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Social network and radical innovation: evidence from the U.S. pharmaceutical and biotechnology industry

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Social Network and Radical Innovation: Evidence From the U.S. Pharmaceutical and Biotechnology Industry

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CHAPTER 1

General introduction

1.1 Introduction

Innovation is a key driving force of economic growth and social progress (Schumpeter, 1942). It plays an essential role in firms' competitiveness and long-term success (Anderson et al., 2014; Kock et al., 2011; Kraft & Bausch, 2018). For example, Schumpeter (1942) considered firm innovation as the "fundamental impulse that sets and keeps the capitalist engine in motion" and coined the term "creative destruction", a process that new innovation "revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one." However, innovations come in different types, ranging from run-of-the-mill innovation that bring incremental changes to existing technologies to radical innovation that break from existing trajectories (Anderson & Tushman, 1990; Verhoeven et al., 2016). For example, Anderson and Tushman (1990) distinguished between competence-enhancing and competence-destroying technological discontinuities. 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 create new directions. Following previous literature, this PhD dissertation focuses on the technological perspective of innovation, and defines radical innovation as innovation that brings intensive destruction and changes technology trajectories.

Radical innovation has received a lot of attention from innovation scholars and practitioners, and it is considered as the core of entrepreneurial activity and wealth creation (Ahuja & Morris Lampert, 2001; Schumpeter, 1942; Verhoeven et al., 2016). For example, the turbojet engine is a radical innovation compared with the traditional propeller engines, which opens up new directions for many subsequent innovations and realizes considerable growth in the aviation industry. Considering the importance of radical innovation, unpacking the determinants and consequences of radical innovation is of major interest to academia and industry.

Prior studies have extensively investigated technological origins of radical innovation. However, we know relatively little about the social determinants of radical innovation in the organizational and social environment. In social network literature, there is a long discussion about the advantages and disadvantages of different types of network structure on creativity and innovation, in particular

debates between strong and weak ties, and between network cohesion and structural holes (Burt, 1992; Coleman, 1988; Granovetter, 1982; Uzzi, 1996, 1997). Competing theories are developed and empirical evidence is also mixed. Some researchers highlight the benefits of weak ties and structural holes, while others suggest advantages of strong ties and network cohesion for radical innovation (Burt, 1992; Coleman, 1988; Granovetter, 1973; Nahapiet & Ghoshal, 1998). This dissertation (Chapter 2) separates two faces of weak ties and structural holes: their informational advantages in accessing the diverse knowledge that is needed for radical innovation, and their relational disadvantages linked to a weaker shared understanding and trust. More importantly, this dissertation (Chapter 2) explores how weak ties and structural holes collectively effect on radical innovation, which provides a promising direction for reconciling competing theories about network effects.

Another reconcile direction 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 & Mannucci; Reagans & McEvily, 2003; Tortoriello & Krackhardt, 2010). Building on this line of literature, this dissertation (Chapter 3) explores how collaboration network for idea production affects the diffusion of the produced idea and highlights that the same social structure that is conducive for producing a creative idea might hamper its diffusion. Investigating differential effects of network structure on idea production and diffusion provides valuable insights into the complex network effects. Moreover, this dissertation (Chapter 3) examines the moderating effect of innovation radicalness, considering the fundamental differences between radical and incrementation innovations. This complements the innovation research about the contingency effects of innovation types.

In addition to examining the contingency effects of innovation, this dissertation (Chapter 4) also investigates radicalness as the independent variable. Exploring how radicalness affects the private value for the innovating firm, this dissertation (Chapter 4) provides empirical evidence that radicalness has important influence on firms' private value. Considering the diverse approaches for conceptualizing and operationalizing radicalness, this dissertation (Chapter 4) differentiates between two

dimensions of radicalness: destructiveness and dissimilarity. This dissertation (Chapter 4) provides a useful approach for reconciling seemly conflicting empirical findings in previous literature and makes an original contribution to the literature of radical innovation by unpacking the novelty concept into two components.

The aim of this PhD dissertation is to integrate radical innovation and social network literature to broaden theoretical understanding, especially contribute to the literatures of social networks, creativity, and innovation, and inform innovation management by unpacking the drivers and effects of radical innovation.

We study the network effect on radical innovation in the context of multinational corporations' internal R&D collaboration networks. Overseas R&D is playing an increasingly important role in the R&D networks of multinationals, and the competitiveness of the firm relies on its ability to coordinate its R&D activities across the globe (Alcácer & Zhao, 2012; Almeida & Phene, 2004; Belderbos et al., 2021; Du et al., 2022; Kuemmerle, 1997). While prior studies have systematically investigated drivers of R&D location decisions and strategies for coordinating subsidiaries, it has not yet studied how the network structure affects radical innovation at a particular R&D location. To test 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.

1.2 Structure and research questions of this PhD dissertation

To advance our understanding about the existing innovation literature, this dissertation investigates the determinants of radical innovation and its social and economic impact. Specifically, Chapter 2 studies the social driving forces of radical innovation; Chapter 3 demonstrates the social impact of network structure and the role that radicalness plays in their relationships; Chapter 4 explores the economic impact of different dimensions of radicalness. To summarize, Chapter 2 to Chapter 4 aim to answer the following three research questions:

Research Question 1: How does network structure affect innovation radicalness?

The innovation and social network literatures have long highlighted the importance of network structure for individual and organizational innovation performance. The literature among researchers exhibits varying perspectives on the influence of tie strength and network structures in promoting radical innovation (Burt, 1992; Coleman, 1988; Fleming et al., 2007; Granovetter, 1973; Nahapiet & Ghoshal, 1998; Perry-Smith, 2006; Rost, 2011). For example, the brokerage view, which is grounded on Burt's (1992) structural hole theory, contends that sparse networks which full of structural holes can benefit innovation because of the nonredundant information. By contrast, the bonding view which builds on Coleman's (1988) view, argues that cohesive network facilitates innovation because of cultivate trust, common understanding, and reciprocity. This dissertation aims to reconcile these competing theories. Chapter 2 explores how network structure affects radical innovation in the context of corporate R&D networks. Specifically, Chapter 2 separates two faces of weak ties and structural holes: their informational advantages in accessing the diverse knowledge that is needed for radical innovation, and their relational disadvantages linked to a weaker shared understanding and trust. To test hypotheses, Chapter 2 builds a unique panel dataset consisting of 19,343 firm-location-time observations for 16,011 unique firm-locations belonging to 93 U.S. pharmaceuticals and biotechnology companies on the EU Industrial R&D Investment Scoreboard. Following Funk and Owen-Smith (2017), radicalness is measured as the extent to which the focal patent family destabilizes existing technology trajectories. Tie strength between two R&D locations is captured as their frequency of co-inventing patent families, and structural hole is calculated as the share of missing ties in an egocentric network excluding the ego itself. Findings of this chapter provide empirical evidence of how tie strength and structural holes collectively affect innovation radicalness at a location within an innovation firm. More specifically, findings of this chapter demonstrate that the informational advantages of structural holes can be mobilized if there are strong ties for mitigating the relational disadvantages of structural holes. Similarly, network cohesion is needed for mobilizing informational advantages of weak ties. This chapter provides a promising direction for reconciling competing theories about network effects.

Research Question 2: How does collaboration network structure influence the adoption and future use of its innovation? Would their relationship condition on innovation types (e.g., incremental innovation and radical innovation)?

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; Bharadwaj & Menon, 2000; Fleming et al., 2007; Lavie & Drori, 2012; Obstfeld, 2005; West, 2002). The prior literature has categorized various steps in the creative process (Csikszentmihalyi, 1997; Perry-Smith & Mannucci, 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, Chapter 3 investigates 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. The empirical analysis is based on a unique panel dataset of 93 most innovative U.S. pharmaceuticals and biotechnology companies from 2001 to 2013, with a total number of 19,343 location-time observations. Innovation success is measured as the average number of patent family citations that a focal location received. Tie strength is operationalized as the frequency of collaboration, and network cohesion is calculated as the share of collaborating ties in one location's egocentric network. The radicalness index adopts from Funk and Owen-Smith (2017). Findings of this chapter highlight the contingent effect of radical innovation.

Research Question 3: How does the private value of a patent depend on its radicalness? Would destructiveness and dissimilarity have the same effect on private value?

Studying how the radicalness predict future economic value, especially the different aspects of radicalness, is a very interesting research topic in innovation literature. However, the empirical evidence is mixed considering there are diverse approaches for conceptualizing and operationalizing innovation radicalness (Arts et al., 2021; Verhoeven et al., 2016). Chapter 4 investigates the association between the private

value of a patent for the innovation firm and its technological radicalness by differentiating between two important dimensions of technological radicalness: destructiveness and dissimilarity. Using a dataset consisting of 1,066,637 USPTO granted patents, Chapter 4 adopts the private value of individual patents based on abnormal stock market return, developed by Kogan et al. (2017). Following Funk and Owen-Smith (2017), the destructiveness of patents is measured by using citation networks and more specifically the extent to which a patent destabilize the existing trajectories. Following Arts et al. (2021), the dissimilarity of patents based on to what extent the text of a patent is dissimilar to prior patents. Findings of this chapter confirm that the different dimensions of radicalness have distinct effects on private value. More importantly, this chapter provides a useful approach for making sense of the diverse and sometimes competing theories and evidence about technological radicalness.

Chapter 5 summarizes and discusses the main findings presented in chapters 2 to 4. Based on these research findings, the theoretical and practical implications are illustrated for advancing future study. The limitations are also discussed in this chapter.

1.3 Potential contributions

Given the existence of competing theories and the mixed nature of empirical evidence, this dissertation endeavors to reconcile the conflicting viewpoints between social network and innovation studies. By unpacking the drivers and effects of radical innovation, this dissertation contributes to the literatures of social networks, creativity, and innovation. Chapter 2 contributes to the social network and radical innovation literature by proposing a two-faced view of network structures separating informational and relational aspects, and investigating the interaction between different network properties. The conceptual model and empirical findings acknowledge that the same network structure (i.e., weak tie, structural hole) may present both informational advantages and relational disadvantages at the same time. In addition, the informational advantages of weak ties can be mobilized if there are network cohesion to mitigate the relational disadvantages of weak ties. Similarly, the informational advantages of structural hole can be mobilized if there are strong ties to mitigate the relational advantages of structural holes.

Chapter 3 investigates 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. 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 & Benassi, 2000). Chapter 3 extends previous literature and sheds 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.

Chapter 4 expands the literature on radical innovation. Chapter 4 highlights the importance of unpacking different dimensions of innovation radicalness (i.e., destructiveness and dissimilarity), which have distinct effects. Unpacking innovation radicalness also provides a useful approach for making sense of the diverse and sometimes competing theories and evidence about radical innovation.

CHAPTER 2

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

This Chapter is submitted as:

Zhang, J., Wang, J., Winnink, J.J., & Jong, S. Collaboration networks and radical innovation: Two faces of tie strength and structural holes.

Author contributions:

Zhang, J. (Conceived and designed the analysis, Performed the analysis, Wrote the paper)

Wang, J. (Conceived and designed the analysis, Collected the data, Review and revised the paper)

Winnink, J.J. (Collected the data)

Jong, S. (Review and revised the paper)

Abstract: This paper studies the relationship between the structure of corporate R&D collaboration networks and radical innovation, more specifically, 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 tie strength has a negative effect on innovation radicalness, and this negative effect is stronger when the 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 that structural holes have a negative effect on innovation radicalness when tie strength is weak but a positive effect when tie strength is strong. This suggests that strong ties are needed for mobilizing the informational advantages of structural holes.

Keywords: Collaboration network, Multinational R&D, Radical innovation, Tie strength, Structural hole

2.1 Introduction

Schumpeter (1942) considered firm innovation as the "fundamental impulse that sets and keeps the capitalist engine in motion" and coined the term "creative destruction" that "revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one." However, innovations vary in the degree of "destruction" that they bring, ranging from run-of-the-mill innovation that bring incremental changes to existing technologies to radical innovation that break from and make obsolete existing cognitive framework, technological trajectories, 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 has received much attention from innovation scholars. Prior studies have extensively investigated technological origins of radical innovation, as well as its economic implications for the innovating company and industry (Capponi et al., 2022; Rosenkopf & Nerkar, 2001; Schoenmakers & Duysters, 2010; Simms et al., 2021; Ukobitz & Faullant, 2022). These studies have contributed many insights for understanding radical innovation. However, we know relatively little about the social determinants of radical innovation in the organizational and social environment. In this paper, we explore how network structure affects radical innovation.

The creativity and social network literatures have long highlighted the importance of network structure for individual and organizational creative performance (Amabile, 1983; Drazin et al., 1999; Ford, 1996; Perry-Smith & Shalley, 2003; Perry-Smith & Shalley, 2014; Sosa, 2011; Woodman et al., 1993). Some researchers highlight the benefits of weak ties and structural holes, while others suggest advantages of strong ties and network cohesion for radical innovation (Ahuja, 2000a; Burt, 1992; Coleman, 1988; Fleming et al., 2007; Granovetter, 1973; Nahapiet & Ghoshal, 1998; Perry-Smith, 2006; Rost, 2011; Tortoriello & Krackhardt, 2010). In this paper, we separate two faces of weak ties and structural holes: their informational advantages in accessing the diverse knowledge that is needed for radical innovation, and their relational disadvantages linked to a weaker shared understanding and trust. In turn, the informational advantages of structural holes can be mobilized if there are strong ties for mitigating the relational disadvantages of structural holes. Similarly, network cohesion is needed for mobilizing informational

advantages of weak ties.

We study the network effect in the context of multinational corporations' internal R&D collaboration networks. Overseas R&D is playing an increasingly important role in the R&D networks of multinationals, and the competitiveness of the firm relies on its ability to coordinate its R&D activities across the globe (Alcácer & Zhao, 2012; Almeida & Phene, 2004; Belderbos et al., 2021; Du et al., 2022; Kuemmerle, 1997). While prior studies have systematically investigated drivers of R&D location decisions and strategies for coordinating subsidiaries, it has not yet studied how the network structure affects radical innovation at a particular R&D location.

Our study focuses on the 93 most innovative U.S. pharmaceuticals and biotechnology companies according to the EU Industrial R&D Investment Scoreboard. We track their patenting activities from 2001 and 2013. We construct their collaboration networks where nodes are locations of inventors and edges are co-patenting activities. We build a panel dataset consisting of 19,343 firm-location-year observations and fit fixed effect models to examine variations within firm-locations. We found (1) a negative effect of tie strength on radical innovation, (2) an insignificant effect of structural holes, and (3) a positive interaction effect between tie strength and structural holes.

The rest of this paper is organized as follows. In section 2, we review the literature on radical innovation and social networks. We also develop hypotheses concerning the effect of tie strength and structural holes on radical innovation. Section 3 provides a discussion of our data and methods. Using a panel dataset of observations from 2001 to 2013, we conduct empirical analyses to explore the relationship between network structures and radical innovation. In section 4, we present the results of our analyses. Implications and limitations of our findings are discussed in section 5.

