect of structural hole. Given the informational advantage of structural holes, we hypothesize a positive effect of structural hole on innovation radicalness (Hypothesis 2). However, the extend to which this positive effect is realized depends on the ability of the network to mobilize and integrate the diverse information provided by structure holes. Without considering other factors, this positive effect of structural hole may be diminished by the relational disadvantage associated with structural holes. For example, when the network lacks trust or shared understanding, partners may be unwilling or unable to share useful information. In such circumstance, the presence of strong ties can help overcome these challenges by providing the cognitive and relational capital needed to mobilize the informational advantages of structural holes. For example, consider an inventor with an egocentric network rich in structural holes, this inventor has the potential to access to diverse information, but if network partners lack the willingness to share or understand the information, the potential for radical innovation may be limited. However, if strong ties exist between the inventor and their network partners, these partners will likely be more willing and capable to share information. Thus, tie strength magnified the positive effect of structural holes on innovation radicalness by compensating the relational disadvantage associated with structural holes.

How structural holes moderate the effect of tie strength. Similarly, we hypothesize a negative effect of tie strength on innovation radicalness, as stronger ties are associated with less diverse information. However, the negative effect of tie strength can be mitigated by the relational advantages inherent in strong ties. To illustrate this, consider two inventors: Inventor A has strong ties within their egocentric network, while Inventor B has weaker ties. Based on our hypothesis, Inventor A is expected to perform worse than Inventor B due to A's lower access to diverse information. However, Inventor B may not perform as much better as expected because, even though they have access to more diverse information, their network partner connected through weak ties may be unwilling or unable to effectively share information. Therefore, B's performance may not surpass A's as much as we would initially predict. Now, if both A and B have low structural holes (i.e., high network cohesion), network cohesion provides a relational advantage for mobilizing diverse information. This will not benefit Inventor A, who has limited diverse information to mobilize in the first place. However, network cohesion will greatly benefit Inventor B, as it allows B to more effectively leverage the diverse information present in their network. In this sense, network cohesion magnifies the negative effect of tie strength. In other words, structural holes weaken the negative effect of tie strength.

Taken together, we hypothesize that:

Hypothesis 3a. *Structural holes weaken the negative effect of tie strength on innovation radicalness.*

Hypothesis 3b. *Tie strength magnifies the positive effect of structural holes on innovation radicalness.*

3. Data and methods

3.1. Data

We build a unique panel dataset with information about firm R&D locations, their egocentric collaboration networks, and innovation outputs. We combine information from various sources. Our sampled firms are identified from the 2018 edition of *the Scoreboard*, which lists companies with the biggest R&D spending worldwide. We restrict our analysis to firms in the U.S. pharmaceutical and biotechnology industry on this list for three reasons. First, innovation plays an essential role in the pharmaceutical and biotechnology industry since this industry is knowledge-intensive, which provides us with an appropriate setting for this research. Previous research has shown that this industry is suitable and has already been used in many fields to study innovative activities (Hoang & Rothaermel, 2005; Tzabbar & Vestal, 2015). Second, one of the critical competitive strategies of pharmaceutical and biotechnology companies is to forge connections across networks that span different social and geographic spheres (Al-Laham et al., 2011) to gain diverse resources and knowledge. This feature provides us a higher chance to observe collaborations in this industry. In particular, corporate R&D networks that span different geographic locations enable multinational corporations to integrate knowledge and resources from different locations (Alcácer & Zhao, 2012), which means it provides us a good opportunity to study geographically dispersed corporate R&D networks. Third, focusing on a specific industry can control for variances across different industry fields (Audia & Goncalo, 2007; Tzabbar & Vestal, 2015). Using a more homogeneous sample ensures that innovation outputs can be compared. 200 U.S. pharmaceutical and biotechnology firms from the *Scoreboard* have been included in the sample.

For measuring innovation radicalness as well as for characterizing collaboration networks, we rely on patent information. However, retrieving patents for each company is not a trivial task. There are diverse practices in firm patenting policies. For example, some companies always use the headquarters as the applicants (also known as assignees) even though the invention was developed in a subsidiary, while others use the subsidiary as the applicant. Furthermore, the name of a company's subsidiary may not display any connection with the name of the whole company. Therefore, identifying all the names of subsidiaries is critical for retrieving all patents of a company and ensuring measurement quality. For our 200 sampled companies, we manually retrieved names of all subsidiaries listed in Exhibit 21 of the annual report on Form 10-K filed by these firms from 2009 to 2018 with the U.S. Securities and Exchange Commission (SEC). According to the Regulation S-K of the SEC, companies are required to disclose all their subsidiaries, unless the unnamed subsidiaries are viewed as a single subsidiary and do not constitute a substantial subsidiary as of the end of the reporting year. Since our study focuses on R&D collaboration networks across a firm's locations, we exclude 107 firms without subsidiaries. After merging the data, our sample contains 16,011 unique subsidiaries belonging to 93 firms.

To extract the patents of the firms in our sample from the patent database (PATSTAT), we match company names extracted from the SEC database with patent applicant names registered in PATSTAT. We use the 2019 Autumn version of PATSTAT. Name searching and cleaning strategies are applied to standardize the names. To do so, we first identify strings that start with harmonized names of a company's subsidiary, strings containing the harmonized name of a subsidiary, and strings containing characteristics substrings that could identify a company's subsidiary. All found strings are then manually checked against the original applicant's name and the three harmonized name versions ('doc_std_name', 'psn_name' and 'han_name') that are available in the PATSTAT database. In the next step we compare the names we found with the harmonized subsidiary names. The comparison adopts a 3-gram algorithm, that uses sliding windows of three-character strings. The algorithm provides an indicator that shows the similarity between the subsidiary or company name and an applicant's name. Only strings with a matching percentage of over 70% are considered to be potential matches. As a final step we manually check the results of the matching process and only find a few match errors. We search for granted patents held by our sampled companies, for which the patent applications were filed between 2001 to 2013 at the United States Patent and Trademark Office (USPTO), the European Patent Office (EPO), or the World Intellectual Property Organization (WIPO).

