Norwegian School of Economics

Bergen, Fall 2020

Keep your friends close and at a distance

Studying the structural network properties of a regional cluster and it's broader ecosystem through social network analysis

Kari Sofie Mysen Conradsen and Max Hartvig-Larsen

Supervisor: Ivan Belik

Co-supervisor: Eirik Sjåholm Knudsen

Master Thesis, Economics and Business Administration

Majors: Strategy and Management & Business Analytics

NORWEGIAN SCHOOL OF ECONOMICS

Acknowledgement

We would like to begin by thanking our supervisor Ivan Belik, and co-supervisor Eirik Sjåholm Knudsen. Your guidance and constructive feedback on our work has been excellent. Especially your passion and enthusiasm for social network analysis, regional clusters, and fintech has been truly inspirational, both in terms of choice of topic and during more intense periods of finalizing this thesis.

Furthermore, we would like to thank the people that participated in our survey on behalf of actors in the Norwegian fintech community. Without you, this master thesis would not have been realizable. A special thanks to Atle Sivertsen, CEO of NCE Finance Innovation, for supporting us with the data collection. We look forward to witnessing the evolution of fintech in Norway in the years to come. A warm thanks to our friends and family for all your support.

Lastly, we would like to thank NHH and the Student Association for five educational and memorable years. We will value all our strong and weak ties with students, professors, businesses representatives and others in the years to come.

Abstract

Regional clusters and ecosystems are increasingly becoming an important part of many organizations' and countries' strategies for innovation and economic growth. In the context of the Norwegian fintech industry, this thesis aims to investigate the structural characteristics of the networks of interfirm relations that make up a regional cluster and the broader ecosystems which it is embedded. This was accomplished by collecting data through an electronic survey on the relations of both members and non-members of the regional cluster NCE Finance Innovation and analysing these relations through the lens of social network analysis (SNA). Our results indicate that the regional cluster members to a large extent have relations outside the regional cluster's boundaries. Moreover, the regional cluster network exhibits hierarchical properties, where a few actors are significantly more connected, and therefore potentially important for the network's ability to diffuse information and knowledge. We found that traditional financial institutions are highly central with regards to every used centrality measure, which might suggest that the firm-specific characteristics of cluster members to a degree can explain their level of connectedness. Our findings suggest that SNA can be a valuable tool for researchers, cluster facilitators and policy makers by exposing detailed information about the network properties of a regional cluster, such as the distribution of influence and the efficiency of information flows.

Table of contents

1. Introduction

Our understanding of the nature of the firm has evolved considerably from when Ronald Coase (1937) first suggested that firms are not "black boxes", but alternative means for organizing similar kinds of transactions as markets. The old idea was that a firm's boundaries excluded everything that was not legally a part of that firm. Everything outside this sphere was seen as the firm's environment, and it was thought that the firm could not change it. Today there is consensus that firms can and do in fact shape their external surroundings by forming relationships.

Network-thinking has in recent years gained momentum as it has shown to be positively correlated with learning and innovation (Gausdal 2008; Handel & Powell 1990). The attention towards what drives innovation has developed from focusing on the resources held inside firms to increasingly encompass networks of businesses, such as regional clusters and ecosystems (Gausdal, 2008). A regional cluster holds many definitions and is in theory and practice also referred to as a "business cluster", a "cluster of innovation", or simply a "cluster" (Doeringer & Terkla, 1995; Engel, 2015; Porter, 1990). Nonetheless, common themes in most definitions are that regional clusters are made up of organizations that are geographically grouped together and operate in common fields or related industries. These organizations interact and are interconnected through a wide range of relationships, such as customers, competitors, providers and financing partners. The term "ecosystem", which is borrowed from biology, has many applications in different contexts but can in simple terms be defined as "a group of interacting firms that depend on each other's activities" (Jacobides et al., 2018). This thesis simply refers to an ecosystem as the broader community of loosely connected networks in which a regional cluster is embedded.

There is wide consensus in research that networks of actors organized in social systems such as regional clusters and ecosystems can be advantageous for innovation and learning. However, research on these topics rarely apply objective analytical methods for accurately obtaining and analysing intricate details about the nature and strength of the interfirm relations in these networks (see for example, de Man & Duysters, 2005; Santamaría & Nieto; Schilling & Phelps, 2007). In addition, a detailed understanding of how the structural properties of networks affect innovation, is an under-researched topic (Amara & Landry, 2005). For example, Rosenfeld (1997) argues that significant, but often overlooked factors for indicating a regional cluster's synergies and growth prospects are the efficiency of the "flows" of information, and the intensity of cooperation and information sharing, which indicates the level of social capital and trust in a cluster. Giuliani & Pietrobelli (2011) argues that the methods for evaluating clusters by studying their network-properties are still in their infancy. One reason might be that there is no clear consensus on how to measure the connectivity and other insightful properties of a regional cluster's network structure accurately and unbiasedly. In addition, as research suggest that regional clusters are not self-sufficient with regard to the knowledge they draw upon (Gertler & Wolfe, 2004), research might benefit from examining in greater detail how regional clusters are embedded in a larger ecosystem, and how the degree of connectedness to this external environment might affect local innovation in a regional cluster (see for example, Turkina & Van Assche, 2018).

The purpose of this thesis is to add to these gaps in the literature, by studying the structural network characteristics of a regional cluster through the lens of *social network analysis (SNA)*. More specifically, we map and analyse the structural properties of the networks of a regional cluster to study i) how it differs from the network characteristics of the broader ecosystem-network which it is nested, ii) how it corresponds to network characteristics that prior research has highlighted as beneficial/detrimental for innovation, and iii) how influence is distributed among the regional cluster members.

Our empirical setting is the Norwegian fintech ecosystem, and the regional cluster NCE Finance Innovation (NCE FI) that was established in Bergen in 2017. To collect our data, we distributed a survey to 104 Norwegian fintech firms where we asked them to list their most important relations within different relational categories. From this, we generated a rich network of the Norwegian fintech ecosystem, which encompassed both firms within and outside of NCE FI. During our analysis, we analysed the structural characteristics of the network of the members of NCE FI, referred to in this thesis as the *regional cluster network*, and compared and contrasted it with the larger network that also encompassed firms that were not formal members of this regional cluster, referred to as the *organic network.* The combined relations in both networks is referred to as the *maximum network.*

To map and analyse these networks, we used the graph-theoretical toolkit known as social network analysis. We use SNA because it can be a valuable tool for analysing and evaluating regional clusters as it exposes detailed information about a cluster's network that through conventional methods would otherwise remain invisible. SNA can provide profound insights into a network's properties affecting its ability to innovate, such as the distribution of influence and power, critical roles, and how efficient information flows.

Several interesting results emerged from our analysis. We found that most of the regional cluster members' important relations exist with actors outside the boundary of the regional cluster, indicating a broad Norwegian fintech ecosystem. We found that these boundary spanning relations might be beneficial for the regional cluster's ability to innovate by enabling access to diverse, non-redundant knowledge from its outside environment. From studying the structural characteristics of the regional cluster's network and comparing it with the organic network, we found that the regional cluster shows potential for efficient flow of information between the actors, but that it might benefit from strengthening relations within the network, which could create an environment of potentially more trustful relations, better suited to combine and take advantage of novel ideas stemming from the external environment. In addition, we found that the regional cluster network exhibits properties of a hierarchical network where a few actors are highly central and influential compared to the rest of the cluster members. These actors, mostly consisting of traditional financial institutions and consulting firms are seemingly vital to the network as they facilitate the flow of information to the less central actors. These few, highly central actors may constitute a significant vulnerability, as their absence could fragment the network into unconnected subgroups, limiting the flow of knowledge across the network. Our findings also suggest that the most influential actors subjectively perceive that they attain more innovative capabilities from being embedded in the regional cluster than less influential actors.

We believe our thesis contributes to both research and practice. For research, we make at least three contributions. First, our findings suggest that social network analysis can be a useful tool for researchers as it enables deeper insights into the structural characteristics of regional clusters and allows for detailed analysis of the implications of these structural characteristics. Moreover, our findings support existing research by suggesting that regional clusters are not isolated systems disconnected from their external environment, and that the way a regional cluster is embedded in the larger ecosystem might matter for its ability to facilitate innovation locally. Furthermore, our findings suggest that the attributes of the cluster members could matter in terms of how relations form in a regional cluster, and therefore that the resources held inside firms could be important for explaining and predicting an actor's level of connectedness and influence in a regional cluster.

For practice, the insights from this thesis can be used by facilitators and policymakers, to evaluate and potentially steer a regional cluster's development trajectory by applying efficient mechanisms, incentives and policies that facilitate favourable alterations of a regional cluster's network structures.

2. Literary review

This chapter presents important themes in research on networks, regional clusters, and social network analysis. In the first part, we introduce early research on networks as distinct social forms of economic action. Next, the phenomena of regional clusters, its definitions, advantages, and limitations will be explained. Consecutively, basic assumptions and central aspects of social network analysis will be presented. Finally, research on the impacts of various network structures and actors' positioning in networks will be explained, before five propositions of what we expect to find from our analysis will be presented.

2.1 Early research on networks

Research on organizational networks can be traced back to Granovetter (1985) who studied social embeddedness of economic action, where he emphasized the importance of social ties that organizations use to manage their mutual dependencies. Organizations jointly navigate their environments containing interdependencies across markets, resources or technologies that are, at least partly, under control of other organizations (Astley & Fombrun, 1983). Organizations can thereby improve their performance by interacting with other organizations that have complementary resources, technologies, or market access (Shipilov & Gawer, 2020).

Early network researchers were interested in explaining how interorganizational interdependencies are managed within formal relationships, such as alliances and joint ventures. Importantly, they found that beneath these formal relationships there are a variety of informal coordinating mechanisms such as trust, reciprocity, fine grained information transfer and joint problem-solving arrangements (Granovetter, 1985; Uzzi, 1996). Granovetter (1985) argued that transaction costs could be kept to a minimum as the social relations in a network would monitor and sanction opportunistic behaviour.

The work of Handel & Powell (2003) helped develop the concept of "network form" and argued that interfirm cooperation generates incentives for mutual learning, trust, reciprocity, and the spreading of information among independent organizations. In the complex array of economic relations that exist today, the exchange of commodities whose value cannot be easily measured such as know-how, knowledge, innovation, and technological capabilities are more likely to take place in networks than in markets. In addition, networks are especially suitable for dynamic environments where competition is based on factors such as the ability to innovate and translate ideas to new products quickly, and where there is a need for efficient, reliable information (Handel & Powell, 2003).

The term "innovation" is complex and holds many definitions, but a practical and simple definition is "the introduction of new things, ideas or ways of doing something" (Oxford University Press, 2020). Innovation can be further divided into a variety of subcategories, such as process innovation (e.g., finding novel ways to improve production processes), product innovation (e.g., development of a new product), incremental innovation (e.g., gradual improvements on existing products), and radical innovation (e.g., revolutionary technological breakthroughs).

One reason why networks have shown to have a positive effect on innovation might be explained by the fast growing offering of services in our economy (Gausdal, 2008). Research has shown that process innovation is, to a larger degree than product innovation, dependent on abstract, tacit and context dependent knowledge (Newell, Robertson, Scarbrough, & Swan, 2002) Because this type of knowledge can only be shared through interaction, the development of social relations and participation in social networks proves to have a positive effect on innovation (Hansen, Nohira, & Tierney, 1999).

2.2 Regional clusters

Insights from early research on networks such as the works of Handel & Powell (1990) and Granovetter (1985) can perhaps to some degree explain the growth and success of regional clusters, which in recent years have been appearing in dynamic, technology- intensive environments where innovation among the embedded firms to a large extent depend on their ability to use external knowledge. As such, regional clusters have gained much popularity both in theory and practice due to the realization that in modern economies, firms embedded in social systems where relations are based on trust, mutual learning, and joint problem-solving, attain benefits isolated firms do not.

Following Porter (1998), a regional cluster can be defined as a "geographic concentration of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities" (Rocha, 2004; Wennberg & Lindqvist, 2010). The term "interconnected" suggests that clusters can be viewed as geographically limited networks, containing various types of entities that have some form of relation with one another. However, there is no single definition of a regional cluster, as the concept can be a subject of multiple interpretations (Martin & Sunley, 2003). Regional clusters are for example often characterised as *regional networks,* which underpins the premise that *network* is an inherent part of the concept.

Many empirical studies have shown that regional clusters are efficient in promoting entrepreneurship, innovation, and job creation (Delgado, Porter, & Stern, 2014). According to Rosenfeld (1997)**,** being in close proximity to suppliers, complementors, customers, and competitors reduces transaction costs, makes it easier to resolve problems efficiently, and increases early learning about innovative technologies and practices. Firms co-located with similar and related companies also provide the advantage of boosting collective learning processes through frequent opportunities for formal and informal exchanges (Maskell & Malmberg, 1999). Porter (1998) argued that geographical proximity makes repeated personal interaction easier, which in turn increases trustful relations which facilitates the flow of tacit knowledge. Trust is, according to (Lorenz, 1996), essential for innovative collaboration.

Research also illuminates the difficulties and potential pitfalls of embeddedness in networks such as regional clusters. Some argue that participation in regional clusters is time consuming and that many are of symbolic character, without particular activities or content (Inkpen, 1996). Others focus on the pitfalls of strong relations due to increased demand on resources, and potential "lock-in" effects that hinder inflow of new information (Grabher, 1993). Research also indicates that even though the potential for learning in networks is significant, it is difficult to predict the outcome or "rewards" of investing in networks (Lawson & Lorenz, 1999). Moreover, regional clusters as social systems can be designed or organically developed, and research indicates that organic networks are more robust and better at promoting innovation than externally designed networks (Checkland, 1999; Gausdal, 2008).

Since the 1990's, interest in the development and improvement of regional clusters has gained significant traction in policy making as a means to stimulate economic growth. Many cluster initiatives involve collaboration between private and public actors and involve a broad range of activities such as institutional building, supply chain development, strengthening key organizations, and providing infrastructure facilities. Creating and strengthening networks, however, seems to be a common factor in many cluster initiatives (Giuliani & Pietrobelli, 2011). Porter (2000) argues that regional clusters' interfirm relations are more important to productivity growth than the characteristics of the individual firms. He also states that the mere presence of a cluster does not guarantee functioning relations, as many of a cluster's benefits are based on personal relationships that facilitate relations, foster open communication, and build trust. Therefore, facilitators must ensure efficient and regular communication. Rosenfeld (1997) argues that an important, but often dismissed factor in explaining a cluster's success is the "current", or the flow of information, innovations, and technological knowledge. He therefore states that initiatives seeking to improve the productivity of regional clusters should focus on understanding the often intangible mechanisms by which information, capital and innovation move through the system, as it can enable governments and facilitators to remove bottlenecks and improve flows.

Despite considerable research on the advantages and limitations of regional clusters, and how to improve their productivity, much research lacks analytical methods for acquiring detailed knowledge on the nature and strength of the interfirm relations. In addition, there is limited research on how such detailed insights can contribute to the understanding of potential limitations to innovation in regional clusters and embedded firms (see for example, de Man & Duysters, 2005; Santamaría & Nieto, 2007; Schilling & Phelps, 2007). According to Amara and Landry (2005), understanding the impact of networks remains an under-researched topic, such as what type of networks favour innovation. Moreover, even though cluster policies have put great emphasis on networks as a way of stimulating learning and innovation, there is a lack of analytical emphasis in the approach of studying their impacts (Giuliani & Pietrobelli, 2011). One reason might be that there is a lack of knowledge on how to measure connectivity other than through loose and irregular indicators. For example, some might consider the mere participation in a regional cluster as a networking process, without taking into consideration the nature and strength of the existing relations (Aragón et al., 2009).

Based on the above, an objective, analytical tool which can be used to analyse and evaluate the nature and strength of relations between actors in a regional cluster can therefore provide important insights that can potentially enrich research on clusters. The next section will present basic assumptions and central aspects of social network analysis, to more fully understand how it can be applied to study interfirm relations in a regional cluster.

2.3 Social Network Analysis

Social network analysis can be described as a graph-theoretic toolkit which is used to analyse the patterns and implications of social relations which exists among various entities (Wasserman & Faust, 1994). Graph theory is a mathematical discipline that arose in the 18th century and has been applied by social science since the start of the 20th century (Newman, 2003). Researchers argue that SNA is not a formal theory, but an analytical tool or methodology, used for mapping and measuring relationships among social entities, such as individuals, organizations, or other social units (Marin & Wellman, 2010). Based on graph theory's mathematical applications, SNA enables relationships to be represented and described systematically and compactly (Scott, 2013; Hanneman & Riddle, 2005) and can be compared to an "organizational X-ray"-tool, as it illuminates aspects of a network which other methodologies cannot (Serrat, 2009). SNA uses empirical data together with computational models to identify, and often visualize, influential actors, communities and flows of information in a network, among many other tasks. According to Mohr (2014), SNA metrics provide an unbiased way of interpreting relationships. This can be considered a significant strength of SNA, as it can provide precise objective measures which makes it an applicable tool for researchers studying networks.

To understand how SNA can be used as a tool to acquire deeper insights into interfirm relations within a regional cluster one must first get a grip of the basic assumptions of social networks. Social networks, or sometimes just networks, can be defined as "a set of nodes that are tied by one or more types of relations" (Wasserman and Faust, 1994). *Nodes*, or network actors, are the units that are connected by the patterns we study (Marin & Wellman, 2010). Most often, the nodes we study are persons or organizations, but in principle nodes can be any unit that can be connected to other units, such as web pages, countries, and firm-departments. The relations, in SNA called *ties* or *edges,* linking these nodes together, can be in the form of collaboration, friendship, information flow, or any other possible connection (Wasserman and Faust, 1994). SNA's defining feature is its focus on the structure and strength of the relationships or bonds that bind these nodes together. Ties can therefore be *weighted*, meaning that the relations in a network differ in terms of intensity or strength, which can provide deeper insights into the relations of interest. Importantly, ties in a network interconnect through shared endpoints that also indirectly link nodes that are not directly connected. The pattern of ties in a network therefore creates a particular structure which can, when analysed, yield insights into strengths and weaknesses of a network in different contexts (Borgatti & Halgin, 2011).

