Turning creative ideas into successful innovations: Differential effects of network structure for radical and incremental innovation

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Abstract: This paper examines how the collaboration network structure of an innovation site influences the adoption and future use of its innovations. We explore the effects of tie strength and network cohesion, with a particular focus on the moderating role of innovation radicalness. While prior research emphasizes the benefits of strong ties and network cohesion for idea transfer—due to increased trust, information exchange, and reciprocity—we argue that these effects are contingent on the innovation's radicalness. Specifically, we suggest that these effects hold for incremental innovations but may become negative for radical innovations, as the impact of radical innovations may not align with reciprocity norms and could be sanctioned by the network. Additionally, the lack of information diversity may hinder the identification of new applications for radical innovations. Our empirical analysis is based on a dataset of 93 of the most innovative U.S. pharmaceutical and biotechnology companies, with 16,011 unique sites observed from 2001 to 2013. This results in a panel dataset with 19,343 site-time observations, using 3-year rolling windows. Our findings support our hypotheses, contributing to the literature on social networks, creativity, and innovation. We show that different types of innovations require different network conditions for diffusion, and that reciprocity norms can be burdensome, particularly for radical innovations. We also demonstrate that non-redundant information is crucial not only for generating novel ideas but also for identifying new applications for radical innovations. The findings have implications for innovation management, particularly at geographically dispersed sites.

Keywords: Collaboration networks, Tie strength, Network cohesion, Radical innovation, Creativity

1. Introduction

Firms increasingly deploy their technological innovation activities in geographically dispersed sites, and the competitiveness of the firm relies on its ability to coordinate its R&D activities across the globe (Alcácer et al., 2012; Almeida et al., 2004; Belderbos et al., 2021; Du et al., 2022; Kuemmerle, 1997). The structure of one site's collaboration network not only shapes the nature of ideas that it generates but also influences how the initial ideas is being adopted by future users (Fleming et al., 2007; Lee et al., 2015; Wang, 2016). Furthermore, some studies have explored that network effect on innovation might be contingent on the type of innovation (Vanhaverbeke et al., 2012). However, the contingency effects of innovation types are largely understudied and insufficiently understood. In this paper, we explore the moderating effect of innovation radicalness, considering the fundamental differences between radical and incrementation innovations. In other words, we study how the structure of the collaboration network for producing the idea affects diffusion of incremental and radical innovations differently.

There are long-standing debates in the social network literature regarding which types of networks are more advantageous for creativity and innovation, in particular debates between strong and weak ties, and between network cohesion and structural holes (Burt, 1992; Coleman, 1988; Granovetter, 1983; Uzzi, 1996; Uzzi, 1997). Competing theories are developed and empirical evidence is also mixed. One fruitful direction to reconcile these competing theories and mixed empirical evidence is to examine different stages of the creative process, and the common wisdom is that information diversity provided by weak ties and structural holes are particularly beneficial for generating novel ideas, while reciprocity norms, trust, and fine-grained information exchange offered by strong ties and network cohesion are advantageous for idea implementation, transfer, and adoption (Burt, 2004; Fleming et al., 2007; Perry-Smith et al.; Reagans et al., 2003; Tortoriello et al., 2010).

Building on this line of literature, we zoom in on how collaboration network for idea production affects the diffusion of the produced idea and explores how these effects are contingent on the radical nature of the innovation. In turn, we make two theoretical contributions. First, we explore the two-sided effect of reciprocity norms, which are usually considered as beneficial in the literature. Reciprocity norms promote cooperation but at the same time sanction behavior that is not aligned with cooperation, and such "non-reciprocal" behavior might be more desirable for some agents in some contexts, for example, not providing information for an information provider (Gargiulo et al., 2009), and adapting their networks for a manager in a changing environment (Gargiulo et al., 2000). We argue that incremental innovations consolidate existing technology and is aligned with reciprocity norms, and its diffusion is facilitated by strong ties and network cohesion. On the other hand, radical innovations bring a disruptive impact and are not aligned with reciprocity norms, and its diffusion is penalized by strong ties and network cohesion. Second, we question that non-redundant information is only relevant for idea generation but not so essential for idea diffusion. We argue that information diversity is beneficial for identifying new applications for an innovation in domains that are distant from the domain where the innovation originated. Accordingly, weak ties and structural holes that provide non-redundant information is beneficial for the adoption of radical innovations which usually have a broader use in foreign domains.

To test our hypotheses, we construct a panel dataset consisting of 16,011 unique sites (i.e., firm-locations) belonging to the 93 most innovative U.S. pharmaceutical and biotechnology companies according to the *EU Industrial R&D Investment Scoreboard*. We find that tie strength and network cohesion is positively associated with innovation success (based on the social definition of success in terms of being adopted by future users and measured by patent citations) when innovation is relatively incremental, but there is a negative association when innovation is relatively radical, supporting our hypotheses.

The remainder of this paper is organized as follows. In section 2, we develop the theories that drive our arguments on the relationship between network structure and innovation success, and how this relationship is contingent on innovation radicalness. In section 3, we document our method and data. In section 4, we present and interpret data analysis results, in particular test our stated hypotheses. In section 5, we conclude with discussion of our findings and the contributions to current social network and innovation research.