We then aggregate patents at the location level, and inventor addresses are used to conjecture the locations of companies' innovative activities. Considering that subsidiaries often use the address of the headquarters as the applicant address when applying for a patent, inventor addresses are more likely to represent the real geographic origin of the patented inventions than applicant addresses (Belderbos et al., 2017; Deyle & Grupp, 2005). Addresses in the patent database are messy, and we link patent data to the geocoding of worldwide patent data developed by De Rassenfosse et al. (2019). De Rassenfosse et al. (2019) combined multiple data sources for identifying geographic coordinates for inventors' and applicants' locations and provided clean information about corresponding countries and cities. This dataset covers all PATSTAT patents in our studied period. We use the fine-grained city level information for R&D locations of a company. For example, these cities include London (UK) and Berlin (Germany). The city level in the United States corresponds to counties, for example, Middlesex in Massachusetts and Santa Clara in California.

Furthermore, the same technological invention often is published multiple times, e.g., by different patent authorities or as continuations, so we use patent family, more specifically, DOCDB families (Martínez, 2011), rather than single patents, following the field convention. Building on the data of patent families, we construct our final dataset for analysis at the location-time level. For each location, we construct our variables using patent families in a 3-year rolling window, that is, for location i at time point t, the variables are constructed using patent families with the earliest filing date from year $t-2$ to year t. Our final dataset consists of 16,011 unique locations belonging to 93 companies, with a total number of 19,343 location-time observations.

3.2. Variables

3.2.1. Dependent variables

Radicalness. Following Funk and Owen-Smith (2017), we measure radicalness by capturing the degree to which the focal patent destabilizes existing technology trajectories. Funk and Owen-Smith (2017) labeled this measure as the "CD-index" (consolidation/destabilization). However, the term "CD-index" is technical and may reduce readability for a broader audience. Subsequent studies often refer to this measure as "disruptiveness" (Bornmann & Tekles, 2021; Leahey et al., 2023; Leibel & Bornmann, 2024; Park et al., 2023). Yet, using "disruptiveness" in the context of technological innovation could lead to confusion, as "disruptive innovation" is a well-established term introduced by Clayton M. Christensen. According to Christensen and Bower (1995), disruptive innovations are "usually not radically new or difficult from a technological point of view," which contrasts with the concept of radical innovation. Since our study is grounded in the radical innovation literature, we use the term "radicalness" to avoid confusion and ensure consistency with this body of research. Notably, Balachandran and Hernandez (2018) also adopted this measure and labeled it "radicalness." Therefore, for readability, we use the term "radical" or "radicalness" in the main text and discussion. However, we retain the label "CD-index" in technical aspects, such as the names of dependent variables in descriptive statistics and regression tables, to precisely specify the indicator used.

The CD-index examines whether patents citing a focal patent also cite prior patents cited by the focal patent. If patents cite only the focal patent but do not cite its references, then the focal patent is considered to shift the focus of future inventors from the knowledge upon which the focal patent is based, thus destabilizing existing technology trajectories. This measure makes it possible to differentiate between destabilizing and consolidating technologies, even if they exhibit similar impact (Bornmann & Tekles, 2021; Leahey et al., 2023; Leibel & Bornmann, 2024; Park et al., 2023). Balachandran and Hernandez (2018) divided firms' networks into foreign, domestic, and mixed triads according to whether the broker and its partners crosses institutional boundaries and investigated how institutions and networks jointly influence innovation radicalness. The result showed that radical innovation is more likely to be influenced by foreign triads. Several studies have proposed similar measures as Funk and Owen-Smith, following a network approach (Bu et al., 2021; Shibayama & Wang, 2020). Hence, previous research suggests that the radicalness index developed by Funk and Owen-Smith (2017) can serve as a useful measure of the radicalness of a patent. In this study, *radicalness* (*CD-index*) is calculated as follows for a focal patent:

$$\text{Radicalness (CD index)} = \frac{1}{n}\sum_{i=1}^{n} f_i$$

Where i is the index of the future patent families that cite the focal patent family or references therein, n is the number of such future patent families. f_i equals 1 if the future patent family i only cites the focal patent family but not any references of the focal patent family, f_i equals -1 if the future patent family i cites the focal patent family and at least one of its references, and f_i equals 0 if the future patent family i only cites the focal patent family' references but not the focal patent family. The range of *radicalness* (*CD-index*) is from -1 to 1. For calculating *radicalness* (*CD-index*), we adopt a fixed 5-year citation time window, that is, future citing patent families which have an earliest filing date within 5 years after the focal patent family are considered. This allows patent families filed in different years to have the same number of years for accumulating citations. Results are robust when we consider all future patents without a fixed time window.

At the location level, we calculate the average of *radicalness* (*CD-index*) in a 3-year rolling window to characterize the inclination towards radical innovation for the location in this period.