2.2 Theory and hypotheses

2.2.1 Radical innovation

Interest in radical innovation dates back to Schumpeter (1934; 1942), who coined the term "creative destruction," a process that new innovation "revolutionizes the

economic structure from within, incessantly destroying the old one, incessantly creating a new one" (Schumpeter, 1942, p. 83). 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. Anderson and Tushman (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. Ahuja and Morris Lampert (2001)defined radical or breakthrough inventions as foundational inventions that serve as the basis for many subsequent technical developments. 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 shifting future inventors' attention away from the knowledge on which the focal patent builds. 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; Ukobitz & Faullant, 2022), and methods for adapting business models after disruption (Bourreau et al., 2012; Cozzolino et al., 2018; D'Ippolito et al., 2019; Simms et al., 2021). These studies have contributed many insights for understanding radical innovation. However, we know relatively little about the social determinants of radical innovation in the organizational and social environment. In particular, in the context of corporate R&D networks, how properties of collaboration network affect the likelihood of producing radical innovations. Answers to this question will help us to explain why radical innovation emerge in some place but not others, as well as informing innovation strategy about how to create a favorable collaboration network for radical innovation. This paper focuses on two network properties: tie strength and structural hole.

2.2.2 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 (Hansen, 1999; Messeni Petruzzelli et al., 2010; Reagans & McEvily, 2003; Tortoriello et al., 2012), and knowledge creation (Levin et al., 2011; McFadyen & Cannella Jr, 2004; McFadyen et al., 2009; Perry-Smith, 2006; Perry-Smith & Shalley, 2003; Perry-Smith & Shalley, 2014; Smith et al., 2005; Sosa, 2011; Tortoriello & Krackhardt, 2010; 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, 1996; 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 that one important source of novelty constitutes of new combinations of pre-existing knowledge components (Mednick, 1962; Nelson & Winter, 1982; Schumpeter, 1939). Accordingly, exposure to diverse knowledge provides opportunities for identifying new connections and generating novel ideas. This has the potential to destabilize existing technology trajectories. In addition, diverse knowledge enables a broader and 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, 2006; Perry-Smith & Shalley, 2003; Perry-Smith & Shalley, 2014; Zhou et al., 2009). For example, Perry-Smith and Shalley (2014) have shown 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 and we hypothesize that:

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

2.2.3 Informational advantage of structural hole for radical innovation

Different from tie strength, 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 contact networks that are rich in 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, p. 353). Studies have observed benefits of structural holes for career advancement (Burt, 1992; Seibert et al., 2001), generation of novel ideas (Burt, 2004; Fleming et al., 2007), and project performance (Soda et al., 2004; Zaheer & Soda, 2009). 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 knowledge.

Structural holes present informational advantages, more specifically, broader access to diverse knowledge, which is conducive to radical innovation. Prior studies have shown that information is unevenly spread and tends to be homogenous within communities (Burt, 1992; Burt, 2004). Considering the homophily tendency in network formation, that is, actors tend to develop relations with others like themselves (Burt, 1990; Burt, 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 and heterogeneity (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 knowledge 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; Burt, 2004). Knowledge gained through unlinked contacts tends to be additive rather than overlapping, and an actor who occupies a structural hole position has an advantage in being exposed to different information, knowledge, and perspectives from either side of the hole (Ahuja, 2000b; Burt, 1992; Gulati et al., 2000; Hargadon & Sutton, 1997). 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 with connections across structural holes can have early access to diverse 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 hypothesize that:

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

2.2.4 Relational disadvantage of weak tie and structural hole for radical innovation

While both weak ties and structural holes present informational advantages for radical innovation, they present challenges in mobilizing potential information resources. Accordingly, how tie strength and structural holes may affect innovation radicalness is not so straightforward. Both weak ties and structural holes are signifiers of low cognitive capital (i.e., shared codes, language, and narratives) and relational capital (i.e., trust, norms, obligations, and identification) (Nahapiet & Ghoshal, 1998), which present relational disadvantages for radical innovation. Without a common knowledge base between actors, actors may face cognition and

communication challenges in exchanging fine-grained information and tacit knowledge for creative process (Hansen, 1999; Reagans & McEvily, 2003; Uzzi, 1996, 1997; Wen et al., 2021). In addition, without a high level of mutual trust and shared norms between actors, actors may face higher of coordination costs and opportunistic behavior (Krackhardt et al., 2003; Lin & Ensel, 1989; Obstfeld, 2005; Podolny & Baron, 1997). In summary, while weak ties and structural holes provide access to more diverse knowledge, they present challenges in transferring and integrating this knowledge for producing 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; Hansen, 1999; Krackhardt et al., 2003; Reagans & McEvily, 2003; Uzzi, 1996, 1997). Empirical evidence has also been accumulated that strong ties facilitate the exchange of fine-grained information and in turn the creation of new 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; Perry-Smith, 2006; Perry-Smith & Shalley, 2003; 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 two faces: informational advantages on the one hand and relational disadvantages on the other hand. To further understand how these two competing mechanisms collectively affect innovation radicalness, we explore the interaction effect between tie strength and structural hole. More specifically, although an egocentric network rich in structural holes presents advantages in accessing diverse knowledge, such diverse knowledge can be mobilized and integrated for radical innovation if there are strong ties to compensate for the relational disadvantages of structural holes (Rost, 2011; Tortoriello &

Krackhardt, 2010). In other words, tie strength magnifies the positive effect structural holes on innovation radicalness. Similarly, actors with an egocentric network rich in weak ties have problems in translating knowledge advantages into radical innovation, and network cohesion can help to mitigate the relational disadvantages of weak ties. In other words, network cohesion increases the positive effect of weak ties on radical innovation. Taken together, we hypothesize that:

Hypothesis 3. There is a positive interaction effect between tie strength and structural holes on innovation radicalness.

2.3 Data and Methods

2.3.1 Data and sample

To test our hypotheses, we construct a unique panel dataset with information about firm R&D locations, their collaboration networks, and innovation outputs. We combine 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 restrict 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 (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) 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 & 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 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 are 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 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 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 & 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 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 use 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, so we use patent family according to the DOCDB definition (Martínez, 2011), instead of 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 moving time window. In other words, the location *i* at time point *t*, the variables are 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.

2.3.2 Variables

Dependent variables

Radicalness. To measure the radicalness of a patent family, we adopt the radicalness index proposed by Funk and Owen-Smith (2017), which captures the degree to which the focal patent destabilizes existing technology trajectories. Funk and Owen-Smith's measure is a second-order view of the impact that captures the extent to which subsequent inventions build on a technology also rely on that technology's prior arts. More specifically, the radicalness index examines 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. This measure makes it possible to distinguish between destabilizing and consolidating technologies that may have similar impact but very different consequences for existing trajectory. Employing the measure developed by Funk and Owen-Smith (2017), Wu et al. (2019) studied the relationship between team size and destabilizing/consolidating tendency of team product using data about patents, scientific papers, and software products. They found that small teams are inclined to destabilize science and technology, whereas large teams are more likely to consolidate existing ones. Balachandran and Hernandez (2018) divided firms' networks into foreign, domestic, and mixed triads according to whether the broker and its partners across institutional boundaries and investigated how institutions and networks jointly influence innovation. The result showed that foreign triads have a greater influence on radical innovation. Park et al. (2023) applied this measure to papers and patents and found that they are becoming less radical over time. Several studies have proposed similar measures as Funk and Owen-Smith's measure, following a network approach (Bu et al., 2021; Chen 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, we follow Funk and Owen-Smith's (2017) approach, *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.

Independent variables

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. We only consider direct ties but not indirect ties, because direct ties play a more direct and critical role in knowledge creation and transfer (McFadyen & Cannella Jr, 2004), which allow us to investigate the effect of collaboration networks on innovation radicalness. We also need to convert tie strength from the dyadic level to the network level. Following previous research, average network tie strength is used to indicate the overall tie strength in a focal location's egocentric network (Wang, 2016). In this way, tie strength at the network level is a simple aggregation of ties at the dyadic level. In this study, we operationalized tie strength (*tie strength*) as the number of co-inventing patent families in a 3-year moving time window. Specifically, we first count the number of co-inventing patent families between a focal location and its collaborating locations. Then we calculate the tie strength as

the average 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 of the absence of structural holes in the network. This simple formulation also has an advantage that it does not make assumptions about the behavior of actors in the network, 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 number of existing ties between alters divided by the number of all possible alter-alter ties. 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, in other words, the share of missing ties in an egocentric network excluding the ego itself. The range of structural hole is from 0 to 1. A higher value indicates a higher level of richness in structural holes.

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 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 also use a 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.

2.4 Result

2.4.1 Descriptive statistics

Table 2.1 reports descriptive statistics and spearman correlations for our variables in the panel dataset. *Radicalness* 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. We take the natural logarithmic transformation for *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 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=-0.04) and structural hole (r=-0.02) are negatively correlated with radicalness. It is important to interpret these correlations with caution as they do not account for any confounding variables. 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 -.79 with structural hole. 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 without controlling one of any of these controls.

Table 2.1: Descriptive statistics and correlations (*N*=19,343)

	Variable	Mean	S.D.	Min	Max	1	2	3	4	5
1	Radicalness	-0.01	0.06	-0.47	0.90					
2	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 $p < .05$

2.4.2 Regression results

To explore the relationship between network structure and innovation radicalness, we performed fixed-effects linear regressions, using *radicalness* as the dependent variable. For all regression models, we incorporate firm-location fixed effects and estimates within-firm-location effects. We also control for the set of control variables as discussed in the previous section.

Table 2.2 reports results of fixed effects linear models. Column 1 is a baseline model which only include control variables. We found that *innovation productivity*, i.e., the number of patent families, has a significantly positive effect on *radicalness*, suggesting that a location is more likely to produce radical innovation when it is more productive. *Network size*, i.e., the number of co-inventing locations, 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 observations are consistent with the expectation that radical innovation is more likely to come from the peripheral and isolated places in the network (Cattani & Ferriani, 2008).

Table 2.2: Fixed effects linear models: Network structure and innovation radicalness

	Radicalness			
	(1)	(2)	(3)	(4)
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)
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	19343	19343	19343	19343
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.

Column 2 adds tie strength into the regression model. *Tie strength* has a significantly negative effect on *radicalness*. 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 average tie strength of the egocentric network increases.

Column 3 further adds structural holes into the regression model. While the negative effect of tie strength remains significant, *structural hole* does not have a significant effect on *radicalness*, which does not support hypothesis 2 which states a positive effect of structural hole on innovation radicalness.

Column 4 further adds the interaction term between *tie strength* and *structural hole* into the regression. We observe a significantly positive interaction effect. This result supports hypothesis 3. More specifically, structural holes weaken the negative effect of tie strength, and tie strength magnifies the positive effect of structure holes. Note that when the interaction term between *tie strength* and *structural hole* is added, the coefficient of *tie strength (ln)* (i.e., -0.016) indicates the marginal effect of *tie*

strength (ln) on *radicalness* 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* when *tie strength (ln)* equals to 0, which is also the minimum value of *tie strength (ln)*. To facilitate the interpretation of the interaction effect, Figure 2.1A plots the marginal effects (i.e., regression coefficients) of *tie strength (ln)* at different levels of *structural hole*. It shows that when *structural hole* is relatively low, *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 translate into innovation advantages. On the other hand, when the network is rich in structural holes, the informational advantage of weak ties cannot be effectively mobilized, so that the negative effect of tie strength becomes smaller. Similarly, Figure 2.1B plots the marginal effects (i.e., regression coefficients) of *structural hole* at different levels of *tie strength*. It shows that when tie strength is relatively low, structural hole has a negative effect. However, as tie strength increases, the effect of structural hole increases and becomes significantly positive. This finding is also in line with the argument that, having strong ties is necessary for mobilizing informational advantages of structural holes for developing radical innovation.

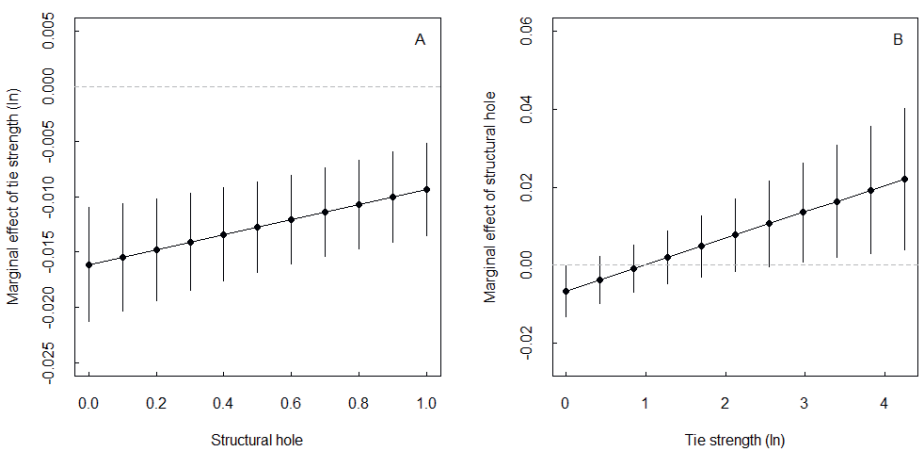

Figure 2.1: Tie strength, structural hole, and innovation radicalness. Points represent the regression coefficients, and vertical bars represent 90% confidence interval.

2.4.3 Robustness tests

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 up to 2019 (i.e., in PATSTAT 2019 Autumn version) without the fixed time window (Appendix Table A1).

Our regression analysis included innovation productivity, network size, and collaboration inclination as control variables, for the reasons discussed in the control variable section. 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. We tried to drop each of them as well as dropping them all together. Results are robust (Appendix Table A2).

2.5 Conclusion

In this study, we investigated the relationship between network structure and radical innovation in the context of corporate R&D networks. In terms of the network structure, we focused on the strength of ties and structural holes. We build a unique panel dataset consisting of 19,343 firm-location-time observations for 16,011 unique firm-locations belonging to 93 U.S. pharmaceuticals and biotechnology companies on the EU Industrial R&D Investment Scoreboard. We fitted fixed effects linear models to investigate within-firm-location effects. On the one hand, we found a significant negative effect of tie strength on innovation radicalness, confirming the informational advantages of weak ties for radical innovations. On the other hand, we do not observe a significant effect of structural hole. More importantly, we observe a significantly positive interaction effect between tie strength and structural hole on innovation radicalness. More specifically, the negative effect of tie strength is weaker when the network is rich in structural holes, and the effect of structural hole is negative when tie strength is weak but positive when tie strength is strong. This suggest that network cohesion is required for mobilizing the informational advantages of weak ties for radical innovation. Similarly, strong ties are needed for

mobilizing the informational advantages of structural holes.

This study has several limitations. First, patent data provide a useful data source for mapping collaboration networks and characterizing innovation radicalness, with the added advantage of avoiding the nonresponse biases that characterize surveys and interviews. However, it also has some disadvantages, which we cannot avoid. Many unimportant inventions fail to be patented, and some breakthroughs may be missed for 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 with varying degrees of radicalness. Future research adopting a broader set of innovation outputs would be valuable to expand beyond patents to other innovative outputs. Second, patent data do not provide direct information for measuring the underlying mechanisms posited by our hypotheses. Our theory separates two faces of weak ties and structural holes: their informational advantages and relational disadvantages, which however cannot be measured using patent data. Future research should address this issue and explore alternative data sources for a more direct test of the theory. Third, like most network studies, this study focuses on the structural aspect of the network but does not account for the characteristics of nodes or the content of things that are exchanged in the context of the tie. Future research should incorporate these aspects for a better and more complete understanding of the relationship between collaboration networks and radical innovation. Fourth, this study focused on the pharmaceutical and biotechnology industry, which may limit the generalizability of our findings to other industries. It is worthwhile for future research to investigate field contingence effects.