2. Theory and hypotheses

Innovation starts from creative ideas, but not all creative ideas will turn into successful innovation that is being adopted and used by others, and it takes multiple steps to develop a creative idea into a successful innovation (Anderson et al., 2014; Baer, 2012; Fleming et al., 2007; Lavie et al., 2012; Obstfeld, 2005; West, 2002). The prior literature has categorized various steps in the creative process (Csikszentmihalyi, 1997; Perry-Smith et al., 2017). One important separation is between an initial production stage where a creative idea is being generated and a latter diffusion stage where a creative idea is being adopted and used by others (Fleming et al., 2007; Lee et al., 2015; Wang, 2016). These studies have highlighted that the social structure for producing the idea not only shapes the inherent characteristics of the initial creative idea but also influences the diffusion of the initial creative idea beyond the social structure in which it was produced. More importantly, the same social structure that is conducive for producing a creative idea might hamper its diffusion. Therefore, exploring differential effects of network structure on idea production and diffusion provides valuable insights into the complex network effects.

Building on this line of literature, in this paper we zoom in on how social structure for producing a creative idea influences its diffusion and make a novel contribution by exploring how this effect is contingent on the radical nature of the creative idea. More specifically, for an incremental idea that consolidates existing technology trajectories, collaboration networks with strong tie strength and network cohesion provide trust, fine-grained information exchange, and cooperation norms, which in turn facilitates its acceptance and use by future users. However, such network may hamper the diffusion of a radical idea that disrupts existing technology trajectories, because of the burden of reciprocity norms and the lack of nonredundant information.

2.1 How tie strength affects innovation success, and how this is contingent on innovation

radicalness

According to Granovetter's (1973) landmark paper, tie strength is defined 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". Building on Granovetter's weak tie theory, studies on social networks have yielded a wealth of insight into how tie strength influences a variety of outcomes, such as job-related rewards (Barbulescu, 2015; Bian, 1997; Garg et al., 2018; Gee et al., 2017; Granovetter, 1995; Rajkumar et al., 2022), the generation of creative ideas (Perry-Smith, 2006; Perry-Smith et al., 2014; Sosa, 2011) and innovation (Capaldo, 2007; Fredberg et al., 2011; Rost, 2011), and effective knowledge transfer (Hansen, 1999; Levin et al., 2004; Reagans et al., 2003; Su et al., 2020). In this study, we develop a theoretical understanding for how tie strength affects idea diffusion, that is, turning creative ideas into successful innovation that is being used by future users. More specifically, strong ties are beneficial due to their higher level of trust, willingness to help, and shared understanding.

Previous literature has shown that strong ties facilitate the formation of trust (Krackhardt et al., 2003; Larson, 1992). Trust is a critical factor influencing the opportunity of knowledge transfer between actors. As trust develops over time, the willingness of knowledge exchange increases (Doz, 1996; Morrison, 2002; Reagans et al., 2003) and the concerns over opportunistic behavior reduced (Jarillo, 1988; Kachra et al., 2008; Levin et al., 2004). Via trust, strong interpersonal attachments decrease chances about creative ideas being ignored or rejected (McEvily et al., 2003; Tortoriello et al., 2012), which may increase chances of creative ideas being used. Second, strong ties are more likely to develop reciprocity norms that generate social pressure to provide needed support (Coleman, 1988; Granovetter, 1983). In other words, "strong ties have greater motivation to be of assistance and are typically more easily available [than weak ties]" (Granovetter, 1983). The above argument about willingness suggests that the more emotional attachment involved between focal actors and their contacts, the contacts are more likely to spend time and effort to make creative ideas work and be useful. Third, shared vision and understanding play an important role in the process of ideas implementation (Perry-Smith et al., 2017). During this phase, a shared understanding can reduce the potential resistance. If knowledge receivers cannot fully understand the idea and recognize its value, they may discard it as nonsensical. Prior literature has indicated that common understanding facilitates the process by which ideas are properly interpreted and accepted (Carlile, 2004; Carlile et al., 2003). Compared with weak ties, strong ties with a higher level of shared understanding facilitates the further co-development of the creative idea and adoption.

However, we expected that these abovementioned advantages of strong tie for idea diffusion are contingent on the type of impact that the creative idea will bring to the network partners. More specifically, we expect that these advantages will weaken or even turn into obstacles when the creative idea is more radical as opposite to incremental. Studies of technological innovation has long highlighted the difference between radical and incremental innovation. For example, Henderson et al. (1990) defined radical innovation as innovation that disrupts both existing components and architecture. Anderson et al. (1990) distinguished between competence-enhancing and competence-destroying technological discontinuities. Henderson

(1993) viewed radical innovation as innovation that obsoletes a company's existing information filters and organizational procedures. More recently, Funk et al. (2017) and Chen et al. (2021) viewed radical innovations as those that destabilize existing technology trajectories or reshape the network of technology interlinkages. The core distinction emphasized in the literature between radical and incremental innovations pertains to their potential impact for the existing technology and work, while incremental innovations bring an additive, enhancing, or consolidating impact, radical innovation brings a disruptive, destroying, or destabilizing impact. Since trust, willingness to help, and shared understanding embodied in strong ties promote reciprocity and sanction destructive behavior, the kind of impact that incremental innovation brings is the kind that is being promoted by strong ties, while the kind of impact that radical innovation brings is the kind that is being sanctioned. Gargiulo et al. (2009) found that strong cooperation norms of a network are a blessing for information recipients but a burden to information providers. Gargiulo et al. (2000) observed that social networks that provide safety of cooperation at the same time constraint manager from adapting to the change. These findings provide insights into the complexity of network effects, in particular, norms of cooperation and reciprocity penalize behavior that is not aligned with them, even though such behavior might desirable for some agents in some contexts, such as not providing information for the information provider and adapting the network for a manager in a changing environment. Hence, we argue that reciprocity norms of a strong tie network may facilitate the diffusion of incremental innovation which is aligned with reciprocity norms but at the same time may hinder the diffusion of radical innovation that is not aligned with reciprocity norms.