Central aspects in social network analysis

Social networks play a critical role as a means of spreading information, ideas, resources, and influence among members (Kempe, Kleinberg, & Tardos, 2003; Lea, Yu, Maguluru, & Nichols, 2006). Essential assumptions of research on social networks are 1) that exchange is embedded in social relations and complex social structures, 2) that relationships do not occur in isolation, and 3) that relationships matter in terms of outcomes at both actor and group levels (Kilduff & Brass, 2010; Kurt & Kurt, 2020).

One important principle of social network analysis is that environments, attributes, or circumstances do not affect actors independently. Social network analysts propose that causation is not solely located in the individual, but in the social structure (Marin & Wellman, 2010). According to Marin and Wellman (2010), "*SNA's essential premise is that the social world and actors within it are created and shaped by relationships and patterns formed by these relationships*". It perceives the social world in terms of interactions, rather than the aggregation of entities acting independently, and the patterns of these relations are the units of analysis (Kurt & Kurt, 2020). In other words, SNA assumes that the relationships of interacting actors are essential to explain their nature, behaviour, and outputs (Giuliani & Pietrobelli, 2011). This is the foundation of *network theory,* which refers to the processes and mechanisms that interact with network structures to produce certain outcomes for individuals or groups. Important contributors to network theory are Granovetter (1973), who found that weak ties were important as they provide access to novel resources, and Burt (1992) who argued that individuals hold certain positional advantages or disadvantages from how they are embedded in social structures. These perspectives are fundamentally different from individualist and attribute-based methodologies often used to describe an actor's behaviour and outcomes. Thus, and importantly for this thesis, we assume that the nature and structure of the relations between organizations, such as actors in a regional cluster, matter in terms of behaviour and outcome. Accordingly, the focus for this thesis is not on the specific firm's skills and characteristics as the source of their ability to innovate, but on the idea that innovation is a result of the effectiveness in which firms can gain access to external sources of assets such as knowledge and valuable information (Kline & Rosenberg, 1986; Kogut, 1988).

Another important aspect of SNA deals with how to measure the different properties of networks. This is called *network measurement* and relies on mathematical representation of network concepts. Measures in SNA are the metrics in which networks and the actors in it can be assessed and compared. This allows analysts to provide more precise representations of social science concepts such as “power”, “influence” or “strength of connection”. This makes it possible to predict for example why some organizations are successful, and others are not. Some of the most common and useful measures which have been used in our analysis will be presented in the following section.

2.4 Measuring the properties of a network

This section will investigate how SNA can provide detailed insights into a network’s structural properties and positioning of individual actors. More specifically, we will discuss why it can be beneficial to unravel the structure of a network and actors’ positions in these networks, and how this can be achieved by applying distinct analytical network measures. One can use SNA to measure network properties at multiple levels of analysis. To start, the focus will be on measuring properties applicable to the network as a whole. Subsequently, measures related to the properties of the individual actors at the node level of analysis will be presented.

2.4.1 Implications from how a network is structured

An important insight from Newman (2003) is that real networks are non-random, meaning that there are possible mechanisms that could be guiding the formation of networks, and therefore that one can exploit the network structure to achieve certain aims. The non-randomness also implies that the structure reflects an actor’s strategies and purposeful choices, meaning that the structure of the network depends on the individual’s choice of whom to connect with. However, one can assume that most actors in networks most likely have little knowledge on how their choices of connectivity affect the global network structure (Watts, 2004; Giuliani & Pietrobelli, 2011).

This makes the study of the entire structure important for analysts of networks, as this for example allows them to identify which actors that are most likely to generate disrupting effects to the network. Before we identify strengths and weaknesses of common types of network structures, we will first introduce some of the most commonly used and robust measures used to quantify important aspects of networks.

Network Density

The *density* of a network is defined as the number of existing ties relative to the number of potential ties between any two pairs of nodes. This measure can vary from 0 to 1, and a completely dense network implies that each node in the network has a relation to all other nodes. This measure provides insight into how connected the network actually is, in comparison to how connected it could potentially be. Analysts studying regional clusters often rely on the network density-measure as the primary indicator of the cluster's health and functionality. There is, however, a common misunderstanding that sparsely connected networks necessarily are weak and non-functioning, and vice versa. As such, one might overlook that different network structures can reveal different types of collective advantages and disadvantages of the network of interest (Giuliani & Pietrobelli, 2011).

The calculation of density differs for undirected and directed networks. In undirected networks, the tie between two nodes has no particular direction. This means that a tie from fintech actor i to j in a network is considered the same as the tie from j to i (Scott, 2000). Thus, the calculation of total possible ties for an undirected network is half of the total number of possible ties, $n(n-1)/2$, where n is the number of nodes in the network (Wasserman & Faust, 1994). The formula for network density in undirected networks, where l is the number of existing ties is:

$$(1)\ \ Density(undirected\ network) = \frac{l}{n(n-1)/2}$$

For directed networks however, the direction of the tie is taken into consideration and visualized in graph networks with an arrow pointing from the source node to the target node, indicating the direction of the relationship. The total number of possible ties in directed networks is therefore $n(n-1)$. The formula for network density in a directed network is:

$$(2)\ \ Density(directed\ network) = \frac{l}{n(n-1)}$$

Average path length

Average path length is defined as the average number of steps across the shortest paths for all possible pairs of network nodes (Barabasi & Albert, 1999). In large networks, most nodes are linked together indirectly, requiring information to flow through intermediaries in order to reach another node. This measure is insightful for analysis of networks, as it indicates the distance information must flow in average in order to reach any node in the network. The more actors that can be reached by any path from a given actor, the more knowledge that firm can potentially access (Schilling & Phelps, 2007). According to Watts (1999) the diffusion of information and knowledge happens faster and with more integrity in networks with short average path lengths. Therefore, average path length is an indication of the network's efficiency of information-flow, as a large number of firms can reach more information quickly and with less risk of information distortion. The calculation of average path length in a network is the following:

$$(3)\ Average\ path\ length = \frac{1}{n(n-1)} * \sum_{i \neq j} d_{ij}$$

The number of nodes in the network is represented by n. The shortest path between node i and j is denoted by d_{ij}.

Clustering coefficient

The clustering coefficient is a measure of the tendency of nodes in a network to cluster together (Jackson, 2008). The global version gives an overall indication of the clustering in the network, while the local version indicates the embeddedness of individual nodes. A firm's clustering coefficient can be computed as the proportion of its connections that are themselves directly linked to each other. A relatively high global value indicates that actors in a network are connected well locally, meaning that the network has dense subgroups. Having information on the degree of clustering in a network is valuable as high clustering signals a higher information transmission capacity of the network, as information introduced in a cluster will quickly reach other firms in the cluster. As there are many pathways this information can flow in a dense subgroup, the fidelity of information increases as firms can compare the piece of information from multiple partners (Schilling & Phelps, 2007). High local connectivity is important for the emergence of trustful relations and reciprocity norms, which in turn increase the flow of high-quality knowledge, such as tacit and proprietary knowledge (Giuliani & Pietrobelli, 2011). Networks characterised by having a high global clustering coefficient can make firms more willing and able to share information (Ahuja, 2000) which can lead to more effective joint problem- solving and the reduction of transaction costs. The reason being that this type of network has a strong implicit governing mechanism as the dense subgroups reduces both information asymmetries and uncertainty in the interaction between two actors (Coleman, 1988).

The calculation of the global clustering coefficient is based on triplets of nodes, where a triplet is formed by three connected nodes (Jackson, 2008). In an open triplet, three nodes are connected by two ties, while in a closed triplet the nodes are connected by three ties. The global clustering coefficient for a network can be calculated by dividing the number of closed triplets over the number of all triplets (open and closed). The formula for undirected networks is the following:

$$(4)\ \ Global\ clustering\ coefficient\ = \frac{\sum_{i;\ j\neq i;k\neq j;k\neq i} g_{ij}g_{ik}g_{jk}}{\sum_{i;j\neq i;k\neq j;k\neq i} g_{ij}g_{ik})}$$

Where two edges, such as (i, j) and (i, k), from the same node i examines the frequency of how often (j, k) also is represented in the network (Jackson, 2008).

Characteristics of common network structures

Identifying similarities and differences to structural properties found in many real-world networks can give useful indications of the strengths and vulnerabilities of the network being analysed.

Cliques

One of the most common interests of network analysis is identifying subgroups of actors that show higher average connectivity to each other than with the rest of the network's actors. This phenomenon is often referred to as *cohesive subgroups* or *cliques* (Giuliani & Pietrobelli, 2011). According to Wasserman and Faust (1994) cliques have relatively strong, intense, frequent or positive ties. Cliques are defined by Luce and Perry (1949) as "groups of at least three actors that are all connected to each other". This means that they create a dense substructure of the network where all actors are connected to each other. The local clustering coefficient, as mentioned in the previous paragraph, is closely related to the concept of cliques as it quantifies how close a node's neighbours are to being a clique.

Networks that are characterised by cliquish substructures can, given high local connectivity, be expected to show the same benefits as networks having a high global clustering coefficient. Thus, the advantages of cliques are that they facilitate a cooperative environment, where social monitoring, trust and resource sharing are likely to emerge**,** creating an environment for innovation. In addition**,** cliques are by definition non-hierarchical networks where resources are distributed in an egalitarian way. Zaheer and Bell (2005) found that actors who have dense connections to their alters acquire more innovative capabilities, because it deepens their understanding of a particular innovation. Alters are the nodes whom the focal node is directly connected to, often referred to as the focal node's neighbourhood. On the downside, too closely embedded firms can be detrimental to a firm's innovative capabilities, because the too strong internal cohesion can cause the information and knowledge shared to become homogenous and redundant (Burt, 1992; Granovetter, 1973). The actors can get "trapped in their own net" (Gargiulo & Benassi, 2000) because of relational inertia. This means that the firm's relations over time will get too sticky, leading the firm to only rely on information from its trusted alters, therefore generating a risk of negative technological "lock-in". This will, in turn inhibit innovation performance (Giuliani, 2008).

Identifying cliques is also an important part of understanding how the network as a whole is likely to behave. In a network where the cliques overlap, one can expect that information occurring locally spread over the entire network. However, when they do not overlap, emergent knowledge and innovation taking place in one part of the network may not diffuse into other parts of the network. In addition, Giuliani & Pietrobelli (2011) points out that completely cohesive networks rarely occur in the real world. Most networks are fragmented and often formed by many smaller and non-overlapping cliquish structures. Identifying cliques can thereby predict both opportunities and constraints for different groups of actors, and for the network as a whole.

Small-world

Small-world networks are characterised by local cliques connected to each other by sparse or weak ties. The famous Harvard experiment of "small-world", often known as "six degrees of separation", conducted by Stanley Milgram in the late 1960's was further developed by Watts and Strogatz (1998) into a mathematical model for describing large networks with small-world properties. The model's core properties are high local density, meaning that the neighbours are densely connected to each other, and that there are few connections with other distant actors, implying that the ties connect different cliques to each other. Small-world structures are often characterised by having a high global clustering coefficient and short average path length (Giuliani & Pietrobelli, 2011).

Despite the overall low density of ties, these networks are efficient because actors are linked to each other by a relatively small number of intermediaries, lowering the distance the information has to flow to get to actors. Baum et.al (2003) states that small-worlds are efficient "in moving information, innovations, routines, experience and other resources that enable learning, adaptation and competitive advantage". Another benefit is the high level of local trust, cooperative environment, mental models and shared consensus enabled by the high density of local cliques. Furthermore, it ensures that local cohesive groups are not isolated, but connected to distant actors through a few local clique-members. Baum et. al (2003) propose that business organizations strategically and deliberately form distant ties in search of competitive advantage. This structure is nonetheless highly dependent on the brokers between local and distant cliques, and thus constituting a vulnerability if these actors were to leave the network (Giuliani & Pietrobelli, 2011).

Core-periphery

Another type of network structure is *core-peripher*y, which is composed of a tightly connected core, such as a dense, cohesive subgroup, and peripheral group of actors that is poorly connected to the dense core and each other (Borgatti & Everett, 1999). The core actors have the advantage of being part of a central group and can sometimes constitute an "elite" as opposed to the peripheral actors. This structure can be identified by visually inspecting the network and seeing if the most connected actors are located in the core of the network.

Research on wine clusters in Chile has shown that in such networks, only the actors that were a part of the core had a high absorptive capacity, while the peripheral actors were only marginally included in the knowledge generating networks, indicating that their position was hampering their innovation and learning capabilities (Giuliani & Bell, 2005). This hierarchical type of network may generate and sustain a divide between network actors, and can in a regional cluster-context, thus hamper the overall productivity and long-term vitality of the network.

Scale-free

The network structure known as *scale-free* networks is inherently hierarchical and has been found to represent many real-world networks (Barabasi & Albert, 1999). It is called scale-free because the distribution of the number of direct contacts an actor in this network has, i.e., the degree centrality distribution, is right skewed with a heavy tail. This means that the majority of actors have a low average degree of connection, and that a small fraction of actors has many times the connections than what is average (Giuliani & Pietrobelli, 2011). These heavily connected actors are usually called "hubs". The suggested mechanisms creating these kinds of networks are population growth and *preferential attachment* (de Solla Price, 1976). As actors join the network, it grows, and the mechanism of preferential attachments means that new actors are more likely to form connections with actors that are already well connected. This can be explained by the fact that new actors usually lack information about which actors to connect to. Gould (2002) explains that thorough quality judgements are costly, and new entrants will therefore tend to connect to highly reputable actors. Actors generate a favourable reputation as they accumulate a critical mass of linkages, leading to them being targeted by most of the new entrants in the network, subsequently fortifying their centrality over time. Real life scale-free networks are typically found in industrial clusters, where a few large vertically integrated firms surrounded by suppliers dominate and orchestrate the value chain. These networks are characterised by polarization of power and having an uneven and highly concentrated distribution of resources. These types of networks can also be characterized as being highly centralized, where the network is dominated by one or few central nodes. Such networks are particularly vulnerable for attack to these hubs, as their departure from the network can lead to the network being fragmented into unconnected subnetworks, which will obstruct the flow of information in the network (Giuliani & Pietrobelli, 2011).

Propositions for the regional cluster networks' structural characteristics

Based on the above discussions, we showed how social network analysis can be a viable toolset which can be used to study the structural dynamics of regional clusters. In particular, we showed how SNA can be used to map structural features of a network such as density, average path length and clustering coefficient. Our theorizing also showed that the emergence and development of regional clusters often are politically motivated and involve initiatives such as institutional building and strengthening relations between actors. This might be distinctively different from situations where interfirm relationships emerge more organically between actors in a broad ecosystem through the everyday competition and cooperation between market actors such as providers, competitors, and customers. From this, it seems plausible that the underlying structural characteristics of the interfirm network between members of a regional cluster might differ from the network within a broader ecosystem that develops more organically.

Our theorizing showed that regional clusters usually involve co-located companies, facilitating frequent interactions, trustful relations, and efficient flow of knowledge between the cluster members. Based on this, we can expect the members of NCE FI to be highly connected between each other, and that trustful relations are facilitated by firms clustering together in subgroups, which increases the efficiency- and reduces the distance information has to flow to reach any cluster member, compared to these members relations in the more organically developed network. Transferred to a network setting, this means that the network of NCE Finance Innovation should be well connected, and have a) higher density, b) higher global clustering, c) more cliques, and d) lower average path length than the organic network. This leads to our first proposition:

Proposition 1: The regional cluster network has a higher density, higher global clustering coefficient, more cliques, and a lower average path length, compared to the organic network.

Furthermore, our presented theory proposes that repeated personal interaction which facilities trustful relations, can yield benefits such as reduced transaction costs, easier problem solving and increased learning capabilities for the actors embedded in a regional cluster. Therefore, we expect that the cluster members' most important relations to a large extent are located within the regional cluster. This means that the relations between the cluster members should be highly visible in the more organically developed networks.

From a network perspective this means that a) we expect to see the cluster members of NCE FI densely connected in the core of the organic network, and b) that the organic network does not deviate significantly from the maximum network, which consists of all the relations in both the organic and regional cluster network. This leads to our second proposition:

Proposition 2: The regional cluster members are densely connected and at the core of both the organic network and the maximum network.

Moreover, based on the literature describing common properties found in real networks, we expect that the regional cluster exhibits properties of a scale-free network where there are a few actors, or hubs, that are highly connected and facilitate much of the network's information flow. This has been shown to characterize industrial clusters and could apply in a fintech context as well. The reason being that there are a few actors, such as the larger traditional banks and consultancies, which have significantly more resources than most of the actors in the regional cluster. We therefore assume that these firms might have a greater ability to create and maintain relations in the regional cluster, and therefore that they will be much more connected compared to most other firms. This leads to our third proposition:

Proposition 3: The regional cluster network shows characteristics of a scale-free network.

2.4.2 Implications of positioning in networks

In addition to the proposed beneficial insights from studying the structure of the network, uncovering how the individual actors are positioned in a network can yield important insights both for the individual firms and the network as a whole. Because networks implicitly or explicitly represent a flow of resources such as information or influence, identifying the specific actors that can potentially facilitate, obstruct, or otherwise broker this flow can give indications of vulnerabilities or "weak spots" in the overall structure of the network. Depending on the nature and characteristics of an actor's connections, the position of an actor can thereby indicate the distribution of power, influence, and control of resources in a network (Giuliani & Pietrobelli, 2011).