This paper makes theoretical contributions to several areas of research. First, it contributes to the social network literature, by proposing a two-faced view of network structures separating informational and relational aspects, and investigating the interaction between different network properties. This provides a promising direction for reconciling competing theories about network effects (Burt, 1992; Coleman, 1988; Granovetter, 1982; Granovetter, 1973; Uzzi, 1996, 1997). Our conceptual model and empirical findings acknowledge that the same network structure (i.e., weak tie, structural hole) may present both informational advantages and relational disadvantages at the same time. In addition, the informational advantages of weak ties can be mobilized if there are network cohesion to mitigate the relational disadvantages of weak ties. Similarly, the informational advantages of

structural hole can be mobilized if there are strong ties to mitigate the relational advantages of structural holes. Second, this study contributes to the radical innovation literature. Prior studies have extensively investigated the technological origin and economic consequences of radical innovation. This study explored the social determinants of radical innovation in the organizational and social environment. In particular, characteristic of collaboration networks. Third, this study contributes to the R&D location decisions literature, while prior studies have long investigated factor driving multinationals' overseas R&D location choices and strategies for coordinating subsidiaries (Alcácer & Zhao, 2012; Belderbos et al., 2021; Du et al., 2022; Kuemmerle, 1997; Lewin et al., 2009), this study explores how the structure of firm R&D networks affects its ability of producing radical innovation.

Our study also has important implications for innovating companies aspiring to develop radical innovation. Our findings suggest that having weak ties are generally more conducive for radical innovation, but it is especially beneficial when weak ties are accompanies by network cohesion. On the other hand, structural holes are beneficial for developing radical innovation if there are strong ties to mitigate its relational disadvantages.

CHAPTER 3

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

This Chapter is submitted as:

Zhang, J., Wang, J., Winnink, J.J., & Jong, S. Turning creative ideas into successful innovations: Differential effects of network structure for radical and incremental innovation.

Author contributions:

Zhang, J. (Conceived and designed the analysis, Performed the analysis, Wrote the paper)

Wang, J. (Conceived and designed the analysis, Collected the data, Review and revised the paper)

Winnink, J.J. (Collected the data)

Jong, S. (Review and revised the paper)

Abstract: This paper studies how the collaboration network structure of an innovation site (i.e., firm-location) affects the adoption and future use of its innovations. We investigate the effects of tie strength and network cohesion and more importantly the moderating effect of innovation radicalness. Prior studies have highlighted the advantages of strong ties and network cohesion for idea transfer and diffusion, due to their associated higher level of trust, fine-grained information exchange, and reciprocity norms. However, we argue that these effects are likely to be contingent on the radical nature of the innovation. More specifically, these effects might only hold for incremental innovation that consolidates existing technologies and aligned with reciprocity norms. These effects turn into negative when the innovation is radical and disrupts existing technologies, because the kind of impact that radical innovation brings to network partners is not aligned with reciprocity norms and therefore sanctioned by the network. In addition, the lack of information diversity also hinders the identification of new applications for radical innovations. Our empirical analysis is based on a unique panel dataset of 93 most innovative U.S. pharmaceuticals and biotechnology companies from 2001 to 2013, with a total number of 19,343 site-time observations. Our findings support our hypotheses and contribute to the literatures of social networks, creativity, and innovation. More specifically, the findings highlight that different types of innovations require different network conditions for diffusion, the reciprocity norms are not always beneficial but can become a burden, and non-redundant information is not only beneficial for generating novel ideas but also for identifying new applications for radical innovation. The findings also inform innovation management especially at geographically dispersed sites.

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

3.1 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 & Zhao, 2012; Almeida & Phene, 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 (Ozer & Zhang, 2019; 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, 1982; Uzzi, 1996, 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 & Mannucci; Reagans & McEvily, 2003; Tortoriello & Krackhardt, 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 & Benassi, 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.

3.2 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; Bharadwaj & Menon, 2000; Fleming et al., 2007; Lavie & Drori, 2012; Obstfeld, 2005; West, 2002). The prior literature has categorized various steps in the creative process (Csikszentmihalyi, 1997; Perry-Smith & Mannucci, 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.

3.2.1 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 & Telang, 2018; Gee et al.,

2017; Granovetter, 1995; Rajkumar et al., 2022), the generation of creative ideas (Perry-Smith, 2006; Perry-Smith & Shalley, 2014; Sosa, 2011) and innovation (Capaldo, 2007; Fredberg & Piller, 2011; Michelfelder & Kratzer, 2013; Rost, 2011), and effective knowledge transfer (Hansen, 1999; Levin & Cross, 2004; Reagans & McEvily, 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 & McEvily, 2003) and the concerns over opportunistic behavior reduced (Jarillo, 1988; Kachra & White, 2008; Levin & Cross, 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, 1982). In other words, "strong ties have greater motivation to be of assistance and are typically more easily available [than weak ties]"(Granovetter, 1982). 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 & Mannucci, 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 & Rebentisch, 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 and Clark (1990) defined radical innovation as innovation that disrupts both existing components and architecture. Anderson and Tushman (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 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. 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 and Benassi (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, 1982; Granovetter, 1973; Uzzi, 1996; 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). 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 & Shalley, 2003; Perry-Smith & Shalley, 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 & Winter, 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.

3.2.2 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, network cohesion is particularly relevant for idea implementation, knowledge transfer, and coordinated actions (Fleming et al., 2007; McEvily et al., 2003; Obstfeld, 2005; Tortoriello et al., 2012). For example, Uzzi and Spiro (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 and Zhang (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 & Fleming, 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 & Zhang, 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.*

3.3 Method

3.3.1 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 & Yang, 2016; 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) 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 & 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 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 & Grupp, 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.

3.3.2 Variables

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).

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 and Owen-Smith (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 and Hernandez (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.

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.

3.4 Result

3.4.1 Descriptive statistics

Descriptive statistics and Spearman correlations are reported in Table 3.1. 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 radicalness* 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 3.1: 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 $p < .05$.

3.4.2 Regression results

Table 3.2 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 3.2 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 3.2: 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 3.1 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.

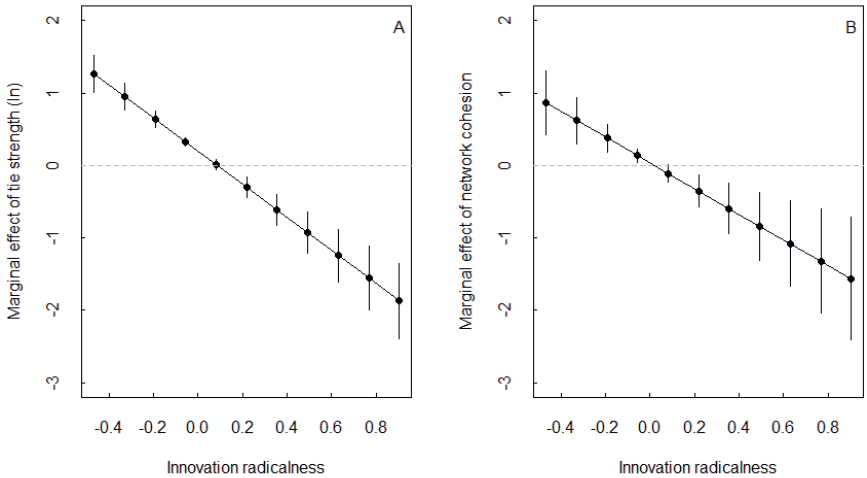

Figure 3.1: Tie strength, network cohesion, and innovation success. Points represent the regression coefficients, and vertical bars represent 90% confidence interval.

3.4.3 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 3.3 and marginal effects of tie strength and network cohesion at different levels of innovation radicalness are plotted in Figure 3.2. 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 3.3: 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. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

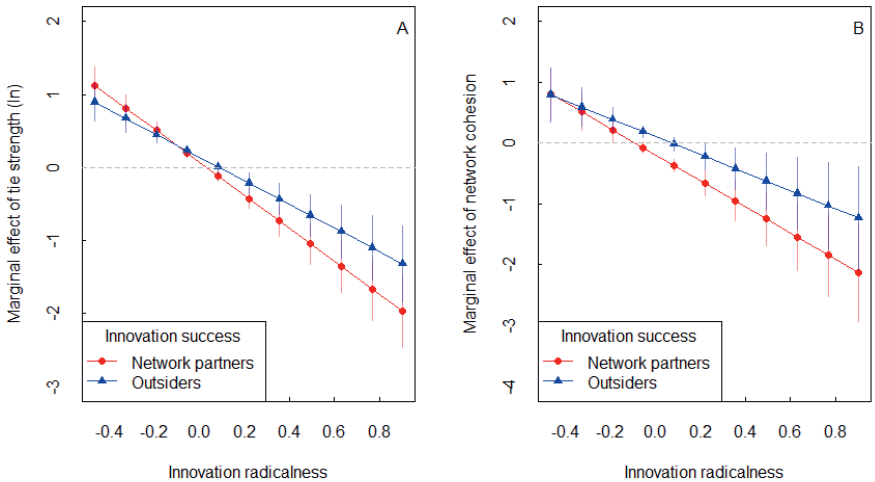

Figure 3.2: Separating adoption by network partners and outsiders. Points represent the regression coefficients, and vertical bars represent 90% confidence interval.

3.4.4 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 B1, Figure B1).

3.5 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. In addition, 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.

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 & Zhang, 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 & Mannucci; Reagans & McEvily, 2003; Tortoriello & Krackhardt, 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 attentions to how to bring other management interventions to magnify desirable underlying mechanisms and mitigate undesirable ones.

CHAPTER 4

Patent radicalness and private value: Unpacking destructiveness and dissimilarity effects

This Chapter is submitted as:

Zhang, J., Wang, J., & Jong, S. Patent radicalness and private value: Unpacking destructiveness and dissimilarity effects.

Author contributions:

Zhang, J. (Conceived and designed the analysis, Collected the data, Performed the analysis, Wrote the paper)

Wang, J. (Conceived and designed the analysis, Collected the data, Review and revised the paper)

Jong, S. (Review and revised the paper)

Abstract: Innovation is a key source of economic growth and firm competitiveness, but the economic impact of different innovations varies widely. In this paper, we study how the private value of a patent for the innovating firm is associated with its radicalness, differentiating between two dimensions of radicalness: destructiveness and dissimilarity. We argue that the private value is lower for patents that are more destructive to existing technology trajectories, because of their higher risk and uncertainty, longer road to profit, and incompatibility with existing firm capabilities. On the other hand, the private value is higher for patents that are more dissimilar to the exiting knowledge, due to the reception reward to novelty and ambiguity. Furthermore, dissimilarity makes it difficult for the market to understand the patented invention and therefore weakens the negative effect of destructiveness. These hypotheses are supported by a patent-level analysis of 1,066,637 USPTO granted patents.

Keywords: Patent; Radicalness; Destructiveness; Dissimilarity; Private value

4.1 Introduction

Studies of technological innovation have long distinguished between radical innovations that deviate from or obsolete existing technology trajectories and incremental innovations that only refine or improve existing technology trajectories (Dosi, 1982; Freeman, 1982; Henderson & Clark, 1990; Mansfield, 1968). Innovations vary in the degree of radicalness, which has important implications for not only innovation adoption and diffusion, but also firm organization and performance (Anderson & Tushman, 1990; Henderson, 1993; Henderson & Clark, 1990; Tushman & Anderson, 1986; Utterback, 1996). Scholars have extensively investigated the antecedents and consequences associated with these different innovation types (Ahuja & Morris Lampert, 2001; Arts et al., 2018; Arts et al., 2021; Bernal et al., 2019; Bourreau et al., 2012; Fazlıoğlu et al., 2019; Fleming, 2001; Funk & Owen-Smith, 2017; Kaplan & Vakili, 2015; Lopez-Vega & Moodysson, 2023; Schoenmakers & Duysters, 2010; Shane, 2001; Verhoeven et al., 2016). While many studies have focused on the social value of different types of innovations, namely the value for the whole economy and society, recent studies have explored how innovation radicalness is associated with private value for the innovating firm (Bartoloni & Baussola, 2018; Fitzgerald et al., 2021; Hirshleifer et al., 2013, 2018). Understanding the relation between innovation radicalness and private value is important for informing firm strategy as well as innovation policies. However, empirical evidence is mixed.

One obstacle in reconciling competing theories and empirical evidence regarding innovation radicalness pertains to the diverse approaches for conceptualizing and operationalizing it. This is also reflected in the diversity of used terminologies in the literature (e.g., radical, novel, explorative, destructive, disruptive, unfamiliar, dissimilar) and measurement approaches (see Verhoeven et al. (2016) and Arts et al. (2021) for an overview).

In this paper, we differentiate between two important dimensions of innovation radicalness: destructiveness and dissimilarity. Destructiveness is about the degree to which a patented invention disrupts existing technology trajectories. Dissimilarity is about the degree to which a patented invention is dissimilar to existing knowledge. While destructiveness has important implications for firm performance, dissimilarity leads to perception biases in the valuation and diffusion processes in the marketplace.

We argue that destructive patents have a low private value for the innovating firm, because such patents are associated with higher risks and uncertainties, a longer road to profit, and incompatibility with existing firm capabilities. In contrast, dissimilar patents have a high private value because the market, when valuating technological innovation, has a preference for novelty and ambiguity in the cognition process. Furthermore, dissimilarity makes it more difficult for the market to understand information encoded in patents and in turn weakens the negative effect of destructiveness. These hypotheses are supported by our empirical analysis of 1,066,637 USPTO granted utility patents.

The contributions of this paper expand the literature on radical innovation. We highlight the importance of unpacking different dimensions of innovation radicalness (i.e., destructiveness and dissimilarity), which have distinct effects. Unpacking innovation radicalness also provides a useful approach for making sense of the diverse and sometimes competing theories and evidence about radical innovation.

The remainder of the paper is structured as follows. In section 2, we develop hypotheses concerning the effect of destructiveness and dissimilarity on private value, building on the literature on creative destruction and categorical theory. In section 3, we describe our sample, the variables, and the analyses we will conduct. In section 4, we present the results of descriptive statistical analysis, OLS regression, and quantile regression. In section 5, we discuss the implications of these findings and draw conclusions.

4.2 Theory and hypotheses

Firm innovation is considered the "fundamental impulse that sets and keeps the capitalist engine in motion" (Schumpeter, 1942). However, innovations come in different types, ranging from radical ones that are new and bring revolutionary changes to incremental ones that bring small improvements on existing technologies. Despite the rising interest in radical innovation, it remains an abstract and complex concept, easy to intuit but hard to define (Arts et al., 2021; Kaplan & Vakili, 2015; Verhoeven et al., 2016).

