Studies on interorganizational networks:

The case of two regional clusters in Norway

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Abstract

The overall purpose of this dissertation is to study interorganizational networks. Firms are open systems and simultaneously embedded in interorganizational networks of various kinds. Interorganizational networks consist of a group of organizations and relations between these organizations, reflecting the allocation and flow of resources among network members. Conceivably, network structures largely affect involved firms' different behaviors. Nevertheless, such knowledge is insufficient without knowing how interorganizational networks emerge and develop into a specific structure. Using a sociometric structural approach, this dissertation contributes to two related topics: (1) the influence of network properties on firms' behaviors (Articles 1 and 2) and (2) the dynamics of network structures (Article 3).

A firm's position in a network has implications for its opportunities and constraints (Brass et al., 2004). The first two empirical articles focus on the influence of network structures on firms' behaviors. In Article 1, I demonstrate how firms adapt exploration strategies according to network properties. Management research has alluded to environmental and organizational antecedents for firms' exploration. I complement this knowledge by applying a network perspective to explain how a firm may adjust its exploration strategy based on its position within the interorganizational network. I particularly focus on two network constructs: closeness centrality and local cohesion. Closeness centrality captures a firm's distance to network knowledge and resources, and local cohesion shows the connection between a focal firm's alters. The findings show positive impacts of closeness centrality and local cohesion on exploration strategy, and local cohesion has a more significant impact. I offer insights into antecedents of exploration by underscoring the network drivers.

In Article 2, I study firms' prosocial behavior in dyads within a broader network context. Research on relationship marketing has traditionally focused on dyadic properties to explain behaviors within dyads. This article adds to this body of research by investigating network-

level antecedents of prosocial behaviors in dyadic relations. Prosocial behavior refers to a firm's beneficial actions toward another firm beyond formal requirements. Since a contract is normally incomplete, such behavior is desirable in business relationships. Our findings show that in-degree centrality (i.e., the number of ties received from other network members) has an inverted U-shaped relationship with a focal firm's prosocial behavior. Besides, triadic embeddedness (i.e., the number of common third parties) is likely to facilitate prosocial behavior between involved parties, regardless of firms' in-degree centrality. This study shows the need to consider the dyadic relationship in a wider network context.

While Articles 1 and 2 implicitly assume network properties are static, Article 3 contributes to knowledge of network development in the interorganizational setting. Sociologists and management scholars provide explanations mainly for dyadic tie formation, such as alliance formation and joint ventures. Limited is known about system-level structural dynamics. Specifically, I focus on two system-level properties: small-world and scale-free networks. Small-world networks are characterized by dense local clustering and short path length between actors. Scale-free networks are centralized with a small portion of central actors spanning the structure and take a skewed degree distribution. Some empirical networks demonstrate both properties simultaneously, yet few studies have aimed to discuss the dynamics and interrelation of these properties. In article 3, I retrospectively visualize the annual structures of two empirical networks to show how small-world and scale-free properties together explain the development patterns. The results show that the small-world and scale-free properties have an inversed dynamic pattern, and the scale-free structure may be less common in the interorganizational setting. Altogether, this study adds to the understanding of the dynamics and development of interorganizational networks in terms of small-world and scale-free structures.

Contextually, I investigate two regional industry networks in western Norway, focusing on the media industry and fintech. Overall, this dissertation provides an in-depth analysis of these two interorganizational networks by focusing on multiple levels and aspects of a network and adds to the current literature on management, relationship marketing, and network dynamics. Moreover, this dissertation combines network data and survey data for hypotheses testing in Articles 1 and 2, which is unique and increases the validity of the findings. I also present key findings, discuss the implications and limitations of this work, and suggest future research directions.

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Lin, Y., Aarstad, J., & Rokkan, I. A. (2023). Network position and firms' exploration strategies: A study of two regional industry clusters in Norway.

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Article 2:

Lin, Y., Rokkan, I. A., Aarstad, J. (2023). The role of in-degree centrality and triadic embeddedness in prosocial behavior: A study of two regional industry clusters.

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Article 3:

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1. Introduction

The focus of this doctoral dissertation is interorganizational networks. Contextually, I study two regional clusters in Bergen, Norway. I discover how different network structures influence business members of the clusters and the dynamics of the overall network structure. To this end, I study the network properties of the regional clusters from three perspectives: (1) how network properties influence firms' exploration strategy (Article 1); (2) how network properties influence firms' prosocial behavior in cooperation within the cluster (Article 2); and (3) how the overall network structures develop since established (Article 3).

In the following section, I describe the motivation and background for the dissertation. In addition, I discuss the three specific research questions I aim to answer and how the findings can add to existing knowledge. I then introduce the research methods. In the subsequent section, I briefly present the three independent articles. I close the Kappe with a discussion of findings, implications, limitations, and future research opportunities.

1.1. Motivation of the study

Firms are rarely independent, self-contained units in the business world. A core area of research on business study concerns how relationships work between firms and influence firms' performance because "a firm's critical resources may span firm boundaries (Dyer & Singh, 1998, p. 660)." Due to the fact that dyadic relationships exist within a wider network of other dyads involving multiple relevant actors, scholars have emphasized the importance of studying interorganizational networks (Achrol, 1997; Brass et al., 2004; Choi & Wu, 2009; Zaheer et al., 2010).

The focus of this dissertation is interorganizational networks[1]. In particular, I adopt the social network approach that focuses on the structure of relationships or positions of firms and discuss the impacts (e.g., Ahuja, 2000; Kilduff & Brass, 2010; Powell et al., 1996). In an interorganizational context, the linkages reflect the allocation and access of resources, which bring opportunity and constraints to involved firms (Brass et al., 2004; Gulati & Gargiulo, 1999). Beyond access to information, resources, markets, and technologies outside its boundary, scholars find that interorganizational networks can also facilitate learning, scale and scope of economies, and allow firms to achieve strategic objectives, such as sharing risks and outsourcing value-chain stages and organizational functions (Gulati et al., 2000; Phelps et al., 2012). The application of the social network perspective has become a common theoretical framework in several research domains, such as strategic management (e.g., Ahuja et al., 2009; Gulati, 1999), supply chain management (e.g., Carnovale et al., 2019; Carnovale & Yeniyurt, 2014), organizational learning and innovation (e.g., Hargadon, 2002; Phelps, 2010), relationship governance (e.g., Haugland et al., 2021; Sa Vinhas et al., 2012), and entrepreneurship (e.g., Hallen et al., 2020).

Despite the diverse research domains and focuses, a general way to categorize interorganizational network research is to see whether a network is considered the cause of certain consequences or the consequence of organizations' interaction and behavior (Borgatti & Halgin, 2011). The first category focuses on the (nonnetwork) outcomes of network structures, such as how a firm's central position influences its innovation performance. An influential work in this stream is by Granovetter (1985), where he presented a model ground between under-socialized economic theory and over-socialized sociological theory. He

[1] I use "organization" instead of "firm" here because in our research context, we also include non-commercial organizations—such as research institutions and public organizations—for network analysis. However, the essential focus of the dissertation is on firms.

contends that ongoing networks of social relations between individuals are bonds that deter malfeasance. Another distinct model considers network ties as pipes that allow flows of resources and information between actors. Firms' resource bases and capabilities differ, and they rely on network ties to share or access these resources and capabilities (Uzzi & Lancaster, 2003). As Zaheer and colleagues (2010) summarize, the logic of using a network perspective is "that the pattern or structure of ties among organizations and the tie strength and content have a significant bearing on firm behavior and on important firm outcomes such as performance (p. 62)". The general theme in this category is *the process within a network that leads to certain consequences*. Unsurprisingly, this perspective dominates earlier research in the business and management field since one needs to know how and why network matters.

As the field continued to develop, scholars noticed that understanding the consequences of certain network structures is incomplete without knowing the generation and dynamics underlying the structure (Ahuja et al., 2012; Borgatti & Halgin, 2011). In particular, if *X* leads to *Y*, then what causes *X*? Also, when considering network properties as an independent variable, an implicit assumption is that the network structure is static, which is not the case. Scholars have underscored the need to understand the development of networks, such as what makes various networks demonstrate a similar structure. This belongs to another category proposed by Borgatti and Halgin (2011), explaining the formation and development of network properties. In this category, the focus can be tie formation between two actors or the changes at the system-level structure. Sociologists focus on individual attributes and explain tie presence/absence as a consequence of different preferences, such as gain access to desired resources controlled by others (i.e., complementary resource, Teece, 1986) or individuals share similar characteristics have a higher chance to connect (i.e., homophily, Mcpherson et al., 2001). At the system level, scholars aim to explain the occurrence of particular typologies. For example, from the physicist's perspective, Watts and Strogatz (1998) explain how networks can demonstrate a small-world structure—locally clustered with few shortcuts linking the overall system.

Overall, organizations' behaviors are likely to be influenced by the network around them. The network structure is also continually shaped by the interactions of firms and the formation of ties. These two categories complement each other and are important for understanding interorganizational networks.

In this dissertation, I offer insights into both categories and seek to make three main contributions. First and foremost, I emphasize the importance of considering the dynamics of network structures when considering their impacts. Social network research has been criticized for putting too much emphasis on the consequences and omitting how network properties emerge in the first (Borgatti et al., 2014; Gupta & Saboo, 2021). I consider network properties as independent variables in Articles 1 and 2 in explaining different outcomes, and in Article 3, I take a dynamic view to study network-level structural change. On one hand, I demonstrate that network properties can affect the behaviors of firms. The social network, on the other hand, is a constantly changing system rather than a static one. Together, these three articles provide a more comprehensive understanding of interorganizational networks.

The second contribution is related to the impacts of network properties. Scholars in different research streams focus on different kinds of outcomes. Articles 1 and 2 in this dissertation focus on different consequences of network properties and contribute to two distinct research streams. In particular, Article 1 adds to management literature by explaining the network antecedents of the firm's exploration strategy. In the existing literature, antecedents of exploration are either a firm's idiosyncratic features or environmental factors (Duysters et al., 2019; Lavie et al., 2010); Few discussed the impact of network structures. In article 1, I address network antecedents on firms' exploration strategy. Article 2 adds to the marketing literature by investigating the influence of network properties on dyadic-level interaction within the network. Most network studies in marketing are concerned with the performance of individual firms or of the system as a whole (Gupta & Saboo, 2021; Tracey et al., 2014). Few empirical studies show the network impact on dyadic level interaction using a quantitative method. Article 2 presents a model of how network properties influence prosocial behavior in dyads within the network and test it empirically.

The third contribution is related to network dynamics in the interorganizational setting. While a scholarly understanding of relationship formation exists, system or network-level dynamics remain a research issue that requires more attention (Ahuja et al., 2012; Chen et al., 2022). In article 3, I retrospectively reconstructed the annual system structure of two interorganizational networks and applied statistical models to identify particular patterns of structural change. Taken together, this dissertation adopts a structural approach to study interorganizational networks and discover the consequences and dynamic patterns of network properties.

1.2. Theoretical positioning and research focus

Despite the growing interest in interorganizational networks, some research gaps remain. Due to the diverse research focuses on interorganizational networks, I address gaps related to the three independent articles. In particular, the first two articles belong to the category that considers network structure as the independent variable, and the third relates to the second category that considers the dynamics and development of the network structure.

1.2.1. Network antecedents on exploration in management literature

The first gap lies in the nexus between network structure and seeking new opportunities (i.e., exploration, March, 1991). In the management field, a group of scholars investigates the impact of networks on knowledge outcomes (i.e., innovation) as the manifestation of exploration in knowledge-intensive contexts (e.g., Gilsing & Duysters, 2008; Phelps et al., 2012; Phelps, 2010). The causal argument links the actor's network position to knowledge outcomes. However, the process was largely omitted; innovation results from successful exploration. An understanding of what motivates firms to explore and what supports exploration success is essential, especially when the same factors impact different stages of the exploration process differently. Concerning the antecedents of exploration, existing literature largely focus on a firm's characteristics or environmental factors (Lavie et al., 2010). Therefore, we have limited knowledge concerning network antecedents on exploration. Accordingly, the research question guiding article 1 is: *What are the network antecedents on firms' exploration*?

1.2.2. Network properties and dyadic interaction in marketing literature

The second gap concerns the impact of interorganizational networks on dyadic relationships. There has been a growing interest in applying the network approach to marketing research (Gupta & Saboo, 2021; Wuyts & Van den Bulte, 2012). Many studies have investigated the impact on firm-level sales, profit, sales growth, and the introduction of new products (see Gupta & Saboo, 2021 for a review), while others focus on the system-level performance (e.g., Tracey et al., 2014). Limited studies have investigated the network's impact on dyadic relations. Marketing researchers have emphasized that interactions and business relationships are fundamental, and traditional research largely focuses on dyadic exchange relationships (Heide, 1994; Wuyts & Van den Bulte, 2012).

Nonetheless, the dyadic relationship is part of a larger context in which many other relationships are also involved. Scholars find that networks can have control and coordination benefits for inter-organizational governance (Wuyts & Van den Bulte, 2012). A study by Haugland and colleagues (2021) has investigated how triadic embeddedness influences relationship learning and trust-based governance in dyads. However, in addition to triadic structures, it has not been explored what effects other network properties may have on dyadic interactions. Therefore, a research gap exists concerning the impact of network properties (beyond triadic embeddedness) on dyadic interaction. Accordingly, article 2 focuses on this topic and studies *how network properties influence prosocial behavior in dyads within the network*.

The two threads discussed above concern the first category, where network structures are considered (static) independent variables to explain different outcomes. The next research gap relates to the second category, which explains *how an interorganizational network develops and demonstrates particular patterns*.

1.2.3. Network dynamics at the systemic level

As the previous discussion indicates, networks often perform significant function roles. These functions are dependent on the existence of particular structures. Works that explain network dynamics are distributed across many fields and provide diverse explanations. Sociologists and management scholars provide explanations mainly for dyadic tie formation[2], such as alliance formation and joint ventures. Yet, it provides less direct implications for network-level properties. At the system level, physicists provide some general models and mechanisms for explaining the dynamics of complex structures, which are independent of the nature of the system (Albert & Barabási, 2002; Watts & Strogatz, 1998). Limited works are available which examine empirical social or economic systems using quantitative methods of network science. Therefore, in article 3, I aim to study *the system-level dynamics in the interorganizational setting concerning the development of particular structures*.

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[2] A more detailed discussion is presented in section 2.3.

1.3. Summary

In this section, I present the broad focus of this dissertation—interorganizational networks, and discuss the focus of independent articles connected to different research streams. Figure 1-1 shows how independent articles are positioned under the broad theme of interorganizational networks. Existing interorganizational network studies on this topic can be categorized into two categories. In the first category, researchers consider network structure as a reflection of certain processes to explain various outcomes; I collectively call theories in this domain *Influence of social networks* in the Kappe. The second category considers network structure as a constantly changing system and investigates the process of determining certain network properties. I call this domain *Network dynamics* since it explains the development and dynamics of network structures.

This dissertation consists of articles in both categories. By combining (1) the impact of network properties and (2) the dynamic patterns of the structure, I show that the network structure at a single point in time is a consequence of a long development process, which is likely to influence members' behaviors.

The rest of the Kappe is organized as follows. In section 2, I review the literature on relevant theories and present the framework for independent articles. Section 3 introduces the research design and method. Section 4 presents long abstracts of independent articles. Section 5 presents the main findings of this dissertation, its limitations, and possible directions for future research.

Figure 1-1. Overall framework

2. Literature review

The purpose of this chapter is to present the theoretical background and literature review. I start by defining networks. Then I review literature related to interorganizational networks. In accordance with the subthemes in this dissertation, the review of interorganizational network research will be done based on two categories: Influence of social networks and Network dynamics. Next, I discuss the general idea for individual articles. I close this section by providing an overview of independent articles.

2.1. What is a network?

The components of a network are simple: a group of nodes and a group of ties representing relationships between the nodes (Brass et al., 2004). One can study networks using either an egocentric or sociometric approach. The egocentric network focuses on the focal actor (ego), which consists of the ego and alters (Wasserman & Faust, 1994). This approach can provide information concerning the number of alters an ego connects to (i.e., degree centrality) and the composition of the network. In contrast, a sociometric network involves mapping and analyzing patterns of ties between actors within a defined boundary (Borgatti et al., 2018). A sociometric network is often referred to as the whole network. In the sociometric approach, all actors report their ties with other network members (Opsahl, 2013). Applying a sociometric approach can avoid missing important parts of a network and provide a more accurate visualization. It is possible to subtract egocentric network data from sociometric data. The sociometric approach could produce better network data than the egocentric approach; however, it is more difficult to conduct.

When studying a network, two questions naturally follow concerning (1) which nodes should be included and (2) how the ties are defined. The first question implies consideration of who the actors in the network are or what the network boundary is (Robins, 2015). Not all networks need to have a clear nature boundary. Nevertheless, in some cases, the boundaries are indeed clear. For example, if we study students in a classroom, the actors are students who show up in the classroom at a specific time. Alternatively, we may be interested in firms operating in the retail sector; the actors are the registered firms that claim their business activities are related to retail. Since ambiguity may exist in each of these cases, in the latter case, we may define a more precise boundary by adding inclusion criteria such as being established after 2000, being registered in Norway, and there should be more than ten formal employees. The network boundary affects the scope and the network structure one aims to study (Conway, 2014; Robins, 2015). The boundary specification should be reasonable and relevant to the research question.

The second question concerns what type of relational ties are relevant. There are countless types of relationships between different actors. Scholars have categorized two practical types of social ties: state-type and event-type (Borgatti & Halgin, 2011). If actors are individuals, the relationships can be between friends, schoolmates, colleagues, and spouses. All these mentioned relationships are state-type ties since they are persistent. Event-type ties are intermediate, such as having a meeting, sending emails, or giving advice. In this dissertation, I am interested in firms. A direct association would be business relationships between firms, such as alliances and supplier and buyer relationships, which are state-type ties. However, there are other types of connections—for instance, the mobility of employees from firm A to firm B, partaking in the same chamber of commerce,[3] and communication by sending emails and attending workshops—which belong to event-type ties. In addition, these different types of ties could coexist. For example, two individuals can have a friendship tie (i.e., state-type tie) and

[3] Some scholars consider this type of tie as improper since it lacks social process; see Borgatti and Halgin, 2011, for details.

send text messages (i.e., event-type tie) to share information. The event-type tie may be able to reflect what has been transferred between two actors, but it is a temporary act. In contrast, the state-type tie indicates an existing connection between two actors, but it does not reveal much about the nature of their interaction.

To conclude, the decision concerning network boundary and proper relational ties should be related to the research question, context, and the social process one expects in operation (Robins, 2015). As these two questions determined the research design and method adopted for this dissertation, I return to these two questions in section 3, where I discuss the research design.

2.2. Influence of social networks

In the Influence of social networks category, scholars explain involved firms' behaviors based on the network around them. To illustrate the influence of network properties on firms, scholars classify the mechanisms that networks exert on firms into competence and control sides (Gilsing & Duysters, 2008; Wuyts & Van den Bulte, 2012). From the competence side, most interorganizational network studies focus on the flow of information and resources through network ties, and actors gain competence and prestige based on their network positions. As Salancik (1995) pointed out, in organizational studies, social network theories normally incorporate other influential theories regarding firms and relationships between firms. This stream of studies relies heavily on the resource-based view of the firm (Barney, 1991, 2001), the relational view (Dyer & Singh, 1998), and resource-dependence theory and power (Emerson, 1962; Pfeffer & Salancik, 1978).

The resource-based view of the firm has played a critical role in interorganizational network studies and highlights those resources and capabilities inside a firm that differentiate firms in a market, which predicts firms' performance (Barney, 1991, 2001). As the business environment becomes increasingly networked, a firm's own resource is no longer sufficient (Whipple et al., 2015). Dyer and Singh (1998) claim that firms' critical resources can locate beyond its boundary or even be embedded in interorganizational routines. As such, firms join a network to pool their resources and rely on their business networks to gain access to external resources and capabilities to improve performance. For individual firms, their network positions indicate their accessibility to network resources (both tangible and intangible) and reflect their interdependence on the network (Brass & Burkhardt, 1993; Emerson, 1962). The most commonly used network measure concerning accessibility is centrality, including different types of centralities based on how it is measured[4]. Despite the different centrality measures, occupying a central position is considered advantageous.

Two well-known social network theories concerning the content of resources accessed in a network are from Granovetter (1973) and Burt (1992, 2004). Granovetter (1973), in his work, distinguished strong and weak ties. The distinction between strong versus weak is about the distance or familiarity between the ego and the alter. Strong ties are normally intensive social relations such as family and close contacts, often forming a densely connected structure. Information exchanged through strong ties is often familiar and redundant. Weak ties, on the contrary, are with loosely connected actors such as acquaintances, which have a higher chance to provide heterogeneous information. In sum, a firm accesses different content of information from different ties. Due to the distinct features, firms may design their interorganizational relations according to conditions and goals to gain competence.

Burt (1992) proposed the idea of structural holes and suggested that bridging disconnected social structures can bring benefits. As maintaining relationships is costly, firms should maintain bridging ties instead of redundant ties to increase efficiency. Structural holes

[4] Appendix IV provides a more detailed discussion of different types of centrality measures.

exist between separate parts and can provide information access, referrals, and control benefits (Gilsing & Duysters, 2008). Burt's idea emphasizes the structural importance of brokerage to gain competence. Granovetter and Burt's ideas emphasize the importance of accessing fresh and non-redundant information to gain *competence*.

For individual firms, different network positions induce inequity among actors, reflecting their interdependencies among network members (Gulati, 1998; Gulati & Gargiulo, 1999; Wasserman & Faust, 1994). The social capital theory (Coleman, 1988), on the other hand, suggests that a network can be a source of constraint and countervailing power equities when everyone knows each other. Coleman (1988) suggests that cohesive structures are more suitable for generating benefits such as trust, norms, and shared identities to sustain interaction. Another scholar—Georg Simmel (1950), was the first to propose the idea of triadic analysis, which is the smallest unit of a network. Focusing on triads lays the foundation of the cohesive structure idea. The dyads' quality, dynamics, and stability will change fundamentally with an existing common third party. Coleman points out the benefits of having cohesive networks for the potential to build social capital. The social capital developed in cohesive structures can facilitate the function of norms and sanctions, which may facilitate cooperation and hinder improper behavior. As such, cohesive structures function as a social *control* mechanism to prevent uncertain behavior and sustain coordination (Rowley et al., 2000; Walker et al., 1997). Coleman's idea can be relevant to the governance of interorganizational relations. The control and governance perspective is of interest to relationship marketing scholars (Wuyts & Van den Bulte, 2012).

These theories demonstrate that network ties enable the exchange of resources and information (network ties as *pipes*) and serve as a means of aligning and coordinating action (network ties as *bonds*). Granovetter, Burt, and Coleman's ideas have different considerations and lead to different conclusions concerning a suitable network structure. Their views are not necessarily contradictory, yet it indicates that the optimal structure depends on the expected outcome.

2.3. Network dynamics

The second category of interorganizational network studies focuses on network dynamics and development. In this stream, studies are conducted to determine why two actors are connected or why many networks demonstrate similar structures. According to a recent review by Chen et al. (2022), network dynamics is considered an umbrella term covering a wide territory. In this study, I limit my focus to what they called *network change*, referring to change in who is connected to whom for specific types of ties. In other words, this work considers models that change the states of relations, such as tie formation and dissolution. It can be agreed that tie formation and dissolution are dyadic-level activities. Yet, the result can also be overserved at the actor level (e.g., the change in degree for individual actors) and the network level (e.g., the centrality and average path length of a given network). For instance, assume in a friendship network among students in a class, a popular student with many friends is a central actor and may attract more people to be friends with her. Consequently, this student tends to have more friends, and the friendship network can be more centralized around the popular students. To sum up, network dynamics is defined as the change in conditions or patterns of connections that can be observed at multiple levels. Some scholars focus on the dyadic level change, while others focus on the system-level structure change.

At the dyadic level, sociologists suggest assortative mechanisms and explain that tie creation, maintenance, and termination depend on the compatibility and complementarity of actors' attributions (Rivera et al., 2010). In other words, the connection between two actors is associated with their similarities or dissimilarities. The similarity, or compatibility, leads to the dynamics of homophily. McPherson et al. (2001) find that individuals show a strong tendency of homophily and establish connections with similar individuals. Similarities among individuals can be gender, age, religion, values, geographic location, and education. Homophily is a universal tendency because a certain level of overlapping background makes interaction easier. Following this idea, the more similar two actors are, the more stable the relationships can be. When dissimilarity appears, connections have a higher chance of breaking apart. Homophily is more likely to appear in an individual setting, such as teams in new business start-up teams, online communities, and friendship networks.

In contrast, dissimilarity or complementary leads to dynamics of heterophily. In some cases, diversification is essential. For example, the board of directors in large companies should offer resources from diverse channels (e.g., financial, political, technological, and societal resources). Collaboration networks of other forms, such as academic co-authorship and movie writing, also appreciate diversity. A particular emphasis is placed on complementarity in the interorganizational context; firms tend to select partners with complementary qualities, skills, and knowledge relevant to solving the problem or achieving their goals (Dyer & Singh, 1998; Teece, 1986). Whipple et al. (2015) have pointed out that the resources or skills needed can hardly be controlled by a single firm; thus, firms need to collaborate with firms that are different from their specialization. Preference for complementary partners has been found in several industry networks, such as biotechnology (Powell et al., 2005) and venture capital (Sorenson & Stuart, 2008). Complementarity seems to be a more common cause for interorganizational tie formation because the advantage of compatibility at the interorganizational level may be substituted by formal contracts (Granovetter, 1985).

Other dyadic-level dynamics are about changes in relationship conditions, including reciprocity and repetition. A straightforward example of reciprocity is a friendship tie. Assume two individuals, *i* and *j*; when *i* considers *j* a friend, *j* is more likely to offer friendship back to *i*. Reciprocity is common in individual networks since people tend to like others who like them to form a balanced relationship (Newcomb, 1956). Most of the time, reciprocation does not occur solely; the relationship exists as each party contributes (Rivera et al., 2010). One-way friendship has a high chance of dissolving. In sum, reciprocation can sustain a relationship, and a lack of reciprocation may lead to relationship termination. It is worth noting that the reciprocation can be both events (e.g., A sends B an email or A buys goods from B) or state (e.g., friendship). It is worth noting that the reciprocity discussed here differs from the generalized moral norms of reciprocation (Gouldner, 1960). Reciprocity here is considered a mutual activity (e.g., I send an email to you, and you send me an email back), while norms of reciprocity are regarded as a code of conduct or duty.

In relationships that can last for a long term, the frequency of repetition is another feature that scholars are interested in. Repetition is only suitable for studying event-type of ties, not state-type ties, because event-type of ties are temporary, while state-type ties are persistent. For example, a supplier and a buyer have a long-term relationship (i.e., state-type tie), and the buyer purchase from the same supplier several times (i.e., event-type tie). Repetition of ties has been considered a measure of relational strength in social and economic contexts (Rivera et al., 2010). Beyond the strength of the relationship, repetition is also an indicator of trust (Gulati & Gargiulo, 1999; Uzzi & Lancaster, 2004) and relational embeddedness in economic exchange (Uzzi, 1996). In interorganizational contexts, repeated ties are common. For instance, Uzzi (1996) found that contractors work with the same manufacturers multiple times in the appeal industry. Thus, existing ties increase the chance of repetition in the future.

At the network or system level, clustering and closure is the most common mechanism in social networks. Among individual networks, clustering has been observed in Broadway musical artists (Uzzi & Spiro, 2005), Hollywood movie actors (Watts, 1999), and inventors (Fleming et al., 2007). Concerning interorganizational networks, firms tend to tie together through alliances (Kogut & Walker, 2001) and geographical co-location (Lazzeretti et al., 2019). Sociologists propose several explanations for nontrivial clustering. Granovetter (1973) suggested that a shared third party is likely to increase the chance of incidentally encountering each other, even without a formal introduction. The two unconnected individuals will tend to connect after some referrals or informal interactions, forming a closed triadic structure. Following the idea of social capital, a closed triadic structure promotes collective norms, curbing uncooperative behavior and mitigating conflicts (Coleman, 1990; Krackhardt, 1999; Uzzi, 1997), eventually making the social structure stable. Another explanation for triadic closure is to decrease the distance between two previous unconnected actors (Rivera et al., 2010). In a social network, two disconnected actors may need to go through intermediates to reach each other. However, when they establish a relationship, they no longer rely on intermediates, increasing the efficiency of interaction. Therefore, clustering or closure is common in social networks.

Another systematic level mechanism is based on actors' degree distribution or centrality—the number of ties individual actors possess. Preferential attachment, or the rich-gets-richer, means that actors who occupy central positions can attract more actors and form more ties to enhance their central positions (Albert & Barabási, 2002). Consequently, the network demonstrates a scale-free property, where most actors have only a few ties, while a small number have a lot. Such a structure has been found in the citation network of papers in neuroscience (Jeong et al., 2003) and some interorganizational settings such as tourism destinations (Baggio et al., 2010) and collaboration networks in the biotechnology industry (Gay & Dousset, 2005). Moreover, scholars noticed that the preferential attachment mechanism might be diminished by factors that moderate actors' resources for tie formation, such as time and money. For instance, in interorganizational networks, firms differ in size, directly influencing their capacity for collaboration (Shan et al., 1994). Also, it has been found that the central position may be less attractive in an inter-firm network than other factors, such as complementary or fitness in the market (Powell et al., 2005). Therefore, preferential attachment has been observed in individual and interfirm networks, and some factors may weaken this mechanism.

As discussed in section 2.1, network ties can be state type (e.g., collaboration and alliance) and event type (e.g., phone calls and seeking advice). These two are different phenomena, and the event-type of ties can be less stable since events are non-continuous and can be reciprocated and repeated. In addition, state-type ties can be reciprocated (e.g., I consider you as a friend, and you consider me as a friend) but are hard to repeat. The triggers for these two types of ties are also different. In this study, I follow Brass et al. (2004) and consider ties that are 'maintained over time, thus establishing a relatively stable pattern of network interrelationships (p. 795).' More specifically, I focus on state-type ties, which are stable and allow a set of behavioral rights, obligations, and expectations built upon norms developed over time (Mitchell, 1969).

In this section, I discuss the dynamics at the dyadic and system levels. At the dyadic level, I discuss assortative and relational mechanisms. The dyadic level change in the interorganizational setting is more likely due to complementary instead of similarity. Board interlocks have been a main context for studying interorganizational dyadic ties changes (Chen et al., 2022). At the system level, I discuss structural mechanisms. Most network-level dynamics studies in the interorganizational context focus on a firm's ego network concerning network composition instead of the wider network structure (ibid). Limited is known about the systematic structural dynamics. In article 3 of this dissertation, I study dynamics at the system level (beyond an egocentric) structure concerning the state type of ties.

In summary, when considering the consequences of network properties, an implicit assumption is that the social system is static. Network studies were often criticized for failing to recognize the dynamic nature of organizations and groups. When only considering network dynamics, one may question why it matters. This dissertation aims to provide a more complete explanation of their dynamics and consequences. I show that interorganizational networks are changing social systems and influencing involved firms' behaviors. In the following section, I present the theoretical framework of independent articles.

2.4. Presentation of theoretical models for independent articles

2.4.1. Article 1: Network antecedents on firms' exploration strategy

Article 1 investigates network antecedents on exploration strategy. Despite the strong focus on the consequences of exploration, exploration tendencies vary among firms. Our knowledge about antecedents of exploration alludes to environmental factors that facilitate it, such as competitive intensity and environmental dynamics (Hannan & Freeman, 1984; Jansen et al., 2006; Sørensen & Stuart, 2000). These factors uniformly influence firms in the same market and cannot explain the different levels of explorative efforts. On the other hand, some studies show firm-specific characteristics, such as firm size, age, culture, and organizational structures, which consider firms fully independent in deciding the level of exploration (Lavie et al., 2010). In the current study, I argue that firms' tendencies to explore are associated with their network position.

In particular, I consider two network constructs: closeness centrality and local cohesion. Closeness centrality is associated with a firm's searching cost and efficiency to reach others in a network (Wasserman & Faust, 1994). I choose this construct because it reflects the ease of reaching network resources. To motivate exploration, firms may need diverse and dissimilar input of knowledge and information from external partners (Greve, 2007; Jansen et al., 2006). Considering that a firm seeks external resources within a network, high closeness means a short distance to network members, which can be beneficial for accessing distant knowledge. The core idea here is the efficiency of reaching network resources instead of the content of information accessed.

Local cohesion refers to the connectivity between the focal firms' direct partners (Wasserman & Faust, 1994). Firms with a high level of local cohesion can benefit from the sustained trust, norms, direct communication, and sharing of less public information (Coleman, 1998; Uzzi, 1997), which increase the quality of input from partners and facilitate organizational learning. Cohesive structures provide a supportive environment for exploration. I suggest that closeness centrality and local cohesion can influence firms' exploration strategy. Therefore, I contribute to the literature by shedding light on the network antecedents of exploration strategy.

2.4.2. Article 2: Network antecedents on prosocial behavior at the dyadic level

Article 2 investigates network antecedents on prosocial behavior at the dyadic level. Firms' activities in interorganizational relationships can be either mandatory behavior required by the contract or voluntary behaviors beyond formal requirements (Wang et al., 2017). Because contracts can hardly be complete, some beneficial behaviors beyond formal requirements can improve cooperation (Wuyts, 2007). In the interorganizational context, prosocial behavior refers to a firm's beneficial actions toward another firm beyond formal requirements (O'Reilly & Chatman, 1986), which can be desirable in business relationships. Examples of prosocial behavior can be proactively considering the interest of partners and willingness to support partners to achieve their business goals. Beyond dyadic relationships, such behavior is also beneficial for larger interorganizational networks, such as regional clusters and innovation systems, which rely on members' interaction for final output. Dyadic-level prosocial behavior can be an indicator of the network's 'well-being.'

Following the traditional relationship marketing literature, current knowledge about antecedents of prosocial behavior is mostly at a dyadic level. Wuyts (2007) categorized antecedents into instrumental and communal factors. Examples of instrumental factors are the high switching cost of a particular actor (Wuyts, 2007) and previous interaction (Wang et al., 2017). Communal factors include trust (Hewett & Bearden, 2001), commitment (Li, 2010), relational norms (Lusch & Brown, 1996), and reciprocity (Hoppner & Griffith, 2011). Zhou and colleagues (2020) also considered the influence of relationships between individuals that are boundary spanners. They suggested that network properties could be an important driver for prosocial behavior, yet it has been overlooked.

Beyond dyadic-level antecedent factors, I focus on two specific network constructs: in-degree centrality and triadic embeddedness. In-degree centrality captures power generated in the network and the visibility of behaviors by other network members (Brass & Burkhardt, 1993; Wasserman & Faust, 1994). I tend to connect in-degree centrality to instrumental factors such as interdependence and reputation management. Triadic embeddedness is related to communal factors due to better-aligned incentives and group norms developed in closed structures (Coleman, 1988; Krackhardt, 1999). Accordingly, I contribute to the marketing literature by extending the dyadic focus and investigating how network-related antecedents influence firms' prosocial behaviors.