3.2.2. Independent variables

Average tie strength. Many studies focus on the frequency of interactions as the most important property and use it to capture the essence of what Granovetter was referring to when he spoke of the strength of a tie (Fleming et al., 2007; Granovetter, 1973; Wang, 2016). In this paper, we follow this common approach and measure tie strength between two R&D locations as their frequency of co-inventing patent families. At the egocentric network level, we use the average network tie strength to capture the overall tie strength in a focal location's egocentric network. At the dyadic level, we operationalized tie strength as the number of co-inventing patent families in a 3-year moving time window. Specifically, we count the number of co-inventing patent families between a focal location and its collaborating locations. Then, for a focal location, we calculate its average tie strength among all its collaborating ties. The calculation formula of tie strength is as follows for a focal location:

$$\text{Average tie strength} = \frac{1}{m}\sum_{j=1}^{m} f_j$$

Where m is the number of co-inventing locations in the focal location's egocentric network, j is the index of co-inventing locations, f_j is the number of co-inventing patent families between the focal location and its collaborating location j. Fig. 1 provides an example of calculating tie strength.

Structural hole. Several different formulas for structural hole have been proposed and used in the literature (Borgatti, 1997; Burt, 1992; Rodan, 2010). Among them the density of a location's egocentric network provides an intuitive indication for the absence of structural holes. This simple formulation also has an advantage that it does not make assumptions about the behavior of actors, while Burt's original indicator relies some assumptions about the behavior of nodes and tie formulation (Burt, 1992; Rodan, 2010). We follow this approach and first calculate the density of an egocentric network, as the share of possible ties that do exist. Same as for measuring tie strength, we use co-inventing as a tie, and use a 3-year moving time window for identifying alters and ties. As network density is the opposite to structural hole, we calculate structural hole as 1-density, that is, the share of missing ties in an egocentric network excluding the ego itself. The range of structural hole is from 0 to 1. Structural hole is calculated using the following formula for a focal location:

$$\text{Structural hole} = 1 - \frac{\sum_{j=1,\ j\neq k}^{m} f_{j,\ k}}{m(m-1)/2}$$

Where m is the number of co-inventing locations in an egocentric network, accordingly $\frac{m(m-1)}{2}$ is the total number of possible ties in this egocentric network (excluding the foal location). j and k are the index of co-inventing locations. $f_{j,k}$ equals 1 if there are co-inventing patent families between location j and k; and 0 otherwise. Fig. 1 illustrates an example of calculating structural hole.

3.2.3. Control variables

Our analyses account for possible confounding variables to mitigate the risk of spuriousness. We use fixed effects models incorporating firm-location fixed effects, so that we can account for unobservable time-invariant location heterogeneity and test for variations within firm-location. For example, different locations might focus on different technological areas and equipped with different resources and capabilities, and incorporating firm-location fixed-effects allows us to rule out these important differences between

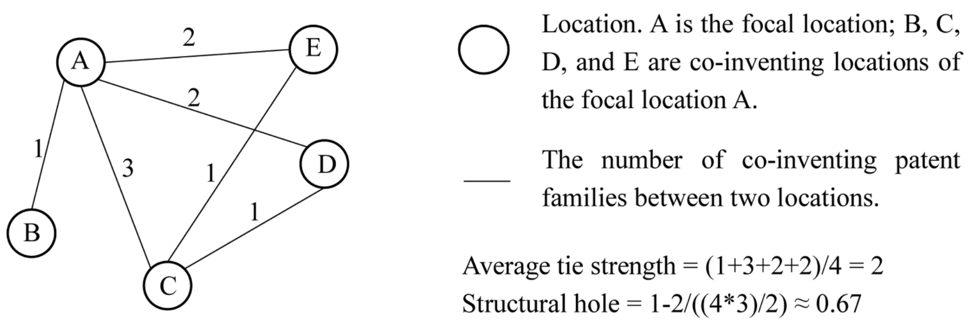


Fig. 1. An egocentric network to illustrate the calculation of average tie strength and structural hole.

locations, to the extent that such characteristics do not change over time. *Innovation productivity*, calculated as the number of patent families, is included, as a more productive location might also have a higher chance of forming certain types of networks and at the same having a higher chance of producing innovation that is more radical (Fleming et al., 2007). To estimate the effect of network properties net of network size, we incorporate *network size*, the number of co-inventing locations. Controlling the number of co-inventing locations can help to rule out the possible explanation that it was the network size that predicted variation in network properties and radicalness. To account for the general inclination towards collaborating, we also included the share of a location's patent families that are co-invented with other locations (*collaboration inclination*). For *innovation productivity, network size*, and *collaboration inclination*, we use a 3-year rolling window for constructing these variables. Time (i.e., one time period is three years) dummies are also included to control for general time differences applying to all sampled firm-locations.

4. Results

4.1. Collaboration network example

We first present an analysis of a corporate R&D collaboration network using Merck & Co. as an example. Merck & Co., one of the largest pharmaceutical companies globally, operates across numerous locations. Fig. 2 illustrates the entire R&D collaboration network consisting of 73 locations within Merck & Co. for the year 2013. In this network, each node (circle) represents a location, and each edge (gray line) represents a co-inventing tie. Node size reflects the number of co-inventing patent families associated with each location, while edge thickness represents the strength of the tie, measured by the number of co-inventing patent families shared between locations.