According to Lauman and Pappi (1976) and Freeman (1979), central actors are considered to be in advantageous positions relative to less central actors. With regards to communication and information access, this seems intuitive. The more central the firm, the higher the number of direct ties with other firms in the network, thus increasing the firm's opportunities for learning and acquiring skills and experience. Firms with multiple information sources will additionally be less likely to miss vital information (Giuliani & Bell, 2005). An important insight is however, that too many connections can overload an actor in terms of redundant information, which can in itself be costly. The fact that building and maintaining relationships takes time and resources means that redundant connections will incur the opportunity cost of time invested in other value-creating activities (Giuliani & Pietrobelli, 2011).

There are many ways to measure an actor's connectedness and influence, and we will in the following first present four common and useful measures of centrality: *degree centrality, out-degree centrality, in-degree centrality*, and *betweenness centrality.* Subsequently, we will discuss how it can be beneficial to identify actors that occupy *structural holes* by applying a measure called *Burt's constraint score.*

Degree Centrality

The most basic and intuitive way to measure centrality is by counting the number of direct ties each node has, called the degree centrality. This measure can be used to find actors who are very connected and can quickly connect with the wider network. Actors with high degree centrality have easier access to information, knowledge, and resources in the network, than actors with low degree centrality (Giuliani & Pietrobelli, 2011). In directed networks, it can also be useful to know if the direct connections lead out of (out-degree) or into the node (in-degree). This can provide more intricate information on the node's importance given the nature and direction of its ties. For example, people with high out-degree centrality can be perceived sociable, while people with high in-degree centrality can be perceived as being popular. Degree centrality is given by the number of ties a node v has to another actor in the network, denoted as $deg(v)$:

$$(5)\ Degree\ centrality\ =\ deg(v)$$

Out-degree and in-degree centrality can only be measured for directed networks. Out-degree centrality, denoted as $deg(v)$, is the number of outgoing ties which originates from the node v. In-degree, on the other hand measures the number of direct ties which leads into the node, denoted by $deg(v)$ (Giuliani & Pietrobelli, 2011; Freeman, 1979).

Betweenness centrality

Betweenness centrality is the degree to which an actor can connect others that would otherwise be disconnected. It is measured by quantifying the number of times a node acts as a bridge along the shortest path between two other nodes. This type of centrality is synonymous with control over the flow of assets or resources between actors, meaning that they are actors "on whom others are locally dependent to get access to resources and assets are central in the network" (Wasserman & Faust, 1994). Actors with a high degree of this type of centrality can often be viewed as having the role of gatekeepers having high influence and control of the flow of resources. When analysing a business network, identifying these actors is useful as their power is related to them being essential to the network as a whole. The reason being that their absence is likely to have disruptive effects, as it could split the network into unconnected subnetworks, thus hindering the flow of information or resources across the entire network. This implies that if there are only a few actors with high betweenness centrality, it may disrupt the network causing a vulnerability risk (Giuliani & Pietrobelli, 2011). The formula for betweenness centrality is the following:

$$(6)\ Betweenness\ centrality\ =\sum_{s\neq v\neq t}\frac{\sigma_{st}(v)}{\sigma_{st}}$$

The total number of shortest paths between node s to node t is represented by σ_{st}. The number of the shortest paths that goes through v is $\sigma_{st}(v)$.

Structural holes

Researchers have in some cases argued that creative ideas and radical innovation is better generated by informational diversity (Laursen & Salter, 2006). This diversity is achieved when an actor's direct connections are themselves not densely connected to each other, implying that there is a "hole" in the network structure. The theory of Structural holes developed by Burt (1992) explains how an actor can benefit from being in a position where the actor's neighbours are not, or poorly, connected to each other. The theory argues that opinions and behaviour are more homogeneous within, than between groups, so people located in the intersection of multiple groups will be familiar with alternative ways of thinking and behaving, thus increasing their innovative capabilities (Burt, 2004). In addition, actors positioned on structural holes act as brokers between two disconnected actors and get strategic benefits such as control and access to new information. Actors that fill structural holes can therefore, due to their structural position, often be viewed as attractive relations by other actors. Identifying actors on structural holes yield insights for analysts of regional clusters as these actors have access to potentially unique and more diverse knowledge which can enhance the firm's, and therefore indirectly the regional cluster's exploitation of new ideas and the development of radical innovations (Ahuja, 2000; Rowley, Behrens, & Krackhardt, 2000; McEvily & Zaheer, 1999; Zaheer & Bell, 2005). In addition, these actors are crucial for the flow of valuable information in a network, as they act as gatekeepers between groups of actors that would otherwise be disconnected.

A commonly used measure of structural holes is Burt's constraint (Burt, 2004), which measures how much the actor's neighbours are also connected among themselves. This implies that the larger the constraint score, the less structural opportunities a node has for bridging structural holes. Subsequently, actors with lower scores are not as constrained by its connections, enabling the node to get access to new information outside a cohesive group. Burt's constraint score (BCS) varies from 0 to 1 and the formula consists of two components which tells if node i's time, resource and energy (weight) is spent directly (p_{ij}), and indirectly ($\sum_q p_{iq}p_{qj}$) on j (Labun & Wittek, 2014). The direct component p_{ij} represent the proportion of tie weight from i to j. The indirect component consists of an indirect path between node i, j and q, where the amount of indirect time, resource and energy is the product of the proportion of edge weights between i to q, and q to j. The formula for Burt's constraint is:

$$(7)\ \ Burt's\ constraint\ score = \Big(p_{ij} + \sum_q p_{iq}p_{qj}\Big)^2, i \neq q \neq j$$

Propositions for how the regional cluster members are positioned

The theory presented above explains how different measures of centrality can provide insights into how the embedded actors' positioning in a network can say something about their influence, access to information, and control of resource flow. We expect that in most real networks, the more mature and sizable firms in terms of for example number departments and employees, will have resources which can enable them to form and maintain more relations, than smaller, more nascent firms. As suggested in proposition three, we therefore expect that traditional financial institutions occupy more influential positions in the regional cluster network, compared to other types of actors, and therefore that these actors a) will be highly central in the networks with regards to the presented centrality measures, and b) to a larger degree occupy structural holes by having on average a lower Burt's constraint score. This leads to our fourth proposition:

> **Proposition 4:** Traditional financial institutions have on average the highest degree-, in-degree- and out-degree centralities, and the lowest Burt's constraint scores in the regional cluster network.

Finally, we expect there to be a positive relation between how connected firms are in a regional cluster, and their perceived innovative ability from cluster membership. The reason being that the more central actors should, to a higher degree than less connected actors, be able to gain access to knowledge and valuable information in the regional cluster, which the presented theory suggests enhances their ability to innovate. Because of this, we expect that actors that perceive many cluster members as important relations is an indication that these firms have a greater ability to take advantage of external knowledge, and therefore find their membership to be important for their ability to innovate. In addition, we expect that actors that to a large degree act as bridges between otherwise disconnected actors, and therefore have high influence and control of resources in the network, should perceive membership in the cluster as more important for their ability to innovate, than other actors. Based on these expectations, we present our fifth proposition:

> **Proposition 5:** Regional cluster members with high out-degree centrality and betweenness centrality find their membership in the regional cluster to be more important for their ability to innovate within fintech than members who have a lower score on these measures.

3. Data collection and Methodology

This section will first present this thesis' research context, namely the Norwegian fintech ecosystem. Second, a thorough review of the assumptions and choices we made regarding how we collected our network data, based on fundamental methodological principles of data collection within network analysis will be accounted for. Third, a detailed description of the survey design- and distribution will be presented. Thereafter, we will discuss some ethical considerations regarding our data collection approach, and the validity of the collected data. Lastly, this section elaborates on the methods we have used to prepare and analyse our data.

3.1 Research context: The Norwegian fintech ecosystem

The financial industry has traditionally seen low levels of innovation and use of patent filing (Beck, Chen, Lin, & Song, 2016). In the age of the digital economy however, there are opportunities for nascent firms to innovate and challenge firmly established incumbents. This applies to a large extent to the financial industry, where fintech start-ups has increasingly gained a foothold with new user-friendly and innovative financial services (Arner, Barberis, & Buckley, 2016; Hornuf & Haddad, 2019). According to Knudsen and Bienz (2019) this recent disruptive development is closely linked to "changes in regulations, increased digitization, the emergence of alternative sources of financing, changing customer preferences, and so on". As a result, the fintech sector, and fintech start-ups especially, have received significant investments globally in the last few years (Rubini, 2019).

The term "fintech" represents the intersection between finance and technology in the bank- and finance industry and involves a transformation of the industry by cutting costs and improving quality of service delivery (Castro et al., 2020; Frame et al., 2018). Fintech holds many definitions, and Financial Stability Board's (FSB) (2020) describes fintech as

"technologically enabled innovation in financial services that could result in new business models, applications, processes or products with an associated material effect on financial markets and institutions and the provision of financial services." (Financial Stability Board (FSB), 2020).

Rubini (2019) argues that government support, a developed culture of innovation, proximity to customers, specialized talent, and flexible regulators are important factors that contribute to fintech growth. Taking these factors into account, regions like London, Singapore, Hong

Kong, New York, and Silicon Valley have over the years been traditionally well suited for fintech innovation, as these areas have long standing status as financial hubs and technological centres for development (Rubini, 2019). More recently, Norway has seen a surge in new start-ups and investments within fintech, from around 30 fintech start-ups in 2016 to more than 130 in 2019 (Bentsen & Bjørne, 2019). In addition, there has been a significant increase in public and private initiatives such as the development of government supported fintech clusters, specialized MBA-programs, incubators, and regulatory changes (Bentsen & Bjørne, 2019).

Since the early 2000's, Norway has supported the growth of regional clusters through national cluster programs (Innovation Norway). *Norwegian Innovation Clusters* are government supported programs that seek to trigger and enhance collaborative activities in the Norwegian industry. Among these programs are the Norwegian Centres of Expertise (NCE) which was initiated in 2006 and supported by Innovation Norway, the Research Council of Norway and SIVA. The programs aim to support growth in national and international markets through targeting, improving, and accelerating the clusters' development-processes.

In the wake of the recent development within fintech and cluster initiatives, the NCE Finance Innovation (NCE FI), which is now a part of the NCE program, was established by business leaders in banking, finance, insurance, and academia in 2017 on the Norwegian west coast. NCE FI is a formal institution aimed at supporting and facilitating interaction and cooperation between cluster participants. Its mission is to empower the Norwegian fintech community by facilitating technological innovation and collaboration in the intersection of finance and technology. Today, NCE FI has around 75 members, consisting of large incumbent banks, consulting firms, investors, academia and start-ups, among others (NCE Finance Innovation; Innovation Norway).

We chose the Norwegian fintech context as the basis for this thesis' analysis for several reasons. First, the growing interest in fintech in international and national policy making suggests that new insights into this field can be useful for policy makers. Second, the financial industry in Norway is changing rapidly, and new start-ups increasingly challenge the traditional, established financial firms. However, there seems to be growing recognition among the established actors that cooperation and strategic partnerships are efficient ways to face this challenge (Bentsen & Bjørne, 2019). Therefore, studying a nascent regional fintech cluster such as NCE FI through the lens of social network analysis can provide new insights into the relational characteristics of the Norwegian fintech ecosystem. This is especially interesting in the wake of the Revised Payment Services Directive (PSD2), an EU-directive that was initiated in September 2019, aimed at improving security, and boosting competition, cooperation, and innovation by for example having traditional banks share customer information with third parties through API's (Application Programming Interface) (European Commision , 2020).

Moreover, since NCE FI is by conventional standards a young cluster, it makes initial analysis of its network suitable for social network analysis. The reason is that the network might be less contaminated by sticky, potentially unproductive historic relations. Thus, it provides a better snapshot of more recent strategic relational choices made by the fintech actors. Moreover, as SNA can be used to analyse the development of networks by comparing them at different points in time, capturing the early version of the network enables more fundamental insights into how the regional cluster and the Norwegian fintech ecosystem are developing by studying the networks again later. This also enables facilitators to more efficiently apply incentives and policies to change the growth trajectory of the network structure towards favourable outcomes before the interfirm relations get too cemented.

3.2 Methods for collecting network data

When collecting network data, one must make decisions and assumptions as to what type of networks and relations to study. In addition, one must make decisions regarding which dimensions of a network that is relevant for the analysis. In the following we will present the assumptions behind our approach for collecting relational data between fintech actors inside and outside of NCE Finance Innovation.

With regards to delimiting the network which will be analysed, Lauman et al (1983) proposes three main approaches to address network boundaries: *position-based* approach, *relation-based* approach, and *event-based* approach. In a position-based approach, actors who are members of an organization or hold formally defined positions are included. A relation-based approach starts with a small set of nodes from the population of interest and expands to include other actors the first nodes share relations with. In an event-based approach, boundaries in a network are defined by looking at which actors have participated in key events for the populations (Marin & Wellman, 2010).

We used the position-based approach to identify the population of interest for our analysis, which was fintech actors in Norway. We started by identifying the members of NCE Finance Innovation, which was our main population of interest. Thereafter, we targeted fintech actors outside this regional cluster in order to generate a broader set of actors, that would be part of the organic networks. These actors were for example members of other Norwegian fintech clusters or were found in publicly available online databases. In total, we targeted a population of in total 103 actors, of which 74 were members of NCE Finance Innovation.

Furthermore, we used the relation-based approach to identify the actors whom the targeted population had relations with. Through a survey, we asked respondents representing these actors of the targeted population to identify a limited number of organizations with whom their organization had relations with. We then compiled those lists and cross-connected them to create our dataset of relations. Before this step however, we needed to decide on which type of relations to analyse.

According to Borgatti et al (2009), there are four broad categories of relations: *similarities, social relations*, *interactions, and flows.* Similarities between nodes occur when two or more nodes share the same kinds of attributes frequently (Marin & Wellman, 2010). Such attributes can be demographic characteristics, attitudes, locations, or group memberships. Nodes with social relations often have commonly defined roles such as friend or student. These relations are influential and typically based on often the node’s feeling for one another or cognitive awareness. Interactions are based on ties of behaviour between nodes like speaking with, helping, or inviting into one’s home. Lastly, flows describe relations based on exchanges or transfer between nodes, such as resources, information, or influence (Marin & Wellman, 2010).

The relational types we collected were the fintech actors’ innovation collaborators, providers, customers, competitors, and financing partners. We chose these relations as we argue that they are broad and together can encompass most of the possible relations occurring between organizations in a regional cluster. Based on the definitions above, these relations can be viewed as social relations as they have defined roles, such as “innovation collaborator of”- and “customer of” - the actor in question. Importantly however, we argue that both interactions and flows between actors are important mechanisms of these social relations. In other words, we argue that these relations are not mutually exclusive, and we made broader assumptions as to what these relations contained, based on our chosen tie-measure which is described in the following.

In order to measure the chosen relations, we asked the fintech actors to list and rank their maximum 10 most important providers, customers etc., where the relation the respondents ranked as number one was the most important, the actor listed as number two was the next most important, and so on. This allowed us to study each individual actor's opinion of how important another actor in the network was to that actor in terms of a specific relational type. This meant that the ties could be measured as directed and weighted, which gave us more detailed insights, rather than just recognizing the existence of the relations in terms of an undirected tie that states in binary terms if the relation exist or not.

With regards to the weighting of ties, the scale we used in our survey reflects differences in degree of intensity, meaning that we can get insights into the strength of the relations between the actors. We assumed that the specific role, such as supplier, customer etc., indicates the social relation itself, and that the degree of "importance" from the ranking of an actor gives an indication of the intensity of the relation, which says something about the degree of flows occurring in that relation.

For the networks we created for our analysis, all the relational types were collapsed, such that the networks would consist of ties to innovation collaborators, suppliers, customers, competitors and financial partners. As such, a tie in one of our networks reflects many different types of relations. Even though there are important differences in the flow occurring between these relations, we argue that it is rational to assume that the more important any of these relations are to an actor, the more often these actors interact, and the more often they transfer knowledge and information between each other. We therefore assume that the weight of the ties between actors is a reasonable parameter for the degree of flows of information and knowledge between the actors, regardless of the specific type of relationship. This assumption allowed us to treat the strength of a tie similarly across all relational types, which made it possible to perform the network measures used to analyse our networks.

3.3 Survey design

Relational data can be collected through questionnaires or interviews, observations and/or texts. There was limited available data on observations or text that gave us information about the relations between our chosen population, and much less on the strength of the relations. In addition, considering that the population of fintech companies in Norway consists of at least 130 actors (Bentsen & Bjørne, 2019), we evaluated that data collection of relations through interviews would be too time consuming. For our data collection, we therefore chose "Qualtrics", a web-based survey tool which was used to distribute the survey through e-mail, something that allowed us to efficiently gather information about relations and their strength.

The assumptions and choices described in section 3.2 established the foundation for our survey design, which is explained in detail in the following. Appendix C shows the original questions from the distributed survey in Norwegian.

The survey consisted of 23 questions in total, distributed into three parts. In part one, both members and non-members of NCE Finance Innovation were asked to list and rank their maximum 10 most important innovation collaboration partners, then their maximum 10 most important providers, competitors, customers, and finally financing partners. We provided definitions of all the relational types in the survey in order to minimize the risk of participants misinterpreting a relation, and therefore answer inaccurately. As an example, we defined the first relational type, innovation collaboration partners, as:

"Private and public companies, educational institutions, or other types of organizations that your company collaborates with when it comes to innovation. This includes, for example, collaboration on the development of new products and services, improvement of existing products and services, and collaboration to solve relevant industry-specific issues" (translated from Norwegian, which was the language used for the survey).

We collected the first set of relations in part one of the survey using a "free-recall" approach, which means that respondents could name any relation they considered important within the five relation types (customer, competitor etc.) (Giuliani & Pietrobelli, 2011). These relational data are the base for what we refer to as the "organic network", where the respondents listed and ranked actors without a predetermined list to choose from. This means that the respondents in this part of the survey were not restricted to just listing other members of the regional cluster and could therefore include both members and non-members of NCE FI.