2.4.3. Article 3: The dynamics of system-level properties in interorganizational networks

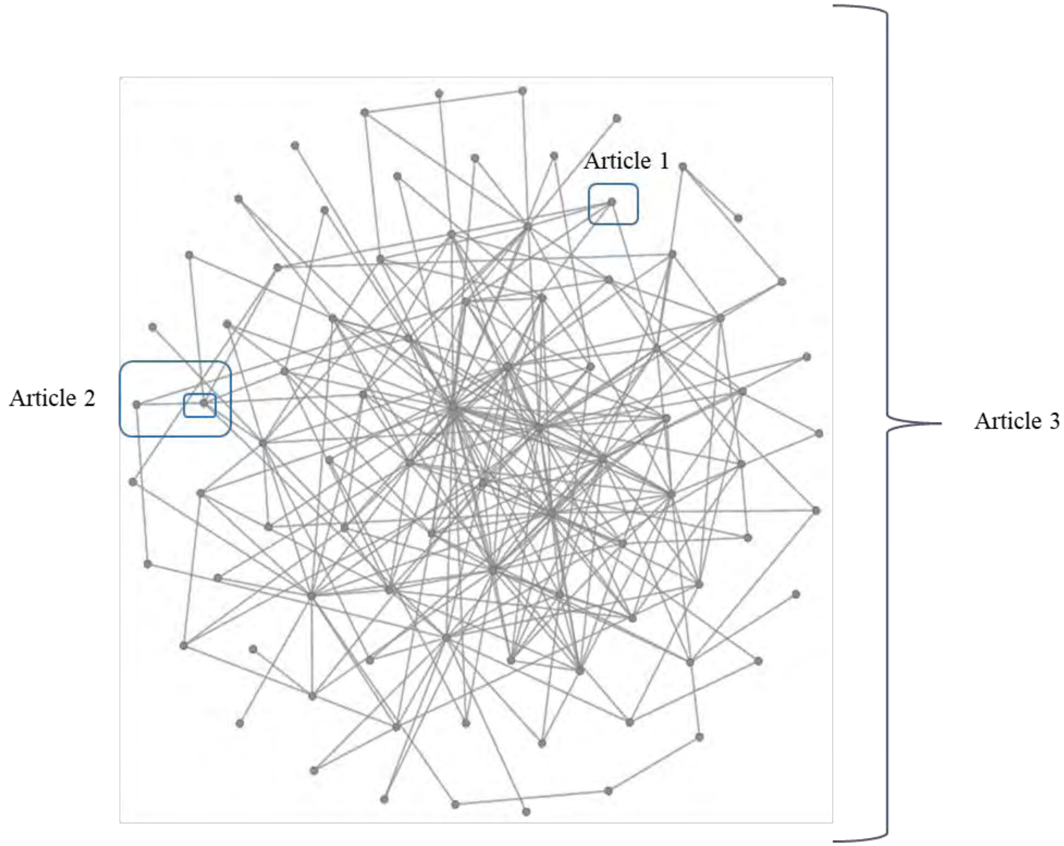
Article 3 studies the dynamics of interorganizational networks at the system level. Under the broad theme of network dynamics (as discussed in section 2.3), I am interested in the system-level dynamics in terms of small-world and scale-free structure. These two network structures have been found to characterize a wide range of social networks and can shape economic actions and performance (Baggio et al., 2010; Gay and Dousset, 2005; Gulati et al., 2012; Jeong et al., 2003). Small-world structure refers to a short path length and is highly clustered (Watts & Strogatz, 1998). Due to its structural features, a small-world network is increasingly considered a driver of individual and collective action (Gulati et al., 2012; Uzzi & Spiro, 2005). Watts (1999) noted explicitly that a small-world network is decentralized in that no dominant central actor exists. The scale-free structure, on the contrary, is centralized with a few central actors with a large number of peripheral actors with limited connection (Barabási & Albert, 1999). Yet, some empirical networks have been found demonstrating properties of both (e.g., Baggio et al., 2010; Baum et al., 2004; Gay & Dousset, 2005). Limited is known concerning how empirical networks can simultaneously take small-world and scale-free properties (Aarstad et al., 2013, 2015a).

Moreover, the theoretical models explaining the development of small-world and scale-free structures are hard to implement in some empirical settings. For instance, in Watts and Strogatz's (1998) model of the small-world structure, a default model is that all network actors have an equal number of connections only to the nearest actors. As the randomness of connection increases, actors tend to have shortcut ties with distant actors without decreasing the local clustering. However, it is rarely the case that empirical networks start with a regular high clustering structure. Similarly, the preferential attachment or the rich-gets-richer is considered the core mechanism for scale-free structure. Scholars hold different opinions about whether the rich-gets-richer mechanism and scale-free structure are common in particular settings. While some observed scale-free structure in interorganizational networks, others found that preferential attachment is contingent on different factors (Powell et al., 2005; Rossmannek & Rank, 2021). To conclude, I study the development of the small-world, scale-free structures and the interrelation of these two in interorganizational networks. The findings improve our understanding concerning how empirical networks can develop to particular structures and whether or not some general network models hold in the interorganizational setting.

2.5. Summary

In this section, I provide a general review of existing literature under the broad theme of interorganizational networks. I discuss the theoretical models when considering network properties as explanatory variables for certain outcomes and systematic structural dynamics. Then I present the framework of independent articles. Figure 2-1 illustrates the focus of three articles. Articles 1 and 2 consider network properties as independent variables that influence actors' behaviors. The network properties investigated in the first two articles focus on individual firms. In other words, I use actor-level network measures as independent variables. The dependent variable in article 1 is firm-level exploration strategy, while article 2 focuses on a focal firm's behavior within a dyad. Article 3 takes a systematic approach to study network-level structural change. Overall, I not only show how network properties matter (Articles 1 and 2) but also show how network properties come about and how they might change over time (Article 3). As such, this project covers both the structural dynamics and consequences of network structures.

Figure 2-1. Summary of independent articles



Source: Network structure of Media City Bergen in 2019.
Note: The dependent variable of Article 2 is prosocial behavior within a dyad. However, the network measures are still ego level. In order to distinguish the research objects from Article 1, I mark Article 2 as dyadic level.

Overall contribution:
It is implicitly assumed that networks are static when we only consider various consequences of network properties. In this study, I not only show how network properties matter (Articles 1 and 2), but also show how network properties come about and how they might change over time (Article 3).

Article 1:
Independent variables: closeness centrality, local cohesion
Dependent variable: exploration strategy
Focus/ level of analysis: firm level
Main contribution(s): (1) Add to management literature antecedents of exploration beyond firm-specific and environmental factors; (2) consider impact on exploration beyond a pure knowledge domain.

Articles 2:
Independent variables: in-degree centrality, triadic embeddedness
Dependent variable: prosocial behavior in a dyad
Focus/level of analysis: dyadic level
Main contribution(s): Adds to marketing literature by illustrating network properties on dyadic-level prosocial behavior.

Articles 3:
Focus/ level of analysis: system level
Main contribution(s): (1) Adds to network dynamics literature concerning the interrelation of small-world and scale-free structures; (2) show that preferential attachment and scale-free structure are less common in the interorganizational setting.

3. Research methods

This chapter covers the methodology used in this study. In the first part, I discuss why I choose a quantitative research design. The next part discusses the empirical setting and explains the reason for choosing this setting. Then, I discuss the data collection instrument and procedure. The next section summarizes the data. The chapter concludes by discussing relevant methodological concerns.

3.1. Research design

3.1.1. Research questions and types of research design

A research question is an inquiry to which the research will attempt to provide an answer. The research question introduces the components of the problem (Malhotra & Birks, 2006). It outlines the goal of a systematic investigation and serves as a guide for the research process. When conducting research, it is critical to ask the right questions so the researcher can collect relevant and insightful information that ultimately impacts the work positively. The choice of method largely depends on the underlying research questions a study aims to solve (Malhotra & Birks, 2006). More specifically, the research question indicates what information is needed to answer the question. A research design reflects the ways in which evidence is chosen and arranged to address a particular research question.

There are two broad categories of research questions: qualitative research questions and quantitative research questions (Creswell, 2014). These two types of research questions can be used independently or co-dependently in line with the focus of a research objective.

Qualitative research questions are normally non-directional, more abstract, and flexible. The words 'what' and 'how' can be used as starting points for qualitative research questions, indicating an open and emerging design. The word 'why' in a qualitative research question often implies that a researcher is trying to discover why something occurs. Research questions that begin with ‘why’ may also be quantitative research questions, in which causal inference may be assumed. However, the qualitative research question aims to find explanations from different perspectives. Some exploratory verbs are common in describing qualitative research, such as report (or reflect), describe, explore, and seek to understand (Creswell, 2014). An example of a qualitative research question can be How do phd candidates evaluate their work? The answer may be different perspectives or standards for evaluation among a group of phds. Common research methods for answering qualitative research questions include interviews (to provide different narratives), case studies (to explore a certain process), or observations (to develop theories).

Differently, quantitative research questions are less open, more precise, and indicate specific relationships between variables. The research normally seeks to understand the relationship between multiple variables under a specific condition. At the beginning of quantitative research, a literature review is needed to provide the direction for the research question or hypotheses. An example of a quantitative research question can be How peer pressure influences phd students’ anxiety? The population is clarified (i.e., phd students), and one seeks to know the relationship between peer pressure and anxiety. Accordingly, researchers will develop hypotheses based on existing literature to describe the prediction of an expected relationship or causal inferences between variables. Then, the researcher uses a reasonable method to collect numeric data for variables and test hypotheses relying on statistical tools. Quantitative research methods normally include surveys and experiments for collecting first-hand data. It is also common to use relevant archival data for hypothesis testing.

To sum up, the research question determines the choice of research method. There are two general types of research questions—qualitative and quantitative. In the next section, I discuss the selection of methods in the dissertation based on the three research questions.

3.1.2. Selection of method

Based on the research questions in this study, I chose a quantitative method. Articles 1 and 2 investigate the influence of specific structural properties on a firm's behavior. I proposed hypotheses describing the expected relationships between different variables. Essentially, the research design is a theory-testing approach, which develops hypotheses based on theories and identifies the components contributing to a particular phenomenon. Quantitative data are needed to validate the hypotheses.

Considering the dyadic or inter-organizational context, this study adopted a quantitative cross-sectional research approach (Creswell, 2014). A cross-sectional design was chosen because it allows for detecting patterns and relationships between variables of interest rooted in theory and making inferences from those associations (Creswell, 2014; Rindfleisch et al., 2008). Furthermore, cross-sectional surveys are useful for collecting network data that can be used in theory testing (Borgatti et al., 2018). It also represents a suitable method for large population-based data collection to efficiently obtain the characteristics of a large sample (Ponto, 2015). Thus, the cross-sectional survey is a reasonable choice for Articles 1 and 2.

Article 3 aims to analyze the structural change of empirical networks. At first glance, qualitative methods may appear to be more appropriate when the research focus is change or dynamics. However, my particular interest is to see the interrelation of two network properties—small-world and scale-free structures. In other words, I would like to see the relationship between two variables. Therefore, a quantitative design is suitable. In addition, a longitudinal design would be ideal for showing the process. However, due to the practical limitations of time and cost, a longitudinal design is not feasible for this study. Instead, I chose a retrospective approach to capture the process by asking about the year of relationship initiation when collecting network data in the cross-sectional survey. Using these data, I could retrospectively reconstruct and model the network pattern over a certain period and calculate network properties in terms of small-world and scale-free structures. Altogether, the cross-sectional survey is a reasonable choice for data collection in this dissertation.

Some qualitative methods were also employed at the beginning of the research by conducting semi-structured interviews with five informants who were managers of interorganizational networks[5] or managers of firms that operated in interorganizational networks. Using qualitative methods was beneficial for gaining a better understanding of the empirical network regarding its actors and activities. The information obtained from the interviews assisted me in understanding the empirical context and in drafting the survey questionnaire.

After selecting the empirical context, I have considered archival data a potential source. I tried to seek proper sources for network data, which are formal relationships between cluster members. I collected information on all registered members and their organizational numbers registered at Brønnøysund Register Center, the national registration system for companies. As innovation is a major goal of regional clusters, I searched for information about joint innovation projects registered in Norwegian national tax offices. The Norwegian government encourages and promotes innovation. Thus, companies can get a tax deduction by reporting their innovation projects to the tax office. Unfortunately, I found that firms report for their innovation projects independently, making it impossible to find partners involved in the same project. Instead, I tried to search by project names to identify involved organizations. However, firms did not use a unified project name when they reported joint innovation projects. The

[5] Managers of networks refers to those in charge of network daily operations. The two empirical networks in this study have independent organizations initiated by the government to manage the operation of regional clusters, such as promoting the regional cluster, recruiting new members, arrange activities and workshops to facilitate members interaction.

dependent variables of the first two articles are firms' behaviors, and I failed to find proper archival data sources. I also noticed that many cluster members are start-ups, and archival data may provide limited information about their activities. Therefore, a cross-sectional survey is suitable for collecting first-hand data directly from the organizations and proper for the particular context.

3.1.3. Limitations of cross-sectional research design

Any research method has its limitations. When using (only) survey data for hypothesis testing, two issues will influence the validity and reliability of results: common method variance and causal inference (Rindfleisch et al., 2008). Several methods can be used to overcome the limitations of cross-sectional design. It has been suggested that using multiple data sources, including variables, and designing a well-designed questionnaire can mitigate the issue of common method bias. (ibid). Despite its limitations, cross-sectional surveys remain the most popular research method in marketing management and business-to-business research (Hulland et al., 2018).

Accordingly, I took measures to reduce the common method bias. In Articles 1 and 2, the independent variables are based on the network algorithms, and the dependent variables are measured using multi-items in the questionnaire. The network data were based on respondent firms' ongoing business relationships with other network members. Although data were obtained simultaneously, the data used for independent and dependent variables were not related. After modeling the network structure and calculating particular network properties, I merged the network data with survey data by firm names. Therefore, the measures of independent and dependent variables are irrelevant in that they use totally different measurement scales and measurements, which reduces common method bias. Moreover, in Articles 1 and 2, I draw theory from well-established domains, such as social capital, the resource-based view of firms, resource-dependence theory, and power theory. Therefore, Articles 1 and 2 have a reasonable theoretical foundation for making causal inferences.

3.2. Empirical context

I select regional clusters as the research context because it is, by nature, an interorganizational setting where multiple organizations join to interact. In general, networks can be classified as either goal-directed or serendipitous (Kilduff & Tsai, 2003). A goal-oriented network is formed to achieve a specific objective among its members and is normally a stable social structure. Regional clusters could be an example because the aim is to facilitate members' interaction to sustain innovation and local economic performance. On the contrary, a serendipitous network can be artificial or formed by chance based on members' social interactions. Board interlocks are examples of serendipitous networks which did not exist to achieve a specific goal but rather for researchers' interests.

Research on regional clusters has been growing rapidly during the last five decades (Bell et al., 2009; Bergman & Feser, 2020). This is unsurprising, as the regional cluster has been portrayed as a political tool to boost innovation and regional economic growth (Martin & Rypestøl, 2018; Martin & Sunley, 2003). Strictly speaking, regional clusters should fulfill four requirements: (1) geographical concentration of similar and related economic activity, (2) these activities are linked through different forms of local collaboration and competition, (3) members have a common understanding to strengthen the cluster, and (4) clusters should facilitate innovation and economic growth (Isaksen, 2018). There are several legendary regional clusters, such as Silicon Valley and Route 128 (Saxenian, 1996). However, there are also many failed cases, such as the 'multimedia super corridor' in Malaysia (Ramasamy et al., 2004). Although all regional clusters are initiated with great ambition, few end up as legends. The last criterion of regional clusters is not easy to achieve.

Researchers have noted that clusters can be ineffective, decline over time and eventually disappear (Menzel & Fornahl, 2009). The reasons for cluster failure can come from individual organizations and the system. For individual organizations, joining a regional cluster does not guarantee better performance. After becoming cluster members, organizations create interactions with other members for their interests and goals. Although regional clusters can pool resources and give access to diverse resources, existing challenges in interaction and coordination remain. In addition, firms can be locked-in in the long term. If a firm only interacts with cluster members, it may lose better opportunities outside the cluster (Isaksen, 2018).

At the system level, failure can be a lack of diversification or involving weakly performing actors (Chaminade et al., 2009). As time goes by, cluster members tend to have a homogeneous knowledge base; without constantly including new sources can harm innovation. In some old industrial clusters, members can be closeminded, and only a restricted group of permanent members are included. As a result of their high level of professionalism and rich experience, these types of clusters may be well positioned in the early stages. However, they are more likely to decline over time due to a lack of novelty. Also, such clusters may be rigid and fail to respond to changing market environment. Concerning the capability of members, involved firms with a weak capability to collaborate, share knowledge, and learn from other members will make interaction inefficient (Isaksen, 2018). Given all these remaining challenges and the goal, a regional cluster is an interesting and meaningful context to study. It is essential to know how firms interact within a regional cluster and how the regional cluster can operate effectively.

Having decided on regional clusters as the research context, I selected two clusters in Bergen, Norway, focusing on the media sector and fintech. Both clusters officially belong to a government-supported program called the Norwegian Center of Expertise (NCE). The NCE project was launched in 2006 to increase innovation, enhance local companies' internationalization, strengthen hosting attractiveness, and provide access to tailored expertise.[6] This project is supported by Innovation Norway, Siva (a state-owned company to facilitate industry growth in Norway), and the Norwegian National Research Council. There are currently 12 NCE clusters in Norway, focusing on aqua technology, seafood, maritime, etc.

The chosen clusters involve both commercial firms and public organizations such as universities and research centers. The media network was established in 2015; members include newspapers; television channels; film and television production companies; technology companies focusing on graphics, audio, video, and artificial intelligence; consulting firms for the media industry; and equipment suppliers. The main goal of this cluster is to facilitate the use and development of advanced technology and facilities in the media industry. The fintech network was established in 2017. Firms involved in the fintech cluster are commercial banks, investment companies, insurance companies, consulting companies, and technology providers for fintech services. The goal of the fintech network is to keep up with the trend of online trading and develop supporting services and adapt to relevant laws and regulations of data. As traditional industries, both clusters are now empowered by digital technologies, resulting in significant changes. The media sector is a creative and cultural industry. The current challenge in this industry is no longer about providing novel content but increasingly about the application and development of technologies to improve content presentation (Martin & Rypestøl, 2018). Financial service providers also need to rely on technology providers to support final delivery to their customers, such as online transactions through a third party or online financial service with a proper handle of customer personal data.

[6] See information at: https://www.innovasjonnorge.no/no/subsites/forside/om_klyngeprogrammet/nce/

3.3. Measurement development

A structured questionnaire was used as the primary instrument for data collection. The questionnaire consists of three parts: the first part dealt with information about the respondent and respondent firms' characteristics, such as the respondent's role and firm size; the second part was related to firms' ongoing relationships with other network members for network data. The informants were also asked to report the year of relationship initiation for each partner they chose. The third part focused on the firm's condition, performance, strategy, and collaboration experience with other network members. Measures in the third part all used a seven-point Likert scale (1= "strongly disagree" to 7= "strongly agree").

The questionnaire was designed in English and translated to Norwegian (by Research Assistant 1), then back-translated (by Research Assistant 2) to ensure conceptual equivalence between the two versions. A pretest of the third part of the questionnaire was conducted with four individuals, including experienced scholars and managers of firms outside the chosen clusters. The questionnaire was refined based on the feedback. I used Quadric for the online-based survey. See *Appendix I* for the complete questionnaire for the media cluster. I replaced the member list when collecting data from the fintech network, and the rest of the questionnaire remained the same.

The network structural properties were calculated based on the involved firms' ongoing business relationships and network algorithms, and I introduce the calculation of network measures in Table 3-1. The rest measures (in the third part of the questionnaire) are developed for the other non-network variables in Articles 1 and 2. The measurement development process normally starts with defining variables, which will be later linked to observable indicators (Bollen, 1989). The dissertation includes four latent variables: exploration strategy, perceived power asymmetry, perceived visibility, and prosocial behavior. The definitions of these constructs are discussed in detail in the articles. I compared different measures of exploration strategy and prosocial behavior and adapted suitable established measures based on the conceptualization and the research context. The items measuring the exploration strategy for Article 1 were adapted from He and Wong (2004). The items for measuring prosocial behavior in Article 2 were adapted from Muthusamy and White (2005) based on the definition of the concept. The rest two variables—perceived power asymmetry and perceived visibility— were included as mediating variables to validate the mechanisms I argued for a hypothesis. Items for these two variables were newly developed.

There are two main ways to operationalize latent variables: a reflective or formative measurement model. In the reflective measurement model, the causality goes from the latent variable to its indicators. The reflective model is common in social science research. In the formative model, the indicators form the latent variable (Howell et al., 2007). The formative model is challenging because omitting indicators will lead to inaccurate measures or even change the meaning of the latent variable (Bollen & Lennox, 1991). I use reflective scales in Articles 1 and 2 to specify the relationships between latent variables and indicators (Howell et al., 2007). The reflective method was chosen because the measures were considered to share a common factor, meaning that the value of indicators is influenced by the value of the latent variables. Table 3-1 provides detailed information for all variables. The non-network variables were generated based on the mean of items. No items have been excluded in this study.

Table 3-1. List of measures

Network variables	Definition	Algorithms	Note
In-degree centrality	The total number of ties received from other network actors (Wasserman & Faust, 1994; directional measure). To eliminate the influence of network size, we use the normalized in-degree centrality measure.	$$C_{in}(n_i) = \frac{\mathrm{d}(n_i)}{g-1}$$ $C_{in}(n_i)$ is the in-degree centrality of node i, $\mathrm{d}(n_i)$ is the total number of received ties, and g is the number of actors in the network.	Independent variable of Article 2.
Local cohesion (Article 1)/ Triadic embeddedness (Article 2)	The ratio between closed triadic structures and all possible triadic structures around a focal actor (Wasserman & Faust, 1994; non-directional measure).	$$C(v) = \frac{K(v)}{\frac{n(n-1)}{2}}$$ v is the focal actor, $K(v)$ denotes the number of closed triads around the focal actor, and n denotes the number of neighbors of actor v.	Independent variable of Articles 1 and 2. Local cohesion and triadic embeddedness are used as synonyms in this dissertation. There are different ways of measuring local cohesion (see Wasserman & Faust, 1994, p.251-p.252), and I chose an equivalent to triadic embeddedness here.
Closeness centrality	The inverse of the sum of the distance from an actor to all the other actors (Wasserman & Faust, 1994; non-directional measure).	$$C_C(n_i) = \left[\sum_{j=1}^{g}(n_i, n_j)\right]^{-1}$$ i is the focal actor, j represents other actors in the network. (n_i, n_j) represents the distance between actors i and j.	Independent variable of Article 1.
Burt's constraint	An inversed measure of structural holes. The measure intends to capture access to redundant	$$C[i] = \left(p_{ij} + \sum_q p_{iq}p_{qj}\right)^2$$	Control variable for Article 2. Burt's constraint cannot be calculated for isolated

	information within a network (Burt, 1992; non-directional measure).	The constraints of an actor are the time and energy consumed in a network. The constraints come from its direct ties p_{ij}, and indirect ties $p_{iq}p_{qj}$.	actors (Everett & Borgatti, 2020).
Small-world property	A network with a high level of local clustering *and* shortcut ties reduces the distance between actors (Watts & Strogatz, 1998).	SW= $\frac{CC}{PL} = \frac{\frac{\frac{Clustering\ (real\ netowrk)}{Average\ degree\ centrality}}{Number\ of\ nodes}}{\frac{Average\ path\ length\ (real\ network)}{\frac{Ln(number\ of\ nodes)}{Ln\ (average\ degree\ centrality)}}}$	The focus of Article 3.
Scale-free property	The skewness of the degree centrality distribution (Barabási & Albert, 1999)	$\gamma\ (k_i) = \frac{k_i}{\sum_j k_j}$ The scale-free property is calculated as the coefficient of the log-log plot of degree centrality distribution.	The focus of Article 3.

Table 3-2. List of measures (continue)

Latent variables	Definition	Items	Note
Exploration strategy	Relying on alliances to seek new opportunities (He & Wong, 2004; March, 1991).	We want to achieve … through alliances: - open up new markets; - extend product(s)/service(s) range; - introduce new generation of product(s)/service(s); - enter a new technology field.	The dependent variable for Article 1; Items adapted from He and Wong, 2004.
Prosocial behavior	Beneficial actions toward another firm beyond formal requirements (O'Reilly & Chatman, 1986).	- While making important decisions in this cooperation, we pay attention to this partner's interest. - We would not knowingly do anything to hurt this partner. - This partner's needs are important to us. - We look out for what is important to this partner in this cooperation.	The dependent variable for Article 2; Items adjusted from Muthusamy and White (2005).
Perceived power asymmetry	The perceived power status within a specific dyadic relationship.	- We have a more powerful position in this relationship. - We normally have more to say than this partner does. - We normally can influence this partner's decision-making related to this relationship.	Triangulated measure for in-degree centrality. Used as a mediator for Article 2; Newly developed for this study.

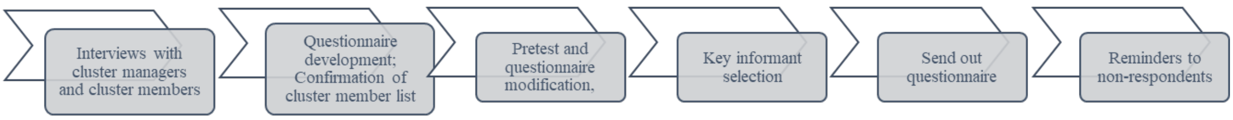
Perceived visibility	The perceived visibility of own activities for other network members.	- Our company's business activity (e.g., investment, new partnership, etc.) can be easily noticed by other members of this cluster. - Our company can always get the attention of other members of this cluster. - It is not difficult for other members of this cluster to seek information about our business activities. - When we conduct a new business activity (e.g., investment, project initiation, new partnership, etc.), other peer companies may notice immediately.	Triangulated measure for in-degree centrality. Used as a mediator for Article 2; Newly developed for this study.

3.4.Data collection procedures

Figure 3-1 shows the complete data collection process. Network data and survey data were collected simultaneously in the same questionnaire, and the same person (key informant) answered questions concerning the network data and the survey data. The data for the media network was collected in the fall of 2019, and the fintech network data was collected in the spring of 2020, following the same process.

The study participants had to be firms with ongoing business relationships to be included in the survey. With the help of research assistants, I confirmed the firm's current membership and whether or not they have ongoing relationships with other cluster members before sending the survey. I sent reminders to non-respondents twice to ensure the response rate.

Figure 3-1. Data collection procedure



3.4.1. Selection of key informants

The key informant selection is another important decision for self-report survey-based data collection. Using key informants is a preferred method for obtaining organizational information about a variety of variables in a short period of time (Seidler, 1974). The researcher must take care to select appropriate informants when the firm is the unit of analysis (Phillips, 1981). In some cases, multiple informants are needed to provide information on different aspects of a firm. According to the research focus, the manager who represents the company in the cluster and knows the firm's performance and strategies are ideal as key informants. These managers are direct participants in network activities and are aware of the firm's overall goal and performance.

Accordingly, I started with the firm representatives in the cluster. On the cluster's official website, each firm has a listed contact person in charge of activities related to the cluster. The listed contact person was first contacted through phone calls. The research assistant explained the research project and confirmed that they had sufficient knowledge to answer the questionnaire. If the contact person had insufficient knowledge, she/he was asked to refer a colleague she/he believes has the knowledge. During the phone call, the research assistant also confirmed the firm's membership and whether there were ongoing relationships within the cluster. If the member did not have any current partners, they were excluded since they could not answer the questions concerning collaboration experience in the cluster. Then, the online-based questionnaire was sent to the email addresses confirmed by informants. Thus, a manager with an in-depth knowledge of the firm's collaboration in the cluster and the firm's strategy and performance was identified as the key informant.

3.4.2. Network data collection

Recall the two questions about network boundaries and relational ties discussed in section 2.1. This dissertation follows the sociometric approach. In Articles 1 and 2, I subtract actor-level network measures based on sociometric data. In addition, article 3 focuses on system-level dynamics, and focusing on egocentric networks cannot provide the information needed.

The network boundary is clear: formal members of the regional cluster. Therefore, I provided a complete member list that was created according to information from the cluster's official website and confirmed by cluster managers and let respondents choose from. This approach is preferred over snowballing or a nomination of partners because it ensures that important actors are not omitted (Robins, 2015). Concerning relational ties, there are different choices, such as the interaction between employees, co-location, co-participation in the same seminars and activities organized by the media cluster, and formal contracts. The choice of relational ties should be relevant to the research questions. The research objectives of Articles 1 and 2 are related to business activities. Therefore, I consider formal business relationships (e.g., joint ventures, supplier-buyer relationships, and joint innovation projects) the most suitable form of ties. Network data was collected by asking respondents to select current business partners from a complete member list.

Only the commercial members were invited to participate in the survey because this study focused on firms. The questionnaire includes a complete list of members, both commercial and non-commercial. I asked the respondents to tick their current business partners on the list. By doing so, the non-commercial members were also indirectly included because the commercial members were able to report collaborations with non-commercial ones. For example, a company could report a joint research project with a research institution. Moreover, I included a question concerning the year of relationship formation for each chosen partner to collect information about individual relationships for Article 3.

3.4.3. Non-network data collection

In addition to network data, Articles 1 and 2 also needs non-network data for the dependent variables, mediators, and control variables. The non-network variables were measured using multiple items in the questionnaire. The unit of analysis for Article 1 is at the firm level, and Article 2 focuses on the firm's behavior in a dyad. The instruments for variables in article 1 are mainly the firm's own experience in the network and their performance and exploration strategy. When measuring dyadic-level prosocial behavior for Article 2, the respondents were asked to recall their collaboration experience with one network member and answer provided questions. Other variables in Article 2 (i.e., perceived power asymmetry and perceived visibility) were measured based on the focal firm's own perception.

3.5. Summary of data and analysis

Based on the final member list, I identified 67 relevant firms in the media cluster. After contacting these firms, I found that seven firms reported that they did not collaborate with other cluster members. Some were not interested or not answering the phone. In the end, I sent out 47 surveys and received 40 complete responses for a response rate of 85%. I also received four incomplete responses from the media cluster. I checked the incomplete responses, and the network data (see Del 2 in Appendix I) from incomplete responses were used for network visualization.

I identified 68 firms from the fintech cluster member list. After the same procedures, I found one firm was no longer a member, and seven firms did not have ongoing relationships. I managed to send out 36 surveys and received 24 complete responses for a response rate of 67%.

In total, I received 64 complete responses from the two clusters[7]. Table 3-2 provides an overview of the firm size in two clusters. Of the 64 firms, about 70% are micro and small firms with 50 or fewer employees, while the largest one has 9000 employees.

Table 3-3 provides an overview of the roles of respondents. In the questionnaire (question 4), I provided five options concerning the respondent's role in the firm: administration director, entrepreneur, leader for technical department/R&D department, leader for economy or marketing department, and others. I investigated those who chose 'others' and

[7] I discuss how I treat incomplete responses in section 3.6.2.

recategorized those who belong to the categories provided (e.g., Daglig leder was recategorized to administration director). Other roles reported were leaders of departments that were not listed (e.g., Head of Strategy and Head of Key Account Management), founders or partners, local managers, and advisors (Rådgiver). Respondents reported more than one position (e.g., Founder and general manager) remained in the category 'others.'

Table 3-3. Firm size (two clusters merged)

Number of employees	Number of firms
0-50 micro & small enterprise	43
50-250 medium enterprise	11
250+ large enterprise	10

Note: the category is based on OECD data. See https://data.oecd.org/entrepreneur/enterprises-by-business-size.htm

There is a borderline significant positive effect that respondents chose 'others' as respondents' roles come from bigger firms. This is cogent since bigger firms tend to have more complex corporate structures and diverse job titles. I did not find the respondents' roles significantly impacted other variables in this study.

Table 3-4. Respondents' role (two clusters merged)

Respondent's role	Total number
Administrative director	28
Entrepreneur	7
Head of technology/research	2
Head of finance/marketing	3
Others	24

Table 3-4 summarizes the number of firms in different industries registered in the national system. These six industries were identified based on respondent firms' organizational numbers registered in Brønnøysund Register Center. Most firms are from the ICT-related industries, namely, information and communication technology. As discussed earlier, the media and fintech industries rely heavily on digital technology to provide services to end customers.

Table 3-5. Number of responses in different industries (two clusters merged)

Industrial sector	Number of firms
Wholesale	3
Information & Communication	39
Financing & Insurance activities	8
Professional, scientific & technical services	12
Business services	1
Teaching	1

For the network data, I modeled a tie from A to B when firm A reports a relationship with B and vice versa. I identified 85 cluster members with 348 ties for the media cluster with 57 duplicate ties (i.e., from A to B and from B to A). The density of the media cluster was 0.082, excluding duplicate ties. For the fintech cluster, I identified 186 ties with 15 duplicated ties. The density of the fintech cluster is 0.111 without duplicated ties.

Among the network variables used in this dissertation, only in-degree centrality is a directional measure; The rest are non-directional measures (Wasserman & Faust, 1994). Directions were omitted when calculating non-directional network measures, and we did not consider the difference between one-way and reciprocated relationships. Local cohesion (in Article 1) and triadic embeddedness (in Article 2) are synonyms; the definition and algorithm are the same.

I analyzed network data and survey data separately. For Articles 1 and 2, network data were analyzed using UCINet 6.707 (Borgatti et al., 2002). Later, I combined network and survey data by the firms' names for hypothesis testing using Stata 17. For Article 3, I used Gephi network visualization software (version 0.9.2) to retrospectively reconstruct the dynamic patterns of two networks and calculate network-level properties. The calculation of network properties was also conducted using Gephi software.

3.6. Issues related to the survey method

3.6.1. Respondents' bias

A possible bias relates to respondents. With the help of research assistants, the respondents' qualifications were confirmed. However, since respondents are individuals, their backgrounds, moods, and characteristics may influence how they respond to the questionnaire. Since I asked the respondents to report the year of relationship initiation, it is also possible that they find it hard to recall the exact year of relationships that formed a long time ago.

I am aware of the different response rates of the two clusters. Data from the fintech cluster were collected at the beginning of the pandemic lockdown in Norway. Firms could no longer operate as usual, and society panicked due to the difficult and uncertain situation. Many firm managers in the fintech cluster expressed concern about their business and were less interested in the study when contacted. Accordingly, respondents from the fintech cluster may have different moods when answering the questionnaire. To control for this difference, I included a cluster dummy as a control variable in the analysis.

3.6.2. Treating missing data

I will discuss missing data from two sides: incomplete responses and incomplete network data. Concerning incomplete responses, four respondents from the media cluster reported their network ties. However, they only answered a few questions in the third part of the questionnaire (see Del 3 in Appendix I), which was irrelevant to the measures used in the dissertation. Therefore, I only used the network data for visualization and calculation; incomplete survey data were excluded. For the fintech cluster, all responses are complete.

For network data, a low response rate can make visualization inaccurate. To check the potential missing network data, I compared the members identified using the network data with the full member list. I managed to model 91.4% of the media cluster members and 75.7% of the fintech cluster members. The remaining firms that I was unable to model are possibly isolated, marginal, or inactive since other firms have not reported relationships with them. Considering that I provided a full list of cluster members, identified some inactive firms before sending the questionnaire, and attempted to reach the remaining firms, I believe that the identified network is substantially similar to the actual one.