The network's density is approximately 0.096, which indicates a relatively sparse connectivity among the locations. Such sparsity is typical in large networks. The global clustering coefficient, standing at 0.466, reveals a moderate level of clustering within the network. This suggests that while some degree of interconnectedness exists among nodes, the network is not excessively interconnected. Further analysis identifies five distinct connected components within the network, with the largest component encompassing 63 nodes. This finding underscores that while most of the network nodes are interconnected, smaller, isolated groups persist. The modularity score of 0.406 supports the presence of a discernible community structure within the network. However, the separation between these communities is not highly pronounced, indicating a noticeable yet not overwhelming modularity.

In terms of centralization, the degree centralization score of 0.439 suggests that the network exhibits a moderate level of centralization. Certain nodes function as key hubs, boasting a higher number of connections compared to others. Nonetheless, the network does not rely heavily on a single node, implying a relatively balanced distribution of connectivity. The betweenness centralization score, at 0.229, reflects a low to moderate level of centralization. This indicates that the network's ability to connect different parts is not overly dependent on a few central nodes, suggesting a more distributed role in facilitating communication across the network. Similarly, the closeness centralization score of 0.261 reveals a relatively even distribution of proximity among nodes. No

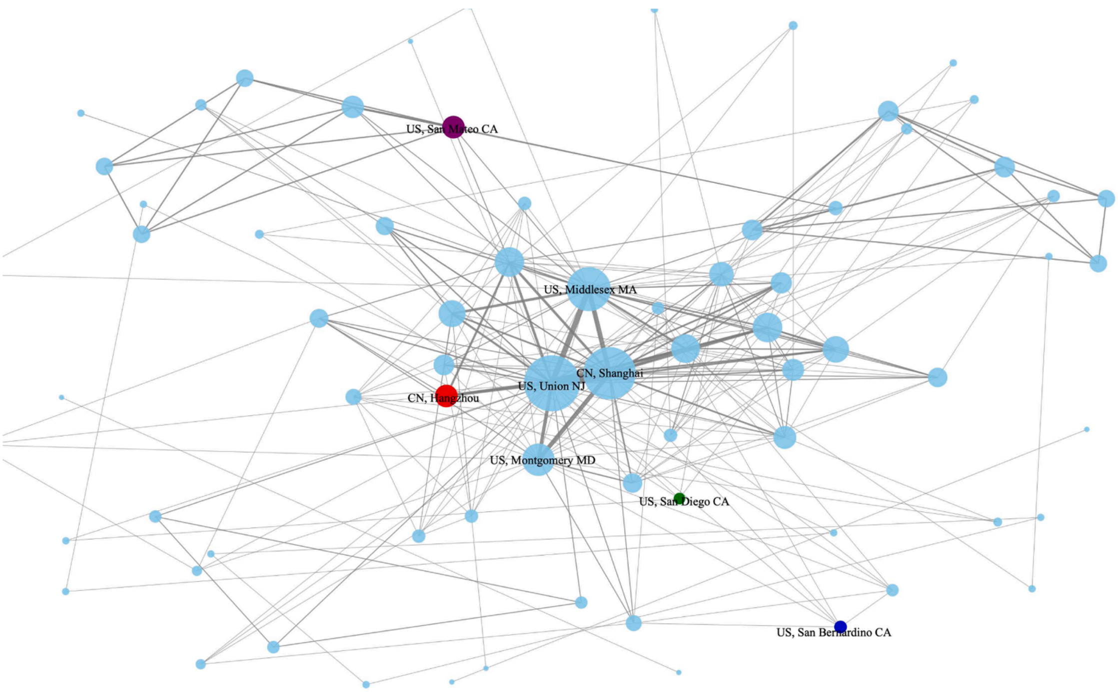


Fig. 2. Collaboration network within Merck & Co. in 2013.

single node is significantly closer to all other nodes, pointing to a balanced communication efficiency throughout the network. These findings align with broader observations in the literature regarding the evolution of global R&D networks in multinational corporations. Historically, such networks have shifted from a “spike” structure, where headquarters connect with subsidiaries with limited direct connections among the subsidiaries, to a more decentralized model. This evolution reflects a trend toward a network where knowledge creation and transfer occur more widely and uniformly across locations (Almeida & Phene, 2004; Bartlett & Ghoshal, 1989; Gupta & Govindarajan, 2000).