Furthermore, a key advantage of weak ties pertains to accessing non-redundant information (Granovetter, 1983; Granovetter, 1973; Uzzi, 1996; Uzzi et al., 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 et al., 2017). Access to diverse information fosters creativity (Page, 2007; Simonton, 1999, 2003). Prior studies have also shown that the benefits of weak ties for generating novel ideas (Baer, 2010; Perry-Smith, 2006; Perry-Smith et al., 2003; Perry-Smith et al., 2014; Zhou et al., 2009). Prior literature has mainly investigated the advantage of weak tie for idea production, but we extend the literature by arguing that non-redundant information is especially important for the adoption of radical innovations, as non-redundant information facilitates the identification of new connections (Mednick, 1962; Nelson et al., 1982; Schumpeter, 1939), which is not only useful for generating novel ideas that makes new connection between pre-existing components, but also for identifying new applications of a radical innovation in technological domains far away from the domain which the innovation originated.

Taken together, we expect that weak ties are beneficial for the adoption of incremental innovation due to their higher level of trust, willingness to help, and shared understanding. However, such positive effect of weak ties weakens or event turn into negative effects when the focal innovation is radical, due to the burden of reciprocity norms and the lack of nonredundant information. In other words, we hypothesize that, *Hypothesis 1. When innovation radicalness is low, an innovation is more likely to be successful if its innovator's collaboration network has stronger tie strength. When innovation radicalness is high, an innovation is less likely to be successful if its innovator's collaboration network has stronger tie strength.*

2.2 How network cohesion affects innovation success, and how this is contingent on innovation radicalness

Coleman (1988) championed the theory that, compared with a sparse network (where an individual's contacts are not connected among themselves), a cohesive network (where an individual's contacts are also interconnected among themselves) brings a higher level social capital through obligations and expectations, information channels, and social norms. However, Burt (1992) developed a competing structural hole theory which highlights the benefits of a sparse network due to information access and brokerage control advantages. While structural holes might be more valuable for generating creative ideas or career success in a competitive setting(Liao et al., 2016; Tóth et al., 2021), network cohesion is particularly relevant for idea implementation, knowledge transfer, and coordinated actions (Fleming et al., 2007; McEvily et al., 2003; Obstfeld, 2005; Panetti et al., 2020; Tortoriello et al., 2012; Xu et al., 2019). For example, Uzzi et al. (2005) found a positive association between network closure and successful musical production. Obstfeld (2005) found that the *tertius iungens* orientation (i.e., orientation towards connecting previously unconnected network members) facilitates involvement in innovation. Ozer et al. (2022) found that the *tertius iungens* orientation leads to high-quality interpersonal relations and in turn a high level of creative performance. Building on this line of literature, we argue that network cohesion is beneficial for turning a creative idea into a successful innovation, due to its easier information exchange and higher inclination towards cooperation.

First, a cohesive structure facilitates information exchange within the network, which is essential for partners to comprehend a creative idea, use it, and co-develop it into a successful innovation. In a cohesive network, actors are well-interconnected and have a higher chance to expose to the same information (Coleman, 1988; Fleming et al., 2007; Hansen, 1999; McEvily et al., 2003), and consequently, actors share a higher level of common understanding and face a lower cognitive barrier to comprehend a creative idea from their partners. Furthermore, once a creative idea is developed, it is easy to be deiminated within a cohesive network due to dense information exchange channels. In contrast, information is likely to be disseminated unevenly in a network with many structural holes. While brokers have the advantage in accessing diverse information and control the information flow which is beneficial for generating creative ideas (Burt, 1992; Burt, 2004; Fleming et al., 2007), they may face obstacles in helping their partners to understand and adopt their creative idea due to the lack of shared understanding (Sorenson et al., 2004). Second, network cohesion encourages cooperation, which provides a supportive environment for further developing a creative idea into a successful innovation. From a promotional perspective, network cohesion creates a social norm towards trust, reciprocity, mutual ownership, and collective problem-solving (Coleman, 1988; Fleming et al., 2007), all of which are conducive for innovation under uncertainty. From a preventive perspective, network cohesion makes it easier to identify and sanction undesirable behavior and imposes stronger obligation for cooperation (Coleman, 1988). Inclination towards cooperation improves the quality of interpersonal relations and in turn innovation success (Ozer et al., 2022).