Article 3 relies on the year of establishment of all dyadic relationships to retrospectively visualize the annual structures. Concerning the duplicate ties (i.e., from A to B and from B to A), if both have year information and are inconsistent, I kept the earlier year. If only one has year information, I kept that value. After excluding the duplicate ties, 18 ties in the media cluster (10.5%) and 24 in the fintech cluster (8.2%) lacked the year of initiation. A reasonable explanation is that these relationships were established long ago, and the respondents failed to recall the exact time. As the visualization started from the year the regional cluster was formally established, I replaced the missing years with the year of cluster establishment.

3.7. Summary

This section introduces my research design and the data collection process. I also provide a summary of data and discuss methodological concerns. The research design is suitable for this study and has several advantages. First, I applied different methodologies in data collection. Although qualitative data was not the main data source for the articles, I managed to understand the research context better and make the questionnaire more suitable for the chosen context. Second, I collected primary data and generated two separate datasets—network data and survey data—which is rarely done. Using two separate datasets for hypotheses testing largely avoided common method bias, referring to systematic errors caused by a single data source (Lindell & Whitney, 2001; Rindfleisch et al., 2008). Finally, I collected data from two clusters focusing on different industries, increasing the findings' external validity. Articles 1 and 2 included a dummy variable to control for cluster effect when testing conceptual models.

4. Presentation of empirical papers

In this section, three articles are presented, with an emphasis on presenting theoretical models and findings in each one. This dissertation focuses on different topics under the broad theme of interorganizational networks from two perspectives: the role of network structures in firms' strategies and behaviors (Articles 1 and 2) and the dynamics of interorganizational networks (Article 3). Table 4-1 presents an overview of three articles. The first empirical article (Article 1) investigates the effects of network properties on a firm's exploration strategy. The idea is how network properties facilitate firms to seek new possibilities. In Article 2, I examine the effect of network properties on dyadic-level prosocial behavior within the network. Compared to Article 1, I shifted the focus from an individual firm's behavior to how the firm interacts with other members. In particular, Article 2 is among the few studies investigating dyadic interaction within a broad network using a quantitative method. The idea underlying Articles 1 and 2 is that firms' behavior can be influenced by the network surrounding them. Although Articles 1 and 2 highlight why networks are important, they treat them as static social systems, whereas the network structure is constantly changing. Article 3, therefore, investigates the dynamics of network structures in interorganizational settings. In general, the results show the importance of understanding the benefits and constraints of different network properties and the dynamics of empirical networks.

Table 4-1. An overview of articles

Article	Article 1	Article 2	Article 3
Title	Network position and firms' exploration strategies: A study of two regional industry clusters in Norway	The role of in-degree centrality and triadic embeddedness in prosocial behavior: A study of two regional industry clusters	A systematic approach to investigate network dynamics concerning small-world and scale-free properties in regional industrial networks
Research question	What are the network antecedents on firms' exploration?	How do network properties influence prosocial behavior in dyads within the network?	System-level structural dynamics in the interorganizational setting concerning small-world and scale-free properties.
Authors	Lin, Y., Aarstad, J., & Rokkan, A.	Lin, Y., Rokkan, A., & Aarstad, J.	Lin, Y.
Status	Under review at the International Journal of Innovation and Technology Management (ABS1), Submitted on July 24, 2022	In revise and resubmit at the European Journal of Marketing (ABS3), Submitted on May 31, 2022, Result received on August 25, 2022	Under review at the International Journal of Business and System Research (ABS1), Submitted on November 27, 2022

4.1. Article 1: *Interorganizational network structures and firms' exploration strategy: A study of two regional industry clusters in Norway*

Article 1 focuses on the competence side of network properties and investigates how firms' exploration strategies are influenced by two network properties: closeness centrality (i.e., the geodesic distances from the focal actor to others) and local cohesion (i.e., connectivity among partners of a focal actor). Exploration strategy is defined as seeking new possibilities through partners in the network, including entering a new market, extending product lines, introducing new generations of products, and entering a new technology field (He & Wong, 2004).

Firms gain access to external knowledge and resources through ties in the interorganizational networks and enhance their competitive advantages. Network structures reflect the distribution of diverse knowledge and resources, and firms may adapt their exploration strategies according to what is available (Burt et al., 2013; Dyer & Singh, 1998). Closeness centrality entails distance to external information and knowledge, reflecting the cost of bringing new elements to the focal firm's knowledge base (Wasserman & Faust, 1994). In other words, a firm with a higher level of closeness centrality can reach distant knowledge faster and making the firm a fast mover. Besides, firms that are central concerning closeness are more experienced and professional in handling distant knowledge (Aarstad et al., 2015b). On the other hand, by utilizing a shared third party and more frequent interaction, cohesive local structures are able to sustain the exchange of resources that are more difficult to value and tacit knowledge[8] (Coleman, 1988; Shipilov, 2005; Tortoriello et al., 2012; Uzzi, 1996). Therefore, I expect closeness centrality and cohesive local structures to facilitate the development of an exploration strategy.

[8] I include a brief discussion concerning tacit knowledge in Appendix III.

Based on the network and survey data of 64 firms from two independent regional industry clusters, the results support the positive impacts of closeness centrality and local cohesion on exploration strategy. I also find that the effect of cohesive local structures is more robust than closeness centrality, indicating that cohesive subgroups motivate exploration strategy more effectively than a central position in terms of closeness.

I also tested how closeness centrality and cohesive local structures influence exploitation strategy, focusing on applying existing knowledge to improve current products and efficiency. However, none of these proposed network structures are significantly associated with the exploitation strategy. Additionally, I tested how exploitation and exploration strategy influence firms' innovativeness, reflecting firms' ability, compared to their competitors, to address innovative products and services to customers. I observed a positive association between exploration strategy and firm innovativeness but not exploitation strategy. These findings confirmed that, due to the distinct features, antecedents and outcomes of exploration and exploitation are different (Wilden et al., 2018).

From a managerial perspective, the issues studied are important, as firm managers might want to know how they can benefit from existing business relationships or embedded networks and whether their strategy will be influenced by their network position. This study also provides insights for cluster managers or policymakers concerning how they can motivate cluster members to explore through a properly designed network structure.

4.2. <u>Article 2:</u> *The role of in-degree centrality and triadic embeddedness in prosocial behavior: A study of two regional industry clusters*

While Article 1 focuses on the competence side, Article 2 sheds light on the control side of network properties. The second article investigates the influence of in-degree centrality and triadic embeddedness on network members' prosocial behavior in cooperation with other network members. Prosocial behavior refers to the beneficial actions toward the recipient beyond formal requirements (O'Reilly & Chatman, 1986). As contracts can hardly be complete, prosocial behavior can be desirable for business relationships. Beyond dyadic relationships, prosocial behavior is also beneficial for interorganizational networks that rely on member interactions, such as regional industry clusters.

Particularly, in-degree centrality (i.e., the number of ties received from other network actors) is connected to power status and visibility within the network (Aarstad, 2013; Brass & Burkhardt, 1993; Wasserman & Faust, 1994). The impact of in-degree centrality is connected to instrumental motivators. Higher visibility will trigger prosocial behavior for a better reputation (Wuyts, 2007). Power status is likely to have an inverted U-shaped relationship with prosocial behavior. Prosocial behavior involves two parties, the sender and the recipient, and I focus on the sender. Drawing on relationship marketing literature, a relationship with an unbalanced power status will hinder prosocial behavior, while a balanced relationship will promote prosocial behavior (Heide, 1994; Lusch & Brown, 1996). I argue that power is generated by the broad network structure, which influences the status of the dyadic relationship. The change from a low to high in-degree centrality reflects the focal firm's status changes from a weaker party to a balanced dyad, eventually to a powerful party. I reason the turning point of the inverted U-shaped relationship of in-degree centrality and prosocial behavior mainly through changing the focal firm's (ego) power status from the weaker party to the stronger party in dyadic relations. Before the turning point, dyadic power asymmetry and visibility jointly influence prosocial behavior. While after the turning point, dyadic power asymmetry is the dominant mechanism influencing prosocial behavior.

Besides, we connect triadic embeddedness to communal factors that can facilitate prosocial behavior. A common third party is likely to soften conflicts in dyads and enhance joint benefit-seeking instead of prioritizing self-interests (Coleman, 1988; Haugland et al., 2021; Krackhardt, 1999; Tortoriello et al., 2015). I expect triadic embeddedness to have a positive influence on prosocial behavior.

As expected, I find empirical support for both hypotheses. I also measured perceived power asymmetry and perceived visibility using the survey method and found both measures have strong positive correlations with in-degree centrality. The results show that in-degree centrality is a proper indicator of perceived power asymmetry and perceived visibility. When modeled as a second-degree polynomial, perceived power asymmetry showed an inverted U-shaped pattern on prosocial behavior but insignificant. For perceived visibility, I did not observe a U-shaped relationship. The insignificant impacts of survey measures may be due to the small sample size or the items being less accurate in measuring these constructs. As such, in-degree centrality is a more reliable measure in this study. The findings also provide insights that firms could form triadic structures to facilitate involved parties' prosocial behavior regardless of their centrality. The findings of this study could provide insight for firm managers in regard to partner selection in networks and could be beneficial for cluster managers in understanding how to facilitate prosocial behavior among members to maintain a well-functioning cluster.

4.3. Article 3: *Exploring the dynamics of small-world and scale-free properties: A study of two regional industry networks in western Norway*

In the third article, I retrospectively reconstructed the annual network structures of two industry networks in western Norway and studied their development of small-world and scale-free properties. Unlike Articles 1 and 2, which consider network structure as static, this article takes a dynamic view. Small-world structures have dense local clusters and a short average path length, making it possible for network members to reach any member within a few intermediaries (Watts & Strogatz, 1998). Scale-free structures are different in that few very central actors function as conduits and link the scattered network, and the majority are peripherals with a limited number of connections (Barabási & Albert, 1999). The theoretical frameworks explaining the formation of small-world and scale-free structures are inapplicable in some empirical contexts. Analyzing the dynamic patterns of two empirical interorganizational networks, I find that (1) a scale-free structure is uncommon in the two networks, (2) although theories emphasize the formation of shortcut ties, transitivity is also an important driver for a small-world structure, (3) empirical networks can have small-world and scale-free structures simultaneously, and (4) the change of small-world and scale-free properties show an inverse trend.

This article adds to the knowledge of the structural dynamics in interorganizational networks at the system level (Chen et al., 2022). Empirically, cluster managers need to understand that the overall network structure is constantly changing. They need to ensure proper structure for desired outcomes and allocate resources properly to cultivating active members and densely connected subgroups to benefit members.

5. Discussion, Limitations, and Future Research

The overall purpose of my dissertation is to investigate interorganizational networks in terms of their influence on members' behaviors and system structural dynamics. The answer is that members' behaviors will be influenced by their network positions and the surrounding structure. In addition, interorganizational networks are constantly changing social systems, and the dynamics may demonstrate particular patterns. More specifically, this dissertation consists of three independent articles corresponding to three research questions: (1) What are the network antecedents on firms' exploration strategy (Article 1), (2) What are the network antecedents on prosocial behavior in a dyad within the network (Article 2), and (3) how does network structure change in terms of small-world and scale-free properties (Article 3). According to the two categories presented in section 1.3, Articles 1 and 2 add to the Influence of social networks category, focusing on the consequences and implications of network properties. Article 3 relates to the Network dynamics category, explaining the dynamics of network structure.

In this concluding chapter, I summarize the findings based on three articles and how these three articles constitute a comprehensive study, then discuss contributions and implications. I conclude this chapter by discussing limitations and potential avenues for future research.

5.1. Main findings

Under the broad theme of interorganizational networks, the three articles in this dissertation cover different network properties across levels. The findings provide new insights into the impact of network properties and the dynamic patterns of interorganizational network structures. This section discusses the findings of independent articles and how these articles are connected. To better present the findings, I include Figure 5-1, which is an extended version of Figure 1-1, to illustrate the main findings and implications of the overall project.

5.1.1. Network antecedents on exploration strategy

In Article 1, I examined the impact of two aspects of a firm's interorganizational network structure – closeness centrality and local cohesion – on its exploration strategy. Closeness centrality and local cohesion have been found to influence exploration strategy positively. The findings add to the knowledge of antecedent factors of exploration by expanding the focus to network properties. Previous antecedents of exploration refer to organizational characteristics (e.g., firm size, structure, and culture), which assume that the firm's exploration is not affected by the external environment; or environmental factors (e.g., market uncertainty, the intensity of competition), which affect all firms operating in the same market in the same manner (Duysters et al., 2019; Lavie et al., 2010). A study by Duysters and colleagues (2019) shows that firms will be influenced by who they connect to. I join the conversation by demonstrating how the network structure around a focal firm may influence its exploration strategy.

In addition, I noticed that the positive impact of local cohesion is more robust than closeness centrality. The results highlight the different roles of closeness centrality and local cohesion in facilitating firms' exploration strategies. Closeness centrality reflects a firm's distance from other network members (Wasserman & Faust, 1994). Accordingly, a short distance from other network members has a positive but limited effect on facilitating exploration. Local cohesion reflects the connectivity between the focal firm's partners (Wasserman & Faust, 1994), which has a more significant impact on exploration. The findings imply that the presence of common partners has a greater impact than the distance to network resources on sustaining members' exploration.

5.1.2. Network antecedents on prosocial behavior

In Article 2, I examine the impact of network properties on prosocial behavior in a dyad. Based on the findings, we gain a better understanding of how network properties influence prosocial behavior in dyads by expanding the focus beyond individual dyads. In particular, this article shows that it is not only dyadic characteristics that influence behaviors in dyads. I found an inverted U-shaped relationship between in-degree centrality (i.e., the number of ties received from network actors) and prosocial behavior. That is, prosocial behavior first increases as in-degree centrality increases. After a certain point, prosocial behavior will decrease as in-degree centrality further increases. The findings suggest that being peripheral or very central may hinder prosocial behavior, while a moderately central position facilitates prosocial behavior. The finding confirms that a firm's behavior can be better understood by examining its position in the broad network (Zaheer et al., 2010).

I included triangulated measures to validate the theoretical arguments regarding the relationship between in-degree centrality and prosocial behavior. Two variables—perceived power asymmetry and perceived visibility—were measured subjectively using survey items and included in the analysis. As expected, both variables positively correlate with in-degree centrality (Brass & Burkhardt, 1993; Wasserman & Faust, 1994), indicating that in-degree centrality is a proper measure of perceived power asymmetry and perceived visibility. I did not find that these two variables significantly influence prosocial behavior. This may be due to a small sample size, less efficient items used to capture the constructs, or both. I consider in-degree centrality a more reliable measure because it is an objective measure that is not directly influenced by the focal firm.

Also, the inclusion of triadic embeddedness corresponds to the call to consider the interplay of dyadic and network relationships (Choi & Wu, 2009; Dubois, 2009). I found a positive relationship between the existence of a third party and prosocial behavior, indicating that having a common third party is likely to facilitate norms and trust to make involved parties more prosocial in dyads. The findings provide empirical evidence for Tortoriello and colleagues' (2012, 2015) statement that prosocial behavior occurs more frequently within cohesive groups. It also corresponds to existing studies that suggest tightly connected structures create unique advantages for dyadic interactions (Haugland et al., 2021; Wuyts & van de Bulte, 2012). This effect holds regardless of the focal actors' in-degree centrality. Thus, having a common third party could facilitate prosocial behavior even though involved actors may differ concerning their network positions.

5.1.3. Network dynamics at the systematic level

The first two articles focus on the influence of different network properties on firms' behaviors. I took a static view and focused on the snapshot of the network structure at the time of data collection. One must know that an interorganizational network is not a static system; instead, it is a constantly changing system with actors joining and leaving and relationships formation and termination. Therefore, I included Article 3 to investigate the dynamics of network structures.

In article 3, I retrospectively reconstruct the dynamic pattern of two empirical networks and examine the interrelation of scale-free and small-world properties (Albert & Barabasi, 2002). Small-world structure refers to a highly clustered network with a relatively short path length between actors. Scale-free structure describes a centralized network with one or a few very central actors and many peripheral actors connected by these central actors. Accordingly, the degree distribution of a scale-free network is skewed. I observed that both networks showed an inverse trend between small-world and scale-free properties, indicating that the development of these two properties may be dependent on each other. This finding may explain why and how some empirical networks demonstrate scale-free and small-world properties simultaneously (Aarstad et al., 2013; Baum et al., 2004; Gay & Dousset, 2005).

I also find that scale-free structure was uncommon among the two empirical networks examined. The temporary occurrence of the scale-free structure found in this study was due to the emergence of a new central actor. Scholars hold different opinions about whether the scale-free structure and the rich getting richer are universal phenomena (Andriani & McKelvey, 2009; Broido & Clauset, 2019; Rossmannek & Rank, 2021). The findings show that the scale-free structure may be less common in an interorganizational context.

To sum up, Articles 1 and 2 demonstrate how networks can offer opportunities and constraints to firms (Brass et al., 2004; Zaheer et al., 2010), influencing their behaviors. The inclusion of article 3 further shows the dynamic nature of the network as a social system instead of a static one (Ahuja et al., 2012).

5.1.4. Network as a multilevel system

This dissertation investigates network properties at different levels using a sociometric approach. Articles 1 and 2 focus on actor-level properties based on their network positions, while Article 3 focuses on the system level (i.e., the overall network). These network constructs studied in this dissertation are closely related. Combining the findings from these three articles may provide further insights.

The focus of Article 3 is small-world and scale-free properties at the system level. Nevertheless, the small-world structure has dense local clustering. Accordingly, many actors in a small-world network will have a high level of local clustering. I noticed that the media cluster has a higher level of triadic embeddedness/local cohesion than the fintech cluster, corresponding to the system-level structures. The findings of Articles 1 and 2 show that dense local clustering around a focal actor is likely to facilitate exploration strategy and prosocial behavior. Thus, actors in a small-world structure have a higher chance to pursue exploration and act prosocially.

The other network property studied in Article 3 is scale-free structure. A scale-free network has a centralized structure: few very central actors connect a large number of low-degree actors. The finding of Article 1 shows that either low or high levels of (in-degree) centrality may impede prosocial behavior. Accordingly, one may not expect actors to be incentivized to conduct prosocial behavior due to the scale-free structure. The path length between actors in a scale-free network can be short due to the bridging role of central actors. In Article 2, I found that high closeness centrality (i.e., distance to other network members) may facilitate exploration, but the impact is limited. As a result of the small number of central actors and a large number of peripheral actors, we may infer that a scale-free structure does not effectively facilitate actors' exploration due to the majority being low-degree actors and a lack of local clustering.

5.1.5. Network mechanisms in terms of competence and control

Articles 1 and 2 consider different network mechanisms that influence firms' behaviors. In section 2.1, I introduce two main perspectives on how network properties influence its members. The first stream focus on the competence side. Firms can gain competence from accessing network resources through network ties. Centrality is the most commonly used network measure to show actors' competence in existing studies (Zaheer et al., 2010). Despite the various kinds of centrality measures, it is mostly based on the total number of ties a firm has with other network members. A general conclusion in this research stream is that being central is beneficial. This can be true at the actor level; central actors can benefit more from their resourceful position than less central actors to achieve their business goals. The findings of Articles 1 and 2 show that central firms can access network resources faster (Hypothesis 1 in Article 1) and are more powerful and visible than other network members (Hypothesis 1 in Article 2). In Article 1, I also find that the competence benefit can be generated in cohesive local groups (Hypothesis 2 in Article 1). The existence of a common third party can improve the quality of information and resource sharing and support learning between organizations. In other words, the common third party does not necessarily influence the access to resources but rather the quality of resources accessed.

When we expand the focus from actors, different network positions can trigger inequity among actors. As Singh and colleagues (2010) conclude, the world is not small for everyone. According to relationship marketing literature, inequity may lead to unbalanced relationships, which may hinder cooperation. The second mechanism discussed in section 2.1 is the control mechanism. In general, the control benefit is realized through the creation of cohesive local structures that enable a group of actors to work together in order to achieve joint goals, such as responding to threats from outside the group (Uzzi, 1997; Coleman, 1988; Wuyts & van den Bulte, 2012). Article 2 shows that cohesive structures can mitigate the impact of different network positions on prosocial behavior (Hypothesis 2 in Article 2), providing evidence for the control benefit. Overall, Articles 1 and 2 provide evidence for the two benefits that networks can offer.

Figure 5-1. Summary of findings and implications

5.2. Theoretical contributions

This dissertation provides several theoretical contributions. In this section, I first discuss the theoretical contributions of each article; then, I discuss the contribution of the overall dissertation.

First, Article 1 adds to management literature by investigating network antecedents for exploration. Much emphasis has been paid to the outcome of exploratory efforts (Lavie et al., 2010; Wilden et a., 2019), yet one needs to understand what triggers exploration to understand the outcomes better. This study serves this end by investigating network antecedents beyond firm-level characteristics and environmental factors. I consider network properties to fall between firm-level characteristics and environmental factors because the influence comes outside the firm's boundary and is firm-specific due to their network connections. Duyster and colleagues (2019) show *whom* a firm connects to matters; Their study examines how the focal firm imitates the exploration activities of its partners. In Article 1, I show *how* a firm is connected to other network members matters; A focal firm's position will influence its access to different resources in terms of speed and quality, which may influence exploration. Moreover, most literature considers the relationship between network and exploration outcomes from a pure technological knowledge domain (Phelps, 2010; Wilden et al., 2018). Patent data has been a common data source for measuring exploration outcomes. Scholars are encouraged to revisit March's (1991) original exploration-exploitation framework (see Wilden et al., 2018, for a review). In his work, exploration is more broadly defined and covers different aspects. Article 1 did not limit the focus on the technological domain but considered exploration in multiple aspects. Based on the 'seeking new opportunities' definition, exploration covers entering new markets, entering new technology fields, and developing new products and services.

Second, Article 2 adds to the marketing literature by investigating prosocial behavior in dyads within a wider network context. Marketing scholars have long emphasized the importance of studying dyads in a wider context because a relationship is embedded in a social system in which multiple relationships operate (Choi & Wu, 2009; Dubois, 2009; Wuyts & Van den Bulte, 2012). There is a group of scholars known as the IMP (Industrial Marketing and Purchasing) group, who are the pioneers in applying network perspectives in business markets (see Håkansson & Gadde, 2018 for s summary of IMP research). IMP research mainly relies on qualitative data to understand the dynamic interactive process between network actors and has its own theoretical frameworks. Some scholars consider IMP research to differ from the main North American stream of marketing management research. The IMP research is mostly developed in isolation. In the mainstream marketing management literature, limited empirical studies examine dyads in networks. Haugland and colleagues (2021) are among the few studies that investigate the impact of network properties on dyadic-level phenomena using quantitative data. Their study focused on the impact of triadic embeddedness on relational governance; network properties other than the triadic structure were not considered. In article 2, I add to this stream by illustrating the impact of in-degree centrality (i.e., the number of ties received from partners) and triadic embeddedness (i.e., the connectivity between a focal firm's partners) on dyadic-level prosocial behavior.

Third, Article 3 adds to the interorganizational network dynamics literature by discussing dynamics at the system level (Chen et al., 2022; Provan et al., 2007; Uzzi et al., 2007). Management scholars found that network structures have implications on overall performance (e.g., Baum et al., 2004; Chen & Guan, 2010; Powell et al., 2005), yet less is known concerning the development or dynamics of particular structures at the system level. I analyze the dynamic pattern of two empirical networks to show the interrelation of small-world and scale-free structures, which may explain why some networks can demonstrate both properties simultaneously (Aarstad et al., 2013, 2015a). This study demonstrates the interrelation of two commonly studied network structures that have typically been studied separately (Aldrich & Kim, 2007; Ghosh & Rosenkopf, 2018). In addition, network scholars hold different opinions concerning whether developing a scale-free structure (i.e., a centralized structure with a few central actors connecting many peripheral actors) is common in the interorganizational setting. The findings of Article 3 support the view that the rich get richer and scale-free structures are less prevalent in interorganizational settings (Andriani & McKelvey, 2009; Broido & Clauset, 2019; Powell et al., 2005; Rossmannek & Rank, 2021). I also provide explanations of why some interorganizational networks lack evidence for a scale-free structure.

Now I discuss overall theoretical contributions. The fourth contribution is that this dissertation shows that network structure should match the specific purpose. Instead of saying participating in a network is good for firms, I argue that different network properties influence firms through different mechanisms. As discussed in section 2.2, Articles 1 and 2 show the competence and control functions of networks, supporting the idea that examining a firm's network position can further understand its behaviors (Brass et al., 2004; Gilsing & Duyster, 2008; Wuyts & van den Bulte, 2012). In particular, the findings of Articles 1 and 2 conform to Coleman's argument of social capital. Cohesive local structures can facilitate information sharing, organizational learning, and collaborative behaviors. However, this conclusion needs to be considered with caution. Burt's (1992; 2004) idea of structural holes and Granovetters's idea of the strength of weak ties (1973) emphasize the content of information and resources accessed, which may alter the conclusion or influence outcomes such as innovation. In sum, the proper network structure should align with particular goals.

Finally, this dissertation suggests considering social networks as a dynamic system instead of a static one. Social network research has been criticized for putting too much emphasis on the consequences and omitting how network properties emerge over time (Borgatti et al., 2014; Gupta & Saboo, 2021). A static view may simplify the process of determining the consequences of certain network properties. However, real-world networks are constantly changing in terms of composition and structure. The inclusion of Article 3 shows that network dynamics may follow certain patterns. Such knowledge could complement and deepen our understanding of the consequences of network properties.

5.3. Methodological implications

The research method used in this dissertation has two advantages. First, I combined network data and survey data in Articles 1 and 2 to test the hypotheses. Using data from two separate datasets can largely eliminate the common method bias (Lindell & Whitney, 2001; Rindfleisch et al., 2008).

Second, I used a sociometric network approach, also known as a complete network approach. The empirical networks studied in this dissertation are with a clear goal to benefit all involved members, not a serendipitous network created according to researchers' interests (Kilduff & Tsai, 2003)[9]. When investigating the influence of networks, egocentric network dominates social network research in the marketing field (see Gupta & Saboo, 2021, for a review). Some scholars consider egocentric networks or triadic structures as arbitrary subsets of a larger network (Dubois, 2009; Robins, 2015; Vedel et al., 2016), especially when the research focus is on the influence of a clearly defined network.

Without a clearly defined boundary, some significant actors may be omitted, which could negatively impact the comprehensiveness of the network data and the accuracy of

[9] I focus on goal-oriented interorganizational networks, where the existence of a network is to achieve an object. In a serendipitous network, members are picked by the researcher and their social relationships are considered network ties. As an example, board interlocks are artificial networks based on researchers' interests. But such a network does not exist to achieve a clear goal.

network measures (Gupta & Saboo, 2021). Methodologically, it is more challenging to collect sociometric network data because all actors need to report their relational ties (Opsahl, 2013). Collecting egocentric network data is easier because only the ego and alters are considered. It is also possible to subtract egocentric network data from sociometric network data. In this case, the ego network data is more accurate than the data collected by snowballing. However, even if the boundaries of a network are clearly defined, it is not necessarily easy to collect complete network data. The probability of biased network measures decreases as the network becomes closer to being complete (Gupta et al., 2019). To ensure the collected network data is highly relevant to the research focus, scholars should carefully define the network boundaries and ties.

As a related point, some research questions can only be solved using a sociometric approach. For instance, if the aim is to understand the dynamic pattern of a network, one must use the sociometric approach. As discussed in section 2.3, many management and organization studies focus on dyadic-level dynamics. It is important to understand why firms establish relationships, such as seeking complementary resources or lining up with similar firms to fight against market change. Yet much less attention has been paid to the overall network dynamics. It is frequently discussed that understanding the overall network is important, but there has been little empirical investigation (see Provan et al., 2007 and Ahuja et al., 2012, for reference). This dissertation contributes to this stream by using a sociometric approach and studying network-level dynamic patterns. A good understanding of the overall network, such as how a network emerges, develops, and ultimately how collective outcomes can be achieved, is particularly important for networks with explicit goals, such as innovation systems and regional clusters.

In addition, much management literature relies on archival data for network visualization and analysis. Some networks are likely to be serendipitous networks (e.g., collaboration data between a selected group of firms from an existing dataset, Ahuja, 2000) that do not have a clear objective to achieve. The inclusion of network actors is dependent on the researchers' interests and experience. In this study, I investigate goal-oriented networks; therefore, a network boundary is required. More importantly, the implications are not only for individual firms to gain competence from networks but also helpful for network managers to sustain network performance. Of course, the current research design has limitations, and I discuss the limitations in section 5.5.

5.4. Managerial implications

The findings of this dissertation have implications for two types of practitioners: managers of firms that are network members and managers of networks. Whether or not they realize it, firms' decisions are influenced by the network around them. The two main benefits of participating interorganizational networks are enhancing competence through accessing pooled resources and sustaining cooperation relying on a cohesive structure. Therefore, beyond who they connect to, firm managers should consider how they are connected to partners.

Because I took a sociometric approach in this study, individual firms may lack information in mapping the overall system and positioning themselves and their partners within the broader picture. The practical implications for firm managers mainly concern the benefits of having triadic or cohesive structures. Based on the findings of article 1, firms could work with partners within cohesive local structures to seek new possibilities because such a structure may improve the quality of shared information and resources and facilitates the development of a common knowledge base for organizational learning. Having a short distance to network resources could also positively influence seeking new possibilities, but the effect seems not very obvious.

The findings of article 2 suggest that facilitating cooperation in a dyad is not only about the particular relationship or partner; having common third parties can also affect the dynamics of a dyad. Firms can establish a relationship with a partner's partner to form a triadic structure; involved parties can benefit from a stable and cooperative social structure. In addition, when selecting partners in a network, firms should be aware that both peripheral and central firms are less likely to behave prosocially.

For network managers (i.e., who manage daily operations of a network), one of their key objectives is to ensure a well-functioning network as a vehicle to benefit involved firms and achieve the network goal. This dissertation shows that a network is a constantly changing social system that influences members' behaviors. Accordingly, network managers should provide active support by constantly modifying the network structure to ensure better system-level performance. This is especially important for networks that rely on members' interaction and co-production. To design a suitable structure, network managers need to be aware of the network structure and its implications to better assist the development process. Articles 1 and 2 show how individual members' behaviors can be better understood by examining their network positions. Accordingly, network managers may influence a firm's network position to indirectly influence its behavior. For instance, network managers could directly facilitate members' collaboration by introducing two disconnected members to each other or indirectly modify an ongoing relationship or joint project by bringing in relevant third parties. Also, network managers need to ensure the overall system structure is relatively stable and suitable for exchanging information and collaboration. A network may have a few key actors, who are often the leading firms in the market and play a vital role in stabilizing and facilitating network connections. Network managers should be aware that other less central members are also important for the network performance, so they should allocate resources wisely to cultivating new active members or densely connected subgroups to benefit the overall system.

5.5. Limitations

As much as this study has offered novel insights into a more comprehensive understanding of interorganizational networks, it is still limited in terms of the methodological choices and the scope of the study, which I will address in the following section.

5.5.1. Limitations concerning methodological choices

In Chapter 3, I have discussed the methodological choices I have made in order to investigate the research questions. As I mentioned in section 3.6, although the choices were made carefully based on the research questions and available methods, there are still some limitations. I emphasize four main limitations here.

First, Articles 1 and 2 are based on a cross-sectional research design, so I should be cautious about drawing causal inferences about the observed relationships. I argue that a firm's position on the network reflects its opportunities and constraints that affect its behavior. However, in order to confirm these arguments, the independent and outcome variables should be measured at different points in time to show the independent variable influences the outcome variable but not vice versa.

Second, for Article 2, the data used for analysis in Article 2 was from only one side of a focal dyad. I collected data about a dyadic relationship from the focal firm reporting their own perceptions of the proposed variables but not the counterparty. The alter firm (i.e., the recipient of prosocial behavior) may perceive the dyad and the ego firm's prosocial behavior differently. I also lack information on the counterpart's network position (relative to the focal firm's network position), which may provide more detailed information about the focal dyad.

Third, in article 3, I analyzed the dynamic patterns of two empirical networks using a retrospective approach. In particular, I asked the respondents to report their current partners in the network and when the cooperation started. It could be challenging to recall the exact year if the collaboration started several years ago. I focused on a rather short time; still, recall bias may influence the accuracy of annual network visualization in Article 3.

Fourth, although cluster managers constantly update the list of cluster members, the current research design did not provide room for respondents to add firms that were not on the list. As the cluster members are constantly changing, the complete list of cluster members is for a particular time. It is possible that respondents may have partners that were previous cluster members or newly joined the cluster but not on the list, which may negatively influence the accuracy of visualized network structure.

The last limitation of the current research design is that I fail to consider the influence of members that left the cluster, terminated relationships, and firms that are not cluster members but are important for cluster activities. Previous members and terminated ties could have long-lasting effects on network development. When contacting informants, I found that some members quit the cluster due to lacking interactions. Researchers may collect network data regularly in the future to map network development patterns, including information about membership withdrawals and terminated relationships, and provide the chance for firms to nominate important partners.

5.5.2. Limitations concerning the scope of the focus

In this dissertation, I focus on network structures (i.e., *how* actors are connected) as abstractions of firms' network conditions that influence their behaviors. However, I do not consider the impact of network composition (i.e., *who* is included in the network). I consider this as a main limitation of the dissertation. Scholars have criticized the over-emphasis on structure rather than characteristics of individual actors, which turned to "be treated as residues of social structures" (Kilduff & Brass, 2010, p. 332). Many social network scholars have stressed the importance of actor characteristics (Kilduff & Brass, 2010; Phelps, 2010). In

Articles 1 and 2, I include only firm size as an actor-level control variable when testing the conceptual models. There are two reasons why I do not include more actor-level control variables. First, the firms I studied are cluster members, and each cluster, by its very nature, induces homogenous firms as they operate in the same industry. Thus, involved firms share many similar characteristics. Second, due to the small sample size, I could not include more individual-level characteristics. Adding more control variables will harm the degree of freedom and the reliability of regression analysis. Still, including information on the actors' characteristics and relational ties could further enhance the findings.

5.6. Future research opportunities

This dissertation can be considered part of the effort made to understand interorganizational networks in terms of the impacts on members' behaviors and structural dynamics. In the following section, I discuss avenues for future research as both ways to avoid the limitations mentioned above and general research directions that may build on this dissertation.

First, future studies may have a longitudinal design to better capture the influence of network properties on network members' behaviors and network development. As an example, Aarstad and colleagues (2015b) in their study collected network data (for independent variables) one year earlier than the survey data (for outcome variables), which provides a better demonstration of the causal effect from the independent variable(s) to the dependent variable(s). Additionally, longitudinal network data allow us to determine whether particular dynamic patterns persist over time.

Second, future studies could apply the network and survey data from both sides of a dyad when studying dyadic interaction within a broader network. Researchers could ask respondents to specify the partner and send a survey with relevant questions to the nominated firm. By doing so, one can consider the relative network position of two parties involved in a particular dyad to generate a more objective evaluation of the dyadic condition and explain different behaviors within the focal dyad.

Third, I find the exploration-exploitation framework by James March (1991) suitable for studying the different benefits of having interorganizational networks. For instance, networks may help achieve operational efficiency in terms of economies of scale and scope but also can support creating novelty. In this dissertation, I focused on antecedent factors for exploration. As exploitation and exploration follow different logics and will be influenced by different factors, future studies could relate to the original definition and develop better measures that capture different aspects of exploitation and exploration to see how they were related to network properties (Wilden et al., 2018).