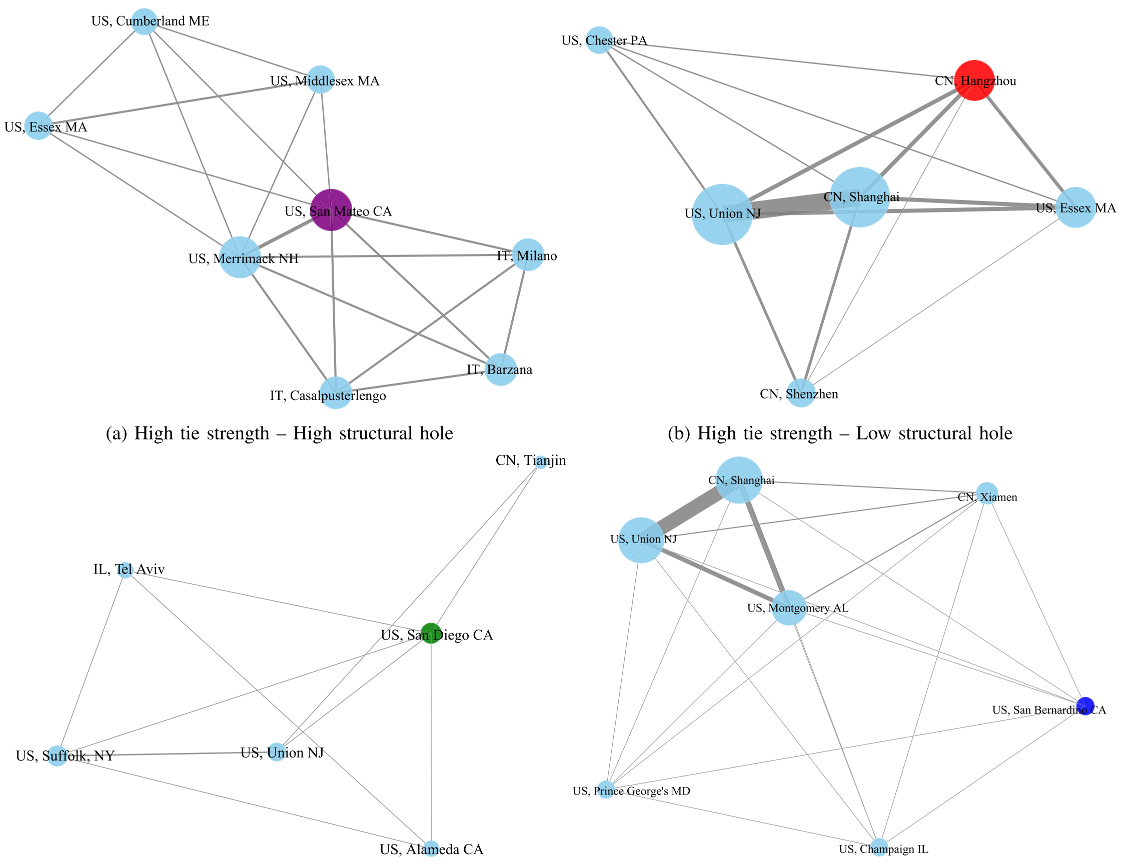
The network’s moderate levels of connectivity and centralization suggest the value of adopting a meso-level focus on nodes’ egocentric networks. Such an approach is beneficial in contrast to or in addition to a macro-level focus that treats the entire company as a unified entity with well-integrated subunits, and a micro-level focus that views nodes as independent entities with minimal regard for network interactions. By balancing these perspectives and adopt a meso-level focus, we can gain a more nuanced understanding of the network’s structure, capturing both the collective dynamics and the unique contributions of individual nodes.

Fig. 3 illustrates the egocentric networks of four selected locations, chosen for their similar and relatively small network sizes to facilitate comparison. Each of these locations has between 5 and 7 collaborating locations, yet their network structures exhibit notable differences.

The top two locations, San Mateo County in California (including South San Francisco) and Hangzhou in China, display relatively high tie strengths of 2.9 and 4, respectively. In contrast, the lower two locations, San Diego and San Bernardino Counties in California, show lower tie strengths, both at 1. The left two locations, San Mateo and San Diego, have higher structural hole scores of 0.4 and 0.5, respectively, indicating they hold brokerage positions that connect otherwise unconnected partners. Conversely, the right two locations, Hangzhou and San Bernardino, have a structural hole score of 0, signifying that they do not occupy such brokerage positions.

4.2. Descriptive statistics

Table 1 reports descriptive statistics and spearman correlations. *Radicalness* (*average CD-index*) has a mean of -0.01, standard deviation of 0.06, and ranges from -0.47 to 0.90. The slightly right-skewed distribution indicates that in general consolidating, incremental innovations are more common than radical innovations. The distribution of *average tie strength* is highly right skewed, with a



(a) High tie strength – High structural hole (b) High tie strength – Low structural hole

(c) Low tie strength – High structural hole (d) Low tie strength – Low structural hole

Fig. 3. Egocentric networks of four selected locations at Merck & Co. in 2013.

mean of 1.86, standard deviation of 2.16, and ranging from 1 to 69.60. We take the natural logarithmic transformation for *average tie strength*, as well as all other count variables (i.e., *innovation productivity* and *network size*) to accommodate the skewed nature of these variables. *Structural hole* has mean 0.80 and ranges from 0 to 1. This suggests that most locations operate in relatively sparse networks that have abundant structural holes. Moreover, there is considerable heterogeneity among locations. On average, the number of patent families (i.e., *innovation productivity*) is 6.72, the number of co-inventing locations (i.e., *network size*) is 7.91, and 97% patents involve collaboration with other locations (i.e., *collaboration inclination*), indicating that sole production of innovation is rare. Correlations show that both *average tie strength* (r=-0.04) and *structural hole* (r=-0.02) are negatively correlated with *radicalness* (*average CD-index*). It is important to interpret these correlations with caution as they do not control for any confounding variables. The correlations between our focal independent variables and control variables (especially *innovation productivity*) are relatively high: *innovation productivity* has a correlation of 0.86 with *average tie strength* and -0.79 with *structural hole*.

To address the multicollinearity concern, we performed Generalized Variance Inflation Factor (GVIF) test. Results show that all adjusted GVIF are below 5, indicating no significant multicollinearity concerns. Therefore, we report results with controlling these potential confounders as main results and then further test the robustness of our results without controlling these control variables.

4.3. Regression results

To explore the association between egocentric network and innovation radicalness, we use fixed-effects linear regressions where *radicalness* (*average CD-index*) is the dependent variable. For all regression models, we incorporate firm-location fixed effects and estimates within-firm-location effects. We also include the previously mentioned set of control variables.