However, we also expect that these advantages depend on the radical nature of the innovation: they are particularly relevant for incremental innovations but turns into obstacles for radical innovations. In the same vein as discussed in the previous section, network cohesion provides strong reciprocity norms, which promote the adoption of incremental innovation which has an impact on network partners that is aligned with reciprocity norms but at the same sanctioned radical innovation which has an impact that is not aligned with reciprocity norms. In addition, a cohesive network also lacks non-redundant information (Burt, 1992; Burt, 2004), which in turn impedes identifying new applications of the radical innovation. Taken together, we hypothesize that:

> *Hypothesis 2. When innovation radicalness is low, an innovation is more likely to be successful if its innovator's collaboration network is more cohesive. When innovation radicalness is high, an innovation is less likely to be successful if its innovator's collaboration network more cohesive.*

3. Method

3.1 Data and sample

To test our hypotheses, we constructed a unique panel dataset with information about firm R&D locations, their collaboration networks, and innovation outputs. We combined information from various sources. Our sampled firms are identified from the 2018 edition of the *EU Industrial R&D Investment Scoreboard*, which provides a list of companies with the largest R&D spending in the world. We restricted our analysis to firms from 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 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 (Dong et al., 2016; Hoang et al., 2005; Tzabbar et al., 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) in order to access diverse knowledge and resources. 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 local knowledge with complementary resources residing elsewhere in the world (Alcácer et al., 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 et al., 2007; Tzabbar et al., 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 success, 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 report all of their subsidiaries, unless the unnamed subsidiaries are viewed as a single subsidiary and do not make up a significant subsidiary as of the end of the year covered by the report. Since our study focuses on R&D collaboration networks across a firm's locations, we excluded 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 tried to match the names of the companies presented in the SEC database with the names of patent applicants appearing in the PATSTAT database. The 2019 Autumn version of PATSTAT was used. Name searching and cleaning strategies are applied to standardize the names. To do so, we identified 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 were 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 compared the names we found with the harmonized subsidiary names. The comparison was done using 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% were considered to be potential matches. As a final step the results of the matching process were manually checked, and only a few match errors were found. We were looking for granted patents held by the firms in our sample, for which the patent applications were filed between 2001 to 2013 at United States Patent and Trademark Office (USPTO), the European Patent Office (EPO), or the World Intellectual Property Organization (WIPO).

We then aggregated patents at the location level, and inventor addresses were used to conjecture the locations of companies' innovative activities. Considering that subsidiaries often use the headquarters' address as the applicant address instead of the subsidiary's 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 et al., 2005). Addresses in the patent database are messy, and we linked 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 inventor and applicant locations and also provided clean information about corresponding countries, regions and cities. This dataset covers all PATSTAT patents in our studied time period. We used the fine-grained city level information for R&D locations of a firm's R&D network. 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 patented at multiple offices, therefore we used the definition of patent families according to the DOCDB definition (Martínez, 2011), instead of single patents, following the field convention. Building on the data of patent families, we constructed our final dataset for analysis at the location-time level. For each location, we constructed our variables using patent families in a 3-year moving time window. In other words, the location *i* at time point *t*, the variables were constructed using patent families with the earliest filing date in the three years 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

Innovation success. We used the average number of patent family citations that a focal location received in a 5-year window to measure innovation success, following the social definition of success in terms of acceptance and adoption by future users (Amabile, 1983; Fleming et al., 2007). Although patent citation is not a perfect measure of innovation success, citation-based indicators have been found to be positively correlated with other measures of patent value or usefulness and have been widely used in innovation research (Fleming, 2001; Harhoff et al., 2003; Kelly et al., 2021; Poege et al., 2019). Therefore, we followed the previous literature and used citation counts as a measure of innovation success. Considering that patents granted earlier have a longer time period to accumulate citations, we adopt a fixed five-year citation time window for counting citations. Prior literature has shown that a five-year window is adequate for a focal patent to gain significant coverage of forward citations (Hall et al., 2001) and has been widely employed in constructing citation-based measures (Hain et al., 2020; Poege et al., 2019).

3.2.2 Independent variables

Tie strength. Tie strength was operationalized as the frequency of collaboration based on a three-year window, including the current and preceding two years. Specifically, we first measured the strength of a tie between a focal location and its collaborating locations separately as the number of co-inventing patent families between them from year *t-2* to *t*. Second, we calculated tie strength at the egocentric network level as the average number of co-inventing patent families.

Network cohesion. We adopted the network density measure. More specifically, divide the number of existing collaboration ties between a location's collaborators by the number of possible ties between these collaborators, in the period from year *t-2* to *t*. Collaboration tie in this context means that there are co-inventing patent families between two locations.

Innovation radicalness. To measure the radicalness of a patent family, we adopt the consolidation-or-destabilization (CD) index developed by Funk et al. (2017). The CD index captures the degree to which the focal patent destabilizes existing technology trajectories by examining whether patents citing a focal patent also cite prior patent cited by the focal patent (i.e., its references). If patents citing the focal patent do not cite its references, then the focal patent is considered to reshape the network of technology interlinkages by shifting future inventors' attention away from the knowledge on which the focal patent builds, thus destabilizing existing technology trajectories. The CD index has been applied to study innovation as well as science (Park et al., 2023; Wu et al., 2019). Balachandran et al. (2018) also adopted the CD index for measuring *radicalness* of innovation at the firm level. We adopt the same approach.

Innovation radicalness is calculated as follows for a focal patent:

$$\text{Radicalness} = \frac{1}{n}\sum_{i=1}^{n} f_i$$

Where i is the index of the future patent families that cite the focal patent family or its references, n is the total 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 not only the focal patent family but also 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. Hence, radicalness indicates the extent to which the focal patent family obsoletes prior arts that it builds on in a dynamic network. The range of radicalness index is from -1 to 1. For calculating radicalness, 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 the fixed time window.

At the location level, we calculate the average radicalness in a 3-year moving time window to characterize the inclination towards radical innovation for the location in this time period.