After listing their relations with the free-recall method in part one, the respondents were asked if they were members of NCE FI or not. Non-members were directed to the end of the survey, while members of NCE FI were asked to list their most important relations once again in part two of the survey. In this part, the actors were given a complete dropdown list of the regional cluster members and could only choose their most important relations from this list. This approach, called "roster-recall" (Giuliani & Pietrobelli, 2011), generated a dataset of relations solely between the members of NCE FI, and the network based on these relations is referred to as the "regional cluster network". The approach of collecting the fintech actors' most important relations first through a free-recall approach, and thereafter through a roster-recall approach allowed us to investigate the differences between the bounded regional cluster network and the broader organic network the cluster members were embedded in. We purposefully chose to initiate the survey with the free-recall approach, in order to minimize a potential bias of respondents listing more NCE FI-members if they had been presented with a list of these in advance.

In part three, the respondents answering on behalf of the cluster member, were asked to answer some questions about the actor's membership in the regional cluster. These answers helped us with identifying traits and the overall opinion of the benefits of being a cluster member.

The first question was: *"Is your company physically represented at the Fintech HUB at Media City, Bergen?"*

This information could potentially provide insights into how personal relations in the network were facilitated and could enable us to investigate if physical proximity was somehow related to the network's structure. We chose however, due to limited time and resources not to prioritize this for our analysis (see "future research" in section 5)

The second question was*: "To what degree do you consider your organization's membership in NCE Finance Innovation cluster to be important for your company's ability to innovate within fintech?"*

This could give an indication of the degree to which the connectivity of an actor in the regional cluster network was important for the actors' ability to innovate within fintech. By comparing the positioning and centralities of different actors to their answers to this question, we could investigate if there were any patterns in the network structure that could explain differences in the actors perceived innovation-benefit from participating in the regional cluster.

The third question was*: "In order to establish a collaborative partnership with another organization in the cluster, how often does your organization first go through NCE Finance Innovation cluster?"* This could give an indication of the role of NCE FI in facilitating relations between the cluster members.

3.4 Ethical considerations

We identified two important ethical obstacles concerning our data collection: 1) collecting sensitive information about the actors, and 2) the risk of identifying the respondent answering on behalf of the fintech actor.

As opposed to other methodological approaches, full anonymity at the stage of data collection for this thesis was not possible. The reason being that respondents had to report the organizational names of fintech actors that they had relationships with. The ethical issue in this regard was that a respondent might report on relationships with actors that did not want to be named. This is especially the case with sensitive relational data. We considered our relational data as sensitive, as information on firms' innovation collaborators, providers, customers, competitors, and financial partners in many cases are not publicly available information. Another problematic aspect with this is that actors may refuse to give information about its relations, and thus refuse to respond (Giuliani & Pietrobelli, 2011). This was one of the major challenges when collecting our data. In order to ensure responses, we had to thoroughly explain to the respondents how sensitive information would be anonymized and kept from the public eye. This meant for example that the relational data would not be shared with other respondents, and that the visualized network maps would not show the names of the actors. Even though the identity of the actors was treated as confidential, a risk is that it might still be possible to guess the names of the organizations by the virtue of their location in the networks. This meant that we had to ensure that the data would be handled in such a way that it would be nearly impossible to identify specific companies by reverse engineering information based on our presentation of findings. We therefore restrained from including characteristics such as number of employees and the age of the organizations in this thesis. Moreover, we ensured the respondents that we would only handle data through dedicated PC's provided by our institution NHH. We anonymized all respondents and named organizations in the survey by giving them unique IDs. In order to keep track of our efforts to handle the data responsibly, we used a data management plan ("Datahåndteringsplan") which we filled out according to NSD's (Norwegian Centre for Research Data) guidelines.

With regards to the risk of identifying persons, we enabled a function in Qualtrics which ensured that the survey did not identify, nor store personal data such as name or email addresses of the respondents. In surveys with open fields however, such as the open free-recall fields used in our survey, there is a possibility for respondents to write personal information. According to the EU-regulation for data privacy, GDPR, the respondents can enforce their rights for privacy, such as the right to know what kind of personal information we have stored and to withdraw their response. Because of these open fields, we obtained IP-addresses to be able to locate the respondent and fulfil the potential privacy rights. Nonetheless, in order to mitigate this risk, we informed the respondents on several platforms to avoid writing anything that could identify the respondent or other individuals. In order to fulfil privacy regulations, we applied for project approval for projects processing personal data through Norwegian

Centre for Research Data. Once this application was approved, we distributed the survey to the fintech actors.

3.5 Data validity

Our main concern regarding the data collection was the response rate of the survey. In order to generate accurate insights from how the relations were distributed in the regional fintech cluster and in the organic network, a relatively high response rate was required. Even though we sent out two reminders to the invited actors, the total response rate was 33% (see table 1), which we considered relatively low. This meant that our network would might not precisely represent the actual connections between the actors, as there were potentially many missing links. There are several potential reasons for a low response rate, whereas a probable reason was the length of the survey. The average time for participants to complete the 23 survey questions was 20 minutes, which was longer than we expected. The response rate may also have been affected by concerns regarding sensitive information and privacy concerns, as mentioned in section 3.4. Despite a response rate of just 33%, we were able to map a larger portion of both the regional cluster network and the organic network by combining both a position- and relation-based approach as explained in section 3.2, where the respondents named many organizations that were not initially targeted. Thus, out of the 34 responses, we were able to map in total 810 unique relations and 453 actors (see table 2), which illustrates a significant advantage with our chosen data- collection approach.

(INSERT TABLE 1 HERE)

During the data preparation, we found that a number of participants had not filled out any relations. In addition, we observed that a few participants in the first, free-recall part of the survey, chose to answer on a general basis. For instance, instead of listing a particular bank as an innovation collaborator, some answered "Banks", which was a connection we had to remove. This indicates that the way our questions were formulated in this part of the survey might have been more precise. However, this applied to relatively few participants.

From table 1 we observe that the response rate for the regional cluster members was higher than for actors outside the cluster, respectively 36% and 24%. A reason for the skewed response rate between the two groups might be that we received direct contact information of all cluster members from the facilitator of NCE Finance Innovation, who also encouraged the members to participate in the survey. That allowed us to send the survey invitation directly to the organization's contact person, whom we assumed either was able to answer on behalf of the fintech actor or knew a person in the organization more capable of answering. For the actors outside the regional cluster, we used the contact information from their home pages. Most of these email addresses were generic email addresses, which made it difficult to know who the survey was sent to in the organization, and if the email invitation became forwarded to the right person in the organization at all.

Another challenge regarding our data collection was that we were not able to ensure that the person that responded on behalf of the organization had the right knowledge about the organization to provide the most accurate answers. In addition, one person's opinion usually differs from another person's opinion, meaning that two persons in the same organization might have answered and ranked the relations differently. This also implies for instance, that the answers about to what degree cluster membership was important for the actors' ability to innovate were subject to individual opinions and not precise objective measures such as the rate of patent filings. This is considered when discussing our results in section 5.

In addition, our approach of ranking actors based on the importance of relations, may not actually reflect equal differences in the strength of the relations (Hanneman & Riddle, 2005). For example, the difference in importance between rank 1 and rank 2 may be larger than between rank 4 and rank 5. We therefore chose to regroup the rankings by assigning weight "5" to the top ranks 1 and 2, weight "4" for the ranks 3 and 4, and so on to weight "1" for rank 9 and 10. If for example two actors would be of similar importance to the respondent, a grouping of ranks would at least to some degree mitigate this inaccuracy.

Another challenge with our chosen approach for ranking and weighting the relations between the fintech actors, is that we did not obtain accurate information about the frequency of information flow between two actors. More accuracy could have been generated by for instance asking how often the respondent had collaborated on projects with another actor in the last year. We assumed however, that with our approach, the respondents would be able to cognitively retrieve and rank their relations without having to rely on external sources of information. By asking detailed questions about frequency and nature of flows between actors, we believed that the information would be either inaccurate or too time consuming, resulting in annoyance and fewer responses from the respondents.

Despite the considerations of data validity mentioned in this section, the data we collected enabled us to create, analyse and generate insightful findings from the resulting networks. We will further explain how we prepared our datasets from the data collection, before we present how we used it to analyse the data.

3.6 Data preparation

In the following, a description of how the collected data was prepared for analysis. We chose to create our networks by organizing our data in “edge lists” and “node lists” in excel. An edge list contains the actual links between the actors which is needed to create network objects, where the first column contains the “source ID’s” and the second column contain the corresponding “target ID’s”. The source ID represents the node that has a connection to the target ID. One such relation constitutes an edge, or link, which can be assigned a weight, representing the strength or magnitude of this relation. A node list is a data frame which at its simplest contains a column with the ID’s of the entities. The advantage of creating a separate node list is that columns of nodes’ attributes can be included, such as names and categorical affiliations. The node list and edge list can then be combined through common ID’s in a software program which creates a network that can be visualized and analysed.

We started assigning names and unique ID’s to all the actors that either participated in the survey, or that were listed by the survey participants. Actors that were listed with the free-recall method, that for some reason were spelled differently, were given the same name manually. As an example, “NHH” and “Norwegain School of Economics” could be two different ways of spelling the institution name. Thereafter, we created five edge lists from the free-recall approach in part one of the survey, based on each of the five relational types (innovation collaborators, providers, customers, competitors, and financing partners). Subsequently, we created a second set of five edge lists based on each of the five relational types from the roster-recall approach in part two of the survey. The ties between the actors in the ten edge lists were assigned weights from 1-5 based on the actors’ perceived importance of another actor, as described in section 3.5.

Thereafter, we made another edge list by collapsing the five edge lists based on the different relational types gathered from the free-recall approach in part one of the survey. This was the foundation for the *organic network*, consisting of 439 actors and 743 relations, whereas 666 relations were unique (see table 2). The difference between the number of unique and total ties means that 77 relations in this network were overlapping. The reason for overlapping ties in our networks is that an actor either listed another actor as more than one relation (e.g., financing partner and provider), and/ or that two actors listed each other as relations. Regarding the weighting of these overlapping ties, we assumed that if an actor had listed another actor in more than one of the five relations, or two actors had listed each other in one or several relations, it would be reasonable to add these weights indicating an even stronger importance of the relation between the two actors.

As an example of how these weights were calculated, if actor *A* listed actor *B* in two relational types (e.g., customer and provider) with the corresponding weights x and y, the total weight of this tie would equal $x + y$. Moreover, if actor *B* also listed actor *A* as an important relation with the corresponding weight z, then the total weight of that tie would be $x + y + z$. This logic applies for all network measures and visualizations used in the analysis.

In addition, we made another edge list by collapsing the five edge lists based on the different relational types gathered from the roster-recall approach in part two of the survey, where the respondents were limited to list and rank only members of NCE FI. This was the foundation for the *regional cluster network*, consisting of 59 actors and 299 relations, whereas 227 relations were unique (see table 2).

Furthermore, the two edge lists used for the organic network and the regional cluster network where collapsed onto one larger edge list consisting of all the relations from both part one and part two of the survey. This was the foundation for the *maximum network*, consisting of 453 actors and 1042 relations in total, whereas 810 relations were unique (see table 2).

(INSERT TABLE 2 HERE)

We made three corresponding node lists to the edge lists for the organic network, regional cluster network, and maximum network. The node lists for each network consisted of all actors' unique IDs from the corresponding edge list, meaning both source ID's and target ID's of the actors. The actors in the node lists for the maximum- and organic network contained an attribute describing if these were members of NCE FI or not.

The actors in the node list for the regional cluster network contained the attributes "fintech category" and "benefit". Regarding fintech category, we categorized the actors in our data into seven broad groups, based on elements of the fintech ecosystem presented in a paper by In Lee & Yong Jae Shin (2018) and somewhat adjusted to better suit the spectre of our responding actors. These categories are presented in table 3. The benefit column contained the actors' responses regarding to what degree they considered their membership in the regional cluster as important for their innovative capabilities (see section 3.3). In this regard, the answers "To a very large degree" were represented by the number 5, "To a large degree" by 4, and so on to "To a very small degree" which was represented by 1. Answers from actors who answered "Not sure" were excluded in order to calculate averages among the different fintech categories for our analysis.

(INSERT TABLE 3 HERE)

Finally, the excel sheets for the edge and node lists for each of the three networks were connected in R through the actor's common unique ID-numbers, which enabled us to analyse and visualize the networks.

3.7 Analysing and visualizing network data

This section describes the network measures we used, and how these were applied in order to investigate our five propositions. There are a number of applications designed for network analysis, and for our analysis we used the programming language "R" with the package "Igraph". We mainly used Igraph to generate network measures from our dataset of relations. We chose to visualize our networks using "Gephi", an open-source software package for visualization of networks. The reason was that, in our experience, Gephi generated clearer representations of our networks with higher resolutions compared to R, something that was important considering that some of our networks were relatively large and intricate.

Proposition one

In order to investigate our first proposition, we applied the following network measures to the organic- and the regional cluster network: density, average path length, and global clustering coefficient (see formula 1, 3, and 4 in the section 2.4.1, respectively). In addition, we counted the number of ties, nodes, and cliques for the networks through algorithms in R.

Most of the actors in the organic network were present because other actors had listed them, not because they had participated in the survey. As a result, many potential outgoing links from these actors were not present in our data. In order to cope with these missing outgoing ties, we applied the network measures on the two networks as undirected. This enabled a more logical comparison of the networks in proposition one.

In order to investigate our second proposition, we visualized the maximum- and the organic network, both as undirected and weighted. As explained in section 3.6, the weight assigned to overlapping ties is the sum of all the weights of the relations between two corresponding actors. From these visualizations we could observe to what degree the regional cluster members were connected in the organic network, and how densely connected they were in the core of the organic network in comparison to the maximum network (which included the relations of both the organic- and the regional cluster network). In order to observe this, the nodes in both networks were given a colour based on their cluster-membership status. In addition, we calculated the percentage of regional cluster members that were listed and ranked by other members in the free-recall method in part one in the survey. This way we could attain more accurate insights into how important the cluster members considered other cluster members to be as relations.

Proposition three

To investigate proposition three, we visualized a generic version of the regional cluster network where the ties were both directed and weighted, as the proportion of missing outgoing links was much lower than in the organic network. This allowed us to visually inspect the structural characteristics of the network and compare these to the characteristics of network structures discussed in the literary review. In addition, we made a histogram of the distribution of the actor's degree centrality scores which allowed us to investigate if the cluster had properties of a scale-free network.

Proposition four

To investigate proposition four, we applied the averages of the actors' degree centrality (including in-degree and out-degree), betweenness centrality, and Burt's constraint score across the seven fintech categories represented in the regional cluster (see formula 5, 6 and 7 in section 2.4.2, respectively). These measures were presented in a table for our analysis. We included both the direction and weight of the ties when calculating these network measures and for illustrating three different versions of the regional cluster network, which are explained below.

In order to observe which actors had the highest degree centrality- and betweenness centrality measure, we first visualized two separate versions of the regional cluster network where the node size represented the actor's degree- and betweenness centrality measure respectively. In order to observe what fintech category the different actors belonged to in these networks, the colour of the nodes represented the different fintech categories. To get deeper insights into how these centrality scores were distributed in the regional cluster, we made a histogram for the distribution of the actors' betweenness centrality scores, in addition to the degree distribution histogram used to investigate proposition three.

To observe structural holes in the network, we created a version of the regional cluster network that highlighted the actors with the lowest Burt's constraint score. The nodes with a BCS of less than 0.15 were given a separate colour from the rest of the network's nodes and included a label of these actors' category affiliation.

Proposition five

To investigate proposition five, we first calculated the average scores for each fintech category based on what the actors answered regarding how important the cluster membership was to the actor's ability to innovate within fintech (see section 3.3 and 3.6). We compared these scores with the categories' average centrality measures, to see if there could be a potential pattern. We also visualized two additional regional cluster networks where the colours of the nodes reflected the degree to which the members answered that they find membership in the cluster important for their ability to innovate within fintech. The more intense (dark) the colour, the more important the actor considered its membership to be. The node sizes in these networks corresponded to the out-degree-, and betweenness centrality measures of each actor, respectively. This way we could see if there were any potential correlation between the size of the node and the degree to which membership was important for the actors' ability to innovate within fintech.

4. Results

This section presents the results of the analysis of our five propositions. Appendix A and B provides the results in tables and network-visualizations. First, we will present some general results from the cluster members answers in part three of the survey.

4.1 General survey results

Table 4 shows the distribution of the regional cluster member' answers when asked how important membership in the regional cluster is for the actor's ability to innovate within fintech. 43% of the respondents answered *to some degree,* which was the most common answer. 29% percent of the respondents answered that the cluster membership was important *to a large degree* (18%) or *very large degree* (11%) for their ability to innovate within fintech. 18% considered their membership as important to a *small degree* (11%) or *very small degree* (7%). The remaining 10% were not sure.

(INSERT TABLE 4 HERE)

In table 5, the regional cluster members' answers to how often the organization first goes through NCE Finance Innovation to establish a collaborative partnership with another organization in the cluster is shown. None of the cluster members who participated answered that they *always* go through the regional cluster. Half of the members answered that they *sometimes* do, while 14% and 25% answered that they *usually* and *never* go through the cluster, respectively. The remaining 11% were not sure.

(INSERT TABLE 5 HERE)

4.2 Proposition one

Proposition one suggested that the regional cluster network had a higher density, lower average path length, higher global clustering coefficient and more cliques than the organic network. As seen in table 6, the regional cluster network has a significantly higher density (0.128) than the organic network (0.007). This indicates that the regional cluster has a higher degree of connectedness and potentially speed at which information diffuses among the embedded actors, than the organic network. Furthermore, the average path length in the regional cluster network (2.439) is lower than in the organic network (3.715). This indicates that the distance information must flow to reach any actor in the regional cluster is significantly lower than in the organic network. The global clustering coefficient is more than five times higher in the cluster network (0.315) than in the organic network (0.059). This indicates a much higher tendency in the cluster for actors to form cohesive subgroups. As indicated by the higher global clustering coefficient, our findings also show that the number of cliques is significantly higher in the regional cluster network (470) than in the organic network (275). As expected in proposition one, the regional cluster network has a higher density, higher clustering coefficient, more cliques, and a lower average path length than the organic network.