Radicalness is a multidimensional construct. For example, Dahlin and Behrens (2005) emphasized three defining features of radical innovation: novel, unique, and having a major impact on future technology. Verhoeven et al. (2016) distinguished between the ex ante and ex post characteristics of radical innovation, where the former is about being new or novel while the latter is about destructive impact. Different prior studies of radical innovation have focused on different aspects. Some have emphasized radical innovation as something that disrupts existing technology trajectories and accordingly has significant economic implications (Anderson & Tushman, 1990; Dosi, 1982; Henderson, 1993; Henderson & Clark, 1990; Martínez-Ros & Orfila-Sintes, 2009; Simms et al., 2021; Tushman & Anderson, 1986; Utterback, 1996; Verhoeven et al., 2016). Others have stressed radical innovation as something that is dissimilar to existing knowledge and accordingly faces perception penalties or rewards in its valuation and diffusion processes (Ferguson & Carnabuci, 2017; Kaplan & Tripsas, 2008; Kovacs et al., 2021; Polidoro, 2020; Rosenkopf & Nerkar, 2001). In this paper, we separate these two aspects and theorize their different effects on the private value of the innovation for the innovating company.

The literature on radical innovation spans several disciplines and uses inconsistent terminologies (i.e., sometimes use different terms for the same thing, while other times use the same term for different things), adding to the difficulty in making sense of seemingly competing theories and evidence in the literature. In this paper, we use more generic terms to label the two aspects of radical innovation to avoid confusion with other often-used terms. We label the ex post destructive characteristic of radical

innovation as *destructiveness*[1] and the ex ante novel characteristic as *dissimilarity*[2].

4.2.1 Destructiveness and private value

One strand of literature on radical innovation focuses on the extent to which a technological innovation disrupts existing cognitive frameworks, technological trajectories, and organizational processes (Anderson & Tushman, 1990; Dosi, 1982; Henderson, 1993; Henderson & Clark, 1990; Martínez-Ros & Orfila-Sintes, 2009; Simms et al., 2021; Tushman & Anderson, 1986; Utterback, 1996; Verhoeven et al., 2016). Schumpeter (1942) coined the term "creative destruction" that "revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one." Later studies have further differentiated innovation on a spectrum of varying degrees of destructiveness. On the one end, incremental innovations introduce minor changes to a current technology trajectory and enhance existing knowledge structures. On the other end, destructive innovations challenge existing ways of thinking and make incumbent technology

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[1] Some researchers might prefer the term "radicalness," especially the radical innovation scholars who focus on its ex post destructive impact. For example, Balachandran, S., & Hernandez, E. (2018). Networks and innovation: Accounting for structural and institutional sources of recombination in brokerage triads. *Organization Science*, *29*(1), 80-99. adopted the same measure as ours but labelled it as "radicalness." Some researchers might prefer the term "disruptiveness," as most studies adopting the same measure refer to it as "disruptiveness." However, "disruptive innovation" is a well-established term coined by Bower, J. L., & Christensen, C. M. (1995). Disruptive technologies: catching the wave. with two defining features: "First, they typically present a different package of performance attributes - ones that, at least at the outset, are not valued by existing customers. Second, the performance attributes that existing customers do value improve at such a rapid rate that the new technology can later invade those established markets." They are "usually not radically new or difficult from a technological point of view." The term of "disruptive innovation" has also been used in the literature broadly and inconsistently Si, S., & Chen, H. (2020). A literature review of disruptive innovation: What it is, how it works and where it goes. *Journal of Engineering and Technology Management*, *56*, 101568. https://doi.org/https://doi.org/10.1016/j.jengtecman.2020.101568 . Therefore, we use the more generic term "destructiveness."

[2] "Dissimilarity" in this paper has the same meaning as "novelty" in Dahlin, K. B., & Behrens, D. M. (2005). When is an invention really radical? Defining and measuring technological radicalness. *Research Policy*, *34*(5), 717-737. and Verhoeven, D., Bakker, J., & Veugelers, R. (2016). Measuring technological novelty with patent-based indicators. Ibid., *45*(3), 707-723. https://doi.org/10.1016/j.respol.2015.11.010 . However, "novelty" is also a complex concept and debated in the literature. We use the more generic term "dissimilarity."

obsolete (Chen et al., 2021; Funk & Owen-Smith, 2017; Trajtenberg et al., 1997).

Destructive innovation has been the subject of wide-ranging scholarly enquiries. Scholars have defined the destructiveness of inventions in terms of its profound impact on subsequent technological development. Previous studies have distinguished between competence-enhancing and competence-destroying (Anderson & Tushman, 1990), technology-consolidating and technology-destabilizing (Chen et al., 2021; Funk & Owen-Smith, 2017), sustaining and destructive (Christensen, 2013), and paradigm-deepening and paradigm-changing inventions (Ahuja et al., 2014; Dosi, 1982). Destructive inventions are defined as challenging the existing trajectories or paradigm (Anderson & Tushman, 1990; Chen et al., 2021; Funk & Owen-Smith, 2017). In this paper we follow this stream of literature and use the concept of destructiveness as describing the extent, to which new inventions consolidate or destabilize existing technology streams and shift inventors' attention away from the knowledge, on which inventions build.

Prior research has investigated how destructive innovation may impact firm performance (Anderson & Tushman, 1990; Henderson, 1993; Henderson & Clark, 1990; Tushman & Anderson, 1986; Utterback, 1996). Building on this literature, we focus on the private value of a technological innovation for the innovating firm and argue that destructive innovations have a lower private value for three reasons. First, destructive innovation is associated with high risks (Martĺnez-Ros & Orfila-Sintes, 2009). Destructive innovations are more likely to lead to high-performing breakthroughs, but at the same time are more likely to fail (Fleming, 2001; Singh & Fleming, 2010). Furthermore, destructive innovations also face a high level of unresolvable uncertainty or ambiguity (Simms et al., 2021; Ukobitz & Faullant, 2022). In other words, it is difficult for the innovating firm or the market to assign probabilities of success or failure for a destructive innovation ex ante (Shleifer & Vishny, 1997). Prior literature has found that individuals tend to be ambiguity-averse and discount uncertain outcomes (Fox & Tversky, 1995). Accordingly, due to the high level of risk and uncertainty associated with destructive innovations, we expect such innovations to be of lower private value for the innovating firm, compared with incremental innovations.

Second, the trajectory towards profitability tends to be longer for destructive innovations than incremental ones. Ideas that challenge existing status quo may a

longer time to take off as these ideas require more follow-on research and development to realize their potential (Pezzoni et al., 2022; Wang et al., 2017). In addition to further technological development, capitalizing on destructive innovations requires a longer process of investments and accumulation of new skills and knowledge because destructive innovation "destroys" firms' existing competences (Anderson & Tushman, 1990; Simms et al., 2021; Tushman & Anderson, 1986; Utterback, 1996). Accordingly, we expect the delay in realizing the potential of a destructive innovation to contribute to its lower private value for the innovating firm.

Third, destructive innovations render existing competences obsolete (Henderson, 1993; Simms et al., 2021). Further developing destructive innovations requires new competences and routines that are distinct from a firms' existing ones. The innovating firm may fail in adopting the destructive innovation due to the incompatibility between the new destructive technology and the firm's existing competences and structures (Clark, 1987; Henderson & Clark, 1990). Therefore, even if the destructive innovation is promising and has a high social value (for the whole economy), the innovating firm might not be the firm to reap the rewards. In other words, while other firms, especially competitors and new entrants, might benefit from a destructive innovation, such an innovation often has a lower private value for the innovating firm due to its incompatibility with the innovating firm's existing competences.

Taken together, we hypothesize the following about the impact of an invention's destructiveness on the private value of this invention for the innovating firm.

> *Hypothesis 1: The destructiveness of a patent is negatively associated with its private value for the innovating firm.*

4.2.2 Dissimilarity and private value

The other defining feature of radical innovation emphasized in the literature is the extent to which an innovation output is new, dissimilar to existing knowledge, or unfamiliar to the audience. The degree of dissimilarity affects human cognition and therefore brings (positive or negative) reception biases in the process of innovation

adoption or valuation. It is important to note that the dissimilarity of a technological innovation affects its private value for the innovating firm through very different mechanisms than that of destructiveness. More specifically, while destructiveness affects the true economic value of a technological innovation, dissimilarity biases the perceived value of a technological innovation.

How different audiences perceive and respond to certain products that are similar or dissimilar to those categorizing a certain market has been a central focus of the literature on classification systems in markets. According to this literature, classifications of existing activities provide an important low-effort mechanism for economic actors to make sense of complex social situations (e.g. Rosch, 1978). As the audience relies on established categories to identify and evaluate innovations, innovations that do not fit existing classification systems are confusing to the audience and subsequently face perception penalties (Zuckerman, 1999; Hsu et al., 2009; Zuckerman, 2003). Similarly, technological innovations that are dissimilar to existing technologies are likely to faces such perception penalties because they do not fit existing cognition frameworks and are difficult for the audience to comprehend.

However, an important distinction that is used to describe how different audiences respond to innovations that are dissimilar to existing activities categorizing a field, is the distinction between *market-takers* and *market-makers* (Pontikes, 2012). Market-takers rely on established categories to find or evaluate goods. Products or services that are more dissimilar are less appealing to market-takers that typically search for specific products or services and may employ evaluation criteria used for already existing products or services in assessing the value of innovations. Accordingly, market-takers discount innovations that are dissimilar to existing ones (Hsu, 2006; Hsu et al., 2009; Zuckerman, 1999).

In contrast, market-makers have an interest in innovations that can give rise to new markets. Market-makers include venture capitalists and investors who generally prefer innovations that are dissimilar from existing activities categorizing a field. Such innovations expand on the existing knowledge landscape and offer market-makers the prospect of novel offerings that open up new markets. Market-makers also value the ambiguity of dissimilar innovations. Dissimilar innovations potentially allow organizations to be more flexible and “multivocal” in appealing to

more, different constituencies. Such appeal across different constituencies is of key value to organizations trying to construct novel fields under conditions of uncertainty (Padgett & Ansell, 1993). Leahey et al. (2017) highlight how market-makers differentially value innovations in the scientific realm. Their findings indicate that interdisciplinary studies are more highly cited by researchers. While Hirshleifer et al. (2018) find that the stock market undervalues firms engaging in innovation that is more *original* (i.e., citing more technology classes), Fitzgerald et al. (2021) observe that firms developing *unfamiliar explorative* patents (i.e., citing technology classes that are new to the firm) are relatively overvalued.

Taken together, we expect the market to respond more favorably to innovations that are more dissimilar from existing knowledge in a field and hypothesize that,

> *Hypothesis 2: The dissimilarity of a patent is positively associated with its private value for the innovating firm.*

4.2.3 Moderating effect of dissimilarity

Furthermore, dissimilarity is likely to moderate the negative effect of destructiveness on its private value. More specifically, for patents that are more dissimilar to existing knowledge, it is harder for the market to understand the new technology and recognize its destructive nature. According to sociological theory on the use of categories, products that do not fit existing classification systems are confusing to the audience and subsequently face perception penalties (Hsu et al., 2009; Zuckerman, 1999; Zuckerman et al., 2003). Information encoded in patents is complex, and it is challenging for investors to assess innovation disclosed in patents and its economic implications for firm value (Cohen et al., 2013; Hirshleifer et al., 2013, 2018). We expect this complexity to be enhanced for inventions that are more dissimilar to the pre-exiting knowledge base. Accordingly, while we have argued that the market is likely to respond positively to dissimilar inventions, we expect that a higher level of dissimilarity makes it more difficult for the market to ascertain the extent to which an invention is destructive. When an innovation is dissimilar from existing knowledge, it is harder for the market to understand its nature and assess its impact, including its potential of destructing existing technology trajectories. When the market has an impended ability to make an assessment, then we expect their

negative response also to be mitigated. Therefore, we hypothesize that,

Hypothesis 3: The dissimilarity of a patent mitigates the negative association between destructiveness and its private value for the innovating firm.

4.3 Method and data

4.3.1 Data

To test our hypotheses, we integrate several datasets. We start from a dataset developed by Kogan et al. (2017) which covers granted USPTO utility patents up to 2010. Kogan et al. (2017) linked patent data to time series of stock prices and estimated the market value in millions of US dollars of each patent as the stock reaction to the event of the patent being granted by the USPTO. We link these patents to the PATSTAT (2019 Autumn Edition) database to retrieve citation links within USPTO for constructing the destructiveness measure. We also merge this dataset with the patent dataset developed by Arts et al. (2021), which extracted and cleaned keywords from patent title and abstracts, for measuring the dissimilarity of patents. In total, our sample covers 1,066,637 USPTO utility patents that were granted between 1980 and 2010.

4.3.2 Measures

Dependent variable

Private Value. The private value of each patent is retrieved from the patent dataset developed by Kogan et al. (2017). Kogan et al. (2017) linked patents to time series of firm stock prices, and estimated the private market value of each patent as the abnormal stock market return (in millions of US dollars) of the inventing company within a three-day window around the event that the patent is granted by the USPTO. Literature shows that a narrow time window is appropriate for capturing the private value of patents, since the increase in abnormal share turnover usually happens in the first two days after the announcement (Kogan et al., 2017). In addition, extending the time window may further introduce noises due to other events or influences. We use this estimated market value as our dependent variable, *private value*.

Independent variables

Destructiveness. For destructiveness we adopt the consolidating-destabilizing (CD) index proposed by Funk and Owen-Smith (2017). More specifically, this destructiveness measure examines whether patents citing a focal patent also cite 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 "disrupting" existing technology trajectories. For operationalization, the destructiveness measure retrieves all future patents that cite the focal patent or its referenced patents. Each citing patent is given a score: 1 if it cites the focal patent but not any patents referenced by the focal patent, -1 if it cites the focal patent and at least one of the patents referenced by the focal patent, and 0 if it does not cite the focal patent but does cite at least one of the patents referenced by the focal patent. The final destructiveness measure of a patent is a ratio, where the numerator is the sum of the scores across all the citing patents, and the denominator is the total number of these citing patents. This measure ranges between -1 (all the patents that cite the focal patent share some references with the focal patent, maximum consolidating) and 1 (none of the patents that cite the focal patent share any references with the focal patent, maximum destabilizing). For constructing this measure, we track all citation links between USPTO patents that are recorded in the PATSTAT 2019 Autumn edition. All future citing patents up to 2019 are considered. For a robustness test, we also use a fixed 5-year citation time window for calculating destructiveness, where only future citing patent within 5 years after the grant date of the focal patent are taken into account. Results are robust.

Dissimilarity. Following Arts et al. (2021), we measure the dissimilarity of a patent based on text similarity between a patent and all prior patents filed in the five years before the focal patents. More specifically, we retrieve all patent keywords for each patent, and then calculate the text similarity between a pair of patents as the cosine similarity between their vectors of keywords. At the patent level, we take the average cosine similarity between a focal patent and all prior patents filed in the five years before the focal patent. Since the cosine score is about similarity, which is the opposite to being dissimilar, we transform the measure by subtracting it from 1. The final variable, *dissimilarity*, ranges from 0 (i.e., perfect overlap in keywords between the focal patent and prior patents; maximum similarity) to 1 (i.e., no overlap in

keywords at all; maximum dissimilarity). We also tried alterative measures such as the share of new keywords or new keyword pairs that never occurred before, and obtained robust results.