3.2.3 Control variables

Our analyses control for possible confounding variables that may lead to spurious correlations between our focal independent and dependent variables. 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. *Innovation productivity*, measured as the number of patent families, is included, considering that 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 radical innovation (Fleming et al., 2007). To examine the effect of network properties net of network size, we control for *network size*, which is the number of co-inventing locations. Controlling for the number of co-inventing locations can help to exclude the possible alternative explanation that it was the network size that predicted variation in network properties and innovation success. 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 used the same 3-year moving time 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. Result

4.1 Descriptive statistics

Descriptive statistics and Spearman correlations are reported in Table 1. Our focal dependent variable, *innovation success*, that is the average number of family citations, has a mean of 14.79, standard deviation of 17.13, and a range from 0 to 200. We take the natural logarithmic transformation for *innovation success*, as well as all other count variables (i.e., *innovation productivity* and *network size*) in the regression analysis to accommodate the skewed nature of these variables. *Innovation* r*adicalness* 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, as expected. The distribution of *tie strength* is highly right-skewed with a mean of 1.86 and standard deviation of 2.16, and ranging from 1 to 69.60. *Network cohesion* has mean 0.20 and ranges from 0 to 1. This suggest that most locations operate in relatively sparse networks that are rich in 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 involves collaboration with other locations (i.e., *collaboration inclination*), indicating that sole-production of innovation is rare. Correlations show that both *tie strength* (r = 0.19) and *network cohesion* (r = 0.13) are positively correlated with *innovation success*. It is important to interpret these correlations with caution as they do not account for any confounding variables. The correlation between *innovation radicalness* and *tie strength* is small (r = -0.04), as well as between *innovation radicalness* and *network cohesion* (r = 0.02). The correlations between our focal independent variables and control variables (especially *innovation productivity*) are fairly high: innovation productivity has a correlation of 0.86 with *tie strength* and 0.79 with *network cohesion*. While for the reasons discussed in the section on control variables, we report results with controlling these potential confounders in this paper and test the robustness of our results by dropping out control variables.

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

	Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6
1	Network size	7.91	9.58	2	122						
2	Innovation productivity	6.72	19.61	1	466	**.62**					
3	Collaboration inclination	0.97	0.11	0.07	1	**-.27**	**-.49**				
4	Tie strength	1.86	2.16	1	69.60	**.46**	**.86**	**-.26**			
5	Network cohesion	0.20	0.28	0	1	**.65**	**.79**	**-.42**	**.48**		
6	Innovation radicalness	-0.01	0.06	-0.47	0.90	**-.09**	-.01	**-.04**	**-.04**	**.02**	
7	Innovation success	14.79	17.13	0	200	**.24**	**.19**	**-.05**	**.19**	**.13**	**-.37**

Note: correlations with bold numbers are significant at $p < .05$.

4.2 Regression results

Table 2 presents the results of the fixed effect linear regression models testing our hypotheses. For all regression models, we incorporate firm-location fixed effect to examine the relationship between network structure and innovation success within the same firm-location. Column 1 in Table 2 reports the results of a baseline model only with control variables. The effect of the number of patent family is not significant, suggesting no significant correlation between innovation productivity and success. On the other hand, *network size* (i.e., the number of co-inventing locations) and *collaboration inclination* (i.e., the share of co-inventing patent families) are positively correlated with innovation success, which suggests that firm-locations that have a larger collaboration network and more inclined towards collaborating with others are more likely to produce innovation that is successful in terms of patent citations.

Table 2 Tie strength, network cohesion, and innovation success

	Innovation success					
	(1)	(2)	(3)	(4)	(5)	(6)
Tie strength (ln)		0.244***	0.222***	0.198***	0.222***	0.199***
		(0.034)	(0.033)	(0.034)	(0.033)	(0.034)
Network cohesion		0.028	0.038	0.028	0.035	0.027
		(0.052)	(0.051)	(0.051)	(0.051)	(0.051)
Innovation radicalness			-2.060***	-1.576***	-1.818***	-1.487***
			(0.169)	(0.187)	(0.197)	(0.203)
Tie strength (ln) * Innovation radicalness				-2.289***		-2.149***
				(0.340)		(0.347)
Network cohesion * Innovation radicalness					-1.766***	-0.868
					(0.567)	(0.575)
Innovation productivity (ln)	0.007	-0.161***	-0.138***	-0.133***	-0.138***	-0.133***
	(0.014)	(0.031)	(0.030)	(0.030)	(0.030)	(0.030)
Network size (ln)	0.211***	0.285***	0.264***	0.264***	0.263***	0.264***
	(0.018)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Collaboration inclination	0.371***	0.079	0.076	0.076	0.068	0.072
	(0.067)	(0.079)	(0.077)	(0.077)	(0.077)	(0.077)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19343	19343	19343	19343	19343	19343
R-square	0.749	0.751	0.757	0.758	0.757	0.758
F Statistic	62.53***	59.04***	64.25***	68.34***	63.93***	66.29***

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

Column 2 adds tie strength and network cohesion into the model. While there is a significantly positively effect of tie strength (b = 0.244, p < 0.01), the effect of network cohesion is insignificant (b = 0.028, p > 0.10). Column 3 further adds innovation radicalness as an independent variable and finds a significantly negative effect of innovation radicalness (b = -2.060, $p < 0.01$).