(INSERT TABLE 6 HERE)

4.3 Proposition two

In proposition two, the goal was to investigate to what extent the regional cluster members' most important relations were in fact with other cluster members, mainly by visually studying how the cluster members were connected in the organic-and maximum network.

In table 6, we observe that the regional cluster network has fewer unique ties and nodes, 227 and 59 respectively, in comparison to the organic network which has 666 unique ties and 439 nodes. First, this means that the participants in the first part of the survey listed a significant number of non-cluster members as their important relations within the five relational types (innovation collaborators, providers, and so on). In addition, as most of the respondents in the survey were cluster members (see table 1), it can indicate that many cluster members listed non-members as their important relations in part one of the survey. Supporting this, we found that just 20% of the relations listed by the cluster members in the first part of the survey were other cluster members.

Figure 1 illustrates the maximum network, where the green nodes are cluster members of NCE FI, and the red nodes are external actors. Figure 2 illustrates the organic network, where the orange nodes are members of the cluster, while the purple nodes are non-members.

(INSERT FIGURE 1 AND 2 HERE)

First, by visually inspecting the organic network we see that many cluster members are visibly connected in the core of the network, but that a significant number of the members are located more towards the periphery. In addition, we see that a large proportion of the cluster members are almost entirely connected with non-cluster members (purple nodes), also supported by the finding that just 20% of the cluster members most important relations are other cluster members.

When visually comparing the organic- and the maximum network, we see that the members are somewhat more densely connected in the core of the maximum network than in the organic network, as indicated by the tighter clustering of the green nodes and greater thickness of the green ties in figure 1, compared to these characteristics in figure 2. This suggests that the cluster members listed fewer cluster members as their most important relations in the first part than in the second part of the survey. However, even though many of the regional cluster members are located more towards the periphery in both networks, nearly every member seems to be connected at least to one other cluster member. This means that the relations between most of the cluster members are at least present in the organically developed network.

To sum up, proposition two is somewhat incorrect. First, by studying the number of unique ties and visually inspecting the organic network, we have found that a large portion of the regional cluster members important relations exist with external actors. In addition, the cluster members are less densely connected in the core of the organic network, compared to the maximum network, suggesting that many of the members' relations within the regional cluster are not as strong as we expected. That is, the regional cluster is to a lesser degree than expected consisting of its members most important relations.

4.4 Proposition three

From proposition three, we suggested that the regional cluster network exhibited characteristics of a scale-free network. By observing figure 3, we can see that the regional cluster network's core is densely connected and that a significant number of nodes are located towards the periphery. In addition, many of the peripheral actors are poorly connected to the core through mostly one or two relations, signalling a hierarchical network structure. The large share of outlying actors can to a large degree explain the low overall density of the network of 12.8%. By first glance, this network exhibits the characteristics of a core-periphery network.

(INSERT FIGURE 3 HERE)

On the other hand, we observe from table 6 that this network has a relatively low average path length (2.439) and a somewhat high global clustering coefficient (0.315), which might suggest that it contains properties of a small-world network. This would indicate an efficient network, despite its low density of just 12.8%. However, compared to the theoretical description of a small-world network, there seems to be too many connections in the centre of the network, speaking against small-world and pointing towards a more hierarchical network.

Figure 9 shows the histogram of the degree distribution for the actors in the regional cluster network. By studying this histogram, we see that the distribution is right skewed with a heavy tail. This implies that a few actors have multiple times the connections than most of the actors in the network. While the network's average degree centrality is 6.27 (see table 7), we see in the histogram that there are as many as 12 actors which have a degree centrality of 1. These actors are connected to only one other actor, meaning that they are the actors observed in the far periphery of the network shown in figure 3. On the other side of the spectrum there are three highly central actors, or hubs, with connections to 25, 29 and 33 other actors. This observation in combination with the observed hierarchical structure of the network can indicate that the regional cluster holds properties of a scale-free network, which is in line with proposition three.

(INSERT FIGURE 9 AND TABLE 7 HERE)

4.5 Proposition four

In proposition four we expected traditional financial institutions in the regional cluster to have on average the highest degree centrality, in-degree and out-degree centralities, and the lowest Burt's constraint score.

In table 7 we observe that traditional financial institutions on average have 13.67 connections, while consultancies have 8.94 -, and technology developers have around 7.09 relations on average, supporting the fourth proposition. Fintech start-ups have in comparison on average 4.72 connections in the network.

Figure 4 illustrating the regional cluster network shows how the degree centrality scores vary between the different fintech actors, where the node size represents the degree centrality score and node colour represents the actor's fintech category. By observing this network, we see that many of the actors in the core of the network have significantly higher degree centralities than the more peripheral actors in the network. By identifying the largest nodes, we observe that the actors with the most direct relations, or alters, in the cluster mainly consist of traditional financial institutions (orange), consulting firms (green) and technology developers (blue). The fintech start-ups (purple) on the other hand are to a large extent located in the periphery of the network and are much less connected, as indicated by these firm's low average degree centrality score in table 7. By comparing traditional financial institutions to the other fintech categories by looking at the average degree centrality from table 7 and figure 4, we see that traditional financial institutions have the highest average degree centrality which is in line with proposition four.

(INSERT FIGURE 4 HERE)

Furthermore, we observe from table 7 that consulting firms on average have the highest number of outgoing relations to other members, with an out-degree centrality score of 5.6. This implies that these firms on average consider the highest number of other actors in the cluster to be important relations, with traditional financial institutions (4.78) and technology developers (4.09) following behind. Fintech start-ups, on the other hand, consider on average just 1.83 members of the cluster as being important relations. Considering that consulting firms have a higher out-degree centrality than traditional financial institutions, this means that our expectation have not been met regarding this centrality measure.

From table 7 we observe that traditional financial institutions by far have the highest average in-degree centrality score of 8.9 and are therefore considered to be important relations by the highest number of actors in the cluster. This is in line with our proposition that traditional financial institutions are highly central and influential in the regional cluster. In comparison, fintech start-ups are considered as important relations by on average 1.83 other members.

In table 7 we see that traditional financial institutions have the highest average betweenness centrality score of 49.65, which again is line with our expectation. This means that a traditional financial institution on average acts as a bridge between two disconnected actors approximately 50 times in the regional cluster network. Nonetheless, technology developers follow just behind with an average score of 43.14. In comparison, fintech actors act as bridges on average just 2.39 times in the network, while investment firms, academia and government never act as bridges in our directed network. Moreover, in the histogram of the actor's betweenness centralities (figure 10) we identify two actors that lie on paths between other actors 320, and 240 times, thus significantly skewing the average scores. Figure 5 of the regional cluster network shows the distribution of betweenness centrality between the different fintech categories, where the node size represents the betweenness centrality score. We observe that the two largest nodes in the network with the highest betweenness centrality scores, are a traditional financial institution (orange) and a technology developer (blue).

(INSERT FIGURE 5 AND 10 HERE)

We observe in table 8 that 11.7% of the actors have a Burt's constraint score (BCS) between 0.00 and 0.15. These actors are the least constrained by their relations in the network. Nonetheless, 45.8% of the actors has a BCS between 0.15 and 0.35, indicating many actors in the network to a large degree occupy structural holes. In figure 6, the regional cluster is visualized and illustrate the seven (green) nodes with a BCS score under 0.15, including a label of their category-affiliation. The red nodes are the 52 nodes with a BCS score over 0.15. We observe the green nodes to be actors from two financial institutions, three consulting firms, one technology developer and one fintech start-up. Moreover, in table 7 we see that traditional financial institutions have the lowest average BCS of 0.26, only shared with academia. This also suggests that with regards to filling structural holes, financial institutions are some of the less constrained actors in the network, supporting proposition four that they occupy the more influential positions in the regional cluster.

(INSERT TABLE 8 AND FIGURE 6 HERE)

In sum our findings strongly support the fourth proposition that traditional financial institutions are the most central and influential actors in the regional cluster network. Despite having the second highest out-degree score behind consultancy firms, traditional financial institutions have on average the highest degree centrality, in-degree centrality, betweenness centrality, and the lowest Burt's constraint score in the regional cluster network.

4.6 Proposition five

In the fifth and last proposition we suggested that cluster members with high out-degree- and betweenness centrality scores should find their membership in NCE FI to be more important for their ability to innovate, compared to cluster members with lower scores on these measures.

In figure 7 we observe the regional cluster network where the size of the node corresponds to the actor's betweenness centrality score, and the intensity of the node colour (green) represents the degree to which the actor perceives cluster membership as important for its ability to innovate within fintech. By observing this network, we see that the larger nodes tend to be darker green than most of the smaller nodes. This indicates that there might be a correlation between an actor's betweenness centrality and its perceived innovation benefit from being a cluster member, supporting proposition five.

(INSERT FIGURE 7 HERE)

In figure 8 we observe the regional cluster network where the node size corresponds to the actors' out- degree centrality score, and the intensity of the node colour (red) represents the degree to which the actor considers their membership as important to their ability to innovate within fintech. Most of the largest nodes in the network are dark red, compared to most of the smaller nodes, suggesting that the actors with highest betweenness centrality scores considers membership as more beneficial for their ability to innovate within fintech, compared to actors with lower betweenness centrality scores. In sum, these findings support proposition five, which suggests that actors with high betweenness-and out-degree scores tend to consider their membership in the cluster to be more beneficial for their ability to innovate within fintech, than less central actors.

(INSERT FIGURE 8 HERE)

Moreover, in table 7, we observe that consulting firms in the regional cluster on average perceive that they benefit the most with regards to their innovative capabilities from being a cluster member, with an average score of 3.83, followed by traditional financial institutions and technology developers with average scores of 3 and 3.2, respectively. From proposition four, we also found that these actors on average are the most central firms in the network. This supports proposition five, as it gives an indication that the most central firms perceive cluster membership as more important for their innovative capabilities than less central firms.

5. Discussion and conclusions

The purpose of this thesis was to contribute to research on regional clusters, by studying the structural network characteristics of a regional cluster through the lenses of social network analysis (SNA). By mapping, analysing, and comparing the structural properties of the networks of members of the cluster NCE FI and the broader ecosystem-network which it is nested, we generated several interesting findings. In what follows, we will present four key insights based on these findings and discuss potential implications. Finally, we present recommendations for the facilitators of NCE FI, the validity of our results, and suggestions for future research.

1st key insight: The regional cluster is highly connected to its external environment

The first key insight is that the regional cluster to a lesser degree than expected contains its members most important relations. That is, the relations of most of the cluster's members stretches beyond the boundary of the regional cluster.

First, this finding can indicate that many of the cluster members' important relations are not located on the Norwegian west coast where NCE FI is headquartered, but in other parts of, or outside Norway. This might imply that geographical proximity is less important to the embedded firm's ability to innovate than traditional literature on clusters indicates. As digitalization minimizes geographic distance and enables alternative forms of collaboration, this might be reasonable to assume (Autio, 2017). Because most business models within fintech are based on digital technology such as cloud computing, AI, cryptocurrency, software-as-a-service, digital banking and so on, it might be the case that geographical proximity to for example customers, providers, or funding partners, is a non-essential factor for well-functioning business relations and joint innovation activities. Boschma (2005) for example suggests that other dimensions of proximity, namely cognitive, social, organizational and institutional to a large degree can explain the likelihood that firms create interfirm linkages.

The fact that the members to a large extent consider external actors to be important relations might suggest that there are less potential beneficial relations in the regional cluster network, or that the relations that do exist are weaker than what was anticipated based on theory. One interpretation from this is that the overall degree of trustful relations, which has been found to facilitate a cooperative, knowledge sharing environment, may be lower than expected, therefore possibly limiting the regional cluster's potential for stimulating innovation. As noted by Porter (2000), the mere presence of a regional cluster does not guarantee functioning cluster linkages. In addition, there might be instances of cluster memberships which are of merely symbolic character, something Inkpen (1996) suggests are the case within many regional clusters. Because building and maintaining relations are costly, the total cost of membership (including the membership fee) would in this case be higher, as maintaining potentially less beneficial relationships incur the opportunity cost of time invested in other value creating activities.

From proposition one on the other hand, we found that the cluster-relations that the members of NCE FI listed in part two of the survey, makes up a network that has a lower average path length and a higher density than the organic network. This may imply that the speed at which information potentially diffuses in the regional cluster is higher than in the organic network, thereby enabling more efficient flow of knowledge between the embedded actors. In addition, as the regional cluster network has a higher degree of local connectivity than the organic network, there could be potential for trustful relations and reciprocity norms, something that can lead to increased flow of tacit, quality knowledge, effective joint problem solving and reduced transaction costs.

Moreover, our findings may imply that the regional cluster is attracting a somewhat narrow set of actors, and that many of the actors' important relations are in the periphery of fintech and are therefore not considered candidates for cluster membership. This also suggests that the strategic relations in the Norwegian fintech ecosystem consists of a larger, possibly more diversified group of actors than one might expect. It might be the case that many important relations exist outside a traditionally defined fintech-sphere, indicating that the term "fintech" is indeed broad, and that it is in the intersection of many overlapping industries, also in Norway. One explanation for this might be that actors outside the financial industry are increasingly making entry and blurring the boundary of what is considered fintech (see for example Schwienbacher & Larralde, 2012; Zachariadis & Ozcan, 2016; Knudsen & Bienz, 2019).

Following that fintech is a broad term, the high number of external relations might also be explained by the composition of firms in the regional cluster. To many of the larger, mature firms in the cluster such as incumbent banks and consultancies, fintech might be just a small part of their business operations, meaning that their most important relations take place with other firms in different industries. In addition, fintech start-ups, which is the largest category of the cluster members in NCE FI, are possibly considered as less important relations by other members, because most start-ups are not yet fully operating and lack resources to create and maintain reciprocally beneficial relations. This seems plausible when considering the fintech start-ups' low average in-degree score of 1.83, compared to traditional financial institutions with about 8.89 actors on average considering these firms as important relations (see table 7).

However, because the regional cluster is young, one could expect that many of the strategic relations are still in their infancy, meaning that they are currently less relevant to the members than older relations existing in the organic network. Moreover, due to the cluster's young age, there might not have been established that many strategic relations yet, as trustful relations take time and resources to develop.

Nonetheless, research indicates that linkages stretching outside a regional cluster can be important, if not essential for a cluster's overall ability to innovate. According to Wolfe and Gertler (2004), regional clusters are not self-sufficient when it comes to the knowledge capabilities they draw upon. Linkages to outside actors can bring in new knowledge that can facilitate local innovation in the cluster. Many successful regional clusters for example deliberately establish international linkages in order to gain access to otherwise locally unavailable knowledge and resources and to avoid technological lock-in (Turkina & Van Assche, 2018). Granovetter's (1973) research suggested that in order to obtain non-redundant information, one should seek information beyond one's closest connections. That is, weak ties are useful, in that they facilitate access to novel information. Friedkin (1982) found that organizations having many weak ties created diversity in the information flow, while strong ties lead to more effective distribution of this information. The fact that the cluster members of NCE Finance Innovation have many external relations might therefore indicate that the regional cluster is positioned in the larger ecosystem-network in a way that enables external, otherwise locally unavailable knowledge to flow into the regional cluster, but that the distribution of this knowledge locally might be better facilitated by strengthening the cluster's internal relations.

Another possible implication from the regional cluster having many ties to the external environment, might be that the regional cluster is positioned to generate radical innovations.

Atuahene-Gima (2005) found that exploration is positively related to radical innovation, while exploitation is positively related to incremental innovation. According to March (1991) the concept of exploration can be linked to activities such as searching, variation-seeking, discovering and experimenting, while exploitation involves activities such as refinement, efficiency-seeking and implementation. Furthermore, regional clusters in more traditional industries are often associated with incremental innovation (Asheim & Coenen, 2005), while complex and disruptive technologies tend to be based in more open systems, utilizing the regional clusters' external networks (Albors-Garrigos & Hervás-Oliver, 2012). This might indicate that a regional cluster such as NCE FI, with seemingly porous boundaries and many connections to the external environment, is well positioned for explorative activities, increasing opportunities for technological breakthroughs. Moreover, as one interpretation of our findings are that the members are somewhat weakly connected internally, the regional clusters ability to facilitate process-innovation might be lower, as this is highly dependent on the sharing of abstract, tacit knowledge facilitated by trustful relations (Newell et. al, 2002).

In sum, despite many possible interpretations from our findings, our data does not enable us to say anything definitive about how the degree of external relations, or the strength of internal relations affect the regional cluster's ability to stimulate innovation among its members. Nonetheless, this discussion suggests that clusters should not be viewed as isolated entities disconnected from the outside world, and that boundary spanning linkages could be an important indicator for the regional cluster's ability to tap into diverse, locally unavailable knowledge, which can facilitate local innovation. Our findings do, however, suggest that the relations existing within the regional cluster might be weaker than what was expected, which can limit the degree of trustful relations and therefore the cluster's ability to take advantage of this external knowledge. Taking this into consideration, our findings can suggest that striking a balance between facilitating strong relations within a cluster, and at the same time ensuring weaker ties that connects the cluster to its larger ecosystem might be beneficial for the regional cluster's ability to obtain innovation generating knowledge, while at the same time being able to efficiently combine, distribute and make use of this knowledge.

2nd key insight: The regional cluster network exhibits hierarchical properties

Our second key insight is that the network of NCE Finance Innovation exhibits characteristics of a hierarchical network. This might indicate that the members in the core constitute an “elite” and that they hold advantages that the peripheral members might lack. Theory suggests that the central firms in these networks have fast access to reliable information and quality knowledge, increasing these firm’s learning capabilities, while the outlying actors are just marginally included in these knowledge-generating networks, thus hampering these actors’ innovative capabilities (Giuliani & Bell, 2005). However, as discussed in the first key insight, one could also argue that peripheral actors that connect the regional cluster to its external environment might be essential for the core actors’ access to novel ideas stemming from the larger ecosystem.