Control variables

For regression analysis, we adopt the model specification from Kogan et al. (2017) and Poege (2019). More specifically, we control for several variables that are potential confounders. There are important differences between technology fields and years, to account for these differences, we incorporate technology class-grant year pair-level fixed effects, to absorb variation across fields and year dimensions, following prior studies. We control for the number of patent references, as building on the broader set of prior technologies might lead to higher economic value on the one hand and higher or lower destructiveness and dissimilarity on the other. For the same reason, we control for the number of patent citations. However, it is unclear whether patent citations should be controlled for as this variable goes longer into the future than the Private Value variable, and is oftentimes used as a measure of patent value by itself (Hall et al., 2005; Harhoff et al., 2003). Therefore, we also tested the robustness of our results without controlling patent citation and obtained consistent results.

4.4 Results

4.4.1 Descriptive statistics and nonparametric analysis

Descriptive statistics and correlations are reported in Table 4.1. The average *private value* of our sampled patents is 23.974 million US dollars, and the distribution of *private value* is highly skewed, so that we take natural logarithm transformation for correlation and regression analysis. *Destructiveness* ranges between -0.958 and 0.997, while the maximum possible range is between -1 and 1. *Dissimilarity* ranges from 0.895 and 1, which is relatively high considering that the maximum possible range is between 0 and 1. This is understandable, as one important criterion of patentability is novelty in the sense of being different from prior art. Nevertheless, there is still variance in dissimilarity across patents for analysis. We observe that patent *private value* is negatively correlated with *destructiveness* (r = -0.092) but positively correlated with *dissimilarity* (r =0.161). Correlations among independent

variables are all moderate, so we are not worried about multicollinearity, except that the correlation between *destructiveness* and *citations* is relatively high (r = -0.399). Together with the reasons discussed in the control variables subsection, we added a robustness check to run regressions without controlling for patent citations and obtained consistent results.

Table 4.1: Descriptive statistics and correlations (*N* = 1,066,637)

	Variable	Mean	S.D.	Min	Max	1	2	3	4
1	Private value (m$)	23.974	73.778	0.000	6208.359				
2	Destructiveness	0.063	0.140	-0.958	0.997	-0.092			
3	Dissimilarity	0.967	0.012	0.895	1.000	0.161	-0.037		
4	Citations	13.815	16.985	1.000	119.000	0.121	-0.399	0.018	
5	References	29.400	54.785	1.000	5537.000	0.141	0.147	0.004	0.128

Note. Private value, Citations and References take natural logarithm transformation before calculating correlations.

Before reporting regression results, we first use a non-parametric approach to analyze the data. To account for differences across fields and years, as well as to accommodate the skewness in the dependent variable, we first transform *private value* into an ordinal ranking variable, *private value rank*. More specifically, within each technology class and grant year pair, we rank patents by their *private value*, where a patent with the lowest *private value* is ranked as 0, and the one with the median *private value* is ranked as 0.5, and the one with the highest *private value* is ranked as 1. The resulting *private value rank* variable follows a uniform distribution. For our focal independent variable *destructiveness*, we partition patents into five quintiles, where the first quintile consists of patents with the lowest 20% destructiveness scores within each technology class and grant year pair, and the fifth quintile consists of patents with the highest 20% destructiveness scores within the same technology class and grant year. We do the same for *dissimilarity*. Figure 4.1 shows the distribution of *private value rank* by *destructiveness* and *dissimilarity* quintiles. The third quintile consists of the 20% patents with middle *destructiveness* scores, within this quintile of patents, the distribution of *private value rank* largely resembles a uniform distribution. When destructiveness is lower (i.e., the first and second quintile), the share of patents with high private value increases while the share of patents with low private value decreases, suggesting an advantage in private value for less destructive patents. A consistent pattern is observed when destructiveness is higher (i.e., moving to the fourth and fifth quintile). Furthermore, we observe a bipolar distribution of *private value rank* among the patents in the fifth quintile of *destructiveness*. In other words, when *destructiveness* is very high, patents are more likely to have very low or very high private value but relatively less likely to be in the middle. This is consistent with the higher level of risk and uncertainty associated with highly destructive inventions. Regarding *dissimilarity*, we observe that as *dissimilarity* increases, the mass of patents shifts from low private value to high private value.

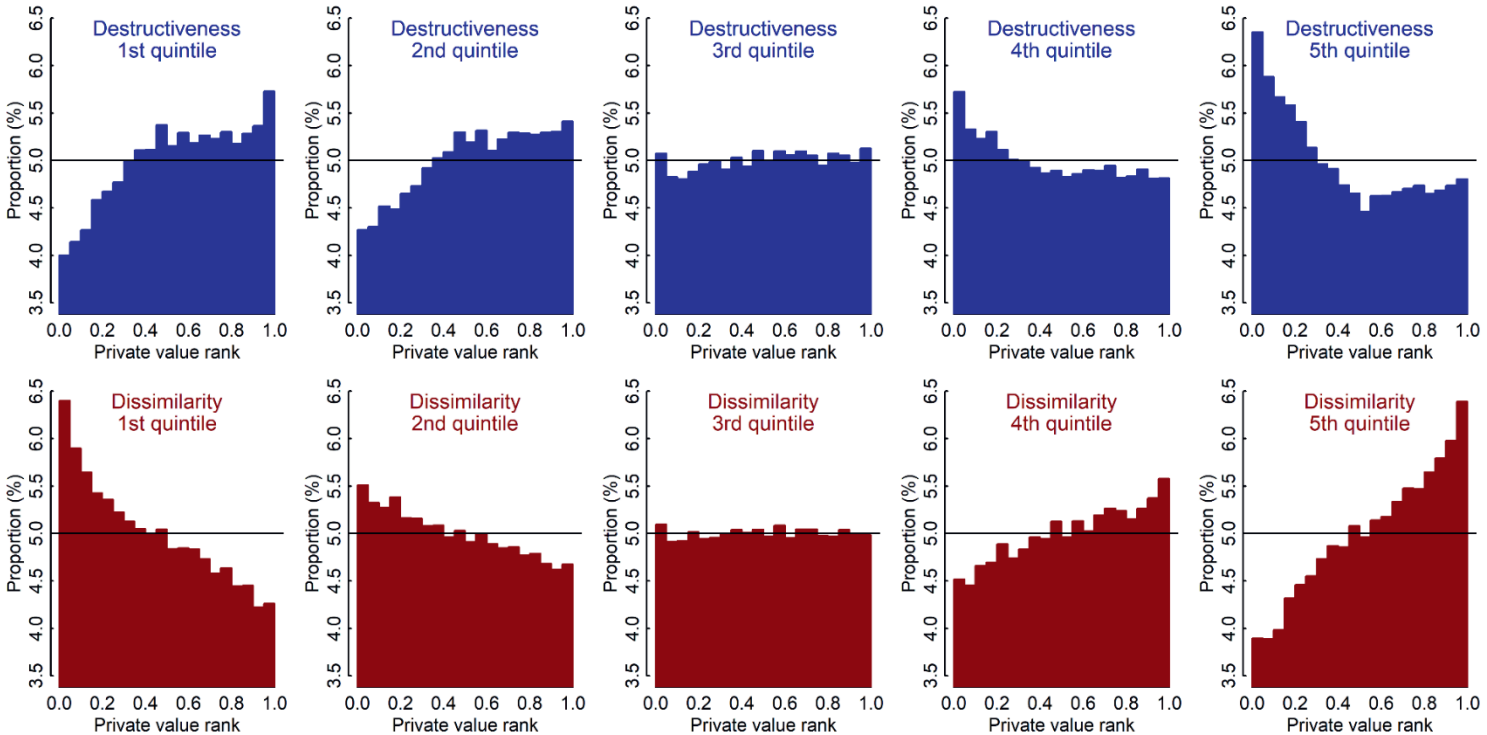

Figure 4.1: Distribution of private value by destructiveness and dissimilarity quintiles.

4.4.2 Regression results

We run regression analysis to test the effect of *destructiveness* and *dissimilarity* on *private value*, at the patent level, controlling for the number of citations, references, and technology class-grant year pair-level fixed effects. The dependent variable is skewed, and we take its natural logarithm and run OLS regressions. To facilitate comparing effect sizes of *destructiveness* and *dissimilarity,* these two variables are standardized for regression. Thus, the coefficient represents the change in the dependent variable as *destructiveness* or *dissimilarity* increases by 1 standard deviation. Number of citations and references also take natural logarithm transformation, following standard practice.

Regression results are reported in Table 4.2. Model (1) focuses on the effect of destructiveness without controlling for dissimilarity. Comparing patents in the same technology class and year, and with the same number of references and citations, when the destructiveness of a patent increases by 1 standard deviation, patent private value decreases by 14.3%, which is an economically sizable change. Model (2) suggests that 1 standard deviation increase in patent dissimilarity is associated with 19.6% increase in patent private value. Model (3) analyzes destructiveness and dissimilarity, and the size of coefficients is comparable to Model (1) and (2) when analyzing them separately. Therefore, both Hypothesis 1 and 2 are supported by the empirical analysis.

Table 4.2: Destructiveness, dissimilarity, and private value

	ln(Private value) OLS			
	(1)	(2)	(3)	(4)
Destructiveness	-0.143***		-0.140***	-0.141***
	(0.004)		(0.004)	(0.004)
Dissimilarity		0.196***	0.193***	0.193***
		(0.006)	(0.006)	(0.006)
Dissimilarity * Destructiveness				0.023***
				(0.003)
ln(References)	0.082***	0.153***	0.092***	0.091***
	(0.006)	(0.006)	(0.006)	(0.006)
ln(Citations)	0.237***	0.209***	0.235***	0.235***
	(0.005)	(0.004)	(0.005)	(0.005)
Patent class * Year fixed effects	Y	Y	Y	Y
N	1066637	1066637	1066637	1066637
R-square	0.204	0.206	0.209	0.209

Note. Destructiveness and dissimilarity are standardized. Robust standard error clustered at patent class * year level in paratheses. *** p<.001, ** p<.01, * p<.05.

In Table 4.2 Model (4) we further interact destructiveness and dissimilarity. Results show a significantly positive interaction effect. This means, as dissimilarity increases, the negative effect of destructiveness on patent private value shrinks. To better understand the moderating effect of dissimilarity, we plot the marginal effect (i.e., coefficient) of destructiveness at different levels of dissimilarity (Figure 4.2A). As shown in Figure 4.2A, as dissimilarity increases, the effect of destructiveness remains negative but the effect size is smaller. This supports Hypothesis 3.

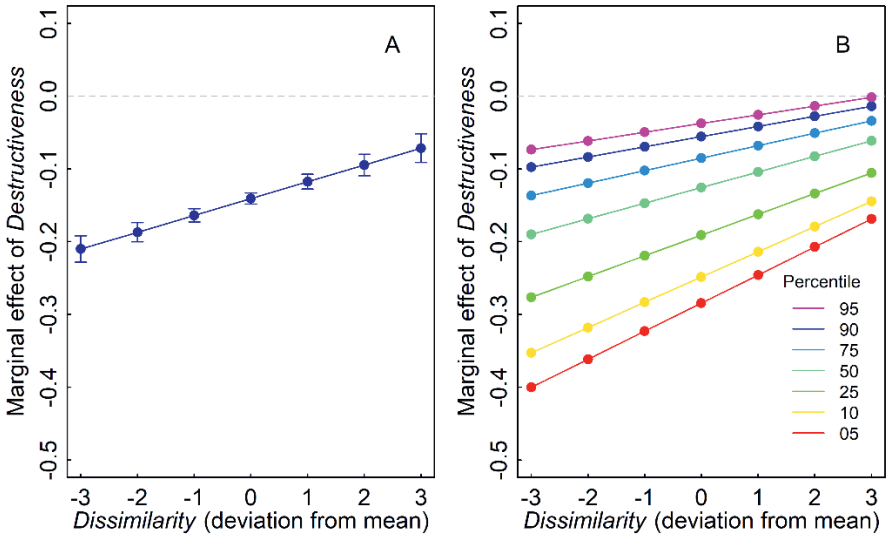

Figure 4.2: Dissimilarity moderates the effect of destructiveness on private value.

OLS estimates effects on the mean of *ln*(*private value*), we further investigate potential differences in effects at different percentiles *private value*. It is possible that as *destructiveness* increases, patents are more likely to have very low or high private value but less likely to have median private value. Then we should observe a positive effect at low and high quantiles of the dependent variable, but negative effects at median quantiles. Quantile regressions use the same model specification as OLS regression (control variables and variable transformations) but model different quantiles of the dependent variable instead of the mean. Considering the heterogeneity of innovation returns, quantile regression can be used to explore a more complete picture of the radicalness-market response relationship, which may provide us new sights to understand the relationship between destructiveness, dissimilarity, and private value. Results are reported in Table 4.3. Results suggest consistent negative effect of destructiveness across all quantiles of private value. The size of the coefficient is larger at lower quantiles than higher quantiles, and this should be interpreted with great caution. Decrease by 28.4% is much more substantial than decrease by 3.8%. However, the 5th percentile of private value is 0.0463 and the 95th percentile is 93.954. Then a 28.4% decrease at the 5th percentile and 3.8% decrease at the 95th percentile correspond to a drop of 0.013 and 3.570 million US dollars. Therefore, depending on the criterion (size of change in percentages or absolute values), the conclusion about whether the effect size is larger at low or high quantiles can be opposite. Therefore, we only conclude from this set

of results that there is a consistently positive effect of dissimilarity on private value. Similarly, we also observe a consistently negative effect of destructiveness, and a consistently positive interaction effect between dissimilarity and destructiveness (Figure 4.2B). In summary, the quantile regression results do not provide evidence that the effects are qualitatively different at different quantiles of private value.

Table 4.3: Destructiveness, dissimilarity, and private value: Quantile regression

	ln(Private value) Quantile regression						
	$\tau = 0.05$	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$	$\tau = 0.95$
Destructiveness	-0.284***	-0.249***	-0.191***	-0.126***	-0.085***	-0.056***	-0.038**
	(0.042)	(0.035)	(0.022)	(0.009)	(0.003)	(0.007)	(0.011)
Dissimilarity	0.317***	0.286***	0.236***	0.180***	0.145***	0.120***	0.104***
	(0.041)	(0.034)	(0.022)	(0.008)	(0.003)	(0.007)	(0.011)
Dissimilarity * Destructiveness	0.039	0.035	0.028	0.021**	0.017***	0.014*	0.012
	(0.037)	(0.030)	(0.019)	(0.007)	(0.002)	(0.006)	(0.010)
ln(References)	0.238***	0.201***	0.142***	0.076***	0.034***	0.004	-0.014
	(0.044)	(0.036)	(0.023)	(0.009)	(0.003)	(0.008)	(0.012)
ln(Citations)	0.440***	0.389***	0.307***	0.214***	0.156***	0.114***	0.088***
	(0.033)	(0.027)	(0.017)	(0.007)	(0.002)	(0.006)	(0.009)
Patent class * Year fixed effects	Y	Y	Y	Y	Y	Y	Y
N	1066637	1066637	1066637	1066637	1066637	1066637	1066637

Note. Dissimilarity and destructiveness are standardized. Robust standard error clustered at patent class * year level in paratheses. *** p<.001, ** p<.01, * p<.05.