In addition, instead of considering exploration and exploitation as two unrelated activities, Nooteboom (2006) suggested that “innovation typically starts with exploration and then moves to exploitation” (p.3). Some scholars have also proposed that the difference between exploitation and exploration is a matter of degree rather than kind, as they compete for firms’ limited resources (Lavie et al., 2010). Accordingly, some scholars suggest measuring exploitation and exploration as a continuous variable between two extremes instead of two discrete choices because they compete for a firm’s limited resources. Future studies may develop proper measures and collect longitudinal data to study the transition between exploitation and exploration and how that transition can be shaped or supported by different network structures.

Fourth, to avoid overemphasizing network structures, future studies should include relevant firm-level characteristics to expand our knowledge of the influence of network properties on different firms or possibly the interactive effects of firm-level characteristics and network properties.

Fifth, future studies could expand the focus beyond firm-firm relationships. Although I have indirectly included non-commercial cluster members in this study, I did not investigate the relationship between commercial and non-commercial members in detail. However, according to the interview of a cluster manager, "It is always difficult when research and education facilities and industry are in joint projects. There will always be some challenges. Both in terms of speed, the university takes longer to work, the companies want to do things fast … and in terms of focus, the commercial versus the education or research … in terms of culture (and) work ethics. It is much easier to put two research institutions together or two companies together since they are more converged." Therefore, studying the collaboration between firms, research institutions, or governmental organizations in networks could further enhance our knowledge of interorganizational networks.

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Articles

Article 1: Network position and firms' exploration strategies: A study of two regional industry clusters in Norway.

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Abstract

Management research has alluded to environmental and organizational antecedents for firms' exploration. We complement this knowledge by applying a network perspective to explain how a firm may adjust its exploration strategy based on its position within an interorganizational network. We particularly focus on two network constructs, closeness centrality and local cohesion. Closeness centrality captures a firm's independent access to network knowledge and resources, and local cohesion shows the connection between a focal firm's alters. Combining network data and survey data on 64 firms that are members of two regional industry clusters in Norway, we reveal that firms' exploration strategies are associated with their network positions. The positive effect of local cohesion is stronger than closeness centrality. Our findings inform research on antecedents for exploration by underscoring the network drivers.

Keywords: Exploration strategy; Regional clusters; Interorganizational networks; Closeness centrality; Local cohesion

1. Introduction

To ensure long-term competitiveness, firms must continuously explore new opportunities. According to March's (1991) definition, exploration involves "search, variation, risk-taking, experimentation, play, flexibility, discovery, and innovation" (p. 71). For firms, exploration (compared with exploitation) requires knowledge and skills beyond those currently available, and its results tend to be highly uncertain and take longer to achieve payoffs (March, 1991; Rosenkopf & Nerkar, 2001). Limited is known concerning why some firms emphasize exploration while most pursue exploitation (Lavie et al., 2010). Antecedents for firms to explore alludes to environmental factors and organizational characteristics (see Lavie et al., 2010, for a review). The environmental factors uniformly shape firms' tendencies to explore, while the organizational characteristics are fully independent. In addition to these factors, Duysters and colleagues (2019) find that beyond these mentioned factors, a firm's exploration tendency can be influenced by its partners' and competitors' tendencies to explore, indicating that the tendencies to explore may be influenced by their social connections. Overall, in addition to environmental conditions and organizational characteristics, the impact of a firm's interorganizational relationships on exploration remains to be understood.

To better understand the influence of social relations on firms' tendency to explore, we draw on a social network perspective, focusing on the configuration of multiple dyadic exchange relationships among a group of actors. A network structure illustrates how diverse knowledge flows and resources are exchanged among the members (Gulati, 1998; Owen-Smith & Powell, 2004). Meanwhile, certain network structures may support firms in absorbing diverse knowledge to generate new ideas (Ahuja, 2000; Gilsing et al., 2008; Reagans & McEvily, 2003). A large body of studies focuses on how interorganizational networks create conditions for innovation, considered the manifestation of exploration (Dagnino et al., 2015; Gilsing et al., 2008; Phelps, 2010). The causal argument links the actor's network position to knowledge outcomes. It is implicitly assumed that firms are equally motivated to explore, which is not the case. Identifying what motivates firms to explore and what supports exploration success is critical, especially when the same factors may influence different stages of the exploration process in different ways.

Moreover, in most network and innovation studies, explorative innovation is defined as the creation of novel technology-related knowledge. These studies rely heavily on patent data (e.g., Phelps, 2010; Rosenkopf & Nerkar, 2001; Katila & Ahuja, 2002; Duyster et al., 2019). However, according to March (1991), exploration is defined in a much broader way (see Wilden et al. 2018 for a review). Beyond technologies, exploration can also occur in other aspects, such as product design (e.g., introducing new products), entering new markets, or changing organizational structure (e.g., business model innovation). Different network structures may offer different benefits for exploration (Gilsing & Duyster, 2008). In light of this, an examination of network-related motivations for exploration beyond a pure technology domain is required. The current study addresses this issue by focusing on the exploration strategy, referring to a firm's proclivity to explore new possibilities, including entering new markets, creating new products and services, and developing new technology through its network partners (He & Wong, 2004; March, 1991).

We investigate the influence of two network constructs: closeness centrality and local cohesion. Closeness centrality refers to the *distance* between a focal actor and other network actors (Freeman, 1978). In an interorganizational context, closeness centrality is associated with a firm's searching efficiency and cost of information and knowledge in a network beyond its direct partners, benefiting distant search for exploration (March, 1991; Wasserman & Faust, 1994). For an individual firm, local cohesion refers to the connectivity among its direct partners (Wasserman & Faust, 1994). If a focal firm's two partners have a partnership, a triadic subgroup is formed. Such triadic subgroups could promote the development of trust and norms, sharing of private information, joint problem-solving, and relationship learning (Haugland et al., 2021; Uzzi, 1997). In sum, we study if closeness centrality and local cohesion influence a firm's exploration strategy.

This study asserts that firms' network position may affect their exploration strategy. It contributes to increased knowledge of antecedents of exploration beyond environmental and organizational factors by discussing and testing how network structures may influence firms' exploration strategies (Lavie et al., 2010; Wilden et al., 2018). We discuss how closeness centrality and cohesive local structures may influence exploration strategy through different mechanisms and can have different effects. In addition, we contribute to interorganizational network studies by focusing on the network effects on exploration strategy. In a review, Wilden and colleagues (2018) observe that many studies consider different phenomena, such as diversification and innovation, as manifestations of exploration. As the relationship between exploration and organizational performance is not always straightforward, this study discusses how network properties may influence firms' exploration strategies instead of consequences.

To test our predictions, we combined network data and survey data from 64 firms from two regional industry clusters in Norway, focusing on media technology and fintech. Both industries heavily rely on digital technology, and firms must keep up with rapid technology change and seek new opportunities to maintain competence. The network data shows the connectivity between network members, and the survey data capture individual firms' exploration strategies. The combination of two data sources enables us to investigate whether closeness centrality and local cohesion are associated with exploration strategy.

2. Theory and hypotheses

2.1. Exploration strategy

The exploration-exploitation framework by March (1991) has inspired scholars in various research domains, including organizational learning, strategic alliances, and innovation (Wilden et al., 2018). According to the definition by March (1991), exploration and exploitation are two fundamental activities that create value for organizations. Exploitation is likely to strengthen a firm's existing advantages and create immediate returns, while exploration can extend a firm's current competence portfolio and increase the potential long-term benefits. Hence, both exploration and exploitation are essential. Scholars hold different opinions on the relationship between exploration and exploitation. One stream of scholars considers exploration and exploitation as the two extremes of a spectrum since they compete for a firm's limited resources (Lavie et al., 2010). The other stream of scholars views these two as distinct constructs that require different routines and capabilities to pursue and lead to different outcomes (He & Wong, 2004; Katila & Ahuja, 2002). We follow the latter view and study only exploration as we are interested in the antecedents of exploration rather than the tension between exploration and exploitation.

An important issue here is that we focus on exploration with network partners. We do not doubt that a firm can explore both independently and jointly with its partners. For instance, a firm can invest in R&D activities alone or collectively with its partners. This study particularly focuses on the influence of resources and knowledge *beyond* an organizational boundary within an interorganizational network.

2.2. Antecedents for exploration

In a review, Lavie and colleagues (2010) summarized antecedents for exploration into three categories: environmental, organizational, and managerial. Environmental factors such as unpredictable market changes often make firms' existing products and services outdated and require firms to explore (Jansen et al., 2006). Exogenous shocks, such as revolutionary transformations, are more unexpected than changes. Some firms may enhance their exploration efforts to prosper in such conditions, while others may stick to exploitation to grasp benefits from what has been invested. The appropriability regime, which refers to the extent to which the environment allows organizations to capture value from the exploration outcome, has been suggested as a positive indicator of exploration (Lavie et al., 2010). If such a regime is weak, firms may be unable to benefit from exploration and withhold efforts in exploration. In sum, environmental context explains systematic exploration tendencies but cannot explain why exploration tendencies differ between organizations within the same industry.

Organizational antecedents relate to an organization's resources, capabilities, structure, culture, age, and size. For example, it has been widely accepted that the ability of an organization to explore is linked to its absorptive capacity—the ability to internalize and apply external knowledge (Cohen & Levinthal, 1990). Absorptive capacity enables organizations to better incorporate external knowledge (Lavie & Rosenkopf, 2006) to engage in exploration. Excess resources or slack has generated inconsistent impacts on the tendency to explore. For instance, Greve (2007) finds a positive association between resource slack and exploration. In particular, slack search is not seeking a solution for an existing problem but is mainly guided by the interest of individuals or a group. In contrast, the opposite perspective argues that firms that do not rely on innovation may use slack resources to enhance current operations regardless of competitive pressure or market change. The conflicting view of the association between resource slack and exploration could be contingent on factors such as the features of slack resources (e.g., administrative or financial resources) and environmental conditions (Lavie et al., 2010). Organizational structure, culture, identity, and size also shape motivation to explore due to the distribution of resources, operation routines, organizational goals, attitudes, and experiences. For instance, Hannan and Freeman (1984) find that firm size may negatively influence exploration due to the increased operational productivity and restricted discovery of new opportunities.

The managerial antecedents refer to organizational decision-makers characteristics, which could also be considered organizational features. Managers' risk aversion, experience, and learning capabilities may influence their preference concerning exploration (Lavie et al., 2010). For instance, because exploration poses a high probability of failure, a manager aiming for survival may not consider it attractive. However, when the organization's performance drops below an acceptable level due to a lack of exploration, dissatisfaction may urge managers to explore (March, 1991).

In sum, environmental antecedents have the same effect on firms operating in the same market, and organizational antecedents are fully independent. Beyond these two categories, a study by Duyster and colleagues (2019) shows that the tendency to explore can also be influenced by the exploration level of its alliance partners and competitors. The findings indicate that a firm's social relations may influence its tendency to explore, yet few studies have investigated the effects.

2.3. Network antecedents for exploration

It is widely acknowledged that the pattern or configuration among organizations has an important impact on firm behavior and outcome (Zaheer et al., 2010). As Parmigiani and Rivera-Santos (2011) summarize, networks can influence exploration because ties can be used to exchange knowledge and learn; also, certain structures can develop trust by not taking advantage of vulnerabilities. To connect network structure and individual firms' exploration strategy, we investigate two constructs—closeness centrality and local cohesion. Closeness centrality entails accessibility to external knowledge and resources and can be related to distant search, while local cohesion can support knowledge sharing and organizational learning.

Firms explore by engaging in distant search. Distant search often involves recombining novel, unfamiliar knowledge (March, 1991). Therefore, the speed of reaching distant knowledge and skills could be highly important for promoting exploration. Interorganizational networks bring together diverse and various knowledge and resources, allowing involved firms to access and apply this knowledge to pursue new opportunities (Gilsing et al., 2008). Network ties indicate the knowledge flow or resources that are accessible to different network members (Zaheer et al., 2010). Some information might be directly available from a connected partner, while others may need a firm to search from indirectly connected organizations. Knowledge from directly connected firms can be more similar, while knowledge from indirectly connected organizations is more likely to be novel. Individual firms' network positions entail access and search costs for external knowledge and resources. The *distance* between a firm and the rest network members determines search efficiency and cost. With an advantageous position, firms are better informed about events occurring within the network, have prompt access to various information, and have more options for exploring new opportunities (Burt, 2004).

In addition, firms face the challenge of absorbing external knowledge. Both direct and indirect ties may influence the development of absorptive capacity (Gilsing et al., 2008; Lavie & Rosenkopf, 2006). Firms must be able to assimilate external information to what they can understand and then find a proper way to apply it (Cohen & Levinthal, 1990). Interactions between firms lead to the development of absorption capacity. According to Haugland et al. (2021), closed triadic structures can benefit relationship learning because the common third party can provide complementary views to assist learning at the dyadic level.

The publicly available knowledge may have limited value for exploration due to a lack of novelty. Tightly connected networks can support sharing of private information and hard-to-price resources (Brass & Burkhardt, 1993; Shipilov, 2005; Uzzi, 1999). Such structures ensure that firms will not take advantage of each other's vulnerabilities, thus promoting firms to share knowledge and resources that can hardly be shared in public. In sum, network properties provide insights concerning firms' accessibility to external knowledge and resource and their willingness and ability to acquire and apply them.

2.4. Role of closeness centrality

Closeness centrality is a specific type of centrality measure that assesses the total path length of an actor to all other actors in the same network (Borgatti & Everett, 2006; Freeman, 1978). A firm that is more central in terms of closeness may be more independent (as its access is not controlled by others) and efficient (as it can reach other members of the network in the shortest amount of time) in searching for distant knowledge (Brass & Burkhardt, 1993). We argue that closeness centrality promotes exploration strategy for two reasons.

First, firms explore by engaging in distant search, which adds new elements to the current knowledge base (Jensen et al., 2006; March, 1991; Phelps, 2010). Firms with a relatively higher closeness centrality index use fewer "steps" to access information beyond directly connected partners. In other words, a high degree of closeness centrality implies an information-rich position in a network. A firm in such a position can tap into a richer information pool that can more efficiently add distinctive knowledge variations to its current domain. For instance, Aarstad, Ness, and Haugland (2015b) find that firms with high closeness centrality in a tourism destination network are able to observe other firms' co-branding practices more quickly and induce imitative behaviors. Similarly, we expect that better accessibility to information may motivate the focal firm to become a fast mover to seek new opportunities and tap into new fields, in line with exploration.

Second, scholars find that central firms, with respect to closeness centrality, can be professional in communicating and interpreting external knowledge (Aarstad et al., 2015b; Wasserman & Faust, 1994). If a problem concerning communication channels occurs, the firm with higher closeness centrality can provide efficient solutions. Due to the ability to access a large knowledge pool, well-connected firms can capture related knowledge in the pool to assimilate external information and knowledge for their use. Aarstad, Ness, and Haugland (2015a) noted that well-connected actors could function as catalysts for information sharing due to better awareness of certain knowledge than less central firms. Such professionalism, in turn, may increase a firm's proactive attitude in pursuing new opportunities and adjusting exploration strategy accordingly. Therefore, we argue that the relationship between firms' closeness centrality and exploration strategy is positive.

Therefore, we propose the following:

H1: There is a positive association between a firm's closeness centrality in the interorganizational network and its exploration strategy.

2.5. Role of local cohesion

While closeness centrality captures a firm's position within an extended network, local cohesion highlights the connectivity in the local structure. Local cohesion refers to the connection of the subgroup around a focal actor (Wasserman & Faust, 1994, p.249). Therefore, if all partners of a firm are directly connected, the local cohesion around the firm will be the highest. We argue that local cohesion promotes exploration strategy for two reasons.

The first benefit of cohesive local structures is that they facilitate the development of trust and cooperation among the participating actors, which facilitates sharing private information and hard-to-price resources between them (Gulati, 1995; Uzzi, 1997). In an empirical study of tourism destinations, Haugland, Ness, and Aarstad (Haugland et al., 2021) find that cohesive structures facilitate trust-based governance in dyadic relations. Such a governance form reduces the threat of exchange hazards and facilitates greater information sharing and a more open interaction pattern (Dyer & Singh, 1998). Uzzi (1999) suggests that ties within cohesive structures promote private knowledge transfer instead of public knowledge since the structure assures the transfer is for mutual benefits. Similarly, Shipilov (2005) finds that firms involved in cohesive local structures can benefit from exchanging fine-grained information and sharing hard-to-price resources. Hence, information and resources shared within cohesive structures are less disordered, richer, private, and of higher quality. Moreover, cohesive structures allow direct communication for disagreement and misunderstanding, increasing mutual benefits from cooperation (Shipilov, 2005). Involved partner firms may work together to address newly arisen situations, such as discussing what information or technology is important but currently lacking and jointly discovering solutions (Uzzi, 1996). Through direct and open communication, involved parties can have more reliable input to reduce the risk and uncertainty associated with exploration.

On the other hand, cohesive structures provide optimal conditions for organizational learning (Haugland et al., 2021; Phelps, 2010; Uzzi & Lancaster, 2003). Learning external knowledge can be hard, especially when such knowledge is not codified and highly contextualized (Becerra et al., 2008). In cohesive local structures, the learning process between two organizations is eased due to the common third party. For example, firm A has business relationships with firms B and C; if there is a link between B and C, this could help A understand C better through B's understanding of C. A third party may be able to offer additional, novel, and complementary perspectives. Consequently, A, B, and C may build a common knowledge base during interactions, supporting them in understanding and integrating new knowledge. Such a structure can help firms build absorptive capacity (Gilsing et al., 2008). In addition, due to the cooperative atmosphere in cohesive structures, firms are likely to invest more time and effort in the knowledge acquisition process (Coleman, 1988; Tortoriello et al., 2012). The existence of a common third party may alter the knowledge-sharing process and influence relationship learning (Haugland et al., 2021). To sum up, a shared third party can improve the understanding of involved parties in terms of content and depth and enhance knowledge acquisition, thereby making involved firms better capable of discovering new opportunities.

Hence, we propose the following:

H2: There is a positive association between local cohesion in a firm's interorganizational network and its exploration strategy.

3. Research methods

In this section, we first introduce the research context and data collection and then discuss measures for variables. We close this section by presenting how the data was analyzed.

3.1. Research context and data collection

As empirical context, we select two regional industrial clusters in western Norway, focusing on the media and fintech. These two regional clusters formally belong to a national innovation cluster program supported by the government and relevant public organizations. Regional clusters are expected to facilitate local firms' competitive advantage and enhance regional innovation and economic growth (Bergman & Feser, 2020; Martin & Sunley, 2003). Member firms' exploration is not only essential for the focal firm, but also important for cluster and regional innovation outcomes. In addition, both clusters are closely related to Information and Communications Technology and experienced significant changes in technology and competition during the past decades, making innovation essential[10] (Tödtling & Grillitsch, 2015). Content providers in the media cluster and traditional financial service providers need to collaborate with technology providers to better serve end customers. Therefore, knowledge

[10] According to the Norwegian Standard Industrial Classification 2007 (SIC2007), 40 out of 64 firms in our sample belong to the Category J – Information and Communication category, matching the sector codes from 58 to 63. See detail at Statistics Norway .

about how cluster members interact and explore enables a better understanding of the firm and system-level performance.

Cluster members include commercial and non-commercial organizations, such as public organizations and research institutions. Commercial members in the media cluster are publishers, TV broadcasters, film and television production companies, technology companies focusing on graphic, audio, video, and artificial intelligence, consultancy for the media industry, and equipment suppliers. The fintech cluster includes banks, insurance companies, consultancy, investment companies, and technology providers in financial services such as mobile payment. Both clusters have a formal membership system. Based on the clusters' official websites, we first identified all formal members of the two clusters. We then asked well-informed local representatives to review the list. We identified 67 firms in the media cluster and 68 firms in the fintech cluster.

Testing the hypotheses requires network data and data about firms' exploration strategies. We collected network data to identify individual firms' positions concerning closeness and local cohesion and applied a survey approach to measure firms' exploration strategies. Network data and survey data were collected simultaneously via an electronic questionnaire. Because our focus is on firms, we did not invite non-commercial members (e.g., municipality organizations and research institutions) to participate in the subsequent survey. However, these non-commercial members were indirectly included, as the commercial members are able to report collaborations with them.

As cluster membership *per se* can barely contribute to the innovation process (Owen-Smith & Powell, 2004), we contacted firms to confirm if they had existing business relationships with other firms within the cluster. Seven firms from the media cluster were excluded due to a lack of existing business relationships. In total, we sent the survey to 47 firms who agreed to participate and received 40 completed responses[11], a response rate of 85% for the media cluster. Following the same procedure, we excluded eight firms from the fintech cluster. One firm was no longer a member, and seven reported no existing relationships. We sent out the survey to 36 firms and received 24 completed responses, with a response rate of 67%.

For the network data, we asked the respondents to identify their current formal business partners from a complete list of cluster members. When visualizing the network structure, we model a tie between two organizations when one or both firms report a formal relationship. This technique allows us to eliminate the bias of non-respondents in the network sample; if only one side of a dyadic relationship responds to our survey, we can still model that relationship between two parties (Aarstad et al., 2015b). The research design also enables us to capture formal business relationships of different forms (e.g., strategic alliances, joint innovation projects, and supplier and buyer relationships). We will discuss how network properties were calculated in *Section 3.2*. As the exploration strategy captures the planned activities of a particular firm, a survey is well suited as a methodological approach to the empirical inquiry.

3.2. Measures

Dependent variables. The concept of exploration is a broad and general one, and existing studies propose a number of measures for assessing this construct, including new alliances (e.g., Beckman et al., 2004), patent citations (Duysters et al., 2019; Katila & Ahuja, 2002; Phelps, 2010), and innovation performance concerning newness (e.g., Bierly & Chakrabarti, 1996). Because our focus is on a firm's intention to explore through its network

[11] Network data from four incomplete responses from the media cluster were used for network visualization. The response rate is based on completed responses.

partners instead of consequence, we adjusted the instruments developed by He and Wong (2004) using a 7-point Likert scale from strongly disagree (coded 1) to strongly agree (coded 7).[12] We asked the respondents what the firm wants to achieve through network ties concerning (1) opening up a new market, (2) extending product(s)/service(s) range, (3) introducing a new generation of their product(s)/service(s), and (4) entering a new technology field. Collectively, we believe that measuring the exploration strategy by using the items above through a survey can determine the ambition of discovering new possibilities and suits our research context (March, 1991).

Independent variables. Independent variables were measured using network data. Closeness centrality was calculated as the inverse of the sum of geodesic distances from actor *i* to all the other actors (Freeman, 1978; Wasserman & Faust, 1994, p. 184). Isolated actors will have an invalid value. To avoid this problem, we have confirmed existing business relationships with respondents before the survey. We use the Freeman normalized value for closeness centrality to eliminate the influence of network size.

Local cohesion is defined as the connectivity of a subgroup around a focal actor. We measure local cohesion as the total number of the closed triad(s) around a focal actor divided by the number of all possible ties (Wasserman & Faust, 1994).

Control variables. Firm size, cluster dummy, and Burt's constraint are included as control variables. Firm size is the number of formal employees a firm has when surveyed. Larger firms tend to be more ponderous and less motivated to explore (Hannan & Freeman, 1984). We include a dummy variable to control the cluster effect. Firms from the media cluster are coded as 0, and firms from the fintech cluster are coded as 1. Burt's constraint is included

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[12] The original measure includes items for both exploration and exploitation. We also measured exploitation strategy in the survey. See *Appendix A* for more information.

to ascertain information redundancy. A higher score of Burt's constraint represents an actor with more redundant contacts and spanned fewer structural holes—spaces between network members that are not directly connected (for further details, see Burt, 2004). The exploration strategy may be weakened if firms access redundant information due to the lack of novel elements of knowledge.

3.3. Data Analysis

We first conduct network analysis for the two regional clusters separately using UCINET 6.707 (Borgatti et al., 2002), then merge and combine the survey and the network data by matching firm names for hypotheses testing using multiple linear regression in Stata 16.1.

Despite the fact that network data and survey data were collected simultaneously, they formed two datasets that are not directly related. Combining data from two different datasets reduces the problems related to common method bias (Aarstad et al., 2015b; Lindell & Whitney, 2001). Furthermore, collecting data from two different clusters enable us to account for potential bias caused by a single cluster. The next section presents network data, descriptive statistics, and hypotheses testing results.

4. Results

4.1. Network data

Using the network data, we manage to identify 85 out of 93 organizations with 291 ties in the media cluster, representing 91.4% of the cluster members. For the fintech cluster, we identify 56 out of 74 organizations with 171 ties, representing 75.7% of the cluster members. The remaining firms that we are unable to model are possibly isolated, marginal, or inactive since other firms have not reported relationships with them. Considering that we provided a full list of cluster members, identified some inactive firms before the survey, and attempted to reach the remaining firms, we believe that the identified network is highly similar to the actual network.

4.2. Measurement model

The exploration strategy is measured by four items, with a Cronbach's alpha of 0.747 (Nunnally, 1978). Thus, we conclude that the measurement model shows satisfactory reliability (Bollen, 1989; Bollen & Lennox, 1991). We then model the exploration strategy using the average scores of the items reflecting each variable.

4.3. *Descriptive statistics*

As the measure of exploration strategy deviates from normality, we applied Van der Waerden's (1953) method for transformation.[13] Then, we generate standardized values for all variables, with the mean equal to 0 and the *SD* equal to 1. *Table 1* shows all variables' mean, SD, and correlation matrix using standardized values.

We notice that closeness centrality and Burt's constraint are negatively correlated, indicating that the higher level of closeness centrality a firm has in a network, *ceteris paribus*, the less constraint. In other words, it is likely for a central firm in a network to receive non-redundant knowledge from different partners. Moreover, we find that firm size is positively correlated with closeness centrality, showing that bigger firms tend to be more central in networks. This is reasonable because bigger firms have a better capacity to form network ties and occupy central positions (Shan et al., 1994). In our data, local cohesion is not significantly correlated with closeness centrality and Burt's constraint.

Comparing the two clusters, we observe that the average firm size from the fintech cluster is bigger than the firm size from the media cluster at a borderline significant level. On

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[13] The transformation was conducted using JMP software (version Trial 16).

average, firms in the fintech cluster tend to have higher closeness centrality at a borderline significant level. We also notice that the media cluster has denser local cohesive structures than the fintech cluster. Different cluster sizes may cause differences in network measures: in our data, 40 members were included from the media cluster, while 24 members from the fintech cluster were included.

Table 1. Mean, SD, correlation matrix.

Mean	*SD*	Variable	ER	CN	LC	BC	SZ
5.406	0.908	Exploration (ER)					
0.440	0.074	Closeness Centrality(CN)	0.244†				
0.136	0.109	Local Cohesion (LC)	0.303**	0.020			
0.382	0.238	Burt's Constraint (BC)	–0.203	–0.744**	–0.013		
290	1154	Firm Size (SZ)	0.019	0.368**	–0.054	–0.145	
0.375	0.488	Cluster (CL)	0.075	0.216†	–0.314*	0.017	0.216†

4.4. Hypothesis testing

Table 2 summarizes the results of the hypothesis testing. Model 1 tested the effect of control variables: firm size, cluster dummy, and Burt's constraint. Only Burt's constraint has a negative borderline significant effect on the exploration strategy. In H1, we propose a positive association between closeness centrality and exploration strategy. Model 2 shows a positive but insignificant effect. This may have occurred due to the strong negative correlation between closeness centrality and Burt's constraint. Model 3 excludes Burt's constraint and tests H1 again. The result is positive and significant ($p < 0.05$), supporting H1. H2 proposes a positive association between local cohesion and exploration strategy. Model 4 provides support for this hypothesis. We also note a negative effect of Burt's constraint at a borderline significant level ($p < 0.1$).

Models 5–6 test H1 and H2 together. Model 5 shows a significant positive effect ($p < 0.01$) of local cohesion but an insignificant effect of closeness centrality on exploration strategy. Due to the strong negative correlation between closeness centrality and Burt's constraint, their effects cancel each other out when included in the same model. Model 6 excludes Burt's constraint, and we observe a borderline significant positive effect of closeness centrality ($p < 0.1$). The significant positive effect of local cohesion ($p < 0.01$) remains, thus supporting H1 and H2.

Despite local cohesion significantly influencing exploration strategy, the effect of closeness centrality is relatively weak. In models 2 and 3, the R^2 and *adjusted* R^2 are small, meaning that closeness centrality only explains a limited portion of the exploration strategy. However, when including local cohesion in the models (Models 4-6), we observe obvious increases in R^2 and *adjusted* R^2. Therefore, while closeness centrality has a limited impact on exploration strategy, local cohesion could be a more important antecedent factor.

Table 2. Results for hypotheses testing.

Dependent variable	***Exploration strategy***					
Model	1	2	3	4	5	6
Control variables						
Firm size	–0.31	–0.083	–0.088	–0.036	–0.070	–0.082
	(0.131)	(0.139)	(0.136)	(0.123)	(0.132)	(0.129)
Cluster	0.175	0.089	0.074	0.388	0.343	0.305
	(0.265)	(0.276)	(0.265)	(0.263)	(0.278)	(0.266)
Burt's constraint	–0.209^{+}	-0.042		–0.207^{+}	–0.096	
	(0.128)	(0.198)		(0.120)	(0.189)	
Independent variables						
Closeness centrality		0.234	0.269*		0.155	0.235^{+}
		(0.213)	(0.136)		(0.204)	(0.130)
Local cohesion				0.360**	0.347**	0.340**
				(0.125)	(0.127)	(0.125)
Constant	–0.066	–0.033	–0.028	–0.153	–0.129	–0.114
	(0.160)	(0.162)	(0.159)	(0.154)	(0.158)	(0.154)
R^2	0.048	0.067	0.067	0.166	0.174	0.170
Adj. R^2	0.001	0.004	0.020	0.109	0.103	0.114
F-ratio	1.02 n.s.	1.07 n.s.	1.43 n.s.	3.38*	2.44*	3.02*
VIF (max)	1.08	2.87	1.18	1.16	2.93	1.20

N = 64. Standard errors are in parentheses.

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

We further check variance inflation factors (VIFs) for all models. The VIFs do not fall within the suggested critical values between 4–10 (see O'Brien, 2007). However, multicollinearity may still be an issue due to the small sample size. The strong positive correlation between firm size and closeness centrality may lead to the higher VIFs in models 2 and 5 and the insignificant F-ratio in models 2 and 3.

5. Discussion

5.1. Discussion of results

This study examines the impact of two aspects of a firm's interorganizational network structure – closeness centrality and local cohesion – on its exploration strategy. The theoretical framework suggests that closeness centrality and local cohesion play different roles in facilitating exploration strategy. According to this framework, closeness centrality is connected to the extended network position that serves two roles. First, an extended network position reflects access to distant knowledge. Second, closeness centrality enables the firm to develop professionalism in processing and communicating information. A cohesive local structure also serves two purposes: (1) facilitating the exchange of private knowledge and difficult-to-price resources and (2) supporting organizational learning. These two network structures expand the diversity of knowledge that a firm can access and enhance the firm's ability to communicate and absorb external knowledge. As we expected, both closeness centrality and local cohesion positively influence exploration strategy. In addition, our findings show that local cohesion has a more robust positive effect than closeness centrality. The findings imply that cohesive subgroups motivate exploration strategy more effectively than a central position in terms of closeness.

We also control for Burt's constraint when testing the hypotheses. Only when closeness centrality is excluded can we observe a borderline negative significant effect. This effect might either be due to the high correlation of closeness centrality. Alternatively, the negative magnitude between Burt's constraint and exploration strategy may indicate that having more structural holes may facilitate the exploration strategy (Burt, 2004).

5.2. Theoretical implications

The findings from this research broaden and deepen our understanding of how firms are motivated to explore and underscore the need to consider existing relationships a firm has in a network. The study adds to the literature on antecedents to exploration (Duyster et al., 2019; Jansen et al., 2006; Lavie et al., 2010). Studies about the antecedents of exploration allude to environmental and organizational factors. An exception is a study by Duysters and colleagues (2019); they find that a firm's explorative tendencies are related to its partners' and competitors' exploration levels. In this study, we reveal the association between the network structure around a firm and its exploration strategy. In particular, we show how network structures may influence a firm's condition and ability to pursue exploration. Hence, this study goes beyond previous studies demonstrating that firms' exploration strategies are shaped uniformly by market conditions or are driven independently by organizational characteristics.

The second contribution of this study is that we studied and measured exploration strategy in the interorganizational network context. Scholars often associate exploration with concepts such as organizational diversity, knowledge generation, and innovation (Wilden et al., 2018). In interorganizational network studies, exploration has been exclusively connected to knowledge creation and has been assessed using the number of new patents filed or applied (e.g., Duysters et al., 2019; Gilsing et al., 2008; Phelps, 2010). Not all firms can execute exploration successfully (Stuart, 1998); focusing on outcomes implicitly assumes that all firms have the same motivation to explore. Besides, what motivates a firm to explore does not necessarily support its realization. Blurring the definition of exploration and innovation might overlook the motivation, unmeasured process, and failed attempts (Rosenkopf & Nerkar, 2001).

This study distinguished between exploration strategy and innovation output in both theorization and measurement[14].

5.3. Managerial implications

This study has managerial implications for both firm managers and cluster managers. Broadly, it shows that closeness centrality and local cohesion are positively associated with a firm's exploration strategy, yet their mechanisms and effects differ. We suggest firm managers consider their network positions when forming their exploration strategy. We found that having access to distant knowledge may have a positive but limited effect on facilitating exploration. Firm managers may work with partners within cohesive structures to seek new possibilities. Such a structure guarantees the quality of shared information and resources and facilitates the development of a common knowledge base. Meanwhile, firm managers should also be aware that cohesive structures could contain redundant information, which may negatively influence the outcome. Thus, it is critical to know the form of benefits from certain network structures that are most likely to be facilitative (Ahuja, 2000).

For cluster managers, our findings suggest ways to motivate cluster members to explore. For example, they show the importance of cohesive local structures. Cluster managers may guide cluster members to form proper structures to facilitate exploration by accelerating collaboration to establish cohesive structures and encouraging closer collaboration where cohesive structures already exist or are just emerging. Cluster managers may also consider bridging disconnected parts to shorten distances between cluster members. Forming cohesive structures promotes exploration more effectively than shortening the distance to external

[14] In Appendix B, we measured firm innovativeness using a survey method. We found that exploration strategy is positively associated with firm innovativeness.

knowledge. Thus, cluster managers can stimulate members' exploration by designing proper structures and increasing the probability of successful innovation to benefit the regional cluster.

5.4. Limitations and future research

The results and contributions of this study should be considered in light of its limitations. First, a firm with a high level of exploration strategy may be more active in forming network ties to shorten its distance to other network members, ending up with a high score on closeness centrality. Powell, Koput, and Smith-Doerr (1996) find that biotechnology firms with more R&D experience are likely to score higher on closeness centrality. In a similar vein, Aarstad, Ness, and Haugland (2015a) also find that innovative firms tend to reduce path length to reach other firms in destinations. We considered an alternative model of a reversed relationship of H1 in Appendix C. Future studies might examine the causal relationship between organizational characteristics and network positions.

Second, we need to be cautious with the research design and network data. Although we are able to model the majority of the two networks, non-respondents may still influence the accuracy of visualization. Besides, although our focus is within a particular network, the current research design may omit important firms outside a cluster. A possible solution is to improve the current design by adding space for nominating partners outside the list, so that respondents can choose their partners inside the cluster and list important partners outside the cluster (Robins, 2015). Another disadvantage of the research design is that relations that are terminated but may have lasting impacts have been omitted. Future studies may follow Aarstad, Haugland, and Greve (2010) and ask respondents to report both ongoing and terminated relationships.