Table 2 reports results of fixed effects linear models. Column 1 shows that *innovation productivity* has a significantly positive effect on *radicalness* (*average CD-index*), suggesting that a location is more likely to produce radical innovation when it is more productive. *Network size* has a negative effect on radicalness, suggesting that when a location holds a more central location within a company's internal network, it is less likely to produce radical innovation. Similarly, *collaboration inclination*, i.e., share of patent families that are co-inventions with other locations, also has a negative effect. These findings are in line with the expectation that radical innovation is more likely to come from the peripheral and isolated places in the network (Cattani & Ferriani, 2008).

Column 2 incorporates *average tie strength* into the regression. Results show that *average tie strength* has a significantly negative effect on *radicalness* (*average CD-index*). Thus, Hypothesis 1 is supported, which is about the informational advantages of weak ties. Within the same firm-location, holding all other variables constant, the expected degree of radicalness decreases as the average tie strength of the egocentric network increases.

Column 3 further adds *structural hole* into the regression. While the negative effect of *average tie strength* remains significant, *structural hole* does not have a significant effect on *radicalness* (*average CD-index*), which seems to reject Hypothesis 2. However, we cannot conclusively claim that *structural hole* does not have an effect, as how it interacts with *average tie strength* is critical here. It is possible that *structural hole* has a positive effect at certain range of *average tie strength* but a negative effect at another range, such that the pooled effect of *structural hole* is insignificant.

Column 4 interacts *average tie strength* and *structural hole*. We observe a significantly positive coefficient on the interaction effect. This result supports hypothesis 3. More specifically, *structural hole* weakens the negative effect of *average tie strength*, and *average tie strength* magnifies the positive effect of *structure hole*. Note that when the interaction term is added, the coefficient of *average tie strength (ln)* (i.e., -0.016) indicates the marginal effect of *average tie strength (ln)* on *radicalness* (*average CD-index*) when *structural hole* equals 0, which is the minimum value of *structural hole* (theoretically and empirically in our sample). Similarly, the coefficient of *structural hole* (i.e., -0.007) indicates the marginal effect of *structural hole* on *radicalness* (*average CD-index*) when *average tie strength (ln)* equals to 0, which is also the minimum value of *average tie strength (ln)*. To better illustrate the interaction effect, Fig. 4A plots the marginal effects (i.e., regression coefficients) of *average tie strength (ln)* at different levels of *structural hole*. It shows that when *structural hole* is relatively low, *average tie strength* has a significantly negative effect, but as structural hole increases, this negative effect shrinks in size. This is in line with the argument that when a network is dense (structural hole is low), the informational advantages of weak ties (i.e., negative effects of tie strength) can be mobilized and translated into innovation advantages. However, the informational advantage of weak ties cannot be effectively mobilized when the network has abundant structural holes, so that the negative effect of tie strength becomes smaller. Similarly, Fig. 4B plots the marginal effects of *structural hole* at varying levels of *average tie strength*. It shows that when *average tie strength* is relatively low, *structural hole* has a negative effect. However, as *average tie strength* increases, the effect of *structural hole* increases and becomes significantly positive. This finding is also consistent with the argument that having strong ties is necessary for

Table 1
Descriptive statistics and correlations (N=19,343).

	Variable	Mean	S.D.	Min	Max	1	2	3	4	5
1	Radicalness (average CD-index)	-0.01	0.06	-0.47	0.90					
2	Average tie strength	1.86	2.16	1	69.60	**-0.04**				
3	Structural hole	0.80	0.28	0	1	**-0.02**	**-0.48**			
4	Innovation productivity	6.72	19.61	1	466	-0.01	**0.86**	**-0.79**		
5	Network size	7.91	9.58	2	122	**-0.09**	**0.46**	**-0.65**	**0.62**	
6	Collaboration inclination	0.97	0.11	0.07	1	**-0.04**	**-0.26**	**0.42**	**-0.49**	**-0.27**

Note: Correlation with bold numbers significant at $p < 0.05$.

Table 2
Fixed effects linear models: Network structure and innovation radicalness.

	Radicalness (average CD-index)			
	(1)	(2)	(3)	(4)
Average tie strength (ln)		-0.013***	-0.011***	-0.016***
		(0.002)	(0.002)	(0.003)
Structural hole			-0.005	-0.007*
			(0.004)	(0.004)
Average tie strength (ln) * Structural hole				0.007**
				(0.003)
Innovation productivity (ln)	0.004***	0.013***	0.011***	0.011***
	(0.001)	(0.002)	(0.002)	(0.002)
Network size (ln)	-0.006***	-0.010***	-0.010***	-0.010***
	(0.001)	(0.002)	(0.002)	(0.002)
Collaboration inclination	-0.014***	0.001	-0.002	-0.001
	(0.005)	(0.005)	(0.006)	(0.006)
Year FE	Yes	Yes	Yes	Yes
Firm-location FE	Yes	Yes	Yes	Yes
N	19,343	19,343	19,343	19,343
R-square	0.696	0.697	0.697	0.698

Note: Robust standard error in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