4.4.3 Robustness tests

We run a set of further analyses to test the robustness of our results. First, we drop the number of citations as a control variable in regression analysis. This is partly due to the multilinearity concerns warned by the high correlation between destructiveness and citations. Furthermore, whether citation count is a confounder in this setting is unclear. Some might argue that citations capture the technological merit of the invention, which affects both radicalness (i.e., destructiveness and dissimilarity) and private value. Some might think that radicalness affects citations which in turn affects private value. Others might think that citation count is another measure of patent value similar as the dependent variable itself. For the reported main results, we choose to control for citations so that we can have a stricter estimation of the effects of destructiveness and dissimilarity when comparing patents with the same number of citations. For a robustness test we use a more relaxed approach and not control for citations. Results are robust (Appendix Table C1).

Second, we use a fixed 5-year time window for counting forward citations and calculating the destructiveness. The reported main results use all forward citing patents up to 2019, and patents in different years have different number of years for accumulating citations, which is accounted by incorporating patent year fixed effects. Nevertheless, we test whether using a shorter and fixed citation time window would lead to the same results. Results are robust (Appendix Table C2), and effect sizes are comparable.

Third, we test an alternative formulation of the destructiveness measure. More specifically, building on the network betweenness centrality concept, Shibayama and Wang (2020) proposed an originality measure for individual scientific publications to capture the degree to which a scientific discovery provides subsequent studies with unique knowledge that is not available from previous studies. It is operationalized as the share of missing ties in the network consisting of the focal patents and all its citing and cited patents, where a tie is a citation link. We adopt this measure for patents and obtain robust results (Appendix Table C3).

Fourth, we also test alternative measures of dissimilarity. Following Arts et al. (2021), and the combinatorial novelty perspective, dissimilarity of a patent can also be

captured by its share of new keywords that never occurred in prior patents and its share of new keyword pairs that never occurred in prior patents. Using these two alternative measures of dissimilarity yields robust results (Appendix Table C4, Table C5).

4.5 Discussion and conclusion

This paper studied the relation between patent radicalness and private value for the innovating firm. More specifically, we differentiated between patent destructiveness and dissimilarity and investigated their differential effects on patent private value. Using a set of 1,066,637 USPTO granted utility patents, we adopted the market value of individual patents based on abnormal changes in firm stock price shortly after the event that a patent is granted, developed by Kogan et al. (2017). We measured the destructiveness of patents using citation networks and more specifically the extent to which a patent destabilize the existing flows, following Funk and Owen-Smith (2017) and the dissimilarity of patents based on to what extent the text of a patent is dissimilar to prior patents, following Arts et al. (2021). We found a negative association between patent destructiveness and private value. This suggests that destructive innovation might bring lower private value for the innovating firm due to its high levels of risk and uncertainty, the longer road to profit, and the incompatibility between destructive innovation and innovating firm's existing capabilities. In contrast, we found a positive association between patent dissimilarity and private value, suggest a reception premium for novelty and ambiguity. Furthermore, patent dissimilarity leads to more difficulties for the market to understand the patented invention and therefore weakens the negative effect of destructiveness on patent private value.

This paper has several limitations. First, although patent data provide an ideal setting for testing our hypotheses, our empirical analysis cannot avoid issues that are common to all studies relying on patent data. 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 with varying degrees of radicalness. Future research adopting a broader set of innovation outputs would be valuable to extend from patents to other

innovative outputs.

Second, we follow Kogan et al. (2017) in measuring patent private value as the stock market reaction to the news that the patent is granted. This measure is only available for patents of publicly traded firms, while patents of private companies, non-profit organizations and governments are ignored. Caution should be taken when generalizing our findings to non-listed companies or institutions, and it may be interesting for future work to test whether our findings are applicable to other types of organizations. In addition, it is difficult to evaluate the exact stock prices for each patent, because the same stock prices are allocated to all patents of the same assignee that were granted on the same day. Future research may further improve the accuracy of the patent private value measure.

Third, we focus on two dimensions of radicalness: i.e., destructiveness and dissimilarity, while radicalness may encompass other aspects or dimensions, it would be interesting for future studies to explore other dimensions and related mechanisms. Fourth, we do not capture the dynamic process through which the technological, economic, and societal impact of a patent invention unfolds. We only study the short-term private value of a patent depending on its dissimilarity and destructiveness. It would be interesting to investigate effects of dissimilarity and destructiveness in longer terms and beyond the innovating firm (i.e., social value).

Nevertheless, this paper makes several theoretical contributions. First, we add to the fast-expanding literature about radical innovation. While prior studies have investigated various technological and economic consequences of radical innovation (Ahuja & Morris Lampert, 2001; Arts et al., 2018; Arts et al., 2021; Fleming, 2001; Funk & Owen-Smith, 2017; Kaplan & Vakili, 2015; Schoenmakers & Duysters, 2010; Shane, 2001; Verhoeven et al., 2016), we explore its effect on patent private value.

Second, we unpack the abstract concept of radicalness and make an important distinction between destructiveness and dissimilarity, which affect patent private value in distinct manners and interact with each other. This provides a useful approach for reconciling seemly conflicting empirical findings in previous literature (Cohen et al., 2013; Fitzgerald et al., 2021; Hirshleifer et al., 2013, 2018). Radical innovation is a complex and composite concept, and explicitly differentiating its

dimensions is essential for a better understanding of it.

Third, accompanying the differentiation between destructiveness and dissimilarity is the separation between (a) theories focusing on substantive technological and economic consequences of destructiveness due to its association with risk/uncertainty and profitability and (b) theories focusing on reception biases related to dissimilarity due to cognition difficulties. These theories explain different aspects of the phenomenon, and integrating them helps us to better understand outcomes that emerge from multiple complex processes, such as private value in terms of stock returns, which depends on true economic value and perception biases.

Our findings also have implications for innovation policy and management. From a practitioner standpoint, it is important to understand consequences of different types of innovation. The negative association between destructiveness and private value warns companies about risks and uncertainties associated with conducting destructive innovation. Companies that engage in such innovation need to carefully manage its higher level of risk and uncertainty, longer time period needed to make it profitable, and potential incompatibilities with existing capabilities. Our findings also shed light on potential biases and sources of mispricing in the stock market. Consistent with prior studies (Cohen et al., 2013; Fitzgerald et al., 2021; Hirshleifer et al., 2013, 2018), our findings suggest that it is difficult for the stock market to understand patented inventions, especially dissimilar ones, for assessing its implications on firm value. Investors should be aware of these difficulties and carefully mitigate associated biases. Innovating companies should also pay attention to how to disclose their innovation and manage market expectations.

CHAPTER 5

Summary and general discussion

This PhD dissertation aims to unpack the determinants of radical innovation and its social and economic impact in the context of multinational corporations' internal R&D collaboration networks. Specifically, Chapter 2 investigates the social driving forces of radical innovation; Chapter 3 explores the social impact of network structure and the role that radicalness plays in their relationships; Chapter 4 examines the economic impact of different dimensions of radicalness. Driven by three research questions proposed in Chapter 1, this PhD dissertation presents answers in Chapter 2 to Chapter 4. This chapter summarizes the main findings, discusses the implications from theoretical and practical perspectives, and shows the limitations and future research prospects.

5.1 Summary of main findings

Research Question 1: How does network structure affect innovation radicalness?

To address this research question, Chapter 2 studies the relationship between the structure of corporate R&D collaboration networks and radical innovation, more specifically, how tie strength and structural holes collectively affect innovation radicalness at a location within an innovating firm. Chapter 2 separates two faces of weak ties and structural holes: their informational advantages in accessing the diverse knowledge that is needed for radical innovation, and their relational disadvantages linked to a weaker shared understanding and trust. Specifically, Chapter 2 argues (1) tie strength has a negative effect on innovation radicalness because of the informational advantage of weak tie for radical innovation; (2) structural holes have a positive effect on innovation radicalness because of the informational advantage; and (3) there is a positive interaction effect between tie strength and structural holes on innovation radicalness considering the relational disadvantage of weak tie and structural hole for radical innovation.

To test hypotheses, Chapter 2 constructs a unique panel dataset with information about firm R&D locations, their collaboration networks, and innovation outputs. Chapter 2 identifies sampled firms from the 2018 edition of the *EU Industrial R&D Investment Scoreboard* and focuses on U.S. pharmaceutical and biotechnology industry. Patents for each company are retrieved and aggregated at the location level. Building on the data of patent families, Chapter 2 constructs dataset for analysis at

the location-time level. The final dataset consists of 16,011 unique locations belonging to 93 companies, with a total number of 19,343 location-time observations. To measure the radicalness of a patent family, Chapter 2 adopts the radicalness index proposed by Funk and Owen-Smith (2017), which captures the degree to which the focal patent destabilizes existing technology trajectories. Tie strength between two R&D locations is captured as their frequency of co-inventing patent families, and structural hole is calculated as the share of missing ties in an egocentric network excluding the ego itself. Besides firm-location fixed effects, confounding variables (e.g., innovation productivity, network size, and collaboration inclination) that may lead to spurious correlations between our focal independent and dependent variables are controlled.

Findings of Chapter 2 show there is a significant negative effect of tie strength on innovation radicalness, confirming the informational advantages of weak ties for radical innovations. On the other hand, Chapter 2 does not observe a significant effect of structural hole in general. More importantly, Chapter 2 observes a significantly positive interaction effect between tie strength and structural hole on innovation radicalness. More specifically, the negative effect of tie strength is weaker when the network is rich in structural holes, and the effect of structural hole is negative when tie strength is weak but positive when tie strength is strong. This suggests that network cohesion is required for mobilizing the informational advantages of weak ties for radical innovation. Similarly, strong ties are needed for mobilizing the informational advantages of structural holes. Chapter 2 enriches the social network and innovation research.

Research Question 2: How does collaboration network structure influence the adoption and future use of its innovation? Would their relationship condition on innovation types (e.g., incremental innovation and radical innovation)?

To answer this research question, Chapter 3 investigates the effects of tie strength and network cohesion and more importantly the moderating effect of innovation radicalness. Chapter 3 contends that 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. Similar as tie strength, Chapter 3 argues that 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.

To test hypotheses, Chapter 3 constructs a unique panel dataset with information about firm R&D locations, their collaboration networks, and innovation outputs. Same as Chapter 2, Chapter 3 identifies sampled firms from the 2018 edition of the *EU Industrial R&D Investment Scoreboard* and focuses on U.S. pharmaceutical and biotechnology industry. Patents for each company are retrieved and aggregated at the location level. Innovation success is measured as the average number of patent family citations that a focal location received in a 5-year window, following the social definition of success in terms of acceptance and adoption by future users (Amabile, 1983; Fleming et al., 2007). Tie strength is captured as the frequency of collaboration based on a three-year window, and network density measure is adopted to calculate network cohesion. As measured in Chapter 2, Chapter 3 measures innovation radicalness by adopting the consolidation-or-destabilization (CD) index developed by Funk and Owen-Smith (2017). Firm-location and year fixed effects are included. Chapter 3 also control for network size, innovation productivity, and collaboration inclination.

Empirical results of Chapter 3 confirm our hypotheses. Trust, fine-grained information exchange, and reciprocity norms associated with strong tie and network cohesion facilitate innovation diffusion. Comparing the results of Chapter 3 and Chapter 2, this provides empirical evidence that the weak tie and structural hole that is conducive for producing a creative idea hamper its diffusion. We also observe that the findings only hold for incremental innovation, which consolidates existing technologies and confirms the reciprocity norms. 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. Findings of Chapter 3 contribute to the literatures of social networks, creativity, and innovation.

Research Question 3: How does the private value of a patent depend on its radicalness? Would destructiveness and dissimilarity have the same effect on private value?

This research question focuses on how the private value of a patent depends on its radicalness. To address this research question, Chapter 4 differentiates between two dimensions of radicalness: destructiveness and dissimilarity. Chapter 4 argues that the private value is lower for patents that are more destructive to existing technology trajectories, because of their higher risk and uncertainty, longer road to profit, and incompatibility with existing firm capabilities. On the other hand, the private value is higher for patents that are more dissimilar to the exiting knowledge, due to the reception reward to dissimilarity and ambiguity. Furthermore, dissimilarity makes it difficult for the market to understand the patented invention and therefore weakens the negative effect of destructiveness.

To test the hypotheses, Chapter 4 integrates several datasets, which are the dataset developed by Kogan et al. (2017), PATSTAT (2019 Autumn Edition) database, and the patent dataset developed by Arts et al. (2021). In total, the sample covers 1,066,637 USPTO utility patents that were granted between 1980 and 2010. The private value is retrieved from the patent dataset developed by Kogan et al. (2017), which is measured as the abnormal stock market return. Following Funk and Owen-Smith (2017), the calculation of destructiveness of a patent is based on citation networks. More specifically, this destructiveness index examines whether patents citing a focal patent also cite its references. Following Arts et al. (2021), the measure of dissimilarity is based on text similarity between a patent and all prior patents filed in the five years before the focal patents. To absorb variation across fields and year dimensions, technology class-grant year pair-level fixed effects is included. The number of patent references and the number of patent citations are controlled.

Descriptive statistics, nonparametric analysis, OLS regression, and quantile regressions are conducted. Findings presented in Chapter 4 show there is a negative relationship between patent destructiveness and private value. This suggests that destructive innovation might bring lower private value for the innovating firm due to its high levels of risk and uncertainty, the longer road to profit, and the incompatibility between destabilize innovation and innovating firm's existing capabilities. In contrast, Chapter 4 finds a positive association between patent dissimilarity and private value. This indicates that the market prefers dissimilar inventions because they have a higher possibility to create new markets. Furthermore, patent dissimilarity leads to more difficulties for the market to understand the patented invention and therefore weakens the negative effect of destructiveness on

patent private value. Chapter 4 confirms the different dimensions of radicalness have distinct effects on private value and makes an important contribution to the literature of radical innovation.

5.2 Implications

5.2.1 Theoretical implications

This dissertation contributes to and extends the existing literatures of innovation and social networks in several ways. First, our study adds to the fast-expanding literature about radical innovation by exploring the social determinants of radical innovation in the organizational and social environment (Chapter 2), how network effect depends on the radical nature of innovation (Chapter 3), and the impact of different dimensions of radical innovation on patent private value (Chapter 4). Prior studies have extensively investigated the technological origin of radical innovation. Chapter 2 examines the social determinants of radical innovation, particularly the characteristic of collaboration networks, which enriches the existing radical innovation literature. Results show that there is a significant negative effect between tie strength and innovation radicalness. More importantly, we observe a significantly positive interaction effect between tie strength and structural hole on innovation radicalness. Chapter 3 explores 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 & Zhang, 2019; Vanhaverbeke et al., 2012). Contribute to this research line, Chapter 3 investigates how tie strength and network cohesion of an innovation site's collaboration network shapes the success of its innovation. More importantly, Chapter 3 examines how these effects are contingent on the radical nature of innovation. Findings show that different types of innovation need different network conditions for diffusion. In particular, we observe opposite network effects for incremental and radical innovations. Chapter 4 contributes to radical innovation by unpacking the abstract concept of radicalness and making an important distinction between destructiveness and dissimilarity, which affect patent private value in distinct manners and interact with each other. This provides a useful approach for reconciling seemly conflicting empirical findings in previous literature (Cohen et al., 2013; Fitzgerald et al., 2021; Hirshleifer et al., 2013, 2018). Radical innovation is a

complex and composite concept, and explicitly differentiating its dimensions is essential for a better understanding of it.