Another interesting finding, signalling its hierarchical properties, is that the regional cluster network inhibits properties of a scale-free network, which is found in many real-world networks. The plausible mechanism for explaining this characteristic is that as the regional cluster grows, new actors are more likely to form relations with the actors that are already well-connected, known as preferential attachment. One plausible reason for this characteristic in our context is that for new actors joining the regional cluster, there could be a lack of information about which actors to connect with. As proposed by Gould (2002), new entrants can find it costly to perform quality judgements and will therefore tend to connect to the highly reputable actors. These actors’ favourable reputations and status are thereby increased by accumulating a critical mass of linkages, drawing even more connections by new entrants, thus cementing their high centrality and influence. This seems plausible in our context as well. Our findings indicate that a significant proportion of the respondents did not use NCE FI to acquire information on which actors who might be beneficial to establish new relations with (see table 5). Therefore, they might mitigate costly quality judgements by forming relations with the more reputable actors. Theory suggest that these few central firms, often referred to as hubs, accumulate influence and power when the clusters grow, and therefore increasingly gain control of much of the network’s resources, such as knowledge and innovations.

In addition to the consequences from possessing characteristics of a hierarchical core-periphery network, the low number of highly central actors in the network makes it vulnerable to attack towards these actors. The reason is that the presence of hubs decreases the average path length as they lower the distance between small degree nodes with fewer connections. If these actors leave the network it could be fragmented into disconnected subnetworks, which obstructs the flow of knowledge and other assets between the cluster members. Nevertheless, the presence of a few highly influential hubs indicate that this network is less vulnerable to random failure, as the chance of a random failure affecting the hubs is relatively small. Moreover, if the less connected actors leave the network, it might not have a large effect on the networks ability to diffuse information internally, as the hubs to a large extent would hold the network together and facilitate efficient flow of information across the network. In addition, an advantage with a centralized structure could be that it may facilitate easier coordination across the network. This can be advantageous for initiating joint problem-solving activities requiring efficient coordination between the members, such as lobbying.

In sum, our discussion suggests that the regional cluster's hierarchical properties may create a divide in terms of which actors are positioned to access to the cluster's knowledge base. In addition, preferential attachment may cause some firms to increase their already substantial influence and power as new members join, which signals that it might be costly for new members to obtain information about other actors in the regional cluster. Furthermore, this mechanism can increase the regional cluster's vulnerability as these highly connected actors are responsible for much of the network's internal diffusion of knowledge. Nonetheless, our findings can suggest that the regional cluster could enhance the overall innovation capabilities in the network by increasingly incorporating the peripheral actors into the knowledge generating core of the network, while at the same time encouraging ties to the external environment.

3rd key insight: The regional cluster network's distribution of influence is skewed

Our third key insight is that there are large differences in terms of which types of actors obtain the most potentially influential positions in the regional cluster network. The actors with the most connections in the network of NCE FI consist of mainly traditional financial institutions and consulting firms. These actors are expected to have easy access to information, knowledge and resources compared to less central actors. Furthermore, traditional financial institutions are on average considered as important relations by the highest number of actors in the cluster. This can imply that most of the information and knowledge from other actors is first transferred directly to these firms, something that may be advantageous as it enables these actors access to potential novel information from several direct sources which also increases their ability to interpret this information and generate quality knowledge. On the other hand, these firms might be at higher risk of relational inertia if their cluster-relations get to cemented, causing shared information to become homogenous and redundant.

Furthermore, consultancies consider the highest number of actors in the cluster to be important relations on average. This can imply that much of the regional cluster network's information and knowledge is first passed on from consultancies as they can directly spread information to the most other cluster members. This puts consultancies in potentially advantageous, influential positions in the network. The reason being that they to an extent might steer the direction of cluster-initiatives by generating support from their direct relations, and thereby control much of the cluster's knowledge generating activities.

Our findings regarding the distribution of betweenness centrality-scores indicate that a significant number of actors in the regional cluster depend on mainly two actors, a traditional financial institution and a technology developer, to make connections with other actors in the network. These firms are possibly influential and powerful, as they control much of the information passing between other actors in the network. Many members in the regional cluster network might therefore be dependent on these highly central actors to access resources, knowledge, and information from otherwise more distant or disconnected actors inside the cluster. The central cluster members can therefore be said to have the role of gatekeepers or mediators and as such might be essential to the diffusion of resources in the regional cluster.

Moreover, traditional financial institutions and consultancies are some of the actors that are least constrained by their connections being tightly connected to each other. These actors occupy structural holes in the network and have the advantage of accessing potentially unique and diverse knowledge from several sources which can enhance these actor's exploitation of creative new ideas and therefore radical innovations. In addition, these actors get control-benefits from brokering information between disconnected actors. As such, these actors are crucial for the flow of valuable information in the network and might be considered attractive relations by other actors, as it enables them to access novel information from more distant actors. The network is likely vulnerable to targeted attacks toward these actors, as their absence could either split the network into unconnected subnetworks, and thereby either completely break off the information flow between groups, or at least disrupt communication between other actors. Their absence could slow the diffusion of information and knowledge and increase the risk of information-distortion. The fact that there are just a few actors controlling most of the information flow between other actors in the network might therefore constitute a potential vulnerability in the regional cluster network.

The fintech start-ups on the other hand are to a large extent located in the periphery of the network and are much less connected, indicating both less and slower access to the network's resources. Fintech start-ups might be at a disadvantage in the network as they obtain much less influential positions and are therefore reliant on the more central firms to obtain information from otherwise relatively distant actors within the regional cluster. This finding is somewhat logical, as one would expect traditional financial institutions and consultancies to have enough resources, such as employees and financial capital, to establish and maintain strategic relationships, as opposed to fintech start-ups often lacking these resources. Besides, our findings imply that larger traditional banks and consultancies have on average a higher number of innovation collaborators, providers, customers, competitors, and financial partners in the regional cluster than fintech start-ups. One plausible reason in the case of customers is that many start-ups in their early phase have not yet established customer-relations with other businesses. Moreover, many fintech start-ups specialize in crowdfunding, money transfer, personal finance, consumer banking etc., in which the customers are often individuals (B2C). In other words, many of their potential customers are not present in the regional cluster as opposed to for example consultancies and technology developers which are more reliant on other businesses as their customers (B2B). Despite having potentially less and slower access to the regional cluster's internal knowledge, fintech start-ups in the periphery of the network with many weak ties to external actors may nonetheless be highly important to the network's innovation capabilities as they can enable influx of non-redundant information from the larger ecosystem.

In sum, our discussion suggests that there are large differences in terms of connectedness and influential positions in the network. The more influential positions are seemingly to a large degree dominated by traditional financial institutions and consulting firms, who theory suggest have faster access to the network's knowledge pool and might be important for the networks ability to diffuse information. In addition, these findings can suggest that the degree of connectedness is not incidental, but that the properties held by the cluster members to a degree determines their positioning and influence in the regional cluster.

4th key insight: Connectedness might matter for perceived innovation benefits

An interesting finding is that having an influential position in the regional cluster, in our case indicated by high betweenness centrality and out-degree, at least to some extent seems to correlate with the degree to which members find cluster-membership important for their ability to innovate. We find that the most central actors in our network, which are consultancies, traditional financial institutions and technology developers, on average stated that they got more benefits from their cluster membership than less central actors. This seems intuitive, as actors with high betweenness centrality possibly have more influence and control of resources in a network and should therefore be able to reap more benefits from being embedded in the regional cluster. In addition, one would expect actors who consider many of the cluster members as important relations to find it more beneficial to be a part of the regional cluster. As research proposes a correlation between trustful, reciprocal relations and the degree to which firms can take advantage of external knowledge, one could expect that actors with stronger relations have a greater ability to innovate. This suggests that, with regards to innovative capabilities, larger, more central firms such as banks and consultancies might be more capable of utilizing external sources of knowledge from cluster membership. On the other hand, one could also have assumed that smaller, possibly less connected firms, such as many fintech start-ups in our network, would be even more dependent on their existent relations in the cluster, and therefore find membership more beneficial than what our results indicate. The reason being that these actors should be more reliant on establishing relations with for example financial partners in order to raise capital and enabling them to "get to market".

In sum, our findings indicate that there could be a correlation between the individual members' connectedness and influence in the regional cluster, and the degree to which membership is important for the actors' ability to innovate. This can suggest that relations matter in terms of outcomes for the individual actor, which is a fundamental assumption of research on social networks (Kilduff & Brass, 2010). This might imply that the resources held inside a firm could be important for explaining or predicting the firm's level of connectedness, and thus for explaining its predicted benefits from regional cluster membership. This is an important insight for cluster facilitators and researchers, as it suggests that start-ups with less resources might find it difficult or costly to establish strategic relations, which can negatively affect their benefit from membership. However, as these interpretations are based on the member's subjective perception of innovation capability, this finding might not reflect actual benefits to innovation performance. In addition, the fact that no actors in the categories funding partners, academia or governments responded to this question, might bias our interpreted results.

Recommendations

We suggest that the regional cluster facilitator investigates possible mechanisms that could both strengthen the existing- and create new relations between the regional cluster members. As suggested by Porter (2000), facilitators should ensure efficient and regular communication in order to increase open communication and build trust. In addition, if there are in fact many potential beneficial relations in the cluster, but the members themselves lack the resources to locate these, the cluster facilitator could implement mechanisms to increase the visibility of other actors in the cluster, which could make potential synergies more apparent. Another possible course of action could be to broaden the regional cluster focus to encompass a more diverse set of actors, and thereby include more potentially beneficial partners. NCE FI recently announced that they would increase their scope and become a nation-wide cluster, thereby including many new actors in the cluster going forward (Skjelsbæk, 2020). This can imply that the regional (in this case national) cluster, will be even more connected to the larger fintech-ecosystem which can boost the number of weak ties and facilitate easier access to novel knowledge and ideas. However, as research suggests that trustful relations are facilitated by frequent personal interaction, facilitators should be aware that it might be more difficult to strengthen interfirm relations and facilitate coordination in a larger, more geographically dispersed network. This might hamper the cluster's overall innovative capabilities stemming from types of innovations that require efficient exchange of tacit, context dependent knowledge.

With regards to the structural characteristics of the network, the hierarchical structure might be altered by implementing strategies to establish new relations between the peripheral actors themselves, such as fintech start-ups, and between the peripheral and more central actors. This can enable the least central companies' greater access to the regional cluster's knowledge creation and increase the overall density of the network. In addition, due to the preferential attachment mechanism causing new members to mainly seek relations with highly central, reputable hubs, facilitators could seek to make information about other actors more available, for example by facilitating increased personal interactions between the different members. In the longer run, this could potentially reduce the regional cluster's dependence on these hubs and thereby decrease the associated risk of these leaving the network. In the short run however, these hubs are possibly vital for the diffusion of information in the network and ensuring their continued membership in the cluster could be necessary. In order to increase the regional cluster's local innovation processes, facilitators could aim at promoting the already somewhat local cliquishness in the network structure, as it facilitates the sharing of high-quality knowledge. Moreover, as connections with distant actors could be desirable as it enables greater access to novel information, the cluster facilitator could promote structural holes and brokerage positions aimed at connecting the regional cluster to other national- and international knowledge networks (Giuliani & Pietrobelli, 2011).

Despite the potential advantages of forming new ties, policy makers and regional cluster facilitators should be aware that redundant connections could be costly to maintain for the members and might reduce the overall level of innovation as too many ties might overwhelm the most central actors with information. Facilitators might therefore consider limiting the encouragement of connections to encompass actors that show potential for synergies.

Lyon & Atherton (2000) argues that the nature of interfirm relations in regional clusters is highly dynamic and constantly evolving, therefore suggesting that attempts to understand clusters through a snapshot and to fix boundaries are not realistic. Considering this, regional cluster facilitators, policy makers and researchers can use SNA to investigate how a policy or initiative has changed a regional cluster network over time. By mapping the network's relations before and after a policy treatment, the changes in actors positioning and the structural characteristics of the network can yield important insights into the impacts of the particular initiative. For example, analysts might investigate how centrality-measures develop over time, to generate insights into how some actors (or groups of actors) have become more influential or not. By studying the changes in the structural characteristics of the regional cluster, one can know whether the cluster has become more or less egalitarian, efficient, fragmented and so on (Giuliani & Pietrobelli, 2011).

Facilitators and policy makers should, however, be aware that network structures should not be imposed on the regional cluster's members. Research suggests that self-organizing systems might be more advantageous for innovation than externally designed networks (Checkland, 1999; Gausdal, 2008). Whether it is even possible to externally steer the development of regional clusters is a debated topic (Gausdal, 2008). However, research suggests that it is possible to initiate mechanisms that support and stimulate development (Human & Provan, 2000; Wenger, Mcdermott, & Snyder, 2002). Nevertheless, this should be done on the members' terms, and the development of a regional cluster should therefore be based on the members' own knowledge and interests. Gausdal (2008) for example proposes that this can be achieved by facilitating collective reflection processes.

Weaknesses and validity of results

As discussed in the methodology section, the relatively low response rate affects our results. One problem with network-data in particular is that non-respondents may significantly distort results. For example, if one highly connected actor is not present in our data, this can lead the mapping of the full network to be misleading (Borgatti & Molina, 2003). However, we expect that the response rate was high enough so that the most central actors were mentioned, and therefore included in the networks.

Due to a relatively low response rate, measurements such as the network density and the distributions of centralities could be biased. Most of the actors in our networks did not participate in the survey and are therefore present only because they were mentioned by survey-participants. Therefore, many of their potential outgoing links are not present in our data, suggesting that the density measures for both the regional cluster network and organic network might be higher. In the case of the regional cluster network, many of the peripheral actors might, due to missing outgoing links, have higher centrality measures than our data dictates, indicating that the distribution of degree centrality might be less skewed than what our results show. This could again indicate a less hierarchical, and more decentralized network than what is argued in this thesis. We believe, however, that the low response rate does not significantly affect our conclusions. We believe the response was high enough to provide enough indications toward the networks' actual properties and distribution of centralities.

Another challenge regarding the response rate, was that very few or none of the participants in the survey represented organizations within investment firms, government, academia, or funding partners. As a result, these fintech actors are at most visible in our networks to a small degree. Thus, we are not able to indicate too much about their positions and potential influence in the regional cluster.

Furthermore, this thesis' aim was mainly to investigate networks in a descriptive manner. One caveat of SNA that network visualisations often can provide vague and imprecise answers. Interpretations can often rely on one's subjective opinion, especially when there is high ambiguity. More precise answers could have been attained by applying econometric techniques such as linear or multiple regression to study effects. This could have been applied to study for example the correlation between different centralities (independent variable) and the innovation-benefits gained from being a regional cluster member (dependent variable). However, we considered the number of responses to be somewhat too low to generate accurate and insightful results from performing regression. In addition, to say something about causal relationships would require a discussion around issues such as random sampling, omitted variable bias, simultaneity, and so on. Therefore, due to the time and resources available, it did not seem achievable to perform a detailed econometric discussion around this in the master thesis. In addition, more accurate insights could have been made possible by having an unbiased, objective performance measure for innovation, such as the number of realized innovation projects, in contrast to our chosen subjective indication of innovation performance.

Lastly, there are multiple aspects to analyse in our data which were not prioritized. We could for example have investigated the different subnetworks (e.g. provider, customer, competitor etc.) in more detail, which could provide deeper insights into how the relations and influence were distributed in the regional cluster. The network measures on the subnetworks from each of the five relational types we collected in the survey, are presented in table 9 and 10 in appendix A for the organic and the regional cluster network, respectively.

Future research

By comparing the structural characteristics of two or more regional cluster networks, and applying accurate performance indicators of innovation, such as the rate of patenting filing, research could gain deeper insights into which structural characteristics might be best suited for innovation. On the actor level, researchers could use multiple regression techniques to explore correlations more reliably between the attributes of actors and their centrality measures in the network. Such techniques could also be used to attain accurate insights into how centralities might affect individual firm performances.

Future research could also investigate how to more efficiently facilitate advantageous alterations to the structure of the network, for instance by establishing or strengthening relations through financial incentives, collective reflection processes, networking activities and so on. In addition, by studying the different subnetworks of a regional cluster's competitors, customers, providers etc. separately, research could gain deeper insights into the relational characteristics of a regional cluster, such as which subnetworks might facilitate or impede innovation (see table 9 and 10 in appendix A). Moreover, this could yield insights into the relational aspects of a regional cluster's competition and coopetition-dynamics, investment behaviour etc., which could provide new insights into ecosystems and regional clusters. In a fintech-context, this might be especially interesting in the wake of PSD2, which is expected to dramatically change the relational dynamics of the financial industry and therefore the fintech ecosystem in the years to come.

Lastly, as digitalization minimizes geographic distance and enables alternative forms of collaboration, geographical proximity might not be as important as traditional research on regional clusters has indicated. Future research could use SNA to investigate the importance of geographical proximity for the formation of trustful relations, by mapping and analysing relations in clusters where the members' business models are mostly digitally driven, and in clusters where members are geographically dispersed.

Bibliography

Ahuja, G. (2000). Collaboration networks, structural holes, and innovation: A longitudinal study. *Administrative Science Quarterly, 45(3),* pp. 425–455.

Albors-Garrigos, J., & Hervás-Oliver, J. L. (2012). Radical innovation and technology diffusion in traditional clusters: How high-tech industries reinvented a traditional cluster. *Comparing High Technology Firms in Developed and Developing Countries: Cluster Growth Initiatives*, *January*, 99–110. https://doi.org/10.4018/978-1-4666-1646-2.ch008

Amara, N., & Landry , R. (2005). Sources of information as determinants of novelty of innovation in manufacturing firms: evidence from the 1999 statistics Canada innovation survey. *Technovation 25*, pp. 245–259.

Anderson, J., & Narus , J. (1990). "A Model of Distributor Firm and Manufacturer Firm Working Partnerships". *Journal of Marketing*, pp. 42-58.