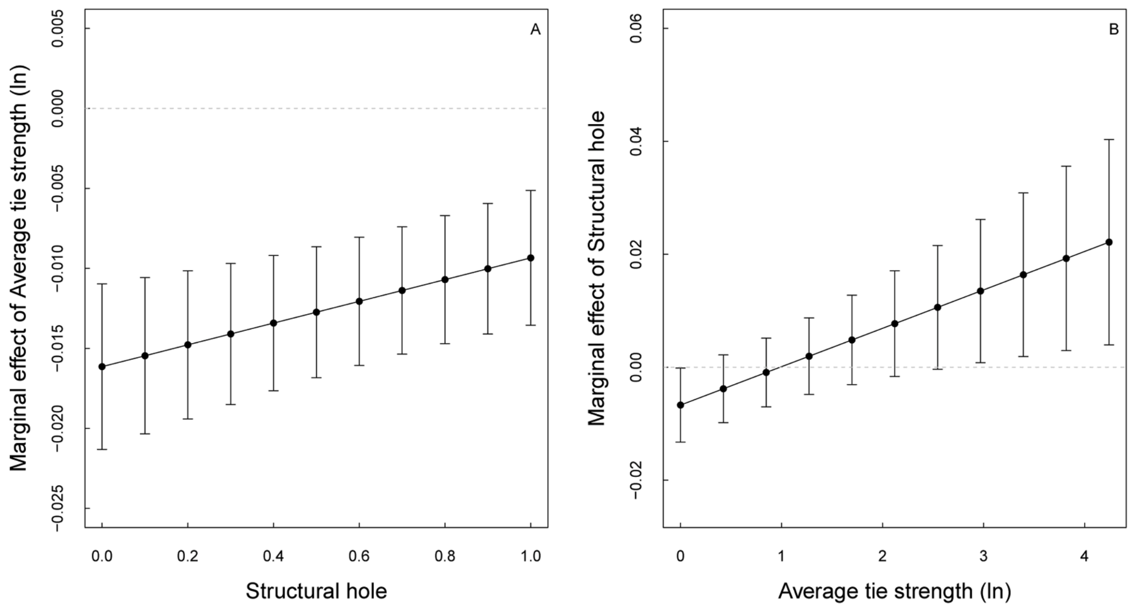


Fig. 4. Average tie strength, structural hole, and innovation radicalness. Points represent the regression coefficients, and vertical bars represent 90% confidence interval.

mobilizing informational advantages of structural holes for developing radical innovation.

4.4. Robustness tests

We conduct a split-sample analysis to test the robustness of the observed interaction effects. Specifically, we divide the sample into two subsets based on structural hole values: one subset with relatively high values and the other with relatively low values. Within each firm-location, we classified structural hole into high or low categories using the median value as the threshold. The results are consistent: when structural hole is higher, the negative effect of tie strength on innovation radicalness is smaller (see Table 3 and Fig. 5). Similarly, we split the sample based on the average tie strength and examined how the effect of structural hole on innovation radicalness varies between the two sub-samples. For the subsample with low average tie strength, the effect of structural holes is significantly negative. In contrast, for the subsample with high average tie strength, the effect of structural holes is positive but not significant.

For calculating *radicalness* (*average CD-index*), we adopted a fixed 5-year citation time window, that is, future citing patent families which have an earliest filing date within 5 years after the focal patent family are considered. This allows patent families filed in

Table 3
Split sample analysis.

	Radicalness (average CD-index)			
	(1) Structural hole low	(2) Structural hole high	(3)Average tie strength low	(4) Average tie strength high
Average tie strength (ln)	-0.016***	-0.011***		
	(0.003)	(0.004)		
Structural hole			-0.012***	0.003
			(0.005)	(0.005)
Innovation productivity (ln)	0.016***	0.008**	0.006***	0.001
	(0.003)	(0.004)	(0.002)	(0.002)
Network size (ln)	-0.011***	-0.006**	-0.011***	-0.000
	(0.002)	(0.003)	(0.002)	(0.002)
Collaboration inclination	0.003	0.009	-0.009	-0.018***
	(0.008)	(0.009)	(0.007)	(0.007)
Year FE	Yes	Yes	Yes	Yes
Firm-location FE	Yes	Yes	Yes	Yes
N	15,453	3890	14,281	5062
R-square	0.765	0.622	0.786	0.764

Note: Robust standard error in parentheses. ***p < 0.01; **p < 0.05; *p < 0.1.

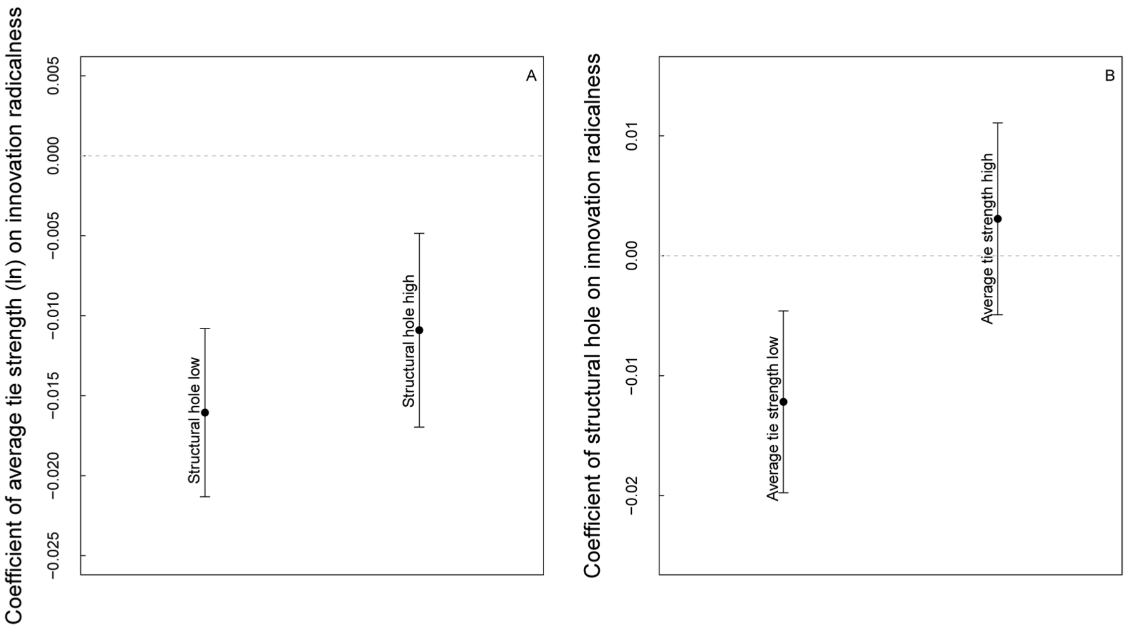


Fig. 5. Split-sample analysis. Points represent the regression coefficients, and vertical bars represent 90% confidence interval.