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 & Mannucci; Reagans & McEvily, 2003; Tortoriello & Krackhardt, 2010). Our study in Chapter 2 contributes to the debate by proposing a two-faced view of network structures separating informational and relational aspects, and investigating the interaction between different network properties. The results show that the same network structure (i.e., weak tie, structural hole) may present both informational advantages and relational disadvantages at the same time. In addition, the informational advantages of weak ties can be mobilized if there are network cohesion to mitigate the relational disadvantages of weak ties. Similarly, the informational advantages of structural hole can be mobilized if there are strong ties to mitigate the relational advantages of structural holes. This provides a promising direction for reconciling competing theories about network effects (Burt, 1992; Coleman, 1988; Granovetter, 1982; Granovetter, 1973; Uzzi, 1996, 1997). Chapter 3 contributes to the debate by shedding light on the complexity of network effects. Previous research has shown that the same social structure that is conducive for producing a creative idea might hamper its diffusion. Chapter 2 and Chapter 3 provide empirical evidence that weak tie and structural hole contribute to the generation of radicalness but hinder the transformation of new ideas into successful innovations. More importantly, Chapter 3 confirms that different types of innovation might need different network conditions for diffusion. In particular, we found opposite network effects for incremental and radical innovations. More specifically, results show 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. We highlight the complexity that there might not be clean separation in the

network effect between the idea production and diffusion stages.

Third, our study contributes to the R&D location decisions literature. Prior studies have long investigated factor driving multinationals' overseas R&D location choices and strategies for coordinating subsidiaries (Alcácer & Zhao, 2012; Belderbos et al., 2021; Du et al., 2022; Kuemmerle, 1997; Lewin et al., 2009). Complementing the literature of R&D locations decisions, Chapter 2 explores how the structure of firm R&D networks affects its ability of producing radical innovation, and Chapter 3 investigates how the collaboration network structure of an innovation site affects the adoption and future use of its innovations.

5.2.2 Practical implications

The findings of this dissertation also have implications for innovating firms and management. First, innovating firms should be careful about network structure configuration when develop radical innovation. Chapter 2 suggests that having weak ties are generally more conducive for radical innovation, but it is especially beneficial when weak ties are accompanies by network cohesion. On the other hand, structural holes are beneficial for developing radical innovation if there are strong ties to mitigate its relational disadvantages.

Second, our findings also have important implications for innovation management, especially across geographically dispersed sites. The structure of collaboration network plays an important role in the process of turning a creative idea into a successful innovation. Chapter 3 informs 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 attentions to how to bring other management interventions to magnify desirable underlying mechanisms and mitigate undesirable ones.

Third, our study helps firms to understand the economic consequences of different types of innovation. The negative association between destructiveness and private value warns companies about risks and uncertainties associated with conducting destructive innovation. Companies that engage in such innovation need to carefully manage its higher level of risk and uncertainty, longer time period needed to make it

profitable, and potential incompatibilities with existing capabilities. Chapter 4 also sheds light on potential biases and sources of mispricing in the stock market. Consistent with prior studies (Cohen et al., 2013; Fitzgerald et al., 2021; Hirshleifer et al., 2013, 2018), Chapter 4 suggests that it is difficult for the stock market to understand patented inventions, especially dissimilar ones, for assessing its implications on firm value. Investors should be aware of these difficulties and carefully mitigate associated biases. Innovating companies should also pay attention to how to disclose their innovation and manage market expectations.

5.3 Limitations and future research

Notwithstanding its contributions, this PhD dissertation has some limitations. 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. 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 with varying degrees of radicalness. Future research adopting a broader set of innovation outputs would be valuable to expand beyond patents to other innovative outputs. In addition, patent data do not provide direct information for measuring the underlying mechanisms. For example, informational advantages and relational disadvantages of weak ties and structural holes, as well as trust and reciprocity norms associated with strong ties and network cohesion, cannot be measured using patent data. Future research should address this issue and explore alternative data sources for a more direct test of the theory.

Second, like most network studies, our study focuses on the structural aspect of the network but does not account for the characteristics of nodes or the content of things that are exchanged in the context of the tie. Future research should incorporate these aspects for a better and more complete understanding of the relationship between collaboration networks and radical innovation.

Third, our study mainly retrieves 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.

Fourth, we follow Kogan et al. (2017) in measuring patent private value as the stock market reaction to the news that the patent is granted. This measure is only available for patents of publicly traded firms, while patents of private companies, non-profit organizations and governments are ignored. Caution should be taken when generalizing our findings to non-listed companies or institutions, and it may be interesting for future work to test whether our findings are applicable to other types of organizations. In addition, it is difficult to evaluate the exact stock prices for each patent, because the same stock prices are allocated to all patents of the same assignee that were granted on the same day. Future research may further improve the accuracy of the patent private value measure.

Fifth, we focus on two dimensions of radicalness: i.e., destructiveness and dissimilarity, while radicalness may encompass other aspects or dimensions, it would be interesting for future studies to explore other dimensions and related mechanisms.

Sixth, we do not capture the dynamic process through which the technological, economic, and societal impact of a patent invention unfolds. We only study the short-term private value of a patent depending on its dissimilarity and destructiveness. It would be interesting to investigate effects of dissimilarity and destructiveness in longer terms and beyond the innovating firm (i.e., social value).

Appendix A

Table A1. Alternative radicalness measure using longer time window

	Radicalness			
	(1)	(2)	(3)	(4)
Tie strength (ln)		-0.010***	-0.008***	-0.012***
		(0.002)	(0.003)	(0.003)
Structural hole			-0.005	-0.007*
			(0.004)	(0.004)
Tie strength (ln) * Structural hole				0.005*
				(0.003)
Innovation productivity (ln)	0.003***	0.010***	0.008***	0.008***
	(0.001)	(0.002)	(0.002)	(0.002)
Network size (ln)	-0.003**	-0.006***	-0.006***	-0.006***
	(0.001)	(0.002)	(0.002)	(0.002)
Collaboration inclination	-0.015***	-0.003	-0.006	-0.006
	(0.005)	(0.005)	(0.006)	(0.006)
Year FE	Yes	Yes	Yes	Yes
Firm-location FE	Yes	Yes	Yes	Yes
N	19343	19343	19343	19343
R-square	0.726	0.727	0.727	0.727

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

Table A2. Fewer controls

	Radicalness			
	(1)	(2)	(3)	(4)
Tie strength (ln)	-0.004*	-0.011***	-0.016***	-0.009***
	(0.002)	(0.003)	(0.003)	(0.002)
Structural hole	-0.019***	-0.009**	-0.006*	-0.012***
	(0.004)	(0.004)	(0.004)	(0.003)
Tie strength (ln) * Structural hole	0.006**	0.009***	0.007**	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)
Innovation productivity (ln)		0.002	0.011***	
		(0.002)	(0.002)	
Network size (ln)	-0.006***		-0.010***	
	(0.001)		(0.002)	
Collaboration inclination	-0.018***	-0.017***		
	(0.004)	(0.005)		
Year FE	Yes	Yes	Yes	Yes
Firm-location FE	Yes	Yes	Yes	Yes
N	19343	19343	19343	19343
R-square	0.697	0.696	0.698	0.695

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

Appendix B

Table B1. Robustness test: Dropping control variables

	Innovation success											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Tie strength (ln)	0.001	0.026	0.003	0.062***	0.080***	0.063***	0.215***	0.237***	0.215***	0.129***	0.146***	0.130***
	(0.031)	(0.030)	(0.031)	(0.016)	(0.015)	(0.016)	(0.028)	(0.028)	(0.028)	(0.015)	(0.015)	(0.015)
Network cohesion	-0.009	-0.003	-0.010	-0.127***	-0.127***	-0.129***	0.046	0.050	0.044	0.165***	0.161***	0.162***
	(0.052)	(0.052)	(0.052)	(0.041)	(0.041)	(0.041)	(0.049)	(0.048)	(0.049)	(0.034)	(0.034)	(0.034)
Innovation radicalness	-1.724***	-1.942***	-1.620***	-1.596***	-1.847***	-1.509***	-1.577***	-1.817***	-1.486***	-1.749***	-1.948***	-1.631***
	(0.197)	(0.208)	(0.215)	(0.189)	(0.199)	(0.205)	(0.187)	(0.197)	(0.203)	(0.198)	(0.208)	(0.215)
Tie strength (ln) * Innovation radicalness	-2.262***		-2.098***	-2.323***		-2.186***	-2.289***		-2.147***	-2.241***		-2.056***
	(0.346)		(0.351)	(0.340)		(0.348)	(0.340)		(0.347)	(0.346)		(0.350)
Network cohesion * Innovation radicalness		-1.890***	-1.013*		-1.763***	-0.849		-1.779***	-0.882		-2.006***	-1.147*
		(0.589)	(0.593)		(0.573)	(0.580)		(0.566)	(0.574)		(0.591)	(0.595)
Innovation productivity (ln)	0.110***	0.103***	0.109***				-0.149***	-0.153***	-0.149***			
	(0.025)	(0.025)	(0.025)				(0.025)	(0.025)	(0.025)			
Network size (ln)				0.221***	0.218***	0.221***	0.270***	0.268***	0.269***			
				(0.017)	(0.017)	(0.017)	(0.019)	(0.019)	(0.019)			
Collaboration inclination	0.495***	0.484***	0.490***	0.281***	0.282***	0.278***						
	(0.073)	(0.073)	(0.073)	(0.065)	(0.065)	(0.065)						
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

	Innovation success											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
R-square	0.753	0.752	0.753	0.757	0.757	0.758	0.758	0.757	0.758	0.752	0.751	0.752
F Statistic	61.96***	56.95***	60.24***	71.38***	66.52***	69.04***	71.73***	67.11***	69.42***	65.95***	60.41***	63.86***

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

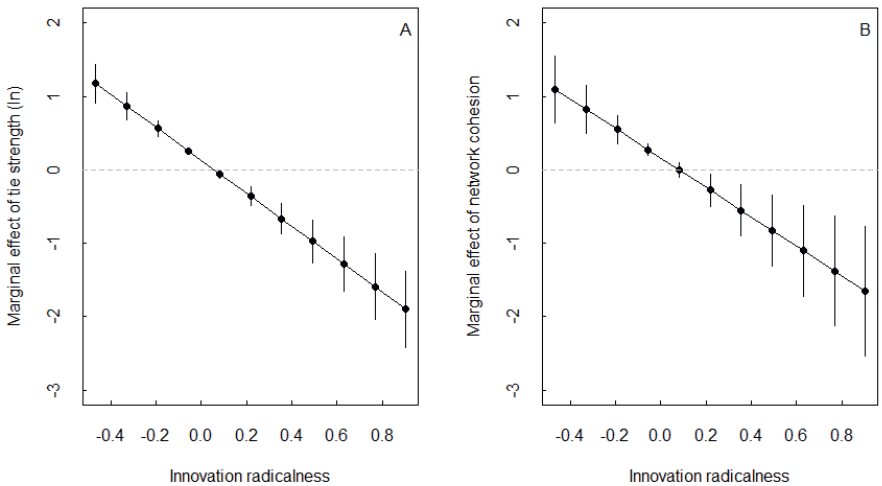

Figure B1. Robustness test: Dropping control variables. Points represent the regression coefficients, and vertical bars represent 90% confidence interval.

Appendix C

Table C1. Do not control the number of citations

	ln(Private value) OLS			
	(1)	(2)	(3)	(4)
Destructiveness	-0.080***		-0.077***	-0.078***
	(0.004)		(0.004)	(0.004)
Dissimilarity		0.199***	0.198***	0.198***
		(0.006)	(0.006)	(0.006)
Dissimilarity * Destructiveness				0.019***
				(0.003)
ln(References)	0.159***	0.198***	0.167***	0.167***
	(0.006)	(0.006)	(0.006)	(0.006)
Patent class * Year fixed effects	Y	Y	Y	Y
N	1066637	1066637	1066637	1066637
R-square	0.193	0.197	0.198	0.198

Note. Destructiveness and dissimilarity are standardized. Robust standard error clustered at patent class * year level in paratheses. *** p<.001, ** p<.01, * p<.05.

Table C2. Alternative destructiveness measure: Shorter and fixed time window

	ln(Private value) OLS			
	(1)	(2)	(3)	(4)
Destructiveness (5Y)	-0.139***		-0.135***	-0.135***
	(0.004)		(0.004)	(0.004)
Dissimilarity		0.203***	0.200***	0.200***
		(0.006)	(0.006)	(0.006)
Dissimilarity * Destructiveness (5Y)				0.024***
				(0.003)
ln(References)	0.109***	0.171***	0.118***	0.118***
	(0.006)	(0.006)	(0.006)	(0.006)
ln(Citations 5Y)	0.202***	0.180***	0.199***	0.199***
	(0.005)	(0.005)	(0.005)	(0.005)
Patent class * Year fixed effects	Y	Y	Y	Y
N	950308	950308	950308	950308
R-square	0.203	0.205	0.208	0.208

Note. Destructiveness (5Y) and dissimilarity are standardized. Robust standard error clustered at patent class * year level in paratheses. *** p<.001, ** p<.01, * p<.05.

Table C3. Alternative destructiveness measure: Originality

	ln(Private value) OLS			
	(1)	(2)	(3)	(4)
Originality	-0.054***		-0.051***	-0.054***
	(0.003)		(0.003)	(0.003)
Dissimilarity		0.196***	0.195***	0.194***
		(0.006)	(0.006)	(0.006)
Dissimilarity * Originality				0.014***
				(0.003)
ln(References)	0.148***	0.153***	0.156***	0.156***
	(0.006)	(0.006)	(0.006)	(0.006)
ln(Citations)	0.210***	0.209***	0.208***	0.208***
	(0.004)	(0.004)	(0.004)	(0.004)
Patent class * Year fixed effects	Y	Y	Y	Y
N	1066637	1066637	1066637	1066637
R-square	0.202	0.206	0.207	0.207

Note. Originality and dissimilarity and are standardized. Robust standard error clustered at patent class * year level in paratheses. *** p<.001, ** p<.01, * p<.05.

Table C4. Alternative dissimilarity measures: Ratio of new keywords

	ln(Private value) OLS			
	(1)	(2)	(3)	(4)
Destructiveness	-0.143***		-0.143***	-0.146***
	(0.004)		(0.004)	(0.004)
Ratio of new keywords		0.008**	0.009***	0.007**
		(0.002)	(0.002)	(0.002)
Ratio of new keywords * Destructiveness				0.012***
				(0.002)
ln(References)	0.082***	0.145***	0.083***	0.082***
	(0.006)	(0.006)	(0.006)	(0.006)
ln(Citations)	0.237***	0.211***	0.237***	0.237***
	(0.005)	(0.004)	(0.005)	(0.005)
Patent class * Year fixed effects	Y	Y	Y	Y
N	1066637	1066637	1066637	1066637
R-square	0.204	0.201	0.204	0.204

Note. Destructiveness and ratio of new keywords are standardized. Robust standard error clustered at patent class * year level in paratheses. *** p<.001, ** p<.01, * p<.05.