Third, the data used in this study were static. Clusters develop over time; accordingly, members' network positions will also change. Moreover, firms will experience further developments or transformations. In the development process, the needs of the firms concerning exploration have also changed accordingly. Future studies could collect longitudinal data for both network structures and exploration strategies to capture the dynamics.

The fourth limitation is the measurement of the exploration strategy. In this study, we adjusted the items developed by He and Wong (2004) to capture the essence of exploring new possibilities. More insights can be gained by studying different aspects of exploration and exploitation, such as governance forms (e.g., joint versus divided decision-making), individual interaction in collaborations (e.g., routinized or ongoing communication process), and organizational structural change (e.g., business model innovation).

Finally, we focused on two technology-intensive regional clusters in Norway, which leads us to question the generalizability of our findings. Future endeavors could examine the topic in other national contexts and industries.

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Appendix A. Exploitation strategy

The original measure by He and Wong (2004) has eight items, four items measuring exploration and four items measuring exploitation. We first conducted a factor analysis to reduce the eight items to two variables that could be interpreted as exploration and exploitation strategies. *Table A1* summarizes the results of the factor analysis. We found that the exploitation strategy and exploration strategy were not significantly correlated in our data (with a correlation of 0.145, $p = 0.255$), which supported the argument that exploitation and exploration are fundamentally distinct types of activities (He & Wong, 2004).

We took the average score of each item and then used the Van der Waerden (1953) method to generate a normal quantile variable for regression analysis. We regressed closeness centrality and local cohesion on exploitation strategy separately and simultaneously, controlled for firm size, cluster, and Burt's constraint. We noticed that neither closeness centrality nor local cohesion significantly affected exploitation strategy (see *Table A2* for the output), corresponding to the idea that the network effect is negligible when firms work on familiar knowledge and markets (Burt, 2000).

Table A1. Items and measurement model for exploration and exploitation strategy.

	Exploitation strategy	***Exploration strategy***
Please indicate what your company wants to achieve through alliances: improve existing product(s)/service(s) quality;	**0.504**	0.372
improve production flexibility;	**0.838**	–0.019
reduce production and operation costs;	**0.847**	0.101
improve operational efficiency;	**0.853**	–0.057
open up new markets;	–0.242	**0.652**
extend product(s)/service(s) range;	0.135	**0.884**
introduce new generation of product(s)/service(s);	0.058	**0.827**
enter a new technology field.	0.176	**0.609**
Cronbach's α	0.777	0.747
CR	0.853	0.836
AVE	0.600	0.565

$N = 64$. Principal components with varimax rotation. Explained variance: 61.6%. High factor loadings reported in bold for each of the two variables indicate satisfactory convergent validity, low factor loadings across the variables indicate satisfactory divergent validity, and high values of Cronbach's α indicate satisfactory reliability.

Table A2. Output for regression analysis for exploitation strategy

Dependent variable	***Exploitation strategy***		
Model	1	2	3
Control variables			
Firm size	–0.111	–0.051	–0.108
	(0.141)	(0.134)	(0.142)
Cluster	–0.068	0.233	0.125
	(0.280)	(0.285)	(0.299)
Burt's constraint	0.253	0.059	0.241
	(0.201)	(0.130)	(0.204)
Independent variables			
Closeness centrality	0.274		0.256
	(0.216)		(0.220)
Local cohesion		0.099	0.077
		(0.136)	(0.137)
Constant	–0.026	–0.088	–0.047
	(0.165)	(0.167)	(0.170)
R^2	0.038	0.021	0.043
Adj. R^2	–0.027	–0.046	–0.039
F-ratio	0.58 n.s.	0.31 n.s.	0.52 n.s.
VIF (max)	2.87	1.16	2.93

N = 64. Standard errors are in parentheses.

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Appendix B. Firm innovativeness

Firm innovativeness was measured using three items adapted from Clauss (2017), using a 7-point Likert scale ranging from strongly disagree (coded 1) to strongly agree (coded 7), reflecting its ability compared with its competitors to address innovative products and services to customers. These three items were: (1) We regularly address new, unmet customer needs; (2) Our product(s)/service(s) are very innovative compared with our competitors; and (3) Our product(s)/service(s) regularly meet customer needs, which are not solved by our competitors. The Cronbach's alpha for firm innovativeness was 0.701, indicating satisfactory reliability (Nunnally, 1978).

We took each item's average score to generate the new variable, firm innovativeness. We checked the correlation between firm innovativeness and exploration versus exploitation strategy. We found that only exploration strategy was positively correlated with firm innovativeness (correlation = 0.416, $p < 0.01$), but not exploitation strategy (correlation = 0.083, $p = 0.513$).

Appendix C. Potential reversed causality

To check for the potential reversed causality for H1, we regressed closeness centrality as the dependent variable and exploration strategy as the independent variable, controlling for firm size and cluster. We observed a positive effect of closeness centrality at a borderline significant level (coefficient = 0.226, $p < 0.1$), indicating that firms with a higher level of exploration strategy will have a higher score on closeness centrality. Therefore, we should be cautious in interpreting our findings.

Article 2: The role of in-degree centrality and triadic embeddedness in prosocial behavior: A study of two regional industry clusters

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Abstract

Purpose- Research on relationship marketing has traditionally focused on dyadic properties to explain behaviors and processes within these entities. This article adds to this body of research by investigating network-level antecedents of behaviors in dyadic relations. Specifically, the research focuses on in-degree centrality and triadic embeddedness to explain focal firms' prosocial behavior - a firm's beneficial actions toward a partner beyond formal requirements.

Design/methodology/approach- This study makes a unique combination of network data and survey data from two regional industry clusters in Norway to investigate the influence of network properties on prosocial behavior in a dyad.

Findings- The results show an inverted U-shaped relationship between in-degree centrality and prosocial behavior, and triadic embeddedness positively correlates with prosocial behavior. The effects of triadic embeddedness can hold regardless of in-degree centrality.

Research implications- This study shows that a firm's behavior at the dyadic level is influenced by the broader network structure in which the particular dyad is embedded.

Practical implications- This study provides managerial insights for cluster members concerning partner selection and cluster managers to ensure the well-being of the cluster.

Originality/value- This study supports the view that firms' behavior in individual dyads is influenced by the broader context of interorganizational relationships.

Keywords: Cooperation; Prosocial behavior; Interorganizational networks; Network structure; Regional clusters

1. Introduction

Firms' cooperative actions can facilitate achieving relational benefits and incorporate two dimensions: actions following mandatory rules or formal contracts, and voluntary and spontaneous behaviors beyond formal requirements (Wang *et al*., 2017). In this study, we focus on the latter and study prosocial behavior, referring to a firm's beneficial actions toward another firm beyond formal requirements (O'Reilly and Chatman, 1986). Because contracts can hardly be complete and costly to draft, prosocial behavior is desirable in business relationships (Wuyts, 2007). Prosocial behavior is an important expression of a firm's goodwill and willingness to help partners outside formal requirements.

Beyond individual relationships, prosocial behavior is also particularly appropriate in goal-oriented interorganizational networks such as regional industry clusters. A regional cluster is normally designed to sustain cooperation and innovation to achieve economic growth (Bergman and Feser, 2020). Members' prosocial behavior in dyadic interaction largely affects a cluster's survival and success. In other words, the level of prosocial behavior in dyadic relationships may indicate the "well-being" of the cluster. The focus of this study is prosocial behavior in dyads within interorganizational networks.

In the tradition of relationship marketing research, current knowledge on drivers of prosocial behavior focuses on dyadic-level characteristics such as the switching cost of a particular partner (Wuyts, 2007), prior interaction with a particular partner (Wang *et al*., 2017), trust and commitment between partners (Li, 2010), and the relationship between boundary spanners of involved parties (Zhou *et al*., 2020). Despite the strong dyadic focus, marketing scholars agree that more attention should direct to broader contexts (Achrol, 1997; Choi and Wu, 2009; Dubois, 2009; Heide and John, 1988; Rokkan and Haugland, 2002; Wathne and Heide, 2004; Wuyts and Van den Bulte, 2012). For example, Wathne and Heide (2004) found that monitoring a downstream customer in supply chain networks depends on relationships with upstream suppliers. Some studies focusing on the triadic structure in supply networks have also emerged (see Wynstra *et al*., 2015, for a review). As Zhou *et al*. (2020) suggest, network embeddedness could be an important driver of prosocial behavior, yet it has been overlooked. This study investigates network drivers for prosocial behavior at the dyadic level.

Furthermore, among existing studies, network data has been derived from a variety of sources. Some studies have used case studies (e.g., Wilhelm and Sydow, 2018), others have utilized secondary data (e.g., Carnovale and Yeniyurt, 2014), and still, others have developed items to measure specific network characteristics (e.g., Wuyts and Geyskens, 2005). Few empirical studies obtained actual quantitative network data to study how dyads are affected by the larger network. An exception can be a study by Haugland and colleagues (2021); they combined network data and survey data and found that triadic, embedded network structures can influence the generation of relational rent by enhancing relationship learning and trust-based governance. However, network characteristics other than the triadic structure were not included. Hence, the network perspective is important for understanding dyadic characteristics, yet limited quantitative empirical research exists.

Our study combines the literature on social networks and relationship marketing to address the paucity of research on network properties and behavior in dyads. We focus on two network constructs—in-degree centrality and triadic embeddedness. In-degree centrality entails a firm's (1) power status in a network (Aarstad, 2013; Brass and Burkhardt, 1993) and (2) visibility of behaviors (Wasserman and Faust, 1994). Triadic embeddedness refers to mutual third parties a firm has with its partners, reflecting network closure (Wasserman and Faust, 1994; Coleman, 1988). Dependence and power, relational norms, and reputation management are the main theoretical resources we draw on to develop the framework (Emerson, 1962; Pfeffer and Salancik, 1978; Wuyts and Van den Bulte, 2012). Specifically, we study if in-degree centrality and triadic embeddedness promote or hamper the development of prosocial behavior at the dyadic level.

Contextually, we examine interorganizational networks in two regional industry clusters in Norway, focusing on media technology and fintech. Cluster members interact to sustain innovation and economic growth. The study combines network data and survey data from commercial members of these two clusters. The network data capture how members are connected, while the survey data focus on a focal firm's prosocial behavior towards another cluster member. Combining two data sources enables us to investigate whether the network constructs of in-degree centrality and triadic embeddedness are associated with prosocial behavior at the dyadic level.

We seek to make the following contributions. First, we enrich the literature on relationship marketing by presenting how dyadic interactions are associated with the broader network structure (Choi and Wu, 2009; Gulati, 1998; Wilke and Ritter, 2006). Our findings ascertain that a firm's behavior at the dyadic level is related to the focal firm's position in a wider network. With the growing trend of business networks, such network antecedents require more attention. Second, we answer the call by Zhou *et al.* (2020) by showing how network structures function as antecedents of prosocial behavior. Existing literature focuses on instrumental and communal antecedents with a dyadic focus, assuming that only relational characteristics influence prosocial behavior. We expand the focus and address how the network structure around a focal firm can influence its prosocial behavior. Third, we used a sociometric or complete network approach to provide more accurate information on a focal firm's network condition. Many network studies use an egocentric approach (the focal actor and its partners), which may not reflect the actual network structure that influences the focal actor's behavior. In this study, actor-level network measures are extracted after visualizing the wider network structure, rather than an arbitrary subset of the network. Our approach enables a better understanding of how dyads are interrelated and influence each other.

This study is organized as follows. In the next section, we review the theoretical foundation of the study. We then develop the hypotheses linking prosocial behavior to particular network structures. After that, we present the research methodology, followed by presenting empirical results. We conclude by discussing the implications of our results for both theory and practice, and suggest future research directions based on the limitations of the study.

2. **Theoretical background**

2.1. *Prosocial behavior in interorganizational relationships*

Prosocial behavior refers to a firm's beneficial actions toward another firm beyond formal requirements (O'Reilly and Chatman, 1986). The notion originated as an individual-level behavior, such as helping and volunteering, and later applied to organizations as employee behavior for the good of the firm (Penner *et al*., 2004). Wuyts (2007) first introduced the notion to relationship marketing literature yet used a different term—extra-role behavior. Some studies consider extra-role and prosocial behavior the same (O'Reilly and Chatman, 1986; Wuyts, 2007). The term extra-role contrasts with in-role, focusing on actions beyond an identified role or formal requirement (Kim *et al*., 2011; Wuyts, 2007). Extra-role behavior emphasizes voluntarity and can be valuable for interorganizational relationships as contracts are mostly incomplete and costly to draft (Wuyts, 2007; Klein, 1996; Macaulay, 1963). Yet, other scholars categorize extra-role behavior into positive and negative forms. The positive form of extra-role behavior is oriented toward helping a partner. The negative form of extra-role behavior, however, may benefit the individual but harm an ongoing relationship, such as when a buyer develops relationships with alternative suppliers (Kim *et al*., 2011). The positive form of extra-role behavior is desired on the partner side, but not necessarily the negative form. The incentive of prosocial behavior should benefit the recipient (Maxham and Netemeyer, 2003). In other words, prosocial behavior and extra-role behavior have conceptual overlap in that both go beyond formal requirements. Yet, prosocial behavior covers only the positive form of extra-role behavior. Therefore, we may conclude that prosocial behavior is a particular form of extra-role behavior, but not vice versa.

Another related construct in literature is relational behavior, referring to actions for promoting a cooperative relationship and closely linked to relational norms characterized by flexibility, solidarity, and information sharing (Griffith *et al*., 2006; Hoppner and Griffith, 2011; Lusch and Brown, 1996). Relational behavior normally derives from a mutual understanding between parties developed from previous interactions or repeated transactions and occurs in long-term relationships. However, prosocial behavior does not require previous interaction between parties; it can occur in newly established relationships without existing relational norms (Salvato *et al*., 2017; Wuyts, 2007). In other words, triggers for relational behavior and prosocial behavior may differ. Donations, for instance, have been considered individual-level prosocial behavior; Donors do this because it makes them feel fulfilled. Prosocial behavior at the firm level can also be inspired by willingness (Miao and Wang, 2016), such as building up its image or reputation as a reliable partner. Relational behavior normally occurs because such behavior is expected from partners due to communal factors like norms. In sum, we have defined prosocial behavior as a firm's beneficial actions toward another firm beyond formal requirements. This study particularly focuses on the sender or the party that conducts prosocial behavior.

2.2. *Core drivers of prosocial behavior*

Wuyts (2007) categorizes various motivations of prosocial behavior as instrumental and communal. The instrumental motivations are related to the utility-maximization rationale, and the communal motivations are associated with relational or social factors. These two categories are not mutually exclusive. From an instrumental perspective, firms may conduct prosocial behavior for profit-making (Zhou *et al*., 2020). For instance, prosocial behavior can derive from reputation concerns (Coleman, 1994; Wuyts, 2007). Reputation becomes extremely important when a firm needs to distinguish itself from competitors, avoid unnecessary termination of relationships and attract potential partners (Wuyts, 2007). Both Kim *et al*. (2011) and Wuyts (2007) find that a firm tends to act prosocially when the firm wants to continue the relationship due to the high cost of relationship termination.

From a communal perspective, firms conduct prosocial behavior in a cooperative environment. Factors related to a cooperative environment include trust (Hewett and Bearden, 2001), relational norms (Lusch and Brown, 1996), reciprocity (Hoppner and Griffith, 2011), incentive alignment (Niesten and Jolink, 2012; Wathne and Heide, 2000), perceived justice (Griffith *et al*., 2006; Li, 2010), and shared values (Maxham and Netemeyer, 2003).

A social dilemma exists when prosocial behavior is studied at the interorganizational level: conducting prosocial behavior can eventually benefit all parties involved, but individual firms may tend to maximize their own material self-interest (Penner *et al*., 2004). Transaction Cost Economics (TCE) stipulates that a firm may behave opportunistically to maximize self-interest when given a chance (Williamson, 1985). By definition, prosocial behavior is voluntary and may not bring immediate benefit to those who act. A firm may behave opportunistically instead of prosocially to maximize profit. Yet, in the longer run, a firm may benefit from prosocial behavior through, for instance, an enhanced reputation or increased relational rent in cooperation. Due to the uncertainty and longer period required to benefit from prosocial behavior, such behavior signals that relational or social factors may constrain a firm from seeking quick compliance.

Thus, we can conclude from the literature that instrumental and communal motivations influence prosocial behavior. However, we have scant knowledge of how network structure may incentivize prosocial behavior.

2.3. *Network drivers of prosocial behavior*

A network refers to a group of actors and the connections between these actors (Brass *et al.*, 2004). Individual firms often participate in multiple business relationships, and network structure can show the pattern of these relationships. To link network structure and individual firms' prosocial behavior, we investigate two particular network constructs: in-degree centrality and triadic embeddedness. We focus on these two constructs because in-degree centrality can be related to instrumental motivation, and triadic embeddedness can be related to communal motivation.

From an instrumental perspective, a firm may act prosocially to establish a positive image and help it stand out among similar companies (Wuyts, 2007). Also, based on social exchange theory (Blau, 1964) and norms of reciprocity (Gouldner, 1960), a firm would engage in prosocial behavior when it expects the recipient to provide future societal or economic benefits. The dependence structure of a relationship can influence the involved parties' expectation of relational rewards. Scholars found that relational norms are more likely to be generated and reinforced in relationships with high mutual dependence than in relationships with imbalanced dependency structures, which in turn influence relational behaviors (Heide, 1994; Lusch and Brown, 1996).

Further, TCE scholars suggest that the imbalanced dependency structure indicates the relationship's exchange conditions concerning which party has a higher cost to leave the relationship and may lead to safeguarding problems (Buvik and Reve, 2002; Heide and John, 1988; Williamson, 1985). A buyer with more power may govern a weaker supplier hierarchically or exploit its advantageous position to pursue self-interest. Several studies show that asymmetric relationships trigger more conflicts and hamper cooperative norms and behaviors, yet symmetric relationships with bilateral dependence incentivize positive relational behaviors (Dwyer *et al*., 1987; Heide, 1994; Lusch and Brown, 1996; Rokkan and Haugland, 2002). In short, dependency structure shapes actors' capability and incentive to behave prosocially in the exchange relationship.

The dependency structure operates through the logic of power. Power is often employed in dyads yet can be generated from a broader social structure (Brass and Burkhardt, 1993). In an interorganizational network, relationships entail resource flows between firms. Network position becomes important because the power of partners over a focal firm increases as the firm becomes more dependent on the resources of these partners (Emerson, 1962; Zaheer *et al*., 2010). In other words, the dependency structure in dyads is an expression of the involved parties' power status generated from the social or exchange system. For instance, a buyer's dependence on a supplier depends on the availability of similar alternative suppliers. Therefore, examining the network around an individual dyad can better interpret the dyadic power or dependency structure.

From a communal perspective, dyadic-level characteristics such as goal alignment, trust, and cooperative atmosphere can be influenced by the broader context in which dyads are embedded. According to Wuyts and Van den Bulte (2012), certain network structures can have control and coordination benefits on dyadic relations. Simmel (1950) has emphasized that isolated dyads and dyads in a cohesive structure will have qualitative differences. Tortoriello and colleagues (2012) state, "Whatever the source, scholars agree that prosocial behaviors occur more frequently within cohesive groups (p. 1027)." However, they do not explicitly study the association between cohesive network structures and prosocial behavior. In sum, taking a network perspective can improve our understanding of dyadic power structure and the environment in which dyads operate.

2.3.1. In-degree centrality

From a structural perspective, in-degree centrality captures the interdependence between a focal firm (ego) and its partners (alters). In-degree centrality is a specific type of degree centrality measure that counts the number of relationships a focal firm receives (i.e., inward ties) from other firms (Provan *et al*., 2007; Wasserman and Faust, 1994). The more ties a firm receives from others, the higher its in-degree centrality. We will argue that in-degree centrality indicates a firm's power and visibility in a network.

In-degree centrality captures a firm's control or access to valuable resources and information that are valuable for other firms, entailing other parties' dependence on the focal firm. Aarstad (2013) finds that in an individual advice network, in-degree centrality is strongly correlated with referral power, which is measured by the participating employees' ratings of each member in the firm through a questionnaire. When a firm receives a tie, it shows that the partner firm relies on certain resources or information for the focal firm. Moreover, in-degree centrality also relates to available alternatives in a network (Brass and Burkhardt, 1993). When several firms report partnership ties to a focal firm, the focal firm's dependence on a particular partner is likely to decrease. Particularly when choices are not reciprocated, in-degree centrality better captures the asymmetry relationships, and those powerful actors are often the recipient rather than the senders. Hence, in-degree centrality is a proper indicator of the focal firm's power in a given network.

In addition, in-degree centrality also indicates the visibility of the focal firm (Wasserman and Faust, 1994). When a firm receives several choices from other firms in a business network, the focal firm is an attractive partner and receives more attention from other firms (Knoke and Burt, 1983; Zaheer *et al*., 2010). Regardless of existing direct connections, other firms may pay attention to the focal firm to follow its business activities or seek opportunities for collaboration. Due to more attention paid to the central firm, the firm's behavior will be more visible to the rest of the network. The visibility effect can influence whether a firm can enjoy reputation benefits or not; firms that occupy central positions are more likely to accumulate reputation benefits than peripheral firms (Ahuja *et al*., 2009). In sum, in-degree centrality entails a firm's power and visibility in the network, which may further influence its behavior in cooperation.

2.3.2. *Triadic embeddedness*

To capture cohesive structures, we use triadic embeddedness in this study. Triadic embeddedness measures the closed triadic structures around a focal firm (Wasserman and Faust, 1994). A triadic structure is the smallest unit that forms a network, referring to the structure with three actors that are directly or indirectly connected (Robins, 2015). A closed triadic structure means all three actors in the triad are directly connected—the more closed triadic structures around a focal actor, the higher its triadic embeddedness.

Triadic embeddedness can be related to network closure (Coleman, 1988). Traditionally, firms' willingness to help and assist one another and the pursuit of mutual benefits are associated with network closure or overlapping relationships (Tortoriello *et al*., 2015). According to Coleman (1988) and Krackhardt (1999), being a member of a closed triadic structure, involved actors' behavior will be largely restricted. Individuals embedded in closed structures can develop and sustain effective cooperative norms, benefit from a higher level of trust, and be better able to pursue collective rather than individual goals (Coleman, 1988). Firms in closed structures tend to demonstrate a greater sense of collective and prioritize common interest instead of self-interest. Within cohesive structures, individual firms' behavior will be guided by group norms that define what group members consider proper or improper

(Wuyts and Van den Bulte, 2012). Cohesive structures also serve as control mechanisms to prevent and solve conflicts at the dyadic level (Krackhardt, 1998). In particular, the mechanisms that occur in closed triads are 'indirect (that is, not directed toward one specific firm) and are intended to align the interests of involved firms' (Wuyts and Van den Bulte, 2012, p. 79)'. In other words, closed triadic structures facilitate a cooperative environment and influence involved firms' behavior.

3. Hypotheses development

3.1. In-degree centrality and prosocial behavior

As discussed in Section 2.3.1, the association between in-degree centrality and prosocial behavior involves the (1) power effect and (2) visibility effect, which function simultaneously. Power is generated from other actors' dependencies and can be employed at the dyadic level. The visibility effect goes beyond an individual dyad. With a high level of visibility, uncooperative behavior can easily get caught, and cooperative behavior can also be easily known, influencing the reputation of the focal firm. We suggest that such an increase in the focal firm's in-degree centrality has a non-monotonic effect on its prosocial behavior toward exchange partners in the network. Specifically, we suggest that increasing in-degree centrality from a low to moderate level will positively affect prosocial behavior. However, this positive effect will increase up to a certain point and then turn negative. That is, we argue that the relationship between in-degree centrality and prosocial behavior takes the shape of an inverted U.

With a low level of in-degree centrality, the focal firm will likely be in a subordinate position in an unbalanced relationship with other network actors. Given that in-degree centrality is related to power, it becomes evident that a firm that receives only one tie is more likely to be less powerful in cooperation than a firm that receives five ties. We expect that lower in-degree centrality is associated with less prosocial behavior for two reasons. First, as low in-degree actors are more likely to be on the weaker side of a relationship, such asymmetric relation is less likely to develop trust and cooperative norms between partners, hindering collaborative actions (Heide, 1994; Rokkan and Haugland, 2002). Second, the weaker party may reciprocate the non-cooperative behavior of the stronger party by undertaking fewer prosocial actions as a result of the stronger party exploiting its advantageous position and monitoring the relationship according to its own interests (Axelrod, 1984).

However, as in-degree centrality increases from a low level to a moderate level, the relationship with the (alter) partner may tend to become more balanced in power. In other words, power symmetry is more likely to appear as the in-degree centrality increase from low to moderate. Studies show that a balanced relationship fosters relational norms and cooperative behavior as the partners perceive each other as behaving on relatively equal terms (Heide, 1994; Lusch and Brown, 1996). In addition, with more balanced power, the focal firm can expect that its prosocial behavior is more likely to be reciprocated by the recipient, increasing the probability of both firms in the dyad engaging in collaborative actions.

The more central a company is in a network, the more easily other network members can observe its behavior. Prosocial acts have a limited effect on reputation building when visibility is low, weakening the motivation to do so. As visibility increases, prosocial behavior can strengthen a focal firm's reputation as a fair partner, increasing the potential for future business. Hence, as in-degree centrality increases from a low level, prosocial behavior toward the (alter) partner firm will also increase due to the increased visibility.

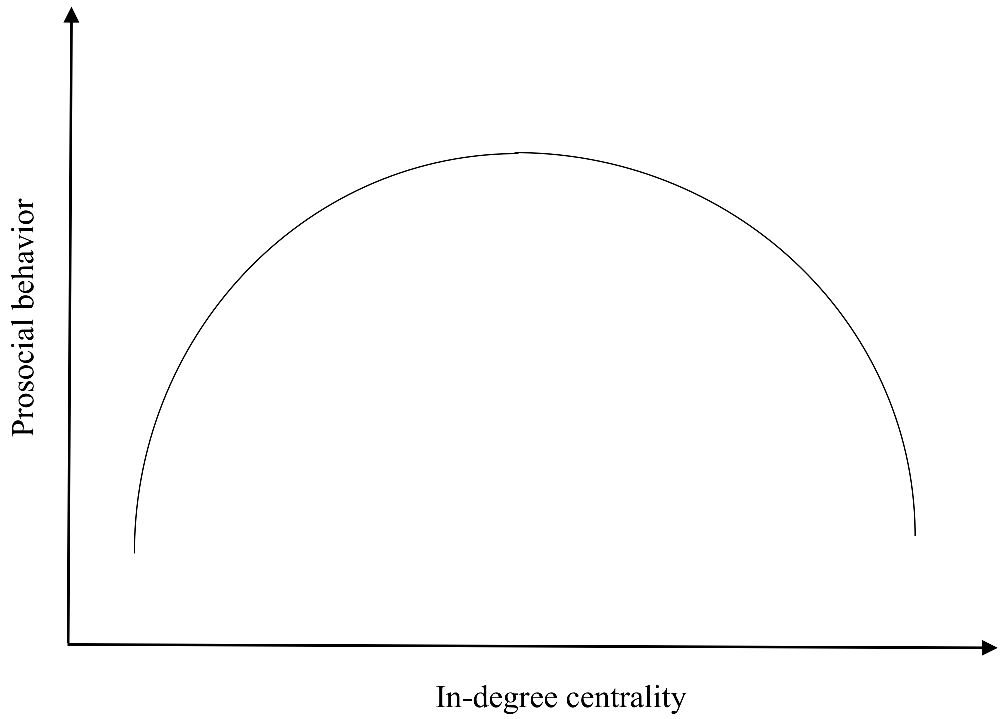
Having argued that increasing in-degree centrality likely decreases power imbalance in cooperation and increases visibility, thus acting as an enhancer for prosocial behavior, we also assume that in-degree centrality beyond a saturation point may have the opposite, constraining effect on prosocial behavior. Beyond a certain level, the focal firm's (ego's) increasing in-degree centrality will, ceteris paribus, make the dyad *less* balanced (i.e., power asymmetry switches in favor of the ego). A high level of in-degree centrality indicates that the focal firm has many alternatives for resources, experience in monitoring relationships, and legitimacy. Being a powerful party, the focal firm will likely govern the relation hierarchically and obtain quick compliance (Cowan *et al*., 2015; Heide, 1994). For the focal firm, using fewer resources in the interest of the exchange partner may bring timely economic benefits to the powerful party. Moreover, imbalanced relations distort prosocial norms and behavior (Heide, 1994). In other words, beyond a certain threshold value, increases in its in-degree centrality will foster power imbalance in its exchange relationships (dyads) as the focal firm becomes more powerful, undermining its proclivity to act in a prosocial manner toward its partners.

For central firms, decreasing levels of prosocial behavior become even more visible. This may, in itself, increase the motivation to behave prosocially. However, other network members' strong dependence on the central firm may lead it to assume that due to its strong power, trading partners are less likely to react negatively to its more ego-oriented behavior and expect the focal firm to act prosocial (Wuyts and Van den Bulte, 2012). Accordingly, the increased visibility is less effective for the central actor's reputation building and facilitates prosocial behavior. Thus, the power effect will be the dominant mechanism for actors with high in-degree centrality.

To summarize the previous arguments, in-degree centrality reflects a firm's possible power position within a dyadic interaction and the visibility to other network members. We suggest that increasing in-degree centrality increases prosocial behavior (left-and side of Figure 1); however, beyond a certain saturation point, a further increase in in-degree centrality decreases prosocial behavior (right-hand side of Figure 1). Actors with a moderate in-degree centrality are most likely to endorse prosocial behavior. Thus, we hypothesize the following:

H1. The relationship between the in-degree centrality of a focal firm and its prosocial behavior towards exchange partners has an inverted U-shaped form.

Figure 1.
The non-monotonic relationship between in-degree centrality and prosocial behavior.



3.2. *Triadic embeddedness and prosocial behavior*

We will now discuss the impact of triadic embeddedness on prosocial behavior in dyads[15]. Triadic embeddedness entails the existence of mutual third parties between the focal firm and its partners. Our core arguments concern cognitive agreement and group norms.

Tortoriello and colleagues (2015) have associated triadic embeddedness with the willingness to help and assist others. Several studies have found that closed triadic structures

[15] There is no specific requirement for the chosen relationship in the survey. It is therefore possible that the dyadic relationship in report is not in a closed triadic structure. However, the possibility that a dyad is embedded in a closed triad increase as the triadic embeddedness increases. When a focal firm has all possible triads closed, any dyads this firm has is in a closed triad.

can ease knowledge transfer and acquisition due to a high level of willingness and effort for knowledge sharing (Reagans and McEvily, 2003; Tortoriello and Krackhardt, 2010). When a firm is embedded in an institutional setting, its cognitive agreement will be shaped by promoting voluntary actions (Krackhardt, 1999; Simmel, 1950). Closed network structures facilitate frequent and repeated interactions, and involved firms will better understand their partners and common goals (Tortoriello *et al*., 2015). Interaction within closed structures can be more efficient and with less friction due to the third party's mediating role and group norms that each member must follow to be part of the collective (Krackhardt, 1999). Particularly, the level of trust and cooperation will be higher within closed structures because of the ease of creating cooperative norms. Haugland *et al*. (2021) find that triadic embeddedness can be an effective source of relational rents in terms of relationship learning and benevolence-based trust. As such, actors involved in closed triadic structures are more motivated to assist one another, which will facilitate prosocial behavior.

Besides, firms embedded in closed triads tend to act according to group norms of solidarity and can better align incentives to encourage self-enforcement and have a shared value (Dyer and Singh, 1998; Uzzi, 1996). Within a high level of triadic embeddedness, a firm tends to be highly involved in the network. In other words, the focal firm can enjoy opportunities difficult to replicate via markets and formal contracts. Eventually, the network's prosperity can positively influence individual firms' development. With a high level of triadic embeddedness, the focal firm may feel obligated to cooperate, help others, and hope other network members do the same. Tortoriello *et al*. (2015) find that individuals with overlapping ties to common third parties are more likely to act as catalysts for innovation that benefits the organization. Altogether, we expect that triadic embeddedness positively correlates with prosocial behavior. Thus:

H2. Triadic embeddedness is positively related to prosocial behavior.

4. Method

4.1. *Research context and data collection*

We select two national industry clusters in a mid-sized city in Norway, focusing on media technology and fintech. Both clusters formally belong to the Norwegian Center of Expertise (NCE) cluster program, supported by the government and other public organizations. Cluster members include commercial and non-commercial organizations, such as research institutions and public organizations. The media cluster was established in 2015. Commercial members include newspapers; television channels; film and television production companies; technology companies focusing on graphics, audio, video, and artificial intelligence; consulting firms for the media industry; and equipment suppliers. The fintech cluster was established in 2017; commercial members include banks, insurance companies, consulting firms, investment companies, and technology companies providing relevant financial services.

Both network data and survey data are needed to test the hypotheses. In order to obtain network data, one needs to specify the network boundary and ties, i.e., who are the target actors and what the ties represent. In this study, we define actors as formal members of a cluster, and ties are formal business relationships of different kinds (e.g., supplier-buyer relations, joint innovation projects, joint ventures, etc.) between these formal members. We first identified all the members from the two clusters' official websites and then asked well-informed local representatives to review our list. For the media cluster, we identified 93 members, including 67 relevant firms. For the fintech cluster, we identified 74 members, including 69 firms. The same process was used to collect data from two clusters.

4.1.1. Network data collection

The network data was collected by asking firm members to select organizations they have ongoing partnerships from a complete list of cluster members. By doing so, we do not omit any members in both clusters. Since our study targets commercial firms, we did not invite non-commercial members to participate. However, non-commercial members were indirectly included because the respondents might report collaboration with them.

We contacted the firms to confirm their membership and if they had ongoing business relationships with other cluster members. When contacting the firms, some did not respond to the telephone call, and some were not interested and refused to participate. For the media cluster, we identified seven that did not have ongoing business relationships. We excluded these firms and sent the questionnaire to 47 firms that agreed to participate and received 40 complete responses[16] for a response rate of 85.1%. By following the same procedure, we found that in the fintech cluster, one firm was no longer a member, and seven firms reported that they did not have ongoing relationships. We sent the survey to 36 firms that agreed to participate and received 24 complete responses for a response rate of 66.7%[17].

Based on the network data, we identified 85 out of 93 organizations in the media cluster, referring to 91.4% of the cluster. For the fintech cluster, we identified 56 out of 74 organizations, referring to 75.7% of the cluster members. The remaining firms that we were unable to model are possibly isolated, marginal, or inactive since other firms have not reported relationships with them. Considering that we provided a full list of cluster members, identified some inactive firms before the survey, and attempted to reach the remaining firms, we believe that the identified network is highly similar to the actual network. Additional information about the respondents and respondent firms can be found in Appendix A.

[16] Network data from four incomplete responses from the media cluster were used for network visualization.

[17] The data collection for the media cluster was fall 2019, and spring 2020 for the fintech cluster. Due to the panic caused by lockdown at the beginning of pandemic, firms in the fintech cluster are less interested in participating the survey. Therefore, the response rate was lower compared to the media cluster.

4.1.2. Survey data collection

The survey data were collected simultaneously with the network data via an electronic questionnaire. In the survey, we collected dyadic-level data by asking respondents to answer questions based on their experience with one current important business partner within the cluster. Other data about the firm was also collected in the survey.