To test our hypotheses about the moderating effect of innovation radicalness, Column 4 and 5 interact innovation radicalness with tie strength and network cohesion, respectively. Note that the coefficient on tie strength in Column 4 (b = 0.198, $p < 0.01$) estimates the marginal effect of tie strength on innovation success when innovation radicalness equals to 0 (the middle point theoretically). More importantly, we observe a significantly negative interaction effect between innovation radicalness and tie strength (b = -2.289, $p < 0.01$). This suggest that when radicalness is low (closer to -1), the effect of tie strength becomes insignificant or might even turn into positive, while when radicalness is high (closer to 1), the effect of tie strength turns into negative. In column 5, we observe an insignificant effect of network cohesion on innovation success when innovation radicalness is 0 (b = 0.035, $p > 0.10$). We also observe a significantly negative interaction effect between innovation radicalness and network cohesion (b = -1.766, $p < 0.01$), indicating a positive effect of network cohesion when radicalness is low but a negative effect of network cohesion when radicalness is high.

To better illustrate the moderating effect of innovation radicalness, as well as examining the significance of tie strength and network cohesion effects at various levels of innovation radicalness (for example, to test whether tie strength has a positive effect or just an insignificant effect when radicalness is low), Figure 1 plots the marginal effects (i.e., regression coefficients) of tie strength and network cohesion at varying degrees of innovation radicalness. The figure confirms that when innovation radicalness is low, both tie strength and network cohesion have a positive effect on innovation success, while when radicalness is high, both have a negative effect, supporting our Hypotheses.

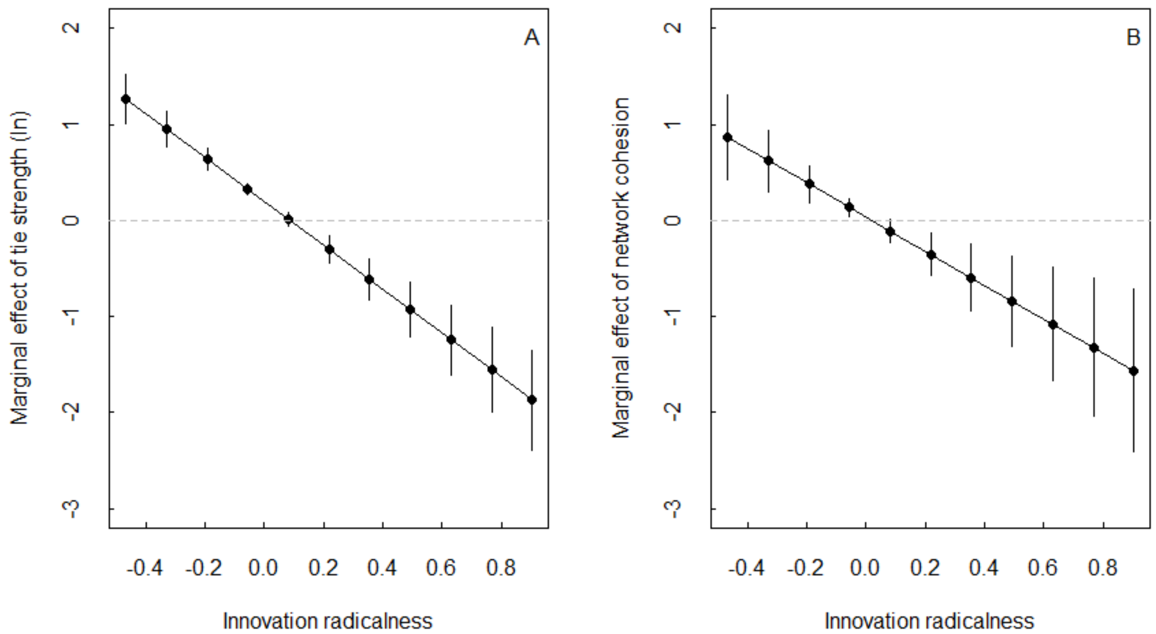

Figure 1 Tie strength, network cohesion, and innovation success. Points represent the regression coefficients, and vertical bars represent 90% confidence interval.

4.3 Additional analysis: Separating adoption by network partners and outsiders

In this paper, we study how the structure of the collaboration network (i.e., tie strength and network cohesion) for producing a creative idea affects the diffusion of the produced idea. One important question is, whether these effects are restricted to network partners or go beyond them. To answer this question, we examine patent citations received from network partners' future patents and patent citations received from others outside the egocentric network of the focal firm-location. Regression results are reported in Table 3 and marginal effects of tie strength and network cohesion at different levels of innovation radicalness are plotted in Figure 2. At low levels of radicalness, marginal effects (i.e., regression coefficients) of tie strength and network cohesion on citations from network partners are comparable to their marginal effects on citations from outsiders. When radicalness is high, the marginal effects are larger for citations from network partners than their marginal effects on citations from outsiders. This is understandable as network structures we are investigating concerns the egocentric network but not beyond, and much of our theoretical discussion is within the egocentric network. However, the findings that there are similar effects beyond the egocentric network is an important finding, which confirms prior studies' assumption that the influence of production network on knowledge diffusion goes beyond the production network itself (Fleming et al., 2007; Lee et al., 2015; Wang, 2016). One possible explanation is that network effects shape the collective behavior of the egocentric network regarding how they further develop the initial creative idea and follow-on innovation, and such behavior affects the social process where the initial creative idea evolves and connects with future innovation, and in turn gain acceptance by outsiders.