Anderson, J., Håkansson , H., & Johanson, J. (1994, (Oct)). Dyadic Business Relationships within a Business Network Context J. *Journal of Marketing 58*, pp. 1-15.

Aragón, C., Aranguren, M. J., Iturrioz, C., Larrea, M., Olarte, J., Aragón, C., & Deusto, E. (2009). A NEW STEP IN CLUSTER POLICY EVALUATION IN THE BASQUE COUNTRY. *Orkestra Working Paper Series in Territorial Competitiveness*, *01*, 1989–1288.

Arner, D. W., Barberis, J., & Buckley, R. P. (2016). The Evolution of FinTech: A New Post-Crisis Paradigm? *Georgetown Journal of International Law 47*, pp. 1271-1319.

Asheim, B., & Coenen, L. (2005). Knowledge bases and regional innovation systems: Comparing Nordic clusters. *Research Policy, 2005, vol. 34, issue 8,* pp. 1173-1190.

Astley, W. G., & Fombrun, C. J. (1983). Collective strategy: Social ecology of organizational environments. *Academy ofManagement Review, 8(4)*, pp. 576–587.

Atuahene-Gima, K. (2005, October). Resolving the Capability—Rigidity Paradox in New Product Innovation. *Journal of Marketing 69(4),* pp. 61-83.

Autio, E. (2017). Digitalisation, Ecosystems, Entrepreneurship and Policy. *Policy Brief 20/2017*.

Barabasi, A., & Alber, R. (1999). Emergence of scaling in real networks. *Science 286:*, pp. 509–12.

Baum, J. A., Shipilov, A. V., & Rowley, T. J. (2003). Where do small worlds come from? ,. *Industrial and Corporate Change 12*, pp. 697-725.

Beck, T., Chen, T., Lin, C., & Song, F. (2016). Financial innovation: The bright and the dark sides. *Journal of Banking and Finance vol. 72*, pp. 28-51.

Bentsen, I., & Bjørne, H. (2019, August). Fintech – fra disrupsjon til samarbeid på rekordtid. *Magma*, pp. 32-36.

Borgatti, S., & Everett, M. (1999). Models of core/periphery structures. . *Social Networks 21*, pp. 375–395.

Borgatti, S., & Molina, J. (2003). Ethical and strategic issues in organizational social network analysis. *Journal of Applied Behavioural Science 39(3),* pp. 337–349.

Borgatti, S., Mehra, A., Brass, D., & Labianca, G. (2009, March). Network analysis in the social sciences. *Science, 323(5916),* pp. 892–895.

Borgatti, S. P., & Halgin, D. S. (2011). On network theory. *Organization Science, 22*(5), 1168–1181. https://doi.org/10.1287/orsc.1100.0641

Boschma, R. (2005). Proximity and innovation: A critical assessment. *Regional Studies. 39,* pp. 61-74.

Burt, R. S. (1992, December 4). *Structural Holes: The Social Structure of Competition.* Cambridge: Harvard University Press.

Burt, Ronald. (2004) ‘Structural holes and good ideas’, *American Journal of Sociology,* 110(2):349–399.

Castro, P., Rodrigues, J. P., & Teixeira, J. G. (2020). Understanding FinTech Ecosystem Evolution Through Service Innovation and Socio-technical System Perspective. *Lecture Notes in Business Information Processing, 377 LNBIP*(January), 187–201.

https://doi.org/10.1007/978-3-030-38724-2_14

Checkland, P. (1999). *Systems Thinking, Systems Practice.!!* . Chichester, England: John Wiley & Sons Ltd.

Coase, R. H. (1937). The Nature of the Firm. *Economica*, *4*(16), 386–405. https://doi.org/10.1111/j.1468-0335.1937.tb00002.x

Coleman, J. S. (1988.). Social capital in the creation of human capital. *Amer. J. Sociol, 94*, pp. 95–120.

Cooke, P. (1998). Introduction: origins of the concept. *Regional Innovation Systems, London, UCL Press*.

De Man, A., & Duysters, G. (2005). Collaboration and innovation : a review of the effects of mergers , acquisitions and alliances on innovation. *Technovation*, *25*, 1377–1387. https://doi.org/10.1016/j.technovation.2004.07.021

De Solla Price, D. (1976). A general theory of bibliometric and other advantage processes. *Journal of American Society for Information Science 27*, pp. 292–306.

Delgado, M., Porter, M., & Stern, S. (2014). Clusters, convergence, and economic performance. *Research Policy, 43(10)*, pp. 1785–1799.

Doeringer, P. B., & Terkla, D. (1995, August). Business strategy and cross-industry clusters (9) . *Economic Development Quarterly, Vol 9, No. 3*, pp. 225-237.

Duncan Luce, R., & Perry, A. (1949). A method of matrix analysis of group structure. *Psychometrika 14(2)*, pp. 95–116.

Engel, J. S. (2015). Global clusters of innovation: Lessons from Silicon Valley. *California Management Review*, *57*(2), 36–65. https://doi.org/10.1525/cmr.2015.57.2.36

European Commision . (2020, November 23). *Payment services*. Retrieved from https://ec.europa.eu/info/business-economy-euro/banking-and-finance/consumer-finance-and-payments/payment-services/payment-services_en

Financial Stability Board (FSB). (2020, December 10). *FinTech*. Retrieved from https://www.fsb.org/work-of-the-fsb/financial-innovation-and-structural-change/fintech/

Frame, W., Wall, L., & White, L. (2018). *Technological Change and Financial Innovation in Banking: Some Implications for FinTech*. *11*(2018).

Friedkin, N. (1982). Information flow through strong and weak ties in intraorganizational social networks. *Social Networks Volume 3, Issue 4* , pp. 273-285 .

Freeman, L. 1979. Centrality in networks: I. *Conceptual clarifi- cation. Social Networks*, 1: 215–239.

Gargiulo, M., & Benassi, M. (2000). Trapped in your own net? Network cohesion structural holes, and the adaptation of social capital. *Organization Science 11(2)* , pp. 183–196.

Gausdal, A. H. (2008). Hvordan skape innovative nettverk? *MAGMA.*

Gertler, M. S., & Wolfe, D. A. (2004, May). Clusters from the Inside and Out: Local Dynamics and Global Linkages. *SAGE Journals Volume: 41 issue: 5-6*, pp. 1071-1093.

Giuliani, E., & Bell, M. (2005). The micro-determinants of meso-level learning and innovation: evidence from a Chilean wine cluster. *Research Policy 34(1)*, pp. 47–68.

Giuliani, E. (2008). What drives innovative output in emerging clusters? Evidence from the wine industry. . *SPRU Electronic Working Paper Series 169, University of Sussex, SPRU – Science and Technology Policy Research.*

Giuliani, E., & Pietrobelli, C. (2011). *Social Network Analysis Methodologies for the Evaluation of Cluster Development Programs*. *November*, 1–53. papers2://publication/uuid/923FABBC-29E0-454D-8BF7-9D6ADB6FE951

Gould, R. (2002). The origins of status hierarchies: A formal theory and empirical test. *American Journal of Sociology 107(5)*, pp. 1143–1178.

Grabher, G. (1993). The Weakness of Strong Ties: The Lock-in of Regional Development in the Rural Area. *The Embedded Firm: On the Socioeconomics of Industrial Networks. London: Routledge.*, pp. 255–277.

Granovetter, M. (1973). The Strength of Weak Ties. *American Journal of Sociology 78(6),* pp. 1360– 1380.

Granovetter. (1985). *Granovetter_85_Seminal.Pdf* (pp. 481–510).

Granovetter, M. (1998). *Betydningen av svake og sterke bånd i sosiale nettverk*. *Scott 1991*.

Hansen, M. T., Nohira, N., & Tierney, T. (1999). What Is Your Strategy for Managing Knowledge? *Harvard Business Review, 77, 2,* pp. 106–117.

Handel, M., & Powell, W. W. (2003). *Neither market nor hierarchy: Network forms of organization*. *March*, 315-330 %@ 9780761987666.

Hanneman, R. A., & Riddle, M. (2005). Introduction to Social Network Methods. *University of California, Riverside*.

Hornuf, L., & Haddad, C. (2019). The emergence of global fintech market: Economic and technological determinants. *Small Bus Econ 53,* pp. 81–105.

Human, S., & Provan, K. (2000). Legitimacy Building in the Evolution of Small-Firm Multilateral Networks: A Comparative Study of Success and Demise. *Administrative Science Quarterly, 45, 2,* pp. 327–365.

Inkpen, A. (1996). Creating Knowledge through Collaboration. *California Management Review, 39, 1,* pp. 123–140.

Innovation Norway. (2020, December 10). *Norwegian Innovation Clusters*. Retrieved from NCE Finance Innovation : https://www.innovasjonnorge.no/no/subsites/forside/om_klyngeprogrammet/kart/nce/nce-finance-innovation/

Jackson, M. O. (2008). *Social and economic networks.* New Jersey: Princeton University Press.

Jacobides, M. G., Cennamo, C., & Gawer, A. (2018). Towards a theory of ecosystems. *Strategic Management Journal*, *39*(8), 2255–2276. https://doi.org/10.1002/smj.2904

Kempe, D., Kleinberg, J., & Tardos, É. (2003). Maximizing the spread of influence through a social network. *Proceedings of the Ninth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 137–146.

Kilduff, M., & Brass, D. J. (2010). Organizational social network research: Core ideas and key debates. *The Academy of Management Annals*, pp. 317–357.

Kline, S., & Rosenberg, N. (1986). *An overview of innovation. In: Landau, R., Rosenberg, N. (Eds.), The Positive Sum Strategy.* Washington, DC.: National Academy Press.

Knudsen, E. S., & Bienz, C. (2019, August). Fintech Hva er det, og hvorfor bry seg? *Magma*, pp. 12-15.

Kogut, B. (1988). Joint Ventures: Theoretical and Empirical Perspectives. *Strategic Management Journal 9*, pp. 312–332.

Kurt, Y., & Kurt, M. (2020). Social network analysis in international business research : An assessment of the current state of play and future research directions. *International Business Review*, *29*(2). https://doi.org/10.1016/j.ibusrev.2019.101633

Labun, A., & Wittek, R. (2014). Structural Holes. In L. Coromina, V. Hlebec, T. Kogovsek, G. Coenders, & G. Gallart, *Encyclopedia of Social Network Analysis and Mining* (pp. 2075-2083). New York: Springer-Verlag New York.

Laumann, E., & Pappi, F. (1976). *Networks of Collective Action: A Perspective on Community Influence Systems.* New York: Academic Press.

Laumann, E., Marsden, P., & Prenskey, D. (1983). The boundary specification problem in network analysis. In R. B. Minor, *Applied Network Analysis* (pp. 18-34). Beverly Hills, CA: Sage Publications.

Lawson, C., & Lorenz, E. H. (1999). Collective Learning, Tacit Knowledge and Regional Innovative Capacity. *Regional Studies, 33, 4*, pp. 305–317.

Laursen, K., A. Salter. 2006. Open for innovation: The role of openness in explaining innovation performance among U.K. manufacturing firms. Strategic Management Journal 27 131–150.

Lea, B., Yu, W., Maguluru, N., & Nichols, M. (2006). Enhancing business networks using social network based virtual communities. *Industrial Management & Data Systems, Vol. 106 No. 1*, pp. 21-138.

Lee, I., & Shin, Y. J. (2018). Fintech: Ecosystem, business models, investment decisions, and challenges. *Business Horizons*, *61*(1), 35–46. https://doi.org/10.1016/j.bushor.2017.09.003

Lorenz, E. (1996). Collective learning processes and the regional labour market, unpublished research note. *European Network on Networks, Collective Learning and RTD in Regionally-Clustered High-Technology SMEs* .

Lyon, F., & Atherton, A. (2000). A business view of clustering: Lessons for cluster development policies. *Foundation for SME Development, University of Durham*, 1–13. http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:A+business+view+of+clustering+:+Lessons+for+cluster+development+policies#4

March, J. (1991). Exploration and exploitation in organizational learning. *Organ Sci 2*, pp. 101–123.

Marin, A., & Wellmann, B. (2010). Social Network Analysis: An Introduction. In P. Carrington, & J. Scott, *Handbook of Social Network Analysis* (pp. 11-25). London: Sage.

Martin, R., & Sunley, P. (2003, January). Deconstructing clusters: chaotic concept or policy panacea? *Journal of Economic Geography, Volume 3, Issue 1*, pp. 5–35.

Maskell, P., & Malmberg, A. (1999). Localised learning and industrial competitiveness. *Cambridge Journal of Economics 23 (2)*, pp. 167-186.

McEvily, B., A. Zaheer. 1999. Bridging ties: a source of firm heterogeneity in competitive capabilities. *Strategic Management Journal* 20(12): 1133–1156

Mohr, J. (2014). *Social Network Analysis Made Easy*. Retrieved from [online] Speaker Deck.: https://speakerdeck.com/jeffcmohr/social-network-analysis-made-easy> [Accessed 8 December 2020]

NCE Finance Innovation. (2020, December 3). *About*. Retrieved from https://financeinnovation.no/about

Newell, S., Robertson, M., Scarbrough, H., & Swan, J. (2002). *Managing Knowledge Work.* Basingstoke: Palgrave.

Newman, M. (2003). The Structure and Function of Complex Networks. *Computer Physics Communications. 147,* pp. 40-45.

Oxford University Press. (2020). *Oxford Learned Dictionaries*. Retrieved from https://www.oxfordlearnersdictionaries.com/definition/english/innovation

Porter, M. E. (1990). *The Competitive Advantage of Nations.* New York: Free Press.

Porter, M. E. (1998, November–December). Clusters and the New Economics of Competition. *Harvard Business Review 76, no. 6,* pp. 77–90.

Porter, M. E. (2000). Economic Development : Local Clusters in a Global Economy. *Economic Development Quarterly*, *14*(15), 14–34. https://doi.org/10.1177/089124240001400105

Rocha, H. O. (2004). Small Business Economics 23. *Entrepreneurship and Development: The Role of Clusters*, pp. 363-400.

Rosenfeld, S. A. (1997). Bringing business clusters into the mainstream of economic development. *European Planning Studies*, *5*(1), 3–23. https://doi.org/10.1080/09654319708720381

Rowley, T., D. Behrens, D Krackhardt. 2000. Redundant governance structures: An analysis of structural and relational embeddedness in the steel and semiconductor industries. *Strategic Management Journal* 21(3): 369–386

Rubini, A. (2019). *Fintech in a flash.* Bosten/Berlin: Walter de Gruyter Inc.

Santamaría, L., & Nieto, M. J. (2007). The importance of diverse collaborative networks for the novelty of product innovation. *Technovation*, *27*, 367–377. https://doi.org/10.1016/j.technovation.2006.10.001

Saxenian, A. (1994). Regional Advantage: Culture and Competition in Silicon Valley and Route 128. *Cambridge: Harvard University Press*.

Schilling, M., & Phelps, C. (2007). Interfirm collaboration network: The impact of large-scale network structure on firm innovation. *ManagementScience*, *53*, pp. 1113–1126.

Schwienbacher, L., & Larralde, B. (2012, September). Crowdfunding of Small Entrepreneurial Ventures. In D. Cumming, *Handbook of Entrepreneurial Finance*. Oxford: Oxford University Press.

Scott, J. (2000). *Social Network Analysis.* London: SAGE Publications.

Scott, J. (2013). *Social network analysis.* London: SAGE Publications.

Serrat, O. (2009). Social Network Analysis. *Knowledge Solutions N° 28, Asian Development Bank, Manila*.

Shipilov, A., & Gawer, A. (2020). Integrating research on interorganizational networks and ecosystems. *Academy of Management Annals*, *14*(1), 92–121. https://doi.org/10.5465/annals.2018.0121

Skjelsbæk, J. (2020, December 4). *Finance Watch*. Retrieved from Startups skal få større plass i NCE Finance Innovation: https://finanswatch.no/nyheter/fintech/article12458221.ece

Tichy , N., Tushman, M., & Fombrun , C. (1979). Social Network Analysis For Organizations. *The Academy of Management Review 4(4),* pp. 507–519.

Turkina, E., & Van Assche, A. (2018). Global connectedness and local innovation in industrial clusters. *Journal of International Business Studies*, *49*(6), 706–728. https://doi.org/10.1057/s41267-018-0153-9

Uzzi, B. (1996). The sources and consequences of embeddedness for the economic performance of organizations: the network effect. *Am Sociol Rev 61*, pp. 674–698.

Wasserman, S., & Faust, K. (1994). Social Network Analysis. *Cambridge: Cambridge University Press.*

Watts, D. (1999). Networks, dynamics and the small world phenomenon. *American Journal of Sociology,105(2)*, pp. 493–527.

Watts, D. J. (2004). The "New" Science of Networks. *Annual Review of Sociology 30*, pp. 243–270.

Watts, D., & Strogatz, S. H. (1998). Collective dynamics of “small-world” networks. *Nature, 393*, pp. 440-442.

Wenger, E., Mcdermott, R., & Snyder, W. (2002). *Cultivating Communities of Practice: A Guide to Managing Knowledge.* Boston: Harvard Business School Press.

Wennberg, K., & Lindqvist, G. (2010). The Effect of Clusters on the Survival and Performance of New Firms. *Small Business Economics 34*, pp. 221-241.

Appendix A: List of tables

Table 1 The survey response rate

Table 1 provides a general overview of the survey response rate. The overview is based on the responses from members of NCE Finance Innovation and external actors (non-members).

Table 1 The survey response rate

Response rate			
Results	Members	Non-members	Total
Invited	74	29	103
Respondents	27	7	34
% Response rate	36%	24%	33%

Table 2 Descriptions of the three networks

Table 2 provides descriptions of the three analysed and visualized networks: the organic network, the regional cluster network, and the maximum network. Since there are cluster members and relations occurring in both the organic- and the regional cluster network simultaneously, the "unique ties" and "nodes" occurring in the maximum network are not sums of the unique ties and nodes of the organic- and regional cluster network.