different years to have the same number of years for accumulating citations. Results are robust when we consider all future patents up to 2019 (i.e., in PATSTAT 2019 Autumn version) without the fixed time window (Appendix Table A1).

Our regression analyses include innovation productivity, network size, and collaboration inclination as control variables. However, there are relatively high correlations between our focal independent variables and these control variables, raising concerns of multilinearity. We test whether our results are sensitive to having these control variables. When we drop each of them or all of them, results are robust (Appendix Table A2).

When measuring tie strength, we count the number of co-invented patent families between two nodes. Fronczak et al. (2022) challenged the traditional network measures of tie strength assuming a symmetric relationship between two nodes and proposed a tie strength measure accounting for the asymmetric, more specifically, tie strength between node A and B (from A's perspective) equals the number of co-inventing patent families divided the total number of patent families invented by A. We adopt this measure as an alternative measure and obtain consistent results (Appendix Table A3).

5. Discussion

This study explores the relationship between egocentric networks and radical innovation within the context of corporate R&D, using a unique panel dataset of 19,343 firm-location-time observations from 93 U.S. pharmaceutical and biotechnology companies.

Our analysis, employing fixed effects linear models, reveals several key findings about the dynamics of tie strength, structural holes, and innovation radicalness. Firstly, we confirm that tie strength negatively affects innovation radicalness, highlighting the informational advantages of weak ties for fostering radical innovation. This supports the notion that weak ties provide critical, novel information that drives radical innovation. However, the impact of structural holes on radical innovation is found to be insignificant in our dataset. Crucially, our study reveals that the negative effect of tie strength on innovation radicalness is magnified when the network is more cohesive, i.e., low in structural holes. Furthermore, structural holes have a negative effect when tie strength is weak but a positive effect when tie strength is strong. These findings indicate that network cohesion is essential for leveraging the informational benefits of weak ties, and strong ties are necessary to fully capitalize on the advantages of structural holes.

This paper makes several theoretical contributions. First, it contributes to the social network literature by introducing a dual perspective on egocentric networks, distinguishing between their informational and relational aspects. We investigate how different network properties interact, offering a promising approach to reconcile competing theories on network effects (Burt, 1992; Coleman, 1988; Granovetter, 1982; Granovetter, 1973; Uzzi, 1996, 1997). Our conceptual model and empirical findings reveal that the same network structure, such as weak ties or structural holes, can simultaneously provide both informational advantages and relational disadvantages. The informational benefits of weak ties can be fully realized when there is network cohesion to counteract their relational disadvantages. Likewise, the advantages of structural holes can be leveraged when strong ties are present to mitigate the relational drawbacks associated with structural holes. Second, this study contributes to the radical innovation literature by shifting the focus from the technological origins and economic impacts of radical innovation to its social drivers within organizational and collaboration networks. By highlighting the role of network characteristics in fostering radical innovation, our research provides new insights into how social dynamics influence innovative outcomes. Third, we add to the literature on R&D location decisions by exploring how the structure of firm R&D networks impacts the capacity for producing radical innovations. While existing studies have examined factors influencing multinational corporations' overseas R&D location choices and strategies for coordinating subsidiaries (Alcácer & Zhao, 2012; Belderbos et al., 2021; Kuemmerle, 1997; Lewin et al., 2009), our research highlights how network structure specifically affects the generation of radical innovations.

This study has several limitations. Firstly, while patent data provide a valuable source for mapping collaboration networks and characterizing innovation radicalness—offering an advantage over survey and interview methods due to their avoidance of nonresponse biases—they are not without drawbacks. One limitation is selection bias: many less significant inventions may not be patented, and some breakthrough innovations might be omitted for strategic reasons. However, it is important to note that there is still meaningful information encoded in the patent data for exploitation, and that the selection biases would only challenge the validity of our findings if they are systematically related to both our independent and dependent variables. Despite these limitations, patent data remain a significant representation of invention outputs and have been extensively used in the literature to study innovation. Future research would benefit from incorporating a broader set of innovation outputs beyond patents to provide a more comprehensive view. Secondly, our study emphasizes the structural dimension of the network but does not consider the characteristics of nodes or the content exchanged within the network ties. Future research should address these aspects to achieve a more nuanced understanding of the relationship between collaboration networks and radical innovation. Lastly, our focus on the pharmaceutical and biotechnology industries may limit the generalizability of our findings. Investigating similar dynamics in other fields would be valuable to assess potential field-specific contingency effects.

In conclusion, our study underscores the importance of both weak ties and strong ties in facilitating radical innovation, contingent upon the presence of network cohesion and structural holes. These insights provide practical implications for companies aiming to foster radical innovation through strategic network management.

Declaration of generative AI and AI-assisted technologies in the writing process

Statement: In the second round of revision, the authors used ChatGPT for proofreading and to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

No.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.joi.2024.101636.

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