Table 3 Separating adoption by network partners and outsiders

	Innovation success Citations from network partners						Innovation success Citations from outsiders					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Tie strength (ln)		0.117***	0.094***	0.070**	0.093***	0.072**		0.172***	0.157***	0.140***	0.157***	0.141***
		(0.034)	(0.034)	(0.034)	(0.034)	(0.034)		(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Network cohesion		-0.200***	-0.190***	-0.200***	-0.194***	-0.201***		0.101*	0.107**	0.100*	0.104**	0.099*
		(0.051)	(0.050)	(0.050)	(0.050)	(0.050)		(0.052)	(0.051)	(0.051)	(0.051)	(0.051)
Innovation radicalness			-2.119***	-1.642***	-1.826***	-1.510***			-1.348***	-1.006***	-1.146***	-0.918***
			(0.155)	(0.166)	(0.180)	(0.180)			(0.165)	(0.189)	(0.195)	(0.207)
Tie strength (ln) * Innovation radicalness				-2.258***		-2.051***				-1.615***		-1.476***
				(0.331)		(0.339)				(0.341)		(0.345)
Network cohesion * Innovation radicalness					-2.139***	-1.281**					-1.475***	-0.858
					(0.535)	(0.536)					(0.564)	(0.572)
Innovation productivity (ln)	0.052***	-0.002	0.021	0.026	0.021	0.025	-0.022	-0.149***	-0.135***	-0.131***	-0.135***	-0.131***
	(0.014)	(0.031)	(0.030)	(0.030)	(0.030)	(0.030)	(0.014)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Network size (ln)	0.208***	0.268***	0.246***	0.247***	0.245***	0.246***	0.178***	0.220***	0.206***	0.206***	0.205***	0.206***
	(0.017)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.018)	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)
Collaboration inclination	0.336***	0.215***	0.212***	0.212***	0.202**	0.206***	0.241***	0.029	0.027	0.027	0.020	0.023
	(0.067)	(0.079)	(0.079)	(0.078)	(0.079)	(0.078)	(0.066)	(0.078)	(0.077)	(0.077)	(0.077)	(0.077)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19343	19343	19343	19343	19343	19343	19343	19343	19343	19343	19343	19343
R-square	0.743	0.745	0.752	0.753	0.752	0.753	0.737	0.738	0.741	0.741	0.741	0.741
F Statistic	37.5***	36.86***	46.16***	48.97***	48.13***	49.52***	63.37***	57.15***	57.42***	57.78***	55.86***	55.38***

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

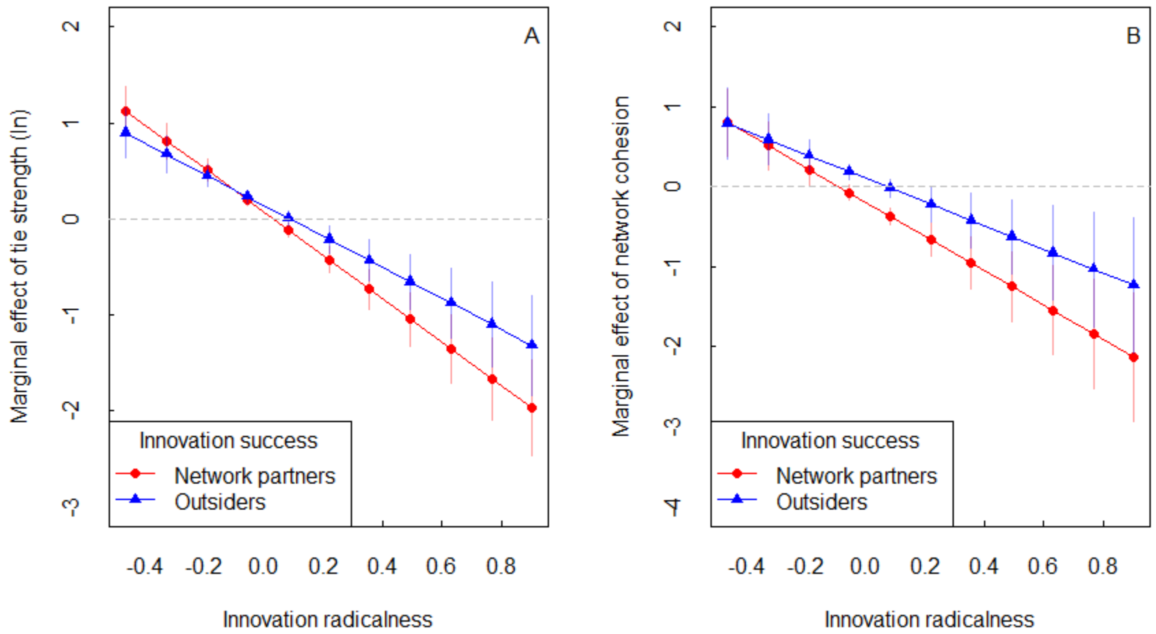

Figure 2 Separating adoption by network partners and outsiders. Points represent the regression coefficients, and vertical bars represent 90% confidence interval.

4.4 Robustness tests

We test the sensitivity of our results with respect to control variables. We drop control variables one by one as well as drop them all together. Correlation analysis shows that our control variables has relatively high correlations with focal independent variables, which indicates there is potential risk of multilinearity. For a robustness test, we drop control variables to check whether our results are sensitive to these controls. Results are robust except for network cohesion (Appendix Table A1, Figure A1).

To measure patent citations and radicalness, we used a five-year citation time window. To test the robustness of our findings, we extend the time window up to autumn 2019, and the results remain consistent (see Appendix Table A2).