Table C5. Alternative dissimilarity measures: Ratio of new keyword pairs

	ln(Private value) OLS			
	(1)	(2)	(3)	(4)
Destructiveness	-0.143***		-0.144***	-0.151***
	(0.004)		(0.004)	(0.004)
Ratio of new keyword pairs		0.031***	0.034***	0.030***
		(0.003)	(0.003)	(0.003)
Ratio of new keyword pairs * Destructiveness				0.020***
				(0.002)
ln(References)	0.082***	0.146***	0.083***	0.081***
	(0.006)	(0.006)	(0.006)	(0.006)
ln(Citations)	0.237***	0.209***	0.236***	0.236***
	(0.005)	(0.004)	(0.005)	(0.005)
Patent class * Year fixed effects	Y	Y	Y	Y
N	1066637	1066637	1066637	1066637
R-square	0.204	0.201	0.204	0.204

Note. Destructiveness and ratio of new keyword pairs are standardized. Robust standard error clustered at patent class * year level in paratheses. *** p<.001, ** p<.01, * p<.05.

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Summary

Innovation plays an essential role in firms' competitiveness and long-term success. It varies from different types, ranging from run-of-the-mill innovation that bring incremental changes to existing technologies to radical innovation that break from existing trajectories. The aim of this PhD dissertation is to integrate radical innovation and social network literature to broaden theoretical understanding, especially contribute to the literatures of social networks, creativity, and innovation, and inform innovation management by unpacking the drivers and effects of radical innovation.

Chapter 1 provides an overview of this dissertation, presents the research questions to be addressed in this dissertation, and the potential contributions. There are long-standing debates in the social network literature regarding which types of networks are more advantageous for innovation. Some researchers highlight the benefits of weak ties and structural holes, while others suggest advantages of strong ties and network cohesion for radical innovation. To address this question, Chapter 2 investigates how tie strength and structural holes collectively affect innovation radicalness at a location within an innovating firm. Specifically, Chapter 2 separates two faces of weak ties and structural holes: their informational advantages in accessing the diverse knowledge that is needed for radical innovation, and their relational disadvantages linked to a weaker shared understanding and trust. To test hypotheses, Chapter 2 builds a unique panel dataset consisting of 19,343 firm-location-time observations for 16,011 unique firm-locations belonging to 93 U.S. pharmaceuticals and biotechnology companies on the EU Industrial R&D Investment Scoreboard. The findings of this chapter support our hypotheses that there is a positive interaction effect between tie strength and structural holes on innovation radicalness. Structural holes weaken the negative effect of tie strength on innovation radicalness, and tie strength magnifies the positive effect of structural holes on innovation radicalness. In other words, the informational advantages of structural holes can be mobilized if there are strong ties for mitigating the relational disadvantages of structural holes. Similarly, network cohesion is needed for mobilizing informational advantages of weak ties. Chapter 2 provides a promising direction for reconciling competing theories about network effects.

Another reconcile direction is to examine different stages of the creative process.

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. 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. Building on this line of literature, Chapter 3 investigates how social structure for producing a creative idea influences the adoption and future use of its innovations and make a novel contribution by exploring how this effect is contingent on the radical nature of the creative idea. Prior studies have highlighted the advantages of strong ties and network cohesion for idea transfer and diffusion, due to their associated higher level of trust, fine-grained information exchange, and reciprocity norms. Chapter 3 argues that these effects are likely to be contingent on the radical nature of the innovation. More specifically, these effects might only hold for incremental innovation that consolidates existing technologies and aligned with reciprocity norms. These effects turn into negative when the innovation is radical and disrupts existing technologies, because the kind of impact that radical innovation brings to network partners is not aligned with reciprocity norms and therefore sanctioned by the network. In addition, the lack of information diversity also hinders the identification of new applications for radical innovations. To test hypotheses, Chapter 3 constructs a unique panel dataset with information about firm R&D locations, their collaboration networks, and innovation outputs. Empirical results support our hypotheses. The findings in Chapter 3 highlight that different types of innovations require different network conditions for diffusion. The reciprocity norms are not always beneficial but can become a burden, and non-redundant information is not only beneficial for generating novel ideas but also for identifying new applications for radical innovation. Chapter 3 contributes to the literatures of social networks, creativity, and innovation.

In addition to contributing to this long-standing debate, this dissertation also investigates how radicalness affects the private value for the innovating firm. Studying how the radicalness predict future economic value, especially the different aspects of radicalness, is a very interesting research topic in innovation literature. However, the empirical evidence is mixed considering there are diverse approaches for conceptualizing and operationalizing innovation radicalness. Chapter 4 investigates the association between the private value of a patent for the innovation firm and its technological radicalness by differentiating between two important

dimensions of technological radicalness: destructiveness and dissimilarity. Chapter 4 argues that the private value is lower for patents that are more destructive to existing technology trajectories, because of their higher risk and uncertainty, longer road to profit, and incompatibility with existing firm capabilities. On the other hand, the private value is higher for patents that are more dissimilar to the exiting knowledge, due to the reception reward to dissimilarity and ambiguity. Furthermore, dissimilarity makes it difficult for the market to understand the patented invention and therefore weakens the negative effect of destructiveness. Using a dataset consisting of 1,066,637 USPTO granted patents, the findings support our hypotheses. Chapter 4 confirms that the different dimensions of radicalness have distinct effects on private value. More importantly, Chapter 4 provides a useful approach for making sense of the diverse and sometimes competing theories and evidence about technological radicalness. This dissertation concludes with summarizing the main findings, discussing the implications from theoretical and practical perspectives, and showing the limitations and future research prospects (Chapter 5).

Nederlanse Samenvatting

Innovatie speelt een essentiële rol in de concurrentiepositie en het langetermijnsucces van bedrijven. Het varieert van verschillende typen, variërend van doorsnee innovatie die incrementele veranderingen aan bestaande technologieën brengen tot radicale innovatie die breekt met bestaande trajecten. Het doel van dit proefschrift is om radicale innovatie en sociale netwerkliteratuur te integreren om het theoretisch begrip te verbreden, in het bijzonder om bij te dragen aan de literatuur van sociale netwerken, creativiteit, en innovatie, en om innovatiebeheer te informeren door de drijfveren en effecten van radicale innovatie te ontrafelen.

Hoofdstuk 1 biedt een overzicht van dit proefschrift, presenteert de onderzoeksvragen die in dit proefschrift zullen worden behandeld, en de potentiële bijdragen. Er zijn langlopende debatten in de literatuur over sociale netwerken over welke soorten netwerken meer voordelig zijn voor innovatie. Sommige onderzoekers benadrukken de voordelen van zwakke banden en structurele gaten, terwijl anderen de voordelen van sterke banden en netwerkcohesie voor radicale innovatie suggereren. Om deze vraag aan te pakken, onderzoekt Hoofdstuk 2 hoe bandsterkte en structurele gaten gezamenlijk de radicaliteit van innovatie op een locatie binnen een innoverend bedrijf beïnvloeden. Specifiek scheidt Hoofdstuk 2 twee gezichten van zwakke banden en structurele gaten: hun informatieve voordelen bij het toegang krijgen tot de diverse kennis die nodig is voor radicale innovatie, en hun relationele nadelen gekoppeld aan een zwakkere gedeelde begrip en vertrouwen. Om hypothesen te testen, bouwt Hoofdstuk 2 een unieke panel dataset bestaande uit 19.343 bedrijfs-locatie-tijd observaties voor 16.011 unieke bedrijfslocaties behorend tot 93 Amerikaanse farmaceutische en biotechnologiebedrijven op het EU Industriële R&D Investering Scorebord. De bevindingen van dit hoofdstuk ondersteunen onze hypothesen dat er een positief interactie-effect is tussen bandsterkte en structurele gaten op innovatieradicaliteit. Structurele gaten verzwakken het negatieve effect van bandsterkte op innovatieradicaliteit, en bandsterkte vergroot het positieve effect van structurele gaten op innovatieradicaliteit. Met andere woorden, de informatieve voordelen van structurele gaten kunnen worden gemobiliseerd als er sterke banden zijn om de relationele nadelen van structurele gaten te verzachten. Evenzo is netwerkcohesie nodig voor het mobiliseren van informatieve voordelen van zwakke banden. Hoofdstuk 2 biedt

een veelbelovende richting voor het verzoenen van concurrerende theorieën over netwerkeffecten.

Een andere verzoeningsrichting is om verschillende stadia van het creatieve proces te onderzoeken. Innovatie begint met creatieve ideeën, maar niet alle creatieve ideeën zullen uitmonden in succesvolle innovatie die door anderen wordt overgenomen en gebruikt, en het vereist meerdere stappen om een creatief idee te ontwikkelen tot een succesvolle innovatie. Een belangrijke scheiding is tussen een initiële productiefase waar een creatief idee wordt gegenereerd en een latere diffusiefase waar een creatief idee wordt overgenomen en gebruikt door anderen. Voortbouwend op deze lijn van literatuur, onderzoekt Hoofdstuk 3 hoe sociale structuur voor het produceren van een creatief idee de adoptie en toekomstig gebruik van zijn innovaties beïnvloedt en maakt een nieuwe bijdrage door te verkennen hoe dit effect afhankelijk is van de radicale aard van het creatieve idee. Eerdere studies hebben de voordelen van sterke banden en netwerkcohesie voor ideeënoverdracht en -diffusie benadrukt, vanwege hun geassocieerde hogere niveau van vertrouwen, fijnmazige informatie-uitwisseling en wederkerigheidsnormen. Hoofdstuk 3 betoogt dat deze effecten waarschijnlijk afhankelijk zijn van de radicale aard van de innovatie. Meer specifiek kunnen deze effecten alleen gelden voor incrementele innovatie die bestaande technologieën consolideert en in lijn is met wederkerigheidsnormen. Deze effecten worden negatief wanneer de innovatie radicaal is en bestaande technologieën verstoort, omdat het soort impact dat radicale innovatie brengt op netwerkpartners niet in lijn is met wederkerigheidsnormen en daarom gesanctioneerd wordt door het netwerk. Bovendien belemmert het gebrek aan informatiediversiteit ook de identificatie van nieuwe toepassingen voor radicale innovaties. Om hypothesen te testen, construeert Hoofdstuk 3 een unieke panel dataset met informatie over bedrijfs-R&D-locaties, hun samenwerkingsnetwerken, en innovatie-outputs. Empirische resultaten ondersteunen onze hypothesen. De bevindingen in Hoofdstuk 3 benadrukken dat verschillende soorten innovaties verschillende netwerkvoorwaarden vereisen voor diffusie. De wederkerigheidsnormen zijn niet altijd voordelig maar kunnen een last worden, en niet-redundante informatie is niet alleen voordelig voor het genereren van nieuwe ideeën maar ook voor het identificeren van nieuwe toepassingen voor radicale innovatie. Hoofdstuk 3 draagt bij aan de literatuur van sociale netwerken, creativiteit, en innovatie.

Naast het bijdragen aan dit langdurige debat, onderzoekt dit proefschrift ook hoe radicaliteit de private waarde voor het innoverende bedrijf beïnvloedt. Het bestuderen van hoe de radicaliteit toekomstige economische waarde voorspelt, met name de verschillende aspecten van radicaliteit, is een zeer interessant onderzoeksonderwerp in de innovatieliteratuur. Echter, het empirisch bewijs is gemengd aangezien er diverse benaderingen zijn voor het conceptualiseren en operationaliseren van innovatieradicaliteit. Hoofdstuk 4 onderzoekt de associatie tussen de private waarde van een patent voor het innoverende bedrijf en zijn technologische radicaliteit door onderscheid te maken tussen twee belangrijke dimensies van technologische radicaliteit: destructiviteit en ongelijkheid. Hoofdstuk 4 betoogt dat de private waarde lager is voor patenten die destructiever zijn voor bestaande technologietrajecten, vanwege hun hogere risico en onzekerheid, langere weg naar winst, en incompatibiliteit met bestaande bedrijfscapaciteiten. Aan de andere kant is de private waarde hoger voor patenten die meer afwijkend zijn van de bestaande kennis, vanwege de ontvangstbeloning voor afwijkendheid en ambiguïteit. Verder maakt afwijkendheid het moeilijk voor de markt om de gepatenteerde uitvinding te begrijpen en verzwakt daardoor het negatieve effect van destructiviteit. Met behulp van een dataset bestaande uit 1.066.637 door het USPTO verleende patenten, ondersteunen de bevindingen onze hypothesen. Hoofdstuk 4 bevestigt dat de verschillende dimensies van radicaliteit verschillende effecten hebben op de private waarde. Belangrijker nog, Hoofdstuk 4 biedt een nuttige benadering voor het begrijpen van de diverse en soms concurrerende theorieën en bewijzen over technologische radicaliteit. Dit proefschrift wordt afgesloten met het samenvatten van de belangrijkste bevindingen, het bespreken van de implicaties vanuit theoretisch en praktisch perspectief, en het tonen van de beperkingen en toekomstige onderzoeksvooruitzichten (Hoofdstuk 5).

Curriculum Vitae

Jia Zhang was born in Changge, China in 1992. She had lived and studied in this city until she graduated from high school in 2011. In the same year, she started her study in Administrative Management at Chang'an University and received her bachelor's degree in Management in 2015. After her undergraduate study, she earned admission to the University of Science and Technology of China (USTC), being exempted from the postgraduate entrance examination. In USTC, she continued her study in Public Administration under the supervision of Assoc. Prof.dr. Xiaobao Peng and received her master's degree in Management Science in 2018. In September 2018, she came to the Netherlands and started her PhD journey in Science Based Business Program at Leiden University. Under the supervision of Prof.dr. Simcha Jong Kon Chin and Dr. Jian Wang, she focuses on social network and radical innovation research.

List of Publications

Manuscripts submitted for publication

- Zhang, J., Wang, J., Winnink, J.J., & Jong, S. Collaboration networks and radical innovation: Two faces of tie strength and structural holes.
- Zhang, J., Wang, J., Winnink, J. J., & Jong, S. Turning creative ideas into successful innovations: Differential effects of network structure for radical and incremental innovation.
- Zhang, J., Wang, J., & Jong, S. Patent radicalness and private value: Unpacking destructiveness and dissimilarity effects.

Scientific contributions in conferences

Oral presentations

- Turning creative ideas into successful innovations: Differential effects of network structure for radical and incremental innovation. DRUID Academy, 2024, Odense, Denmark.
- Collaboration networks and radical innovation: Two faces of tie strength and structural holes. DRUID, 2023, Lisbon, Portugal.
- Familiarity, disruptiveness, and stock returns. Academy of Management Annual Meeting (AOM), 2022, Seattle, USA.
- Familiarity, disruptiveness, and stock returns. PhD Workshop in Economics of Innovation, Complexity and Knowledge (WICK), 2021, Turin, Italy.

Poster presentations

Patent radicalness and private value: Unpacking destructiveness and dissimilarity effects. Summer School for Science, Technology & Innovation Studies (ST&I), 2021, Online.

PhD training

Disciplinary courses

- Bibliometrics and Scientometrics for Research Evaluation (2021, 3 ECTS)
- Statistics (2020, 2 ECTS)

- Applied linear regression models (2020, 2 ECTS)
- Empirical Research Methodology and Measurement (2019, 5 ECTS)
- Advanced Topics in Engaged Strategizing (2019, 5 ECTS)
- Developing Theory and Theoretical Contributions (2019, 5 ECTS)

Mandatory courses

- Scientific Conduct (2021)
- Negotiating for PhDs (2018)
- Communication in Science (2018)
- Effective communication (2018)

Soft skill courses

- Academic writing for PhDs (2021)
- Managing your references using Endnote (2021)

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