4.2. Measures

4.2.1. *Dependent variable*

Prosocial behavior. Prosocial behavior is measured with four items at the *dyadic level* from the survey, using a 7-point Likert scale (1 = *strongly disagree*, 7 = *strongly agree*). We measure how the responding firm (ego) reports its prosocial behavior towards a chosen partner firm (alter). In existing studies investigating the positive form of extra-role behavior, the measurements focused on voluntariness and asked whether a firm was doing more than formal requirements (Wuyts, 2007; Zhou *et al*., 2020). Other researchers suggest specific behaviors appropriate for a given context, such as the agent's voluntary widening sales territories and increasing promotional budget/effort (Li, 2010). We adjusted four items (see Table 1) from Muthusamy and White (2005), among others, based on the constructs' domain in this study, i.e., a firm's beneficial actions toward a partner beyond formal requirements. The items used in this study emphasize altruistic behaviors that are not required by formal contracts.

4.2.2. *Independent variables*

Independent variables were calculated using network data. We model a tie from firm i to j if firm i reported a relationship with j, and vice versa. For the media cluster, we identified 85 organizations connected by 348 ties, with 57 reciprocated ties. For the fintech cluster, we identified 56 organizations connected by 185 ties, with 14 reciprocated ties. We performed all network calculations in Ucinet 6.707 software (Borgatti *et al*., 2002).

In-degree centrality. We measured in-degree centrality at the firm level by counting the number of other firms reporting a relationship with the focal firm (ego) (Wasserman and Faust, 1994). Because in-degree centrality is affected by network size and there is a difference between the sizes of the two clusters in our sample, we use the normalized measure; the result is divided by $n - 1$, where n is the number of actors in the network (Wasserman and Faust, 1994).

Triadic embeddedness. We measured triadic embeddedness as the ratio between the number of closed triads and all possible triads around a focal firm. When calculating triadic embeddedness, the relationship direction is omitted, i.e., a relationship from A to B and from B to A is treated as the same relationship between A and B.

As we discuss power and visibility as two core mechanisms explaining the relationship between in-degree centrality and prosocial behavior, we include perceived power asymmetry and perceived visibility as mediating variables. Perceived power asymmetry and perceived visibility are measured using items developed for this study, using a 7-point Likert scale (see Table 1). In line with Churchill (1979), items were generated based on the domain of the construct. Particularly, perceived power asymmetry and perceived visibility are measured in a subjective way that respondents report their perception of the power structure in the reported relationship and visibility in the network. Due to the potential multicollinearity of these two variables, we included them separately in the models. In this way, we can observe how perceived power asymmetry and perceived visibility are related to in-degree centrality, and whether they mediate the relationship between in-degree centrality and prosocial behavior.

4.2.3. *Control variables*

To ensure the robustness of our results, we include firm size, relationship duration, and a dummy variable identifying which cluster each firm belongs to as control variables. Firm size refers to the number of formal employees when surveyed. Relationship duration measures how many years the relationship has existed, reflecting previous interactions that may influence prosocial behavior (Wang *et al*., 2017). We merged data from two clusters, so we included a dummy variable to capture the difference between these two clusters.

Table 1.
Items, mean, standard deviation, AVE, CR, Cronbach's α.

Variable	Measures	Mean	S.D.	AVE	CR	Cronbach's α
Prosocial Behavior (PB)				0.828	0.951	0.931
	While making important decisions in this cooperation, we pay attention to this partner's interest. (PB1)	5.77	1.06			
	We would not knowingly do anything to hurt this partner. (PB2)	6.08	0.91			
	This partner's needs are important to us. (PB3)	5.92	0.89			
	We look out for what is important to this partner in this cooperation. (PB4)	5.83	1.02			
In-degree Centrality (ID)	The number of direct ties received from other actors in the network.	0.05	0.06			
Triadic Embeddedness (TE)	The proportion of links between the nodes within its neighborhood is divided by the number of links that could possibly exist between them.	0.14	0.11			
Perceived Power Asymmetry (PP)				0.816	0.916	0.792
	We have a more powerful position in this relationship. (PP1)	3.22	1.70			
	We normally have more to say than this partner does. (PP2)	3.11	1.43			
	We normally can influence this partner's decision-making related to this relationship. (PP3)	4.08	1.56			
Perceived Visibility (VI)				0.833	0.902	0.873
	Our company's business activity (e.g., investment, new partnership, etc.) can be easily noticed by other members of this cluster. (VI1)	3.86	1.62			
	Our company can always get the attention of other members of this cluster. (VI2)	4.58	1.49			
	It is not difficult for other members of this cluster to seek information about our business activities. (VI3)	4.58	1.46			
	When we conduct a new business activity (e.g., investment, project initiation, new partnership, etc.), other peer companies may notice immediately. (VI4)	4.08	1.47			
Firm Size (FZ)	The number of formal employees at the time of the survey.	289.56	1153.95			
Relationship Duration (RD)	The number of years cooperated with the chosen partner.	5.56	6.31			
Cluster (CL)	Which cluster is the focal firm located in.	0.38	0.48			

5. Results

5.1. *Measurement model*

First, we calculated the network data for the two clusters. Second, we tested the measurement model of survey data using Minitab 21.1. Finally, we matched the network and survey data based on firm names of the ego and tested the hypotheses using Stata 16.1.

As Table 1 shows, Cronbach's alpha values are above .70 (Nunnally, 1978), composite reliability (CR) values are above .70 (Gefen *et al*., 2000), and average variance extracted (AVE) values are above .50 (Bagozzi and Yi, 1988; Fornell and Larcker, 1981). Table 2 reports cross-loadings. All factor loadings are above .50 (Hulland, 1999) and load the highest on their own constructs. The items for prosocial behavior are adjusted from Muthusamy and White (2005) based on the constructs' domain of prosocial behavior. Perceived power asymmetry and perceived visibility are newly developed for this study. Therefore, we needed to be particularly cautious with regard to their reliability and validity. As noted, all factor loadings are above .50 and higher than other cross-loadings. Furthermore, Cronbach's alpha, CR, and AVE values all fulfill the requirements. Thus, we conclude that the measurement model shows satisfactory reliability and validity (Bollen, 1989; Bollen and Lennox, 1991).

Table 2. Cross loadings.

	PB	PP	PP
PB1	**0.880**	0.048	-0.005
PB2	**0.906**	0.099	-0.057
PB3	**0.946**	0.07	0.037
PB4	**0.906**	0.003	0.068
PP1	-0.028	**0.849**	0.299
PP2	-0.048	**0.903**	0.174
PP3	0.271	**0.696**	0.104
VI1	0.057	0.19	**0.867**
VI2	0.083	0.141	**0.850**
VI3	-0.263	0.105	**0.747**
VI4	0.146	0.224	**0.869**

Principal components with varimax rotation. Explained variance: 77.9%.

Combining data from different datasets is novel and reduces problems related to common method bias (Aarstad *et al*., 2015; Lindell and Whitney, 2001). Furthermore, data from the two clusters enable us to account for potential bias caused by a single cluster.

5.2. *Descriptive statistics*

We calculate prosocial behavior, perceived power asymmetry, and perceived visibility on the basis of average composites of the constructs. Given the estimation method and the proposed polynomial effect of in-degree centrality, we mean-centered all variables (except for the cluster dummy variable) with a mean of 0 and a standard deviation of 1. Table 3 presents correlations of all measures after transformation.

We confirm that in-degree centrality and triadic embeddedness are not correlated in our data, indicating that firms with a higher level of in-degree centrality do not necessarily have more closed triads. We observe that firms with more received ties perceive themselves as relatively powerful in the reported dyadic relationship. This finding confirms that in-degree centrality is a proper indicator of perceived power in relationships. Similarly, perceived visibility is positively correlated with in-degree centrality at a borderline significant level, indicating that firms with a higher level of in-degree centrality perceive themselves as more visible in the network. As such, both perceived power asymmetry in the relationship and perceived visibility in the network partially capture in-degree centrality. We also observe a significant positive correlation between in-degree centrality and firm size, which shows that bigger firms may have a better capacity to engage in more business relationships and occupy central positions (Shan *et al*., 1994). Firm size is positively correlated with perceived power asymmetry at a borderline significant level, confirming that larger firms tend to perceive themselves as more powerful in reported relationships. Firm size is positively correlated with relationship duration, indicating that bigger firms tend to report on longer relationships.

Table 3. Correlation matrix.

	PB	ID	TE	PP	VI	FZ	RD
ID	-0.037						
TE	0.219^{+}	0.094					
PP	0.135	0.317*	-0.143				
VI	0.033	0.231^{+}	0.163	0.417**			
FZ	-0.023	0.426**	-0.054	0.211^{+}	-0.041		
RD	0.120	-0.011	0.164	0.051	-0.079	0.255*	
CL	0.217^{+}	-0.006	-0.314*	0.092	-0.046	0.216^{+}	-0.038

N = 64. All variables have been standardized.

$^{+}$. Correlation is significant at the 0.1 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

The respondents from the fintech cluster reported higher levels of prosocial behavior compared to those from the media cluster, with the difference being borderline significant. We also find a positive correlation between firm size and cluster dummy at a borderline significant level, indicating that respondent firms from the fintech cluster are larger than those from the media cluster. Larger firms may be more concerned about their reputation and report higher scores for their prosocial behavior. Alternatively, the time of data collection may influence the response. The media cluster was surveyed before the pandemic (2019 fall), while the fintech cluster was surveyed at the beginning of the pandemic lockdown (2020 spring). The lockdown could increase the uncertainty of the market condition, making firms more willing to support each other out of difficulties. Therefore, we observe a higher score on prosocial behaviors in the fintech cluster.

We also observe a significant negative correlation between cluster dummy and triadic embeddedness, which shows that the media cluster has more closed triadic structures than the fintech cluster. Because of the different response rates, network sizes, and established time, we should be cautious about comparing the overall structures of these two clusters based on our network data. In sum, the fintech cluster has less triadic embeddedness than the media cluster, yet prosocial behavior is higher.

Table 4. The output of models.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Fixed effects						
Intercept	-0.191	0.051	0.081	0.024	-0.358†	-0.107
	(0.157)	(0.213)	(0.273)	(0.206)	(0.192)	(0.212)
Relationship duration	0.160	0.023	0.018	0.140	0.018	0.017
	(0.129)	(0.019)	(0.020)	(0.126)	(0.020)	(0.019)
Firm size	-0.117	-0.055	-0.040	-0.028	-0.109	-0.044
	(0.132)	(0.143)	(0.147)	(0.149)	(0.127)	(0.140)
Cluster	0.509†	0.460†	0.397	0.480†	0.695*	0.598*
	(0.262)	(0.250)	(0.258)	(0.256)	(0.264)	(0.259)
Perceived power asymmetry			0.116			
			(0.130)			
Perceived power asymmetry squared			-0.079			
			(0.115)			
Perceived visibility				0.114		
				(0.151)		
Perceived visibility squared				0.055		
				(0.108)		
In-degree centrality (H1)		0.380*	0.347†	0.361†		0.296
		(0.178)	(0.183)	(0.183)		(0.182)
In-degree centrality squared (H1)		-0.253**	-0.257**	-0.262**		-0.215*
		(0.084)	(0.085)	(0.086)		(0.086)
Triadic embeddedness (H2)					0.302*	0.222†
					(0.128)	(0.128)
R^2	0.076	0.200	0.224	0.209	0.156	0.264
R^2 Adjusted	0.030	0.131	0.127	0.110	0.098	0.186

Dependent variable: prosocial behavior. N = 64, number of clusters = 2, two-tailed tests of significance. Standard error in parentheses.

† p < .10.

* p < .05

** p < .01

5.3. *Hypotheses testing*

We tested H1 and H2 using OLS regression. Table 4 summarizes the results of the hypotheses testing. In model 1, we test the effect of the control variables, relationship duration, firm size, and cluster. We find that firms from the fintech cluster report a higher score on prosocial behavior than firms from the media cluster, but the effect is borderline significant. However, relationship duration and firm size do not significantly affect prosocial behavior. Model 2 tests H1. As we hypothesize a non-monotonic relationship between in-degree centrality and prosocial behavior taking the shape of an inverted U, we test H1 by modeling the independent variable (i.e., in-degree centrality) as a second-degree polynomial function. We find that in-degree centrality has a significant positive effect and that the squared polynomial effect has a significant negative effect on prosocial behavior, in support of H1. These effects show that, first, increasing in-degree centrality from a low level increases prosocial behavior, but then, in accordance with H1, the effect turns negative.

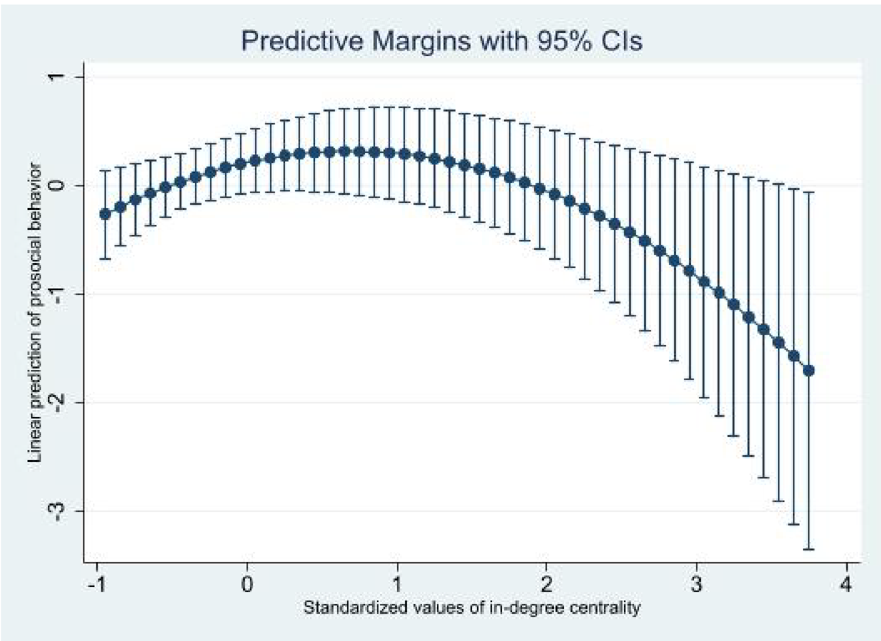
When discussing H1, we argue that power asymmetry in the dyad and visibility in the network would partially mitigate the relationship between in-degree centrality and prosocial behavior. To address this issue, we add the concept of perceived power asymmetry as a second-degree polynomial in model 3, and perceived visibility as a second-degree polynomial in model 4. We observe that H1 still receives empirical support. Moreover, although insignificant, the coefficients of perceived power asymmetry also demonstrate an inverted U-shaped relationship. We did not observe an inverted U-shaped relationship between perceived visibility and prosocial behavior.

Model 5 tests H2. We propose a positive correlation between triadic embeddedness and prosocial behavior; H2 receives empirical support. In model 6, we test H1 and H2 simultaneously, and the effect of triadic embeddedness drops to a borderline significant level. Still, both H1 and H2 receive empirical support. In models 5 and 6, we also observe a significant positive effect of the cluster dummy, showing that firms from the fintech cluster reported higher prosocial behavior than firms from the fintech cluster.

We derive the marginal effects reported in Figure 2 from the estimates in model 6. As the mean value of the standardized measure of in-degree centrality is 0, the minimum value is –. 95, and the maximum value is 3.77; Figure 2 further illustrates that the networks have a few very central firms, which is in accordance with previous research (Barabási and Albert, 1999).

We further check variance inflation factors (VIFs) in all models. The maximum value is 2.40 for the linear item of in-degree centrality in model 3, below suggested critical values between 4 and 10 (O'Brien, 2007). The results indicate that multicollinearity is not a problem in these models.

Figure 2. Average marginal effects of in-degree centrality (with 95% confidence intervals).



6. Discussion

6.1. *Discussion of results*

The findings show that both in-degree centrality and triadic embeddedness is related to dyadic-level prosocial behavior in the regional cluster context, providing insights for our research question. In particular, we find that the relationship between in-degree centrality and prosocial behavior is non-linear, taking the form of an inverted U. That is, an increase in in-degree centrality from a low level to a moderate level promotes prosocial behavior; however, beyond a certain level, a further increase in in-degree centrality undermines prosocial behavior. We reason the turning point of the inverted U-shaped relationship of in-degree centrality and prosocial behavior mainly through changing the focal firm's (ego) power status from the weaker party to the stronger party in dyadic relations. Before the turning point, dyadic power asymmetry and visibility jointly influence prosocial behavior. While after the turning point, the visibility effect weakens, and dyadic power asymmetry becomes the dominant mechanism influencing prosocial behavior. The findings show that a firm's behavior in a dyad is related to its position in the network.

We find that in-degree centrality positively correlates with perceived power asymmetry and perceived visibility, indicating that in-degree centrality is a proper indicator of these two constructs. When modeled as a mediator in Model 3, although insignificant, perceived power asymmetry still demonstrated an inverted U-shaped relationship. Model 4 revealed no inverted U-shaped relationship between perceived visibility and prosocial behavior, possibly due to weakened effects after the turning point. The insignificant effect of perceived power asymmetry and perceived visibility may be due to the small sample size. Another complementary explanation is that the items we developed and applied to measure perceived power asymmetry or perceived visibility did not sufficiently capture these two concepts empirically.

As expected, triadic embeddedness is positively associated with prosocial behavior. The findings indicate that having a common exchange partner may sustain behaviors favoring the recipients due to the generation of relational norms and a high level of interdependency in the local structure (Coleman, 1994; Heide and Miner, 1992; Krackhardt, 1999). Our finding is consistent with existing studies that suggest tightly connected structures confer several unique advantages on dyadic relationships, which improves relationship performance (Haugland *et al*., 2021; Wuyts and Van den Bulte, 2012).

As per our empirical results, in-degree centrality has a stronger impact than triadic embeddedness on prosocial behavior. A possible explanation would be the effect of triadic embeddedness is indirect through group norms in cohesive structures (Wuyt and Van den Bulte, 2012), while the influence of in-degree centrality is directly to the focal firm. Our findings are also noteworthy as they suggest that in-degree centrality and triadic embeddedness are complementary forces determining firms' prosocial behavior in a network. Cohesive local structures can facilitate prosocial behavior regardless of in-degree centrality.

6.2. *Theoretical contributions*

Traditionally, dyadic relations and networks are studied separately. This study shows how different theories, methods, and levels of analysis can be integrated to deepen our understanding of interorganizational relationships. This study adds to the literature on relationship marketing, prosocial behavior, and research methods. First, we add to the relationship marketing literature by testing the idea that the network in which dyadic relationships are embedded matters (Choi and Wu, 2009; Gulati, 1998; Wathne and Heide, 2004; Wuyts and Van den Bulte, 2012. Traditional research on relationship marketing often focuses on how dyadic-level charterers (e.g., trust, dependence structure, or contract type) influence relational performance, mostly relying on subjective measures. However, scholars acknowledge the relevance of addressing dyadic-level phenomena from a higher level (Hingley *et al.*, 2015; Lumineau and Oliveira, 2018; Wilke and Ritter, 2006). Our findings show a firm's behavior in a dyad relates to its position in the broad network the relation embeds. We believe that our findings in regional clusters have implications for other similar contexts that rely on members' interaction to achieve a collective goal, such as supply chain networks (Wilhelm and

Sydow, 2018), tourism destinations (Haugland *et al*., 2021), and innovation networks in other high-tech industries, such as biotechnology industry (Shan *et al*., 1994). Future studies should be conducted in other contexts to investigate the generalizability of current findings.

We also triangulated the measure of power asymmetry at the dyadic level and visibility in the network from a subjective view. We observed strong positive correlations with the corresponding network measure (i.e., in-degree centrality). Our finding supports the idea that power is a property in a social system (Brass and Burkhardt, 1993) that further influences power position in the dyad. When considering perceived power asymmetry as a mediator, we observed an inverted U-shaped but insignificant relationship between perceived power asymmetry and prosocial behavior. We did not find a genuine effect of perceived visibility (as a mediator) on prosocial behavior. The insignificant findings may be due to a low sample size. Future studies may further investigate the mechanisms explaining the association between in-degree centrality and prosocial behavior in larger samples.

Second, we extend knowledge on network antecedents of prosocial behavior in an interorganizational context. Existing studies have uncovered firm-level instrumental and communal antecedents (Wuyts, 2007) and individual-level antecedents like interpersonal relations between boundary-spanners (Zhou *et al.*, 2020). Yet, as Zhou and colleagues (2020) point out, structural embeddedness at the firm level may be an important but overlooked driver. Our study fills this gap by uncovering the impacts of in-degree centrality and triadic embeddedness on a firm's prosocial behavior towards a network partner. In particular, we connect in-degree centrality to instrumental motives and triadic embeddedness to communal motives, then discuss how these two network constructs influence prosocial behavior. Our findings show that triadic embeddedness could, ceteris paribus, facilitate prosocial behavior regardless of the involved actors' in-degree centrality in a network.

Third, our study sheds light on the sociometric network approach. Although many have applied a network approach to study the relationships between organizations, an egocentric approach dominates existing studies (e.g., Carnovale and Yeniyurt, 2014; Maghsoudi-Ganjeh *et al*., 2021). An egocentric network may be an arbitrary subset of a wider network, which may not reflect the broad picture and the actual position of particular firms. Dubois (2009) suggests scholars pay more attention to larger networks. In this study, we do not focus on subsets or egocentric networks but on the wider network structure that impacts firms' prosocial behavior. This approach provides better information on a firm's network condition.

Finally, this study contributes to the research methodology by combining survey and network data. The combination of two datasets strengthens the validity by reducing bias caused by a potential common method bias or variance (Lindell and Whitney, 2001) and enables a comprehensive study of the interplay of dyadic- and network relationships (Haugland *et al.*, 2021).

6.3. *Managerial Implications*

From a managerial perspective, our findings provide insights for cluster members and cluster managers. For cluster members, the implications concern partner selection. Firms that are either central or peripheral are less likely to conduct prosocial behavior in cooperation, making them less desirable partners. Moreover, having a new partner that is already collaborating with current partners would be beneficial. Such a triadic structure brings advantages such as cognitive agreement, better-aligned goals, and group norms to facilitate helping behaviors and improve coordination in the group.

Cluster managers need to understand how to facilitate cooperation between members to maintain a well-functioning cluster. Our study shows that members in different network positions may behave differently in cooperation. Cluster managers may pay more attention to peripheral and central members to facilitate their prosocial actions in cooperation. For peripheral firms, cluster managers can offer more assistance to help them engage in more collaborations to improve their network positions. For central firms, cluster managers can facilitate their prosocial behavior by promoting the formation of cohesive local structures.

6.4. *Limitations and future research*

This study has several limitations, which highlight potential avenues for future research. First, our data were collected on only one side of the dyadic relationship. Although we considered some relational-level characteristics (i.e., relationship duration and perceived power asymmetry), including information about both the ego and alter in a dyad can increase validity. For example, if both the ego and alter's network positions are known, we can infer their relationship is symmetric or asymmetric from a non-subjective perspective. Future studies could favorably include both ego and alter data to generate a better picture of a focal relationship.

Second, we relied on a structural approach for the network concepts but did not consider the idiosyncrasies of inter-firm relationships. Interorganizational network studies often focus on a structural or relational perspective (Gulati, 1998). A structural perspective focuses on the patterns of existing relations. However, cluster relationships can compromise social and economic elements (Heide and Wathne, 2006), and different social interactions can occur simultaneously between firms. Future research could incorporate the relational perspective and explore how different relational characteristics (e.g., forms of collaboration and types of resource/information exchanged) may act as enhancers for prosocial behavior.

Third, in this study, we explored the mechanisms behind the link between in-degree centrality and prosocial behavior. Although we did not receive empirical support, future studies could use different instruments to measure perceptual power and visibility, or investigate other underlying factors that influence prosocial behavior. Future studies could, for instance, investigate the condition that triggers the turning point from prompt to refrain from prosocial behavior.

Finally, although we managed to model the majority of members in both clusters, we still face the challenge of incomplete network structure. To check the reliability of sampled or incomplete network data, some scholars calculate the correlations of different network measures between the actual and sampled network data (Costenbader and Valente, 2003; Huisman, 2014). Since not directly influenced by respondents, in-degree centrality was found to be the most robust and stable centrality measure among others (Costenbader and Valente, 2003). Triadic embeddedness is more sensitive to smaller samples (Huisman, 2014). Moreover, with the predefined network boundary, we may omit critical external firms that cooperate intensely with cluster members. Future studies should apply different methods, such as allowing for the nomination of alters and snowball sampling, to collect data from a wider network.

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Appendix A. Further details about the respondents and respondent firms

Of the 64 firms, about 70% are micro and small firms with 50 or fewer employees, while the largest one has 9000 employees. Table A1 provides an overview of the firm size in two clusters.

Table A1. Firm size

Number of employees	Total (percentage)	Media (percentage)	Fintech (percentage)
0-50 micro & small enterprise	43 (67%)	29 (73%)	14 (58%)
50-250 medium enterprise	11 (17%)	8 (20%)	3 (13%)
250+ large enterprise	10 (16%)	3 (7%)	7 (29%)

Note: the category is based on OECD data. See https://data.oecd.org/entrepreneur/enterprises-by-business-size.htm

Table A2 provides an overview of the roles of respondents in sampled firms. No significant impacts of respondents' role on survey data were found.

Table A2. Respondent's role

Respondent's role	Total (percentage)	Media (percentage)	Fintech (percentage)
Administrative director	25 (39%)	16 (40%)	9 (38%)
Entrepreneur	7 (11%)	5 (13%)	2 (8%)
Head of technology/research	2 (3%)	1 (2%)	1 (4%)
Head of finance/marketing	3 (5%)	3 (8%)	0 (0)
Others	27 (42%)	15 (37%)	12 (50%)

Article 3: A systematic approach to investigate network dynamics concerning small-world and scale-free properties in regional industrial networks

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January 2023

Abstract

Scholars have acknowledged the need to understand social network dynamics. This study uses a systematic approach to investigate the dynamics and development of two regional industrial networks in western Norway in terms of small-world and scale-free structures. Small-world networks are characterized by dense local clustering and short path length between actors. On the contrary, scale-free networks are centralized with a small portion of central actors spanning the structure and take a skewed degree distribution. Some empirical networks demonstrate both properties simultaneously, yet few studies have aimed to discuss the dynamics and interrelation of small-world and scale-free properties. By retrospectively visualizing the annual structures of two networks, I show how small-world and scale-free properties together explain the development patterns. In both empirical networks, a scale-free structure is uncommon. Altogether, this study adds to the understanding of the dynamics and development of interorganizational networks in terms of small-world and scale-free structures.

Keywords: network dynamics; small-world, scale-free networks, interorganizational networks

1. Introduction

In recent decades, network dynamics have received increasing attention in social science, including management and organizational studies (Ahuja et al., 2012; Chen et al., 2022; Provan et al., 2007). Knowledge about network dynamics can complement our understanding of the consequences of network properties. Scholars have provided different models and mechanisms for explaining the dynamics of complex networks. For example, some studies have tried to understand how networks over time demonstrate the structural characteristics of a "small world," indicating dense local clusters connected by few bridging ties (Baum et al., 2003; Watts & Strogatz, 1998). The small-world structure has been found in a variety of contexts, such as industrial networks (Schilling & Phelps, 2007) and patent collaboration networks (Chen & Guan, 2010), and is increasingly considered a driver of individual and collective action (Gulati et al., 2012; Uzzi & Spiro, 2005).

The scale-free structure is another common structure of large-scale networks, characterized by a small number of core actors that connects the rest peripherals (Barabási & Albert, 1999). An extreme example is a star-shaped network where only one core actor connects the rest actors, and the network's degree distribution is highly skewed. Scale-free structures have been observed in tourism destination networks (Aarstad et al., 2013; Baggio et al., 2010), collaboration networks in the biotechnology industry (Gay & Dousset, 2005; Powell et al., 2005), and Canadian investment banks (Baum et al., 2004). In scale-free networks, the stability of the system is maintained by the core actors. Hence, scale-free networks are stable under random attack but vulnerable to attacks targeted at central actors (Aldrich & Kim, 2007).

Some empirical networks have demonstrated characteristics of both small-world and scale-free structures (e.g., Baggio et al., 2010; Baum et al., 2004; Gay & Dousset, 2005). Watts (1999) notes explicitly that a small-world network is decentralized in that no dominant central actor exists. Conversely, a scale-free structure has a skewed degree distribution with few high-degree and many low-degree actors, therefore centralized. How can empirical networks take small-world and scale-free properties simultaneously? To our knowledge, limited studies have aimed at explaining the dynamic and interrelation of these influential concepts empirically (see exceptions, Aarstad et al., 2013, 2015). In sum, there is a dearth of knowledge about how empirical networks develop and simultaneously demonstrate small-world and scale-free properties.

To investigate the dynamics and interrelation of small-world and scale-free structures, I retrospectively reconstruct the dynamics of two regional industrial networks in western Norway, focusing on the media and fintech industries. Regional industrial networks have been considered tools to boost local and regional development, constituting a highly dynamic setting where new members join and members constantly shape their ties to create value (Bergman & Feser, 2020). I compare the annual structures in terms of small-world and scale-free properties and investigate the interrelation between these two since networks were formally established. By doing so, I am able to see (1) whether these two networks demonstrate a small-world or scale-free structure or both and (2) whether the dynamics of small-world and scale-free properties follow particular patterns.

This study adds to the understanding of the changes in the system-level structure of interorganizational networks. I observe how small-world and scale-free networks can co-evolve in two technology-intensive regional clusters. Aarstad and colleagues (2015) analyze the dynamic pattern of tourism destinations, which are more service-oriented and less technology-intensive contexts. Tatarynowicz and colleagues (2016) find that the dynamics of interorganizational networks may differ across industries or contexts concerning technology dynamics. I observed similar patterns concerning the co-development of small-world and scale-free properties in technology-intensive networks. However, I did not find the scale-free structure common in both networks during the periods covered.

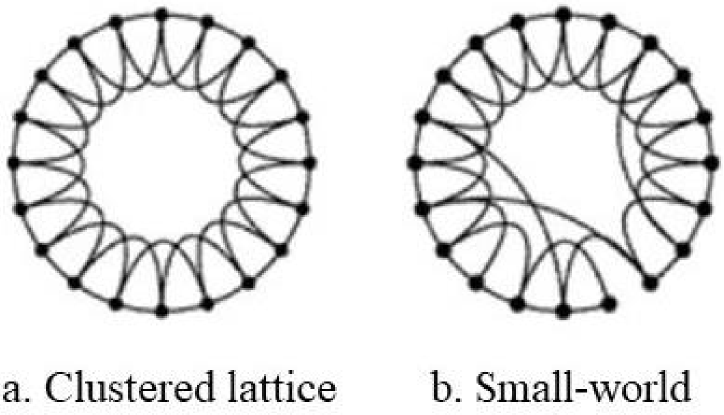
The next section reviews the theory of small-world and scale-free networks and relevant mechanisms that explain the interrelation of these two structures. In section 3, I introduce the empirical context and research design. In section 4, I analyze network dynamics and present results. I close the study by discussing the findings, implications, limitations, and future research directions.

2. Theoretical background and literature review

2.1. Small-world networks

Stanley Milgram proposed the notion of small worlds in the 1960s, and a core feature of such a structure is that any two actors could reach each other through a relatively small number of intermediaries. Small-world networks are also highly clustered, and some actors function as conduits to span local structures to reduce the average path length between any two randomly chosen actors (Uzzi et al., 2007). In their work, Watts and Strogatz (1998) illustrate how small-world structures are generated (see Figure 1). There are two networks in Figure 1, each with 20 nodes, and every node has four ties. The structure on the left-hand side (Figure 1a) is a clustered lattice in which actors only connect to the four closest actors. In other words, ties are never formed at random. Consequently, although local clustering is high, the path to reach indirectly connected network members is long. On the other hand, as illustrated in Figure 1b, the randomness of rewiring increases as some actors form ties with distant actors, leading to a small-world structure. Comparing these two networks, one can observe a few shortcut ties bridging separate parts in the small-world structure without decreasing the clustering. Shortcut ties make it easier to reach distant network members and shorten the average path length. In sum, according to Watts and Strogatz's (1998) model, a small world emerges from a lattice (Figure 1a) where local clustering is already high. The increased randomness leads to the creation of shortcuts that reduce average path length in small-world networks (Figure 1b).

Figure 1. Illustration of small-world network generation



Two realizations of a network with 20 actors and each actor with four ties.
Source: Watts & Strogatz, 1998, p.441.

Watts and Strogatz (1998) introduced two measures to quantify the characteristics of small-world networks, that is, average path length (*PL*) and average clustering coefficient (*CC*). *PL* measures the average path length, calculated as the number of intermediates between any two actors in the network. The shorter the average path length, the faster to reach others in the network. The clustering coefficient for individual actors is calculated as the number of closed triadic structures divided by the number of all possible triads around the actor, which captures how actors are connected in their neighborhoods (Wasserman & Faust, 1994). If ties exist between all neighbors of an actor, the value of the clustering coefficient is one, which is the highest. The *CC* for the overall network is computed as the mean of all actors' clustering coefficients (Wasserman & Faust, 1994). For a given network, increased *CC* means more ties are formed to increase local clustering, decreased *PL* indicates the average path length has been shortened due to newly formed ties, and both will increase the small-world property.

When calculating the small-world property, the existing network was compared to a random network with the same number of actors and ties (Watts & Strogatz, 1998). A random network typically has a relatively long path length and sparse local structure. Scholars have found that, for a random network, if *n* denotes the number of actors and *k* denotes the average degree of actors, *PL random = log n/log k,* and *CC random = k/n* (Watts and Strogatz, 1998). *CCr* represents the *CC* ratio, calculated by *CC actual/CC random*. Similarly, *PLr* refers to the ratio between *PL actual* and *PL random* (i.e., *PL actual/PL random*). The small-world ratio (*SW*) is calculated as *CCr/PLr*. Watts and Strogatz (1998) suggested that small-world networks need to have *SW* substantially greater than 1, and a larger value of *SW* indicates a more prominent small-world property.

Empirical studies of small-world networks have found a specific range of *SW*. I examined some networks in management literature with a particular focus on interorganizational context. The smallest *SW* value was 1.21 for the network of Canadian investment banks between 1952 and 1957 (Baum et al., 2004). The largest observed *SW* value was 531.25; the network was strategic alliances in the chemicals and electronic industries between 1980 and 1996 (Verspagen & Duysters, 2004). A study analyzing US alliance networks from 11 industries between 1992 and 2002 showed that the average *SW* value was 2.71 (Schilling & Phelps, 2007). A study of nine ski destinations in Norway from 1986 to 2008 generated an *SW* ranging from 2.20 to 20.51 (Aarstad et al., 2013)[18].

Small-world networks exhibit specific characteristics. The small-world network structure is persistent despite randomly rewiring many ties (Kogut & Walker, 2001; Watts, 1999). As a result of replacing existing paths with other ties, global connectivity may increase; however, it will not significantly affect the densely interconnected local structures. The densely interconnected members in local structures can find new paths to reach target members, and

[18] There are more recent studies that discuss small-world interorganizational networks. However, many studies capture structural properties using different measures (see Ghosh & Rosenkopf, 2018 for a summary). For consistency, I only include studies use the same measure.

structural autonomy and cohesion remain (Kogut & Walker, 2001). Thus, small-world networks are durable even when many paths are changed.