Table 2: Overview of the three networks

Network descriptions				
Network	Relations included	Ties total	Unique ties	Nodes
Organic	All relations gathered from the free-recall approach in part 1 of the survey.	743	666	439
Regional cluster	All relations gathered from the roster-recall approach in part 2 of the survey.	299	227	59
Maximum	All relations from the organic- and regional cluster network.	1042	810	453

Table 3 Overview of fintech categories

Table 3 describes the seven fintech categories of the members of NCE FI.

Table 3: Overview of the fintech categories

Fintech categories	
Category	E.g
Fintech startups	Payment, wealth management, lending, crowdfunding, capital market, and insurance fintech companies
Technology developers	Big data analytics, cloud computing, cryptocurrency, and social media developers
Consulting	Technology consulting, management consulting
Government	Financial regulators and legislature
Academia	Universities and research institutions
Traditional financial institutions	Traditional banks, insurance companies, and stock brokerage firms
Investment firms	Venture capitalist firms

Table 4 Overview of answers to question two in part three of the survey

Table 4 provides an overview of the responding members of NCE FI's answers to the second question in part three of the survey: *"To what degree do you consider your organization's membership in NCE Finance Innovation cluster to be important for your company's ability to innovate within fintech?"*

Table 4: Distribution of the cluster members' answers to the second question in part three of the survey

Innovation benefit from cluster membership	
Degree	% of respondents
To a very large degree	11%
To a large degree	18%
To a some degree	43%
To a small degree	11%
To a very small degree	7%
Not sure	10%

Table 5 Overview of answers to question three in part three of the survey

Table 5 provides an overview of the responding members of NCE FI's answers to the third question in part three of the survey: *"In order to establish a collaborative partnership with another organization in the cluster, how often does your organization first go through NCE Finance Innovation cluster?"*

Table 5: Distribution of the regional cluster members' answers to the third question of part three of the survey

Go through NCE FI to establish collaboration partnership	
How often	% of respondents
Always	0%
Usually	14%
Sometimes	50%
Never	25%
Not sure	11%

Table 6 Structural characteristics of organic and regional cluster network

Table 6 shows the structural characteristics of the organic- and the regional cluster network. The network measures are applied to the networks as undirected.

Table 6: Structural characteristics of the organic- and regional cluster network

Structural characteristics		
Measures	Organic network	Regional cluster network
Number of unique ties	666	227
Number of nodes	439	59
Number of cliques	275	470
Density	0.007	0.128
Avg. path length	3.715	2.439
Global clustering coefficient	0.059	0.315

Table 7 Average centrality scores across fintech categories

Table 7 shows the average scores of selected network measures across the fintech categories in the directed and weighted regional cluster network. The column for "Benefit" shows the average scores from the second survey question in part three. Among the members who participated in the survey, no actors in the categories investment firms, academia or the government were represented. Their benefit score is therefore "–" in the table.

Table 7: Average scores based on fintech category in the regional cluster network

Average scores based on fintech category in the regional cluster network						
Category	Benefit	Degree	In-degree	Out-degree	Betweenness	BCS
Trad.Fin	3	13.67	8.89	4.78	49.65	0.26
Consulting	3.83	8.94	3.88	5.6	26.57	0.36
Tech.Dev	3.2	7.09	3	4.09	43.14	0.43
Fintech startup	2.78	4.72	1.83	2.89	2.39	0.49
Investment firm	-	4	4	0	0	1
Academia	-	4.5	4.5	0	0	0.26
Government	-	1	1	0	0	1
Total average	3.18	6.27	3.87	2.40	13.60	0.54

Table 8 Burt's constraint score in the regional cluster network

Table 8 shows the distribution of Burt's constraint score (BCS) for members in NCE Finance Innovation.

Table 8: Burt's constraint score in the regional cluster network

Burt's constraints score		
BCS	Number of actors	%
0.00-0.15	7	11.7%
0.15-0.30	27	45.8%
0.30-0.45	8	13.6%
0.45-0.60	5	8.6%
1.00	12	20.3%

Table 9 Structural characteristics of the organic subnetworks

Table 9 shows the structural characteristics of the subnetworks for each of the five relational types that were collected in part one of the survey. Table 9 has not been used in this thesis but was referred to in section 5 regarding future research.

Table 9: The structural characteristics of the five relational types from part one in the survey

Organic subnetworks					
Measures	Innovation	Providers	Customers	Competitors	Funding
Number of ties	163	183	140	172	65
Number of cliques	6	16	2	18	1
Density	0.007	0.009	0.008	0.008	0.013
Avg. path length	1.437	1.534	1.172	1.615	1.044
Global clustering coefficient	0.022	0.051	0.011	0.078	0.016

Table 10 Structural characteristics of the regional cluster's subnetworks

Table 10 shows the structural characteristics of the subnetworks for each of the five relational types that were collected in part two of the survey. Table 10 is not used in this thesis but is referred to in section 5 regarding future research.

Table 10: The structural characteristics of the five relational types from part two in the survey

Regional cluster subnetworks					
Measures	Innovation	Providers	Customers	Competitors	Funding
Number of ties	78	52	72	80	17
Number of cliques	11	9	19	57	1
Density	0.032	0.038	0.041	0.006	0.066
Avg. path length	2.227	1.522	1.565	2.060	1.553
Global clustering coefficient	0.101	0.143	0.160	0.372	0.057

Appendix B: List of figures

Figure 1 Maximum network

Figure 1 illustrates the undirected and weighted maximum network. All the relations from both the organic- and regional cluster network are included. The green nodes represent members of NCE FI, while the red nodes represent actors outside the cluster. Green ties represent relations between two cluster members, while red ties represent relations between two non-members. The thickness of a tie corresponds to the relation's assigned weight.

Figure 1: Maximum network

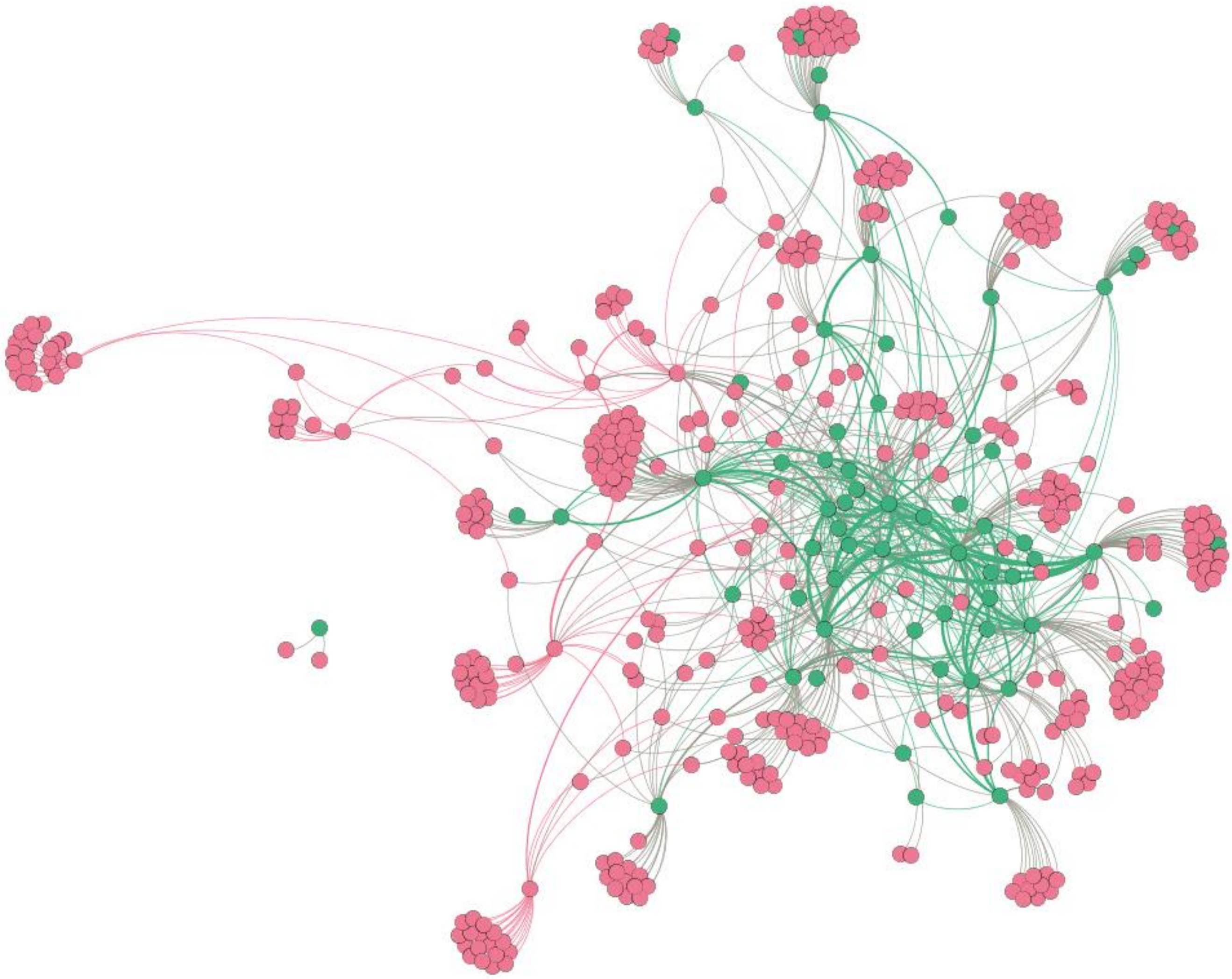


Figure 2 Organic network

Figure 2 illustrates the undirected and weighted organic network. The orange nodes represent members of NCE FI, while the purple nodes represent non-members. Orange ties represent relations between two cluster members, while purple ties represent relations between two non-members. The thickness of a tie corresponds to the relation's assigned weight.

Figure 2: Organic network

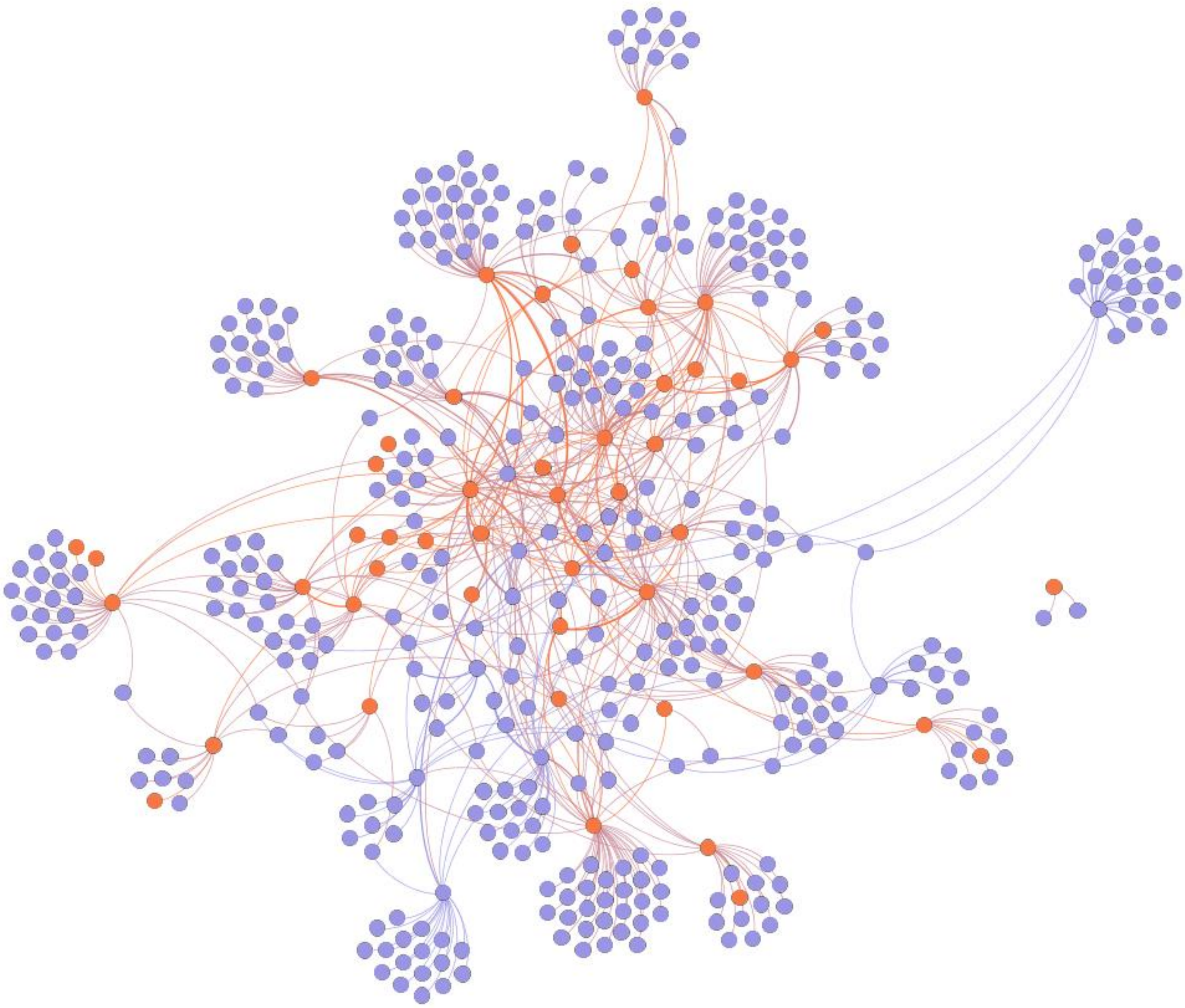


Figure 3 Regional cluster network

Figure 3 illustrates the directed and weighted regional cluster network of NCE Finance Innovation. The thickness of a tie corresponds to the relation's assigned weight, while the direction of the tie is represented by the direction of the arrow.

Figure 3: The regional cluster network

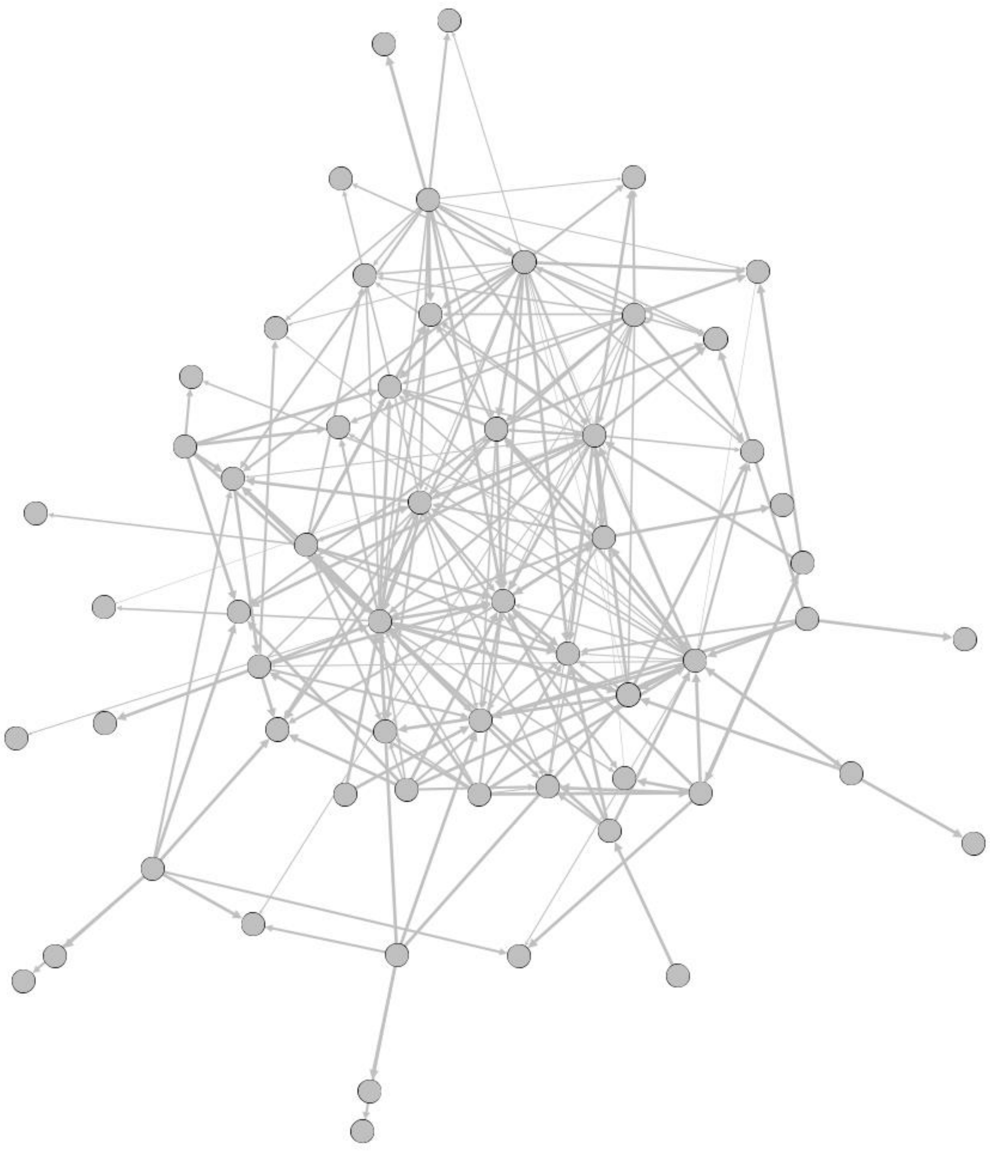


Figure 4 Regional cluster network

Figure 4 shows the regional cluster network as weighted and directed. The node colour represents the member's fintech category affiliation, and the node size corresponds to the node's degree centrality score. The thickness of a tie corresponds to the relation's assigned weight, while the direction of the relation is represented by the direction of the arrow.

Figure 4: The regional cluster network based on degree centrality and fintech category