Our study sample includes firms from both the pharmaceutical and biotechnology industries. Given the significant differences between these sectors, we conduct separate regression analyses for each (Appendix Table A3). The results for pharmaceutical companies are consistent with the main findings. However, for biotechnology firms, the interaction effect between network cohesion and innovation radicalness remains negative but loses statistical significance. This could reflect sector-specific differences or be attributed to the smaller sample size in the biotechnology sector.

5. Discussion and conclusion

In this paper, we investigated how tie strength and network cohesion of an innovation site's collaboration network shapes the success of its innovation, adopting a social definition of success in terms of adoption and future use and measured by patent citations. More importantly, we examine how these effects are contingent on the radical nature of innovation. We argued that trust, fine-grained information exchange, and reciprocity norms associated with strong tie and network cohesion facilitate innovation diffusion. However, this only holds for incremental innovation, which consolidates existing technologies and confirms the reciprocity norms. However, the opposite is true for radical innovation that disrupts existing technologies and has an impact on network partners that is not aligned with reciprocity norms. In addition, the lack of diverse information hinders the identification of new applications for the radical innovation. Therefore, we hypothesized that a network with strong ties and cohesion facilitates the diffusion of incremental innovation but hinders the diffusion of radical innovation. To test our hypotheses, we retrieved 93 the most innovative U.S. pharmaceuticals and biotechnology firms from EU Industrial R&D Investment Scoreboard. Using this distinctive panel dataset consisting of 19,343 site-time observations, we found empirical results supporting our hypotheses.

There are several limitations of this study. First, although patent data avoid response bias and capture a more complete collaboration network than surveys and interviews, it is important to acknowledge that our study suffers from the unavoidable limitations of patent data for studying innovation, such as the file drawer problem and noise in the citation data. For example, For example, many unimportant inventions are failed to be patented, and some breakthroughs may be missed due to firms' strategic reasons (Fleming, 2001). While granted patents are not a perfect archive of technological innovations, the data still represent a considerable share of invention outputs. Future research adopting a broader set of innovation outputs would be valuable to extend from patents to other innovative outputs. Second, this study retrieved data from companies with high R&D investment in pharmaceuticals and biotechnology industry in the United States, which may limit the generalizability of our findings to other industries or other countries. Future research should collect data from broader industry contexts as well as a larger and more diverse sample. Third, our empirical strategy incorporates location fixed effects to account for time-invariant, location-specific differences. However, time-varying factors—such as changes in funding levels, strategic orientations, or the involvement of external stakeholders—could still pose a threat to the internal validity of our findings. To address this, future research could employ instrumental variables or experimental designs to more robustly establish causal relationships and mitigate biases from unobserved, time-varying factors. Fourth, while our study focuses on the role of collaboration network structure in the adoption and future use of innovations, we acknowledge that other contextual factors—such as funding, strategic priorities, and external stakeholders—also play significant roles in shaping innovation outcomes. Future research could examine these factors more explicitly to provide a fuller understanding of how innovation dynamics are driven by both network structures and broader contextual influences. Fifth, our study draws on data from the pre-COVID period (2001–2013), and we acknowledge the limitations of this temporal scope. External shocks, such as the COVID-19 pandemic, can significantly affect the speed and direction of innovation. Future research could explore how these dynamics have shifted post-pandemic, particularly regarding the diffusion of radical innovations and the evolving role of network structures in responding to rapidly changing market conditions. Additionally, examining a broader set of success metrics—such as commercialization rates, revenue generation, or market share—could provide a more comprehensive view of innovation success.

In spite of these limitations, our study contributes to and extends the existing literatures of social networks, innovation, and creativity in several ways. First, this paper explored how network effect depends on the radical nature of innovation. While there is an extensive literature about network effect on idea diffusion, less studied and understood is that these effects might depend on the type of the innovation (Ozer et al., 2019; Vanhaverbeke et al., 2012). Different types of innovation might need different network conditions for diffusion. In particular, we found opposite network effects for incremental and radical innovations.

Second, we contribute to the long-standing debated about which kinds of networks are more advantageous: strong tie vs. weak tie, and network cohesion vs. structural hole. One promising direction to reconcile competing theories and empirical evidence is to separate different stages of the creative process, and the consensus seems to be that non-redundant information provided by weak ties and structural holes are necessary or beneficial for generating novel ideas, while reciprocity norms, trust, and fine-grained information exchange associated with strong ties and network cohesion facilitate idea implementation, transfer, and adoption (Burt, 2004; Fleming et al., 2007; Perry-Smith et al.; Reagans et al., 2003; Tortoriello et al., 2010). However, our findings extend this literature and shed further insights into the complexity of network effects, by showing that reciprocity norms are not always beneficial but can become a burden for some agents in some contexts, where the desirable behavior misaligns with reciprocity norms. In particular, the adoption of radical innovation is hinder because of its destructive impact on existing technologies and the collaboration network.

Third, we also highlight the complexity that there might not be clean separation in the network effect between the idea production and diffusion stages. More specially, non-redundant information is beneficial not only for generating ideas that makes new combinations of pre-existing components, but also for identifying new applications for radical innovations outsides of the field where they were generated.

Our findings also have important implications for innovation management, especially across geographically dispersed sites. It takes several steps to turn a creative idea into a successful innovation, and the structure of collaboration network plays an important role in this process. Our findings inform what types of network structure are more beneficial for the adoption and future use of incremental versus radical innovations. When restructuring the network is not feasible, then the managers should pay attention to how to bring other management interventions to magnify desirable underlying mechanisms and mitigate undesirable ones.

Declaration of Competing Interest:

No.

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