Moreover, dense local clustering and shorter paths have been found beneficial for communication and knowledge diffusion in interorganizational networks (Chen & Guan, 2010; Kim & Park, 2009; Schilling & Phelps, 2007). Dense local clustering enables the development of a common knowledge base through more frequent interaction, which provides the necessary foundation for understanding network knowledge that is less direct and explicit (Ahuja, 2000; Reagans & McEvily, 2003). A short path length for communication enhances the possibility of reaching distant knowledge in the same network more rapidly, which may inspire new ideas and creativity (Burt, 1992; Powell et al., 2005; Uzzi & Spiro, 2005). In sum, past research suggests that small-world networks are robust against random restructuring and are expected to enhance knowledge sharing and creativity.

Yet, the small-world model by Watts and Strogatz (1998) has limitations. As the small-world idea emphasizes that two actors are just a few steps away, their model focus on explaining the emergence of shortcut ties but not the formation of local clustering. According to the model (1998), small worlds appear due to increased randomness of the rewiring of a ring lattice. Similarly, Baum and colleagues (2003) discuss the emergence of small-world in interfirm networks with an emphasis on the spanning ties that cut across existing dense local clusters. However, empirical networks seldom establish following a ring lattice structure. Visualizing the dynamic patterns of nine winter sports destinations, Aarstad and colleagues (2015) found that the network emerged as a scale-free network (i.e., a centralized structure) in the 80s and then developed small-world properties. Watts and Strogatz's (1998) model cannot explain how such a centralized structure can later develop into a small-world structure. The formation of dense local clustering remains to be explained. As Uzzi, Amaral, and Reed-Tsochas (2007) concluded, "we know little about how these small worlds arise outside of theoretical models" (p.88). In addition, it ignores the change in network size (Barabási & Albert, 1999). It assumes a network starts with a fixed number of actors and ties and will not be modified. Altogether, empirical networks can hardly start with a ring lattice structure (as Figure 1a shows), and the network size will change as a network develops.

2.2. Scale-free networks

A scale-free network is a structure with few central and well-connected actors and many peripheral and less-connected actors. There are two mechanisms for the emergence of scale-free networks: (1) networks attach new members over time, and (2) preferential attachment occurs (Barabási & Albert, 1999). Unlike theory of small-world networks, scale-free network theory takes a dynamic view and emphasizes the network development process. Due to the preferential attachment process, tie formation depends on the actors' degree (i.e., the number of existing ties). Newcomers prefer to connect with more central actors, leading to a dynamic of the rich getting richer (Barabási & Albert, 1999). In other words, the growth of connections leads to increased inequities among network members. Consequently, networks with scale-free properties are normally centralized, such that one or a few central actors function as hubs and connect peripheral actors.

Barabási and Albert (1999) proposed a measure, the exponent of degree distribution γ, to quantify the scale-free properties. Mathematically, γ is calculated as the value of the coefficient of a log-log plot of actors' degree distributions (Strogatz, 2001). Due to a limited number of central actors and a large number of peripheral actors in a scale-free network, the degree distribution of a scale-free network is highly skewed, following the shape of power law (Andriani & McKelvey, 2009). Simply put, the value of γ describes the scale-free property. An increase in γ indicates a bigger difference between dominant central actors and peripheral actors concerning degree, making the degree distribution more skewed and vice versa.

Scholars have suggested various theoretical values of γ to confirm that a network is scale-free; a frequently used value is between 1 and 3 (Albert & Barabási, 2002; Strogatz, 2001). Many empirical networks have γ within the suggested value. Gay and Dousset (2005) studied a major segment in the biotechnology industry and reported that γ ranged from 1.02 to 1.73. Studying Canadian investment banks' syndicate networks, Baum and colleagues (2004) reported that the value of γ roughly ranged between 1.3 and 4. Aarstad et al. (2013) reported that γ ranged from 1.390 to 1.825 in their study of nine winter sports destination networks in southern and eastern Norway.

Due to a few central actors, the scale-free network typically indicates a structured hierarchical system that can resist disruptive random attacks but is vulnerable to targeted attacks on high-degree actors (Albert et al., 2000; Aldrich & Kim, 2007). The average path length can be relatively short due to the central actors' dominance in the network, with many peripheral actors having limited connections (Aldrich & Kim, 2007). Therefore, scale-free networks are unlikely to be affected by random attacks but are vulnerable to target attacks on central actors and tend to have a shorter average path length than a random network.

2.3. Small-world networks, scale-free networks, and network dynamics

The discussion above introduced how to identify small-world or scale-free networks, their characteristics, and theoretical development models. Small-world has been considered a non-centralized structure, which seems contradictory to scale-free networks in that a few central actors function as hubs to span the entire network. However, some empirical networks demonstrate the properties of both (see Table 1 for some examples). Scholars have suggested that mechanisms behind small-world and scale-free structures may explain the dynamics of social networks and why some empirical networks demonstrate both small-world and scale-free properties (Aarstad et al., 2015). I will now discuss the mechanisms that form small-world and scale-free networks and explains how these two network properties may interrelate.

As discussed above, small-world networks have dense local clustering of actors, yet Watts and Strogatz's (1998) model did not explain the formation of local clustering. Local clustering means actors with the same partners are likely to connect and form triplets (Holland & Leinhardt, 1971; Newman, 2003; Wasserman & Faust, 1994). The formation of such local clustering relies on a mechanism called transitivity; "a triad involving actors i, j, and k is transitive if whenever $i \rightarrow j$ and $j \rightarrow k$, then $i \rightarrow k$" (Wasserman & Faust, 1994, p. 243). Imagine person A has two friends, B, and C. The possibility that B and C become friends increases due to their common friend A. Ultimately, A, B, and C may form a triadic friendship network[19]. As small-world structure only requires a few bridging ties to shorten path length, transitivity is the core mechanism that leads to dense local clustering for small-world structures.

I have introduced in *section 2.2* that preferential attachment leads to scale-free structures, and transitivity leads to small-world structures; both mechanisms can function independently to increase the probability of tie formation (Powell et al., 2005). Moreover, they can function simultaneously. I now discuss how these two mechanisms may represent two key drivers for network dynamics and make a network demonstrates small-world and scale-free properties simultaneously.

Assuming actor i has n neighbors, it requires $n (n - 1)/2$ ties to complete local clustering (Watts & Strogatz, 1998). Only one tie is needed for an actor with two neighbors to complete the triplet. However, for an actor with ten neighbors, 45 ties are needed to complete all possible triplets. If T ($0 < T < 1$) denotes the probability of complete local clustering (i.e., all triplets are

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[19] Scholars have suggested other reasons for tie formation, such as homophily (Aldrich & Kim, 2007; Krivitsky et al., 2009), that relationships are formed due to similarities, such as hobbies, neighborhoods, workplaces, and geographic location. Alternatively, community structures (e.g., two firms located in the same place are more likely to connect than with firms located in another place) also facilitate tie formation (Newman, 2003). Both homophily and community structures discuss attributes of actors that may lead to tie formation, while transitivity highlights the structural mechanism.

closed) and n is the number of connected actors, T can be calculated by $2/n(n-1)$ (Aarstad et al., 2015). Simply put, the more actors connected, the harder to complete triplets around. By nature, low-degree actors tend to be more clustered than high-degree actors.

Table 1. Examples of empirical networks that demonstrate both small-world and scale-free properties

Authors	**Network**	**Period**	***N* (network size)**	***k* (average degree)**
Baum et al., 2004	Canadian Investment banks	1952-1989	76	2.2
Gay & Dousset, 2004	Biotechnology alliance network	1987-2004	557	2.65
Powell et al., 2005	BioTech inter-firm network	1988-1999	482	Not reported
Baggio et al. 2010	Tourism intra-destination network at Elba, Italy	Not reported	1028	3.19
Leon & Berndsen, 2014	Colombian Financial transaction networks	2012	Large-value payment system 144	9.75
			Sovereign security settlement system 116	5.93
			Spot foreign exchange settlement system 46	10.66

When a network shows a skewed degree distribution (i.e., a scale-free network), it has a large portion of peripheral actors and limited central actors. As the *CC* of a network is calculated as the mean of individual actors' clustering coefficient (Watts, 1999; Watts & Strogatz, 1998; Newman, 2003), low-degree actors tend to influence *CC* more significantly than central actors do. Meanwhile, dense clustering around peripheral actors will dampen the scale-free property. Thus, when tie formation mainly complies with transitivity, *ceteris paribus*, one will observe an increase in clustering (*CC*) and a less skewed degree distribution (i.e., a decrease in γ). Therefore, it is reasonable to conclude that when transitivity predominates preferential attachment, a scale-free network tends to have denser local clusters and less skewed degree distribution in the subsequent time, changing towards a small-world structure.

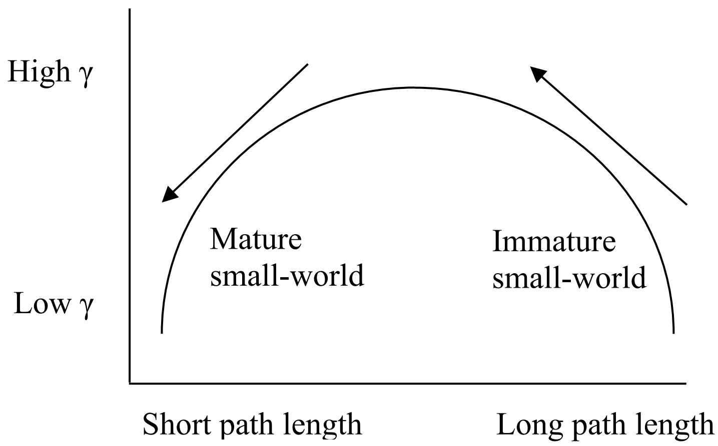
On the other hand, when preferential attachment predominates transitivity, more ties are formed around central actors and enhance the skewness of degree distribution. The local clustering will accordingly remain or even decrease. It is reasonable to expect an increase in scale-free distribution and an (on average) decrease in clustering. Some studies suggest an inversed trend between the skewness of degree distribution and local clustering (Aarstad et al., 2013; 2015). To conclude, due to the dynamic of preferential attachment and transitivity, a network may either increase clustering with decreased skewness of degree distribution, or the other way around.

Scholars have discussed possible patterns for long-term structural dynamics. For example, Gulati et al. (2012) proposed an inverted U-shaped development pattern of small-world properties. When a current network has dense local clustering and a short average path length, the formation of bridging ties may decline, and local clusters may be disconnected (ibid). Therefore, the resulting structure will have a high local clustering without bridging ties, weakening small-world properties. Moreover, exogenous or endogenous interventions could also mingle the original development pattern. For example, environmental shock or institutional change may break the ongoing pattern and lead to the emergence of new central actors and changing structures. The subsequent development will be determined by whether or not preferential attachment dominates transitivity.

2.4. Changes in average path length

Although the small-world and scale-free structures emphasize different characteristics, they both have short average path lengths. Yet causes are different. In scale-free networks, the short path length is due to the small number of highly connected actors that function as hubs to link separate parts. In other words, central actors will form new ties to broker the overall network to decrease average path length and enhance their central positions. Thus, path length will be shorter, and degree distribution will be more skewed. As illustrated in the right-hand part of Figure 2, the association between the average path length and the skewness of degree distribution will be negative. Aarstad et al. (2015) labeled this structure as an *immature* small-world since cutting path length will enhance the skewness of degree distribution.

Figure 2. Non-linear relationship between path length and exponent of the degree distribution



Note: γ denotes the exponent of degree distribution. *Source: Aarstad et al., 2015.*

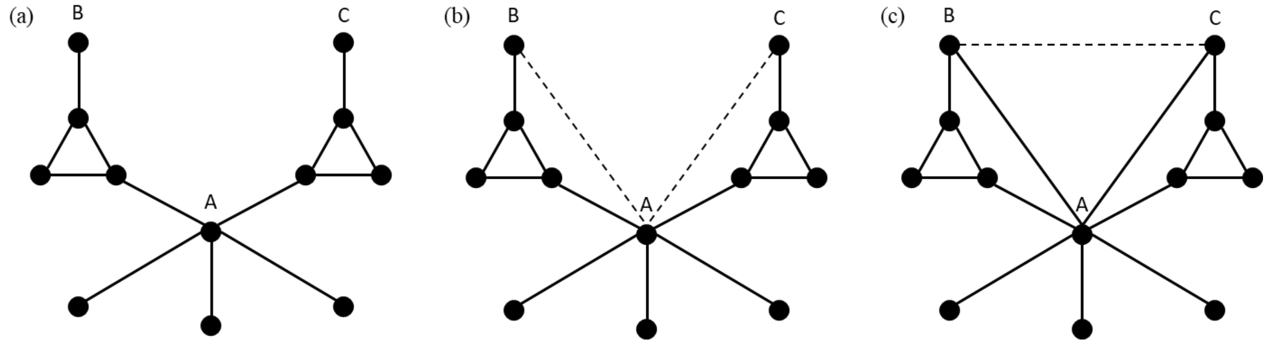
According to Watts and Strogatz (1998), shortcuts in small-world structures occur due to randomization. In that case, we will observe a decrease in path length. However, reduced path length can also be achieved by transitivity (Aarstad et al., 2013). If two peripheral actors were indirectly connected through a hub, this would facilitate forming a direct tie between those two actors (Holland & Leinhardt, 1971). As the unconnected actors connect, the average path length will be reduced. Meanwhile, the degree of the hub would be unchanged, while the degrees of the other two less central actors would increase. This would weaken the skewness of the degree distribution of actors. Therefore, as the left-hand side of Figure 2 illustrates, the skewness of degree distribution will decrease accordingly when the average path length becomes shorter. Aarstad et al. (2015) labeled this structure as a *mature* small-world, as the decrease in path length leads to a decrease in the skewness of degree distribution.

In summary, the relationship between average path length and the skewness of degree distribution is non-linear, depending on the mechanism in operation. Figure 2 summarizes the inverted U-shaped relationship between path length and the exponent of degree distribution. Suppose the preferential attachment is the mechanism that leads to shorter path length; the skewness of degree distribution will be enhanced as average path length decreases (i.e., an immature small-world structure). Nevertheless, if the central actors are already connected to less central actors (i.e., a mature small world), the decreased path length will be achieved by establishing direct ties between less central actors and forming closed triadic structures, weakening the skewness of the scale-free distribution.

2.5. A synergy of theory and the interorganizational context

In this section, I use a figure to summarize the dynamics discussed above and provide examples in the interorganizational context that facilitate or hinder a particular process. Assume the network in Figure 3a is the original structure; actors B and C are disconnected. Node A clearly dominates the network. When the preferential attachment is in operation, B and C may form ties with A (as the dashed line in Figure 3b illustrates). Consequently, the distance between B and C is shortened, as well as the average path length at the system level. Meanwhile, the degree distribution tends to be more skewed due to preferential attachment. This can be labeled an immature small-world structure, as discussed in section 2.4, that decreased path length is associated with a more skewed degree distribution. The vacant tie between B and C will decrease the clustering coefficient since A, B, and C can form a closed triad. As a general trend, the degree distribution exponent (γ) will increase while path length (*PL*) will decrease.

Figure 3. An illustration of network dynamics



Note: From (a) to (b), the degree distribution exponent (γ) will increase, while path length (*PL*) will decrease. The structure in Figure 3a demonstrates an immature small-world. From (b) to (c), path length (*PL*) and exponent of degree distribution (γ) will both decrease. The structure in Figure 3b demonstrates a mature small-world.

Empirically, in an interorganizational context, the preferential attachment may appear due to access to the network resource, enhancing power and control, and as a result of signaling mechanisms (Zaheer et al., 2010). Typically, a central actor could be attractive due to its resourceful position, such as control over network resources and better accessibility to other resources in the value chain. For peripheral actors or newcomers, it can be advantageous to establish relationships with central firms. Sometimes, a central position indicates a better reputation and will be considered an attractive partner (Podolny, 1993). Central firms may also form more relations to maintain their advantageous positions. In sum, preferential attachment is a common mechanism in an interorganizational context.

However, some scholars have proposed that preferential attachment is only probabilistic in social networks, limiting the skewness of degree distribution (Aldrich & Kim, 2007; Andriani & McKelvey, 2009). I list two reasons here. First, it is essential to consider the divergent preferences of individual organizations (Aldrich & Kim, 2007). Preference for a particular partner depends on intra-organizational resources and capabilities. If an organization is not central but has mastered promising technology or information, the organization could also attract partners. As attractiveness depends on a firm's intrinsic value (Gay & Dousset, 2005), organizations may form ties due to fit or complementarity in resources and capabilities other than central position. Meanwhile, forming an interorganizational relationship is a mutual choice. Prominent firms are more flexible in choosing partners that meet their current needs than peripheral firms (Baum et al., 2003). The central actors may be more willing to work with familiar partners than newcomers or have specific preferences for choosing new partners. A study of the US venture capital market found that newcomers to a network have less opportunity to connect to the core firms than those already in the network (Sorenson & Stuart, 2001). In sum, the diverse preference of central and peripheral actors may hinder preferential attachment operation.

Secondly, forming an interorganizational relationship requires resource input from both parties. Unlike links to websites, preferential attachment is limited in interorganizational networks due to capacity constraints. Central actors, as orchestrators, may not have sufficient resources and capacity to interact with all network members and increase their degree unlimitedly (Aldrich & Kim, 2007). Thus, there is a limitation to the skewness of degree distribution in interorganizational networks.

On the other hand, peripheral or low-degree actors tend to cluster. Since B and C are indirectly connected through A in Figure 3b, this may stimulate the formation of a direct link between these two actors, as the dashed line in Figure 3c shows. When the direct tie between B and C is formed, their interaction no longer relies on the previous intermediary, A. The path length is shortened between B and C, also the overall network. At the same time, this will decrease the skewness of degree distribution and increase clustering due to increased degrees of B and C. As discussed in section 2.4, the structure is described as a mature small world. Accordingly, as a general trend, path length (PL) and exponent of degree distribution (γ) will decrease.

In the interorganizational context, scholars observe that third-party ties increase the probability of collaboration between firms (e.g., Gulati & Gargiulo, 1999). Transitivity, or the formation of closed triads, could tackle dyadic power asymmetry, sustain trust and norms, and facilitate cooperation (Coleman, 1988; Krackhardt, 1999; Zaheer et al., 2010). Transitivity normally occurs due to common partners; firm A may cooperate with two firms, B and C. If firm A needs to transfer information received from B to C, firm A may likely introduce B and C to each other to increase efficiency for information sharing. Another possible situation is that firm A may hide certain information to maintain its position as the broker. Consequently, B and C may be motivated to form a direct tie to weaken A's brokering position. Both scenarios will increase the probability that B and C form a direct tie. It has been found that interorganizational networks tend to be decentralized without one dominant central firm to which most other actors are directly connected; instead, there will be local clusters with central and peripheral actors (Gulati & Gargiulo, 1999).

To sum up, preferential attachment and transitivity are common mechanisms that increase the possibility of tie formation and are likely to build on each other. Yet, whether the preferential attachment is common in the interorganizational context remains unclear. Scholars also discussed another possible mechanism beyond a purely structural perspective explaining tie formation (see Hallen et al., 2020, for a review). For instance, to improve its network position, a peripheral firm could form ties with groups of unconnected firms in disconnected local clusters (Baum et al., 2003). Such factors may be less generic mechanisms that influence the systematic dynamics toward scale-free or small-world structures, thus, not the focus of this study.

2.6. Summary

This study considers network dynamics as adding new actors and forming new ties, which leads to system-level structural change. The analysis is focused on small-world and scale-free properties using mathematical models. Table 2 summarizes the network measures used in later analysis and what information these measures convey.

Table 2. Summary of network measures

Network measure	Calculation	Note
Small-world structure (*SW*)	$SW = \frac{CCr}{PLr} = \frac{\frac{Clustering\ (actual\ network)}{Average\ degree\ centrality/Number\ of\ nodes}}{\frac{Average\ path\ length\ (actual\ network)}{\ln(Number\ of\ nodes)/\ln(Average\ degree\ centrality)}}$	A small-world structure should have dense local networks and a short average path length. The value of *SW* should be substantially bigger than 1 to confirm a network to be a small world.
Clustering coefficient (*CC*)	The system clustering coefficient is the average of the nodes' clustering coefficient. The nodes' level clustering coefficient is a measure of how complete the neighborhood of a node is.	The clustering coefficient captures local network cohesiveness. Dense clustering is a core feature of small-world networks. Transitivity will lead to triadic closure, reflected by an increase in *CC*.
Path length (*PL*)	The average distance between all pairs of nodes.	A short path length is a feature of a small-world network. Moreover, as discussed in section 2.4, short path length can also be observed in scale-free networks.
Scale-free structure (γ)	The value of the coefficient of a log-log plot of the nodes' degree distribution.	The change in γ indicates the change in the skewness of degree distribution. The preferential attachment will lead to an increase in γ, indicating a more centralized structure. The value of γ for scale-free structure varies between 1 and 3.

3. Research methods

3.1. Research context and data collection

I studied two regional industry networks focusing on innovation in media technology and fintech in western Norway. Both networks formally belong to the Norwegian Center of Expertise program, supported by the government and other relevant public organizations. The media network was established in 2015. The business units include international media technology firms, television broadcasters, and publishers. Many startups are also involved in solving industry challenges and innovating for the global market. The fintech network was established in 2017. The business units include commercial banks, insurance companies, consulting firms, investment companies, and technology companies that provide relevant services. Both networks have non-commercial organizations such as universities and public organizations.

Data collection was conducted separately for the two networks following the same process. I first checked the network's official website to generate a formal member list. We then contacted well-informed local representatives to review our list. After having a confirmed member list, I conducted a so-called egocentric survey method to collect network data (Krivitsky et al., 2022). This method is suitable for investigating degree distribution, network size, and structural patterns (ibid), thus suitable for this study. I recruited commercial members as respondents to participate in the survey to report their ongoing relationships. However, non-commercial members were indirectly included, as commercial members could report collaborations with them. I also asked the respondents to report the year that they started collaborating with the chosen partners.

Before sending out the survey, I contacted these member firms to confirm their membership and existing business relationships with other network members. Data for the media network was collected in the fall of 2019. After excluding seven firms without existing collaborations, I sent the survey questionnaire to 47 firms. I received 40 complete responses, representing a response rate of 85%. Data for the fintech network was collected in the spring of 2020, following the same process. Seven firms were excluded due to a lack of ongoing relations, and one firm was no longer a member. I sent the survey questionnaire to 36 firms. I received 24 complete responses, representing a response rate of 67%.

3.2. Data analysis

I modeled one tie between two actors if one actor reported a tie to the other or vice versa. In total, I identified 85 members with 348 ties in the media network and 56 members with 185 ties in the fintech network, including duplicated ties (i.e., from A to B and from B to A). The analyses of both small-world and scale-free properties consider dichotomized and symmetric network ties (Baum et al., 2004); in other words, unweighted, undirected ties. Therefore, I omitted the direction and removed duplicated ties. Altogether, the media network had 291 ties in 2019, and 18 ties lacked data about the year of relationship formation. The fintech network had 171 ties in 2020, and 24 lacked data about the year of establishment.

Using the data collected, I managed to identify 91.4% of members from the complete list for the media network and 75.7% of the fintech network members. The remaining firms that I could not model are possibly isolated, marginal, or inactive since other firms have not reported relationships with them. I believe that the identified network is highly similar to the actual network.

I then integrated the information about the collaboration formation year to visualize annual structures retrospectively using the Gephi software (version 0.9.2). As the formation of industrial networks clarifies the network boundary and may be accompanied by new policies and supporting resources that may change the industry environment, I truncate the timeframe to focus on dynamics after both networks are formally established. The media network was officially established in 2015; I replaced the missing data concerning the year of collaboration formation with 2015[20]. I applied the same technique to the fintech network, replacing the

[20] The average year of relationship establishment in the media network is 2014, before the network formally established. As the network boundary can be less clear before the formal establishment, we visualize the network structure from 2015.

missing year with 2017. Figure 4 shows the visualized annual structure. The size of a node reflects its degree, that is, the total number of relationships.

I then combined the network data with the application of network algorithms. Table 3 presents the two networks' annual *SW*, *PL*, *CC*, and γ. It is worth noting network members without ongoing relations will not be included in the visualization and calculation of network-level properties. In addition, it is possible that some actors are connected but isolated from the main component. When disconnected components exist, the path length between the main component and disconnected parts will be infinite (Wasserman & Faust, 1994). The average path length is then calculated based on the main component, and the disconnected components are omitted.

Figure 4. Annual network structure

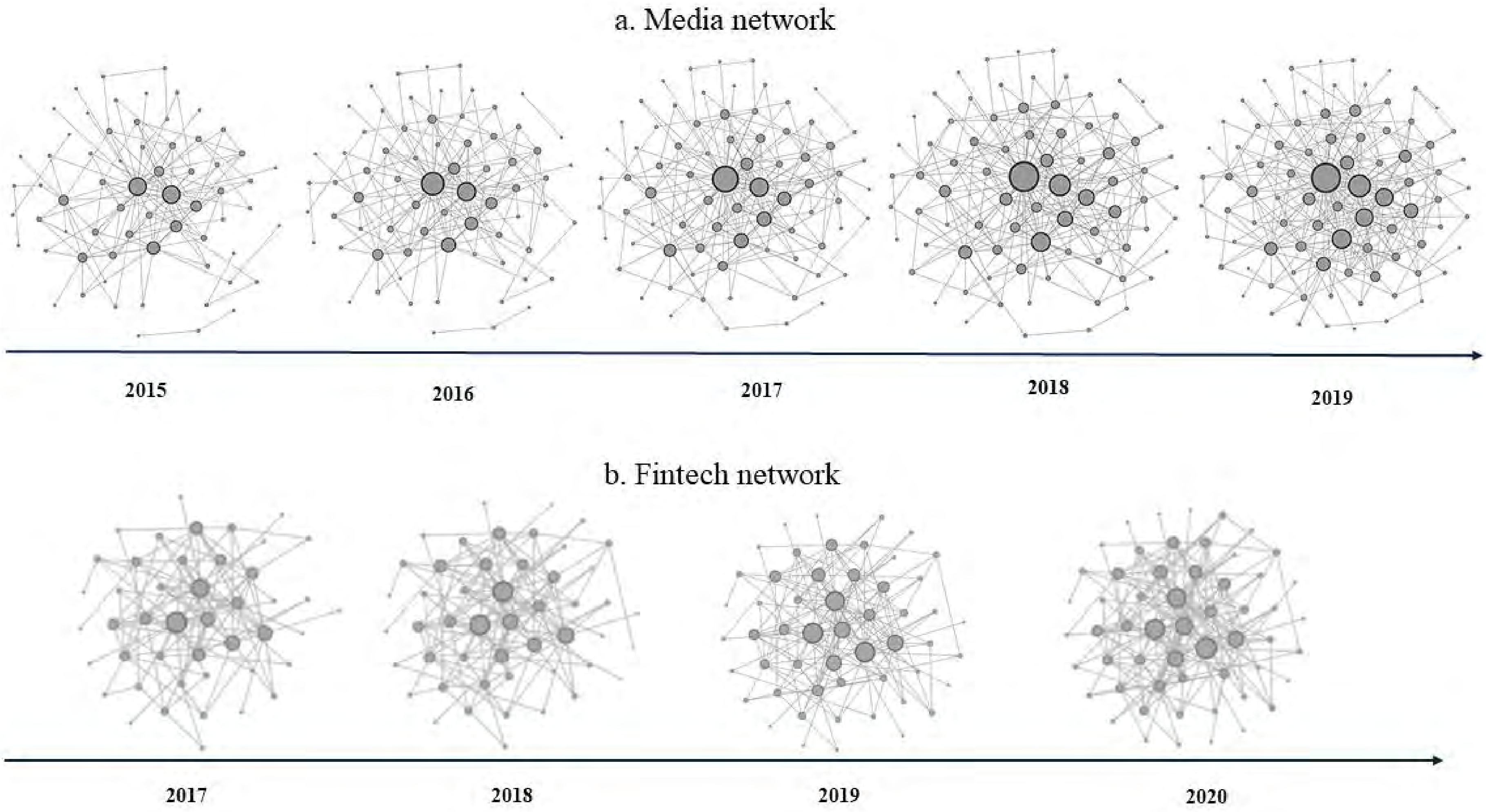


Table 3. Small-world and scale-free properties

	n	*k*	*ln(n)*	*ln(k)*	*PL actual*	*PL random*	*PLr*	*CC actual*	*CC random*	*CCr*	*SW*	*γ*
Media Network												
2015*	64	4.508	4.078	1.506	2.822	2.708	1.042	0.256	0.076	3.350	3.215	0.661
2016*	69	5.188	4.159	1.646	2.657	2.526	1.052	0.27	0.081	3.331	3.167	0.799
2017	75	5.493	4.317	1.703	2.748	2.535	1.084	0.271	0.073	3.700	3.413	0.679
2018	78	6.179	4.357	1.821	2.643	2.392	1.105	0.269	0.079	3.396	3.074	0.925
2019	85	6.847	4.443	1.924	2.553	2.309	1.106	0.319	0.081	3.960	3.582	0.854
Fintech Network												
2017	45	4.978	3.807	1.605	2.469	2.372	1.041	0.255	0.111	2.305	2.214	0.911
2018	49	5.388	3.892	1.684	2.468	2.311	1.068	0.242	0.110	2.201	2.061	0.822
2019	53	6.038	3.907	1.798	2.372	2.208	1.074	0.294	0.114	2.581	2.402	0.700
2020	56	6.107	4.025	1.809	2.405	2.225	1.081	0.269	0.109	2.467	2.282	1.013

Note: The properties measured were network size (*n*), average degree in the actual network (*k*), average path length in the actual network (*PL actual*), average path length in a random network (*PL random*), average path-length ratio (*PLr*), average clustering coefficient in the actual network (*CC actual*), average clustering coefficient in a random network with the same network size and average degree (*CC random*), average clustering coefficient ratio (*CCr*), small-world property (*SW*), and degree distribution exponent (*γ*).

*When isolated components exist, *PL actual* only calculates the main component. In 2015 and 2016, five actors (formed two components) were disconnected from the main component in the media network (as seen in Figure 4). The calculation is based on the main components for these two years except for the exponent of degree distribution ***γ***, which was not influenced by network size.

4. Results

4.1. Small-world network and the scale-free network properties

Table 3 indicates that both networks have dense clustering compared to random networks. The mean *CCr* for the media network is 3.547 (*S.D.* = 0.275) and 2.389 (*S.D.* = 0.169) for the fintech network. The *PLr* is not correspondingly large, with an average of 1.078 (*S.D.* = 0.030) for the media network and an average of 1.066 (*S.D.* = 0.017) for the fintech network. Both networks have an average of *PLr* slightly bigger than 1, indicating that the average path lengths for actual and random networks were comparably short. These findings suggest that, on average, the two networks are weakly separated and highly clustered.

The suggested value for *SW* to confirm a network to be small-world is larger than 1. For the media network, the average *SW* is 3.273 (*S.D.* = 0.220), while for the fintech network, the average *SW* is 2.240 (*S.D.* = 0.142). The values of *SW* provide consistent evidence that both the media and fintech networks exhibited the small-world property for the entire period. On average, the media network has a higher score on *SW*; the difference may be due to the different network sizes. According to our data, the final size of the media network is 85 and 56 for the fintech network.

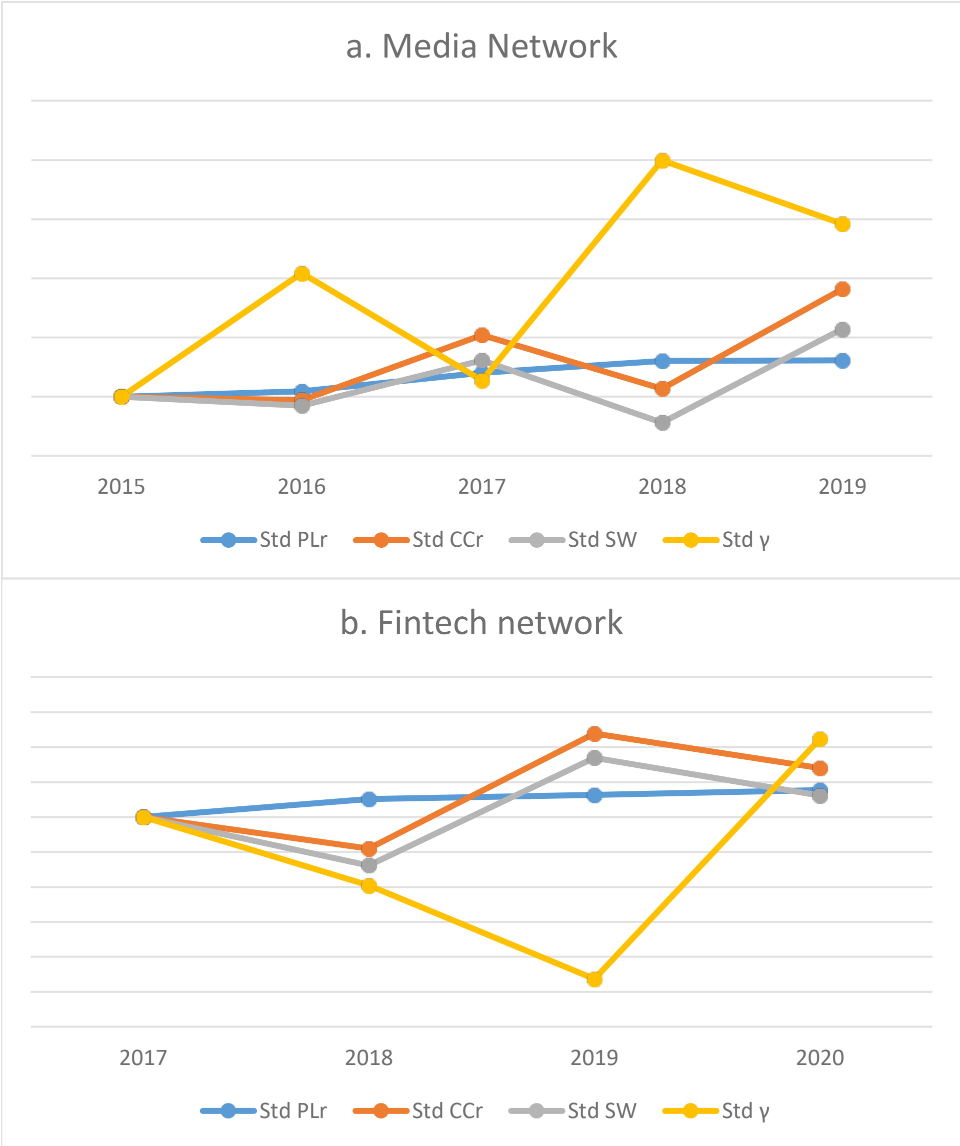
The suggested value for γ to fulfill a scale-free network is between 1 and 3 (Albert & Barabási, 2002). The degree exponent γ has a mean of 0.784 (*S.D.* = 0.113) for the media network and 0.862 (*S.D.* = 0.133) for the fintech network. The media network was not scale-free during the periods studied. The fintech network demonstrated scale-free property in 2020, with $\gamma = 1.013$. The average values of γ for both networks are close to those in previous findings of collaboration networks among individuals, such as the neuroscience co-authorship network and actors' collaboration network; scholars have found that $\gamma = 0.8 \pm 0.1$ (Albert & Barabási, 2002).

4.2. The dynamics of the networks

To make the results more easily interpretable, I report in Figure 5 standardized annual data with the first-year value set as the common value. In other words, in the media network, the standardized values are calculated as the ratio between the current year and 2015. The same method is used for the fintech network. I also calculated the correlation between network measures to show the interrelation in Table 4.

I find that, in both networks, the *PLr* has the mildest change and only increases. Since the *PLr* is almost constant, the trends of the *CCr* and *SW* are consistent. I observe a strong positive correlation between these two measures.

Figure 5. Change of small-world and scale-free properties



In both networks (Figure 5a and 5b), I can observe a clear inverse trend between *SW* and γ, consistent with our prediction and previous studies (e.g., Aarstad et al., 2013, 2015; Gulati et al., 2012). The inversed trend is supported by the negative association between *SW* and γ in Table 4. I observed an exception during 2017-2018 in the fintech network, where SW and γ both decreased.

As discussed in section 2.4, there is a non-linear relationship between path length and the skewness of degree distribution. In Table 4, both positive and negative correlations can be observed between *PLr* and γ, consistent with the non-linear prediction.

Table 4. Correlation matrix of network properties

Media network			
	PLr	CCr	SW
CCr	0.647		
SW	0.370	0.948	
γ	0.684	0.101	-0.168
Fintech network			
	PLr	CCr	SW
CCr	0.501		
SW	0.297	0.975	
γ	-0.048	-0.237	-0.247

5. Discussion

5.1. Discussion of results

Retrospectively visualizing two regional industrial networks in media and fintech, I analyze the dynamics of network structures by focusing on the changes in the following system-level properties: path length (*PL*), clustering coefficient (*CC*), small-world ratio (*SW*) and degree distribution (γ), and their interrelations. According to Figure 5, it is obvious that in both media and fintech networks, there exists "super connectors" like actor A in Figure 3. In the media networks, the two leading actors are a system integrator and professional video production equipment reseller (Mediability) and a leading television broadcaster (TV2). In the fintech cluster, the leading actors are the Norwegian National Bank (DNB) and a leading provider of digital payment technology and services (Nets). These leading members are relatively large or highly professional (Aarstad et al., 2015), and they are important for maintaining a stable structure.

Figure 5 and Table 4 show that scale-free distribution and small-world property demonstrate inverse dynamic relation, which is in line with the discussion in section 2.5. The inversed trend can follow the process from (a) to (b) in Figure 3; the low-degree members connect to central actors. This may describe the process from 2015 to 2016 in the media network (see Figures 4a and 5a). The central actors tend to form more ties and enhance their central positions, enhancing the skewness of degree distribution and weakening small-world properties. Examples can be small and newly formed firms with emergent technology providing services to core media channels in the media network or large banks' payment systems in the fintech network. Alternatively, the process can also follow (b) to (c) in Figure 3, where two indirectly connected members tend to connect. As an empirical example, in Figure 4a, in 2015 and 2016, there were separate subcomponents in the media network. In 2017, these separate parts connected to the main component. One subcomponent (on the bottom of the visualized network) consists of companies providing services concerning digital music (Bach Technology), audiobook platforms (Beat Technology), and visualization for digital products (M'Labs). Later this subcomponent linked to the main part through bridging ties to provide services for local newspapers and other digital service providers. Consequently, the path length was shortened, local clustering became denser, and the overall small-world structure was enhanced. Meanwhile, the degree distribution may be less skewed as more ties were formed around less central actors. In sum, the small-world and scale-free structures demonstrate an inverse dynamic pattern.

I observe a decrease in both small-world and scale-free properties in the fintech network during 2017-2018 in Figure 5b. A possible explanation for this trend is that mechanisms other than transitivity and preferential attachment dominate during the period. Therefore, one can hardly observe an increase in small-world and scale-free properties.

Table 3 indicates that both networks are small-world, but only the fintech network demonstrated a scale-free structure in 2020. In the visualized network in 2020, one highly popular actor emerged (at the bottom right of the visualized network in Figure 4b). This actor was not the most central actor when the network was established in 2017. The newly emergent central actor is an insurance company (FrendeForsikring) offering services for individual customers and companies. One possible explanation is that different members have different preferences. Gay and Dousset (2005) found that firms that form the most ties in the biotechnology alliance network control the most up-to-date technology; put differently, the fitter-gets-richer model overtakes the rich-gets-richer. Similarly, Powell and colleagues (2005) studied a mechanism called follow-the-trend, in which firms in a network tend to react similarly to changes. In both models (i.e., fitter-gets-richer or follow-the-trend), a less central actor can accumulate connections and become a new central actor if it is a highly fit actor under specific conditions, such as the introduction of a new policy (maybe the GDPR concerning private data since 2018) or market environmental change (maybe the pandemic). Therefore, our empirical cases show that preferential attachment may not be a dominant mechanism in the interorganizational setting. Other factors may also play a role in creating a distorted degree distribution and a scale-free structure.

5.2. Theoretical contribution

In this study, I applied a structural perspective to examine the system-level dynamics in terms of the interrelation of small-world and scale-free properties. I make the following four contributions to the literature on network theories and dynamics in an interorganizational context. First, I add to the network studies by discussing the interrelation between small-world and scale-free properties. Scholars find empirical networks can demonstrate small-world and scale-free properties simultaneously, yet most studies focus on one type of structure, and limited study explains their interrelation. Aarstad and colleagues (2013, 2015), as an exception, integrated the theories and discovered the interrelation of these two concepts in service-oriented and less technology-intensive inter-firm networks. In this study, I follow their idea and investigate the dynamic pattern in two high-tech industrial networks covering a relatively short period. Our findings provide support for the inversed trend between scale-free and small-world properties, consistent with previous studies.

Second, scholars hold different opinions concerning whether preferential attachment and scale-free structures are common in the interorganizational setting (Rossmannek & Rank, 2021; Li et al., 2009). The results of our study suggest that scale-free interorganizational networks are less prevalent, and interorganizational networks may exhibit a weak tendency for preferential attachment (Aldrich & Kim, 2007; Andriani & McKelvey, 2009; Gay & Dousset, 2005). The occurrence of scale-free property of the fintech network in 2020 is due to the emergence of a new central actor. The finding shows that mechanisms other than preferential attachment could contribute to a more skewed distribution and drive the network toward a scale-free structure by creating new central actors (Aarstad et al., 2015; Andriani & McKelvey, 2009). However, I lack information in explaining the emergence of a new central actor. Future studies may combine network-level statistics with industrial factors or actor-level information to better understand structural change.

Third, this study adds to Watts and Strogatz's (1988) model concerning the development of small-world structures. Being considered the default model, they emphasize the formation of shortcut ties but not the dense clustering. In particular, their framework assumes a network start from a structure already with a high local clustering; the appearance of shortcut ties leads to a small-world structure. Similarly, Baum and colleagues (2003) study the evolution of interfirm small-world networks, with a particular focus on the emergence of shortcut ties rather than local clustering. This study shows that the dynamic pattern between clustering and small-world is consistent, indicating that transitivity can be an important mechanism leading to the small-world structure.

Lastly, this study contributed to the growing literature on network properties and dynamics in the interorganizational context (Ahuja et al., 2012; Gulati et al., 2012; Chen et al., 2022). I show that interorganizational networks should be viewed as a constantly changing social system instead of a static one and explain the possible dynamic patterns at the system level rather than dyadic tie formation or termination.

5.3. Managerial implications

As this study focuses on the network level, managerial implications are mainly for network managers. Network managers need to understand that industry networks are constantly changing in structure. As the two networks in this study show, the dynamic patterns of interorganizational networks can differ significantly. As network structures have been found to enable different functions (e.g., Uzzi & Spiro, 2005; Singh et al., 2010), network managers need to follow the development of system structure. To enhance the system-level performance, network managers need to understand the overall structure, market environment, and information of individual members.

Relationship formation is a micro-level activity and influences macro-level network structure. Network managers may function as facilitators for interaction between members, eventually influencing the overall system structure. For instance, key actors are often the leading firms in an industrial network and play a vital role in stabilizing and facilitating network connections. However, as these leading members may have limited capacity for collaboration and firms may need diverse resources, managers should allocate resources wisely to cultivating new active members or densely connected subgroups to benefit the overall system.

5.4. Limitations and future research

The limitations of this research suggest several interesting avenues for future research. First, the data for network visualization was collected through a single survey, and respondents may have limited knowledge about specific relationships. For instance, if a respondent joined the company in 2018, the respondent may have insufficient knowledge about relationships formed before 2018. Also, recall bias can occur when the respondents need to provide past information. An annual survey in the future could improve network data quality to capture newly formed interorganizational relationships. It could be relevant to see how networks react to market change and exogenous shocks, such as the pandemic and technology development. Future studies should cover a longer period to observe whether the development repeats a particular pattern.

Second, the network visualization focused on the change in patterns concerning newly formed interorganizational ties, lacking information about relationship features. Although our specification ensured a close representation of two real networks, the unobserved information may have influenced the dynamic of network structures. For instance, the structure may differ if the focus is on knowledge exchange ties or supplier-buyer ties. Future studies may improve the research design to collect more information, such as relationship type, to improve the accuracy of the representation of network structure and composition.

Third, there are opportunities for future contributions to connect the micro-level characteristics and macro-level structures. Figure 4 presents visualized structures using a so-called Fruchterman Reingold layout; the degree of actors decreases from the inside out. In both networks, I observed that newcomers exhibited different abilities in forming relationships; some occupied better positions (i.e., closer to the center) than others who joined the cluster in the same year. Moreover, not all early entrants benefited from their seniority, and some later comers attained prominence (Powell et al., 2005). It would be fruitful to combine dynamic network data and information about individual actors (e.g., actors' resource endowments and newcomers that are spin-offs of central network actors) to unpack the reasons for their different performances after joining the network.

Lastly, this study focused on describing the structural dynamics of two regional industry networks, and future studies may connect the pattern to the macro-environment and specific outcome measures. For instance, one may examine network-level outcomes, such as newly registered innovation projects, funding received each year, or new jobs created by network members, to explore the association with certain network properties.

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Appendices

Appendix I. Survey questionnaire for the media cluster (in Norwegian)

Introduksjon

Consent.
Vi ønsker å invitere deg til å delta i et forskningsprosjekt om samarbeid i Media City Bergen ved å besvare følgende spørreskjema. Spørreskjemaet består av fem deler og vil ta rundt 20 minutter å besvare.
Vennligst besvar spørsmålene på vegne av din bedrift/organisasjon.

All informasjon vil bli behandlet strengt konfidensielt.

Dersom du har noen spørsmål vedrørende denne spørreundersøkelsen eller forskningsprosjektet, vennligst ta kontakt med:
yi.lin@nhh.no

- Jeg ønsker å delta i denne spørreundersøkelsen.

Del 1.

.
Velkommen til del 1 av undersøkelsen.

Vennligst fyll ut generell informasjon om respondenten og bedriften.

Q1. Bedriftsnavn:

Q2. Bransje/Kommersiell sektor:

Q3. Respondentens navn:

Q4. Respondentens rolle:

- Administrerende direktør
- Entreprenør
- Leder for teknisk avdeling/Forsknings- og utviklingsavdeling
- Leder for økonomi- eller markedsføringsavdeling
- Annet, vennligst angi tittel:

Q5. Er bedriften din en del av et større selskap?

- Ja.
- Nei.

Hvis bedriften din er en del av et større selskap, vennligst besvar følgende spørsmål med utgangspunkt i bedriften/enheten som er tilknyttet medieklyngen i Bergen.

Q6.
Hvilket år ble bedriften/enheten medlem av medieklyngen?

År ▼

Q7.
Hvor mange ansatte har bedriften/enheten på nåværende tidspunkt?

Del 2.

Velkommen til del 2 av undersøkelsen.

Q8.
Merk av for alle organisasjonene selskapet ditt jobber med i Media City Bergen på dette tidspunktet. Inkluderer alle relasjoner som er relevante for bedriftens virksomhet. Det kan være joint venture, innovasjonsprosjekt, strategisk allianse, B2B-relasjoner, etc.

Det er svært viktig at du også oppgir året samarbeidet startet med de valgte partnerne i boksen under firmanavnet.

- [ ] 7 Mountains
- [ ] Altibox
- [ ] ANTI BERGEN
- [ ] Lokalavisene
- [ ] Bach Technology
- [ ] Beat Technology
- [ ] BEMANNINGSBYRAAET
- [ ] BERGEN KINO
- [ ] BERGEN PRIVATE GYMNAS
- [ ] BERGEN ROBOTICS
- [ ] Bergens Tidende
- [ ] BERGENSAVISEN

- Bolder
- Bridj
- BRIK
- Broen.xyz
- Capgemini
- DANMON GROUP NORWAY
- Deloitte Digital
- Departementenes sikkerhets- og serviceorganisasjon, DSS
- EDUPLAYTION
- ELECTRIC FRIENDS
- ENERGI OG KLIMA
- Fana Sparebank
- FILMTRIKS
- FONN GROUP
- GOONTECH
- HANDELSHØYSKOLEN BI
- Handmade Films In Norwegian Woods
- Hey Ho Let's Go
- HIGHCHARTS
- HØGSKULEN PÅ VESTLANDET (HVL)
- HUBII
- IBM
- Kameraproduksjon
- KEYTEQ
- KHiB
- KNOWIT EXPERIENCE BERGEN

- [ ] KULTUROPERATØRENE
- [ ] LIFEKEYS
- [ ] LIMELIGHT NETWORKS
- [ ] LIVVIN
- [ ] LYSE
- [ ] M´Labs
- [ ] MBL
- [ ] MEDIABILITY
- [ ] MEDIAFARM
- [ ] MEDIEDEL
- [ ] MEDIEFONDET ZEFYR
- [ ] MER FILM
- [ ] METIS VIDEREGÅENDE BERGEN
- [ ] Miles
- [ ] Mjoll
- [ ] Motion Corporation
- [ ] Motitech
- [ ] MOVIEMASK
- [ ] MYREZE
- [ ] NAGELLD
- [ ] NEVION
- [ ] NorApps
- [ ] NORCE
- [ ] NORDISKE MEDIEDAGER
- [ ] NORGES HANDELSHØYSKOLE

- [ ] NORKRING
- [ ] Noroff
- [ ] NORSK RIKSKRINGKASTING AS (nrk)
- [ ] NUROFY
- [ ] RAINFALL
- [ ] SCANREACH
- [ ] SCARY WEATHER
- [ ] SCREEN STORY
- [ ] shAIRskills
- [ ] SIXTY
- [ ] SONAT CONSULTING BERGEN
- [ ] Sparebanken Vest
- [ ] SPEAKLAB
- [ ] STORMGEO
- [ ] SYNQ
- [ ] TenkLabs
- [ ] TIME TO RIOT
- [ ] TV 2
- [ ] TV BRA
- [ ] TV VEST
- [ ] UNIVERSITETET I BERGEN
- [ ] VILVITE
- [ ] VIMOND MEDIA SOLUTIONS
- [ ] VIS
- [ ] VISUAL CATALYST AS
- [ ] VIMOND MEDIA SOLUTIONS

☐ VIZRT

☐ WEBSTEP

☐ WOLFTECH

Del 3.

.
Velkommen til del 3 av undersøkelsen.

Vennligst ta stilling til følgende utsagn ved å velge det svaralternativet som best beskriver din vurdering, fra «helt uenig» til «helt enig».

** Med «klynge» refererer vi til Media City Bergen i de følgende spørsmålene.*

Q9.
Disse påstandene omhandler makt i medieklyngen.

	Helt uenig	Uenig	Delvis uenig	Hverken enig eller uenig	Delvis enig	Enig	Helt enig
Vi har en sterk posisjon i denne klyngen.	○	○	○	○	○	○	○
Vi har som regel mer å si enn andre klyngemedlemmer ved samhandling mellom våre bedrifter.	○	○	○	○	○	○	○
Andre medlemmer av denne klyngen følger som regel vår vilje.	○	○	○	○	○	○	○

Q10.
Disse påstandene omhandler synligheten til din bedrift.

	Helt uenig	Uenig	Delvis uenig	Hverken enig eller uenig	Delvis enig	Enig	Helt enig
Vår bedrifts forretningsaktiviteter (f.eks. investeringer, nye samarbeidspartnere, etc.) kan lett observeres av andre medlemmer av denne klyngen.	○	○	○	○	○	○	○
Vår bedrift kan alltid få oppmerksomheten til andre medlemmer av denne klyngen.	○	○	○	○	○	○	○
Det er ikke vanskelig for andre medlemmer av denne klyngen å innhente informasjon om våre forretningsaktiviteter.	○	○	○	○	○	○	○
Når vi gjennomfører en ny forretningsaktivitet (f.eks. investering, prosjektinitiering, nye samarbeidspartnere, etc.) vil andre bedrifter i klyngen legge merke til det.	○	○	○	○	○	○	○

Q11.
Disse påstandene omhandler usikkerhet.

	Helt uenig	Uenig	Delvis uenig	Hverken enig eller uenig	Delvis enig	Enig	Helt enig
Sluttbrukernes behov og preferanser endrer seg raskt i vår bransje.	○	○	○	○	○	○	○
Etterspørselen etter våre produkter/tjenester varierer kontinuerlig.	○	○	○	○	○	○	○
Det er vanskelig å estimere etterspørselen for våre produkter/tjenester.	○	○	○	○	○	○	○
Det er ikke mulig å forutsi med sikkerhet verken type eller tidspunkt for fremtidige teknologiske innovasjoner som kan påvirke konkurranseevnen til våre produkter/tjenester.	○	○	○	○	○	○	○

Del 4.

. Velkommen til del 4 av undersøkelsen.

Vennligst ta stilling til følgende utsagn ved å velge det svaralternativet som best beskriver din vurdering, fra «helt uenig» til «helt enig».

Q12.
Sammenlign bedriften din med bedriftens konkurrenter:

	Helt uenig	Uenig	Delvis uenig	Hverken enig eller uenig	Delvis enig	Enig	Helt enig
Vi adresserer jevnlig nye, uoppfylte kundebehov.	○	○	○	○	○	○	○
Våre produkter/tjenester er veldig innovative sammenlignet med våre konkurrenter.	○	○	○	○	○	○	○
Våre produkter/tjenester dekker kundebehov som ikke blir dekket av våre konkurrenter.	○	○	○	○	○	○	○

Q13.
Vennligst indiker hva bedriften din ønsker å oppnå gjennom allianser:

	Helt uenig	Uenig	Delvis uenig	Hverken enig eller uenig	Delvis enig	Enig	Helt enig
Forbedre kvaliteten på eksisterende produkter/tjenester	○	○	○	○	○	○	○
Forbedre fleksibiliteten i produksjonen	○	○	○	○	○	○	○
Redusere produksjonskostnader og driftskostnader	○	○	○	○	○	○	○
Mer effektive driftsoperasjoner	○	○	○	○	○	○	○
Åpne nye markeder	○	○	○	○	○	○	○

	Helt uenig	Uenig	Delvis uenig	Hverken enig eller uenig	Delvis enig	Enig	Helt enig
Utvide produkt-/tjenestesortimentet							
Introdusere nye generasjoner av produkter/tjenester							
Komme inn på et nytt teknologiområde							

Del 5.

. Velkommen til del 5 av undersøkelsen.

Denne delen omhandler din bedrifts erfaringer med samarbeid. Vennligst velg ett firma i medieklyngen som din bedrift samarbeider med på nåværende tidspunkt, og som bedriften din har god kjennskap til. Besvar alle de påfølgende spørsmålene med utgangspunkt i samarbeidserfaringene med denne spesifikke samarbeidspartneren.

Q14.
I hvilket år startet samarbeidet med denne partneren?

År ▼

Q15.
Vennligst ta stilling til følgende utsagn vedrørende dette spesifikke samarbeidsforholdet:

	Helt uenig	Uenig	Delvis uenig	Hverken enig eller uenig	Delvis enig	Enig	Helt enig
Vi har en sterkere posisjon enn partneren i dette samarbeidet.							
Vi har som regel mer å si enn partneren i dette samarbeidet.							
Vi kan som regel påvirke partnerens beslutninger med hensyn til dette samarbeidet.							

Q16.
Vennligst ta stilling til følgende utsagn med hensyn til investeringer foretatt av din bedrift i forbindelse med dette samarbeidet:

	Helt uenig	Uenig	Delvis uenig	Hverken enig eller uenig	Delvis enig	Enig	Helt enig
Våre ansatte har tilegnet seg bedriftsspesifikk eller prosjektspesifikk kompetanse for å kunne levere tilstrekkelig i dette samarbeidet.							
Vi har foretatt betydelige investeringer for å bygge opp dette samarbeidet (ta i betraktning tiden det har tatt å omplassere, kvalifisere, lære opp, foreta investeringer, foreta tester og utvikle et fungerende samarbeid).							

	Helt uenig	Uenig	Delvis uenig	Hverken enig eller uenig	Delvis enig	Enig	Helt enig
Dersom vår bedrift skulle bytte til en konkurrerende partner, ville en betydelig del av investeringene i dette samarbeidet gått tapt.	○	○	○	○	○	○	○
Dersom dette samarbeidet skulle opphøre, ville vi tapt mye kunnskap som er spesielt tilpasset dette samarbeidet.	○	○	○	○	○	○	○

Q17.
Vennligst ta stilling til følgende utsagn med hensyn til investeringer foretatt av samarbeidspartneren deres i forbindelse med dette samarbeidet:

	Helt uenig	Uenig	Delvis uenig	Hverken enig eller uenig	Delvis enig	Enig	Helt enig
Denne samarbeidspartnerens ansatte har tilegnet seg bedriftsspesifikk eller prosjektspesifikk kompetanse for å kunne levere tilstrekkelig i dette samarbeidet.	○	○	○	○	○	○	○
Denne samarbeidspartneren har foretatt betydelige investeringer for å bygge opp dette samarbeidet (ta i betraktning tiden det har tatt å omplassere, kvalifisere, lære opp, foreta investeringer, foreta tester og utvikle et fungerende samarbeid).	○	○	○	○	○	○	○
Dersom denne samarbeidspartneren skulle bytte til en konkurrerende partner, ville de tape en betydelig del av investeringene i dette samarbeidet.	○	○	○	○	○	○	○
Dersom dette samarbeidet skulle opphøre, ville denne samarbeidspartneren tapt mye kunnskap som er spesielt tilpasset dette samarbeidet.	○	○	○	○	○	○	○

Q18.
Vennligst ta stilling til følgende utsagn vedrørende dette samarbeidsforholdet:

	Helt uenig	Uenig	Delvis uenig	Hverken enig eller uenig	Delvis enig	Enig	Helt enig
Problemer som oppstår i denne relasjonen blir behandlet av partene som et felles ansvar og ikke bare som et individuelt ansvar.	○	○	○	○	○	○	○
Begge parter ser det som viktig å gjøre forbedringer som gagner relasjonen som helhet og ikke bare en av oss.	○	○	○	○	○	○	○
Partene i denne relasjonen har ikke noe imot å skylde hverandre tjenester.	○	○	○	○	○	○	○

Q19.
Vennligst ta stilling til følgende utsagn vedrørende når uventede problemer oppstår i dette samarbeidsforholdet:

	Helt uenig	Uenig	Delvis uenig	Hverken enig eller uenig	Delvis enig	Enig	Helt enig
Vi deler alltid problemer og utfordringer med denne partneren slik at vi sammen kan finne løsninger.							
Vi forsøker å få frem alle bekymringer og utfordringer umiddelbart.							
Vi deler våre idéer med denne partneren og ber om partnerens idéer.							
Vi forsøker umiddelbart å bearbeide de områdene hvor vi har ulike oppfatninger.							
Vi forsøker alltid å ha en direkte diskusjon av problemer og utfordringer.							

Q20.
Vennligst ta stilling til følgende utsagn vedrørende dette samarbeidsforholdet:

	Helt uenig	Uenig	Delvis uenig	Hverken enig eller uenig	Delvis enig	Enig	Helt enig
Når vi foretar viktige beslutninger i dette samarbeidet, er vi oppmerksomme på partnerens interesser.							
Vi vil ikke bevisst gjøre noe som kan skade denne partneren.							
Denne partnerens behov er viktige for oss.							
Vi er opptatt av hva som er viktig for denne partneren.							

Q21.
Vennligst ta stilling til følgende utsagn vedrørende samarbeidet med denne partneren:

	Helt uenig	Uenig	Delvis uenig	Hverken enig eller uenig	Delvis enig	Enig	Helt enig
Vi «pynter» av og til på sannheten for å fremme våre interesser i dette samarbeidet.							
Det hender at vi lover ting som vi senere unnlater å gjøre.							
Vi opptrer ikke alltid i henhold til skriftlig(e) avtale(r).							
Noen ganger bryter vi uskrevne regler i vår relasjon til partneren for å fremme våre egne interesser.							
Vi forsøker av og til å dra fordel av uklarheter og mangler i vår(e) avtale(r) for å fremme våre interesser.							

	Helt uenig	Uenig	Delvis uenig	Hverken enig eller uenig	Delvis enig	Enig	Helt enig
Det hender at vi benytter oss av uforutsette hendelser for å oppnå innrømmelser fra partneren.	○	○	○	○	○	○	○

Appendix II. Innovation as an outcome of exploration

Scholars have suggested various ways to categorize innovation. Related to the exploration-exploitation framework, one way to categorize innovation is based on the emergence of innovation. More specifically, innovation can be achieved in two ways: by combining knowledge elements creatively or by improving existing combinations for new uses and applications (Lavie et al., 2010; Fleming, 2001). According to March's (1991) framework, the former is called explorative innovation, and the latter is called exploitation innovation. These two types of innovation are based on different mechanisms. Explorative innovation requires fresh input that is different from existing knowledge, while exploitative innovation is based on recombining existing knowledge and looking for improvement and refinement (He and Wong, 2004; Parmigiani and Rivera-Santos, 2011). Henderson and Clark (1990) proposed a matrix to categorize innovation based on core concepts and components; The four categories are incremental, modular, architectural, and radical, which has been widely used. There are also other ways to categorize innovation, such as focusing on *where* the innovation is happening (e.g., technological, product/service, markets, or business model innovation). In Article 1, I use firm innovativeness to capture the outcome of the exploration strategy. According to Garcia and Calantone (2002), innovativeness is typically used to measure the level of 'newness' of an innovation. Based on the perspective of the firm, firm innovativeness is defined as offering new products/services to customers that are not available from competitors. In my opinion, this measure corresponds to exploration by emphasizing novelty. Also, it does not focus on the knowledge or technology domain but on the product/service domain. The creation of new knowledge may not bring direct business profit for firms, but products and services can bring direct benefit to firms.

Appendix III. Tacit knowledge transfer between organizations

Tacitness is a core feature of knowledge, which makes knowledge hard to codify and communicate (Hansen, 1999). Organizations exchange knowledge at various levels of tactiness with each other. In my understanding, the tacitness of knowledge varies between a spectrum. The two extremes are explicit and fully codifiable knowledge and completely implicit and tacit knowledge. It is widely accepted that codification facilitates knowledge transfer while tacitness impedes it (e.g., Zander & Kogut, 1999). The nature of communication or knowledge transfer between firms occurs in interactions, including one-on-one meetings, group meetings, phone calls, and emails. Knowledge transfer mainly relies on verbal communication and written documents, but can also be done through observations in joint activities. Understanding the feature of knowledge (e.g., complexity, tacitness) is relevant, because it will influence the transfer process and the outcomes.

Over time, organizational members accumulate tacit knowledge by developing expertise, skills, and routines. The transfer of tacit knowledge is challenging since firms need to invest time, effort, and resources (such as human resources) to transform tacit knowledge into less abstract, more concrete, explicit, and codified knowledge (Cowan et al., 2000). Scholars suggest that structural and relational characteristics could influence actors' motivation to invest resources in knowledge transfer (e.g., Reagans & McEvily, 2003; Tortoriello et al., 2012). For instance, relationships that are characterized by trust, frequent interaction, and joint problem-solving, can enhance tacit knowledge transfer (McEvily & Marcus, 2005). Trust and frequency interaction are precursors for creating the conditions for joint problem-solving. Joint problem-solving puts involved parties in the same context, which increases the chance to engage in experimentation, observation, and search for solutions. Tortoriello and colleagues (2015) also find that the existence of a mutual third party makes the involved parties more engaged in knowledge transfer and spend more time in the knowledge acquisition process.

Based on the discussion above, transferring tacit knowledge may be possible or eased if an effort can be made to make the knowledge less abstract and explicit. Relationships with certain characteristics may help transform tacit knowledge.

Appendix IV. Comparison of Different Centrality Measures

Freeman (1978) conceptualized three types of centrality measures, degree, closeness, and betweenness. In Articles 1 and 2, two different centrality measures have been used as independent variables. The committee also mentioned information centrality as a potential independent variable for the exploration strategy for article 1. Below I discuss the differences between in-degree, closeness, and information centrality.

According to the graph-theoretic view, the different centralities are based on different measures and algorithms (Borgatti & Everett, 2006). In-degree and out-degree centralities are degree-like measures with direction. The degree measure counts the number of direct ties an actor has. In-degree and out-degree count the ties pointing to or sending from a focal actor. Meanwhile, closeness is the length measurement. It counts the number of intermediaries or steps needed from one actor to another. Closeness centrality is based on the geodesic distance between a focal actor and the rest actors within a network. As Borgatti and Everett (2006) summarized, degree (both in- and out-degree) focuses on volume based on a focal actor's existing ties, while closeness is a length measure that counts steps (if each tie is one step) to reach other actors.

It is worth noting that in-degree centrality is more reliable than most centrality measures, even at low sampling rates (Costenbader & Valente, 2003). This is because in-degree centrality is calculated as the number of nominations received, not directly influenced by the focal actor. When using undirected network measures, I consider ties from A to B and B to A as the same for two reasons. First, I identify network ties as formal business relationships; if one party reported a formal relationship, it indicates the existence of the relationship. Second, it is a common way to solve missing network data using the survey method. If only one party participated in the survey, this method is an effective treatment for missing data (Huisman, 2009).

Now I discuss the differences between closeness and information centrality. A fundamental assumption of closeness is that communication only occurs along the shortest possible path. The issue with this assumption is that (1) paths are considered indifferent, and (2) communication may not occur along the shortest path but more circuitous routes due to certain hide and shield information in the shortest path. For instance, competitors in the same network may avoid sharing information with direct competitors.

Stephenson and Zelen (1989) introduced information centrality, also have been called S-Z centrality. The meaning of information here is not based on the theory of communication but is that every path can be evaluated for its information content (ibid, p.8). Put differently, 'information' is used in the theory of statistical estimation. When calculating information centrality, each possible path is given a weight according to the geodesic distance. The weight of each path is calculated as the number of steps in a given path. Information centrality combines all possible paths between two nodes based on their weights.

The assumption of using information centrality is that information will not change, lose, or disorder during transmission. Assume a closed triadic structure with three nodes, A, B, and C. When information is transferred from A to B, the information is in the 'original' form. However, if the information transfer from A to C, then from C to B, the information may have 'noise' when B receives it. When transmitting information between two points, the longer the path is, the more 'noise' will be included in the transmission. The use of information centrality may result in non-optimal information since some variated messages (due to the lengthy paths) may be transferred to the recipient.

Information and closeness centrality are in the same category according to Borgatti & Everett's (2006) classification based on graph theories; both are calculated based on paths between two nodes. Closeness centrality focuses on the 'efficiency' of reaching information, represented by the shortest path of reaching any network actors. Information centrality focuses on the information contained in all possible paths in a network. To summarize, closeness centrality assumes information travel through the shortest path and indicates the time required to receive information. Meanwhile, information centrality assumes information travel through all possible paths, and the net effect from the sender to the recipient through different paths is the same. The cost of receiving the information will be higher if not transferred through the shortest path. Therefore, theoretically, I believe closeness centrality is a better measure to capture efficiency or speed to reach network information and resource instead of information centrality.

Also, I replaced closeness with information centrality for regression analyses. The output can be found below. It did not alter any of our previous statistical conclusion.

Dependent variable	***Exploration strategy***			
Models	1	2	3	4
Control variables				
Firm size	–0.073	–0.063	–0.065	–0.060
	(0.130)	(0.130)	(0.124)	(0.123)
Cluster	0.215	0.203	0.414	0.415
	(0.260)	(0.260)	(0.261)	(0.259)
Burt’s constraint	0.248		0.118	
	(0.278)		(0.271)	
Independent variables				
Information centrality	0.518^{+}	0.294*	0.368	0.261*
	(0.282)	(0.126)	(0.276)	(0.121)
Local cohesion			0.324^{*}	0.335^{**}
			(0.127)	(0.124)
Exploration strategy				
Constant	–0.080	–0.076	–0.155	–0.156
	(0.157)	(0.156)	(0.153)	(0.152)
R^2	0.100	0.088	0.190	0.188
Adj. R^2	0.039	0.042	0.121	0.133
F-ratio	1.64 n.s.	1.92 n.s.	2.73*	3.14*
VIF (max)	5.21	1.10	5.46	1.16

N = 64. Standard errors are in parentheses.

$^{+}\,p < 0.1$, $^{*}\,p < 0.05$, $^{**}\,p < 0.01$

Appendix V. Bayesian hypothesis testing for Article 1

I conducted Bayesian hypotheses testing in Stata (ver. 17) for Model 6 in Article 1 using Bayesian linear Regression (default prior). The function is shown below:

Exploration strategy = α + β_1 (Closeness centrality) + β_2 (Local cohesion) + β_3 (Firm size) + β_4 (Cluster dummy) + ε_i

The table below summarizes the output. The coefficients are very similar to OLS outputs. In OLS output, the positive coefficient of closeness centrality is borderline significant. I compared the previous 95% confidence interval [-0.0256394, 0.4930014] in OLS and the 95% credibility interval [-0.0063521, 0.4834943] in Bayes hypotheses testing. The output of Bayesian regression shows a more obvious sign of a positive association between closeness centrality and exploration strategy. It did not alter any of our previous statistical conclusion.

Variables	Coefficient	Std	95% Cred. Interval	
Firm size	-0.085	0.129	-0.344	0.178
Cluster dummy	0.303	0.282	-0.245	0.869
Closeness centrality	0.236	0.127	-0.006	0.483
Local cohesion	0.337	0.130	0.080	0.594
Constant	-0.116	0.154	-0.417	0.186

Appendix VI. Summary of network structure before formal establishment for Article 3

a. Media network:

Based on network data, the earliest year reported for relationship formation is 1990. The average year of relationship formation is 2014. Missing values were replaced using 2015 (the year of the media cluster establishment). The table below shows the number of actors and ties formed using a 5-year window before 2015. The visualized structure are modeled retrospectively for 2000 and 2010.

Years covered	# of actors	# of ties formed	Total number of ties
1990-2000	12	15	15
2001-2005	13	5	20
2006-2010	31	38	58
2011-2015	64	63+15 (missing year ties) =78	136

b. Fintech network:

Based on network data, the earliest year reported for relationship formation is 1980. The average year of relationship formation is 2015. Missing values were replaced using 2017 (the year of the media cluster establishment). The table below shows the number of actors and ties formed using a 5-year window (the last period covers 7 years) before 2017. The visualized structure are modeled retrospectively for 2000 and 2010.

Years covered	# of actors	# of ties formed	Total number of ties
1980-2000	9	8	8
2001-2005	10	2	10
2006-2010	22	23	33
2011-2017	45	55+24 (missing year ties)=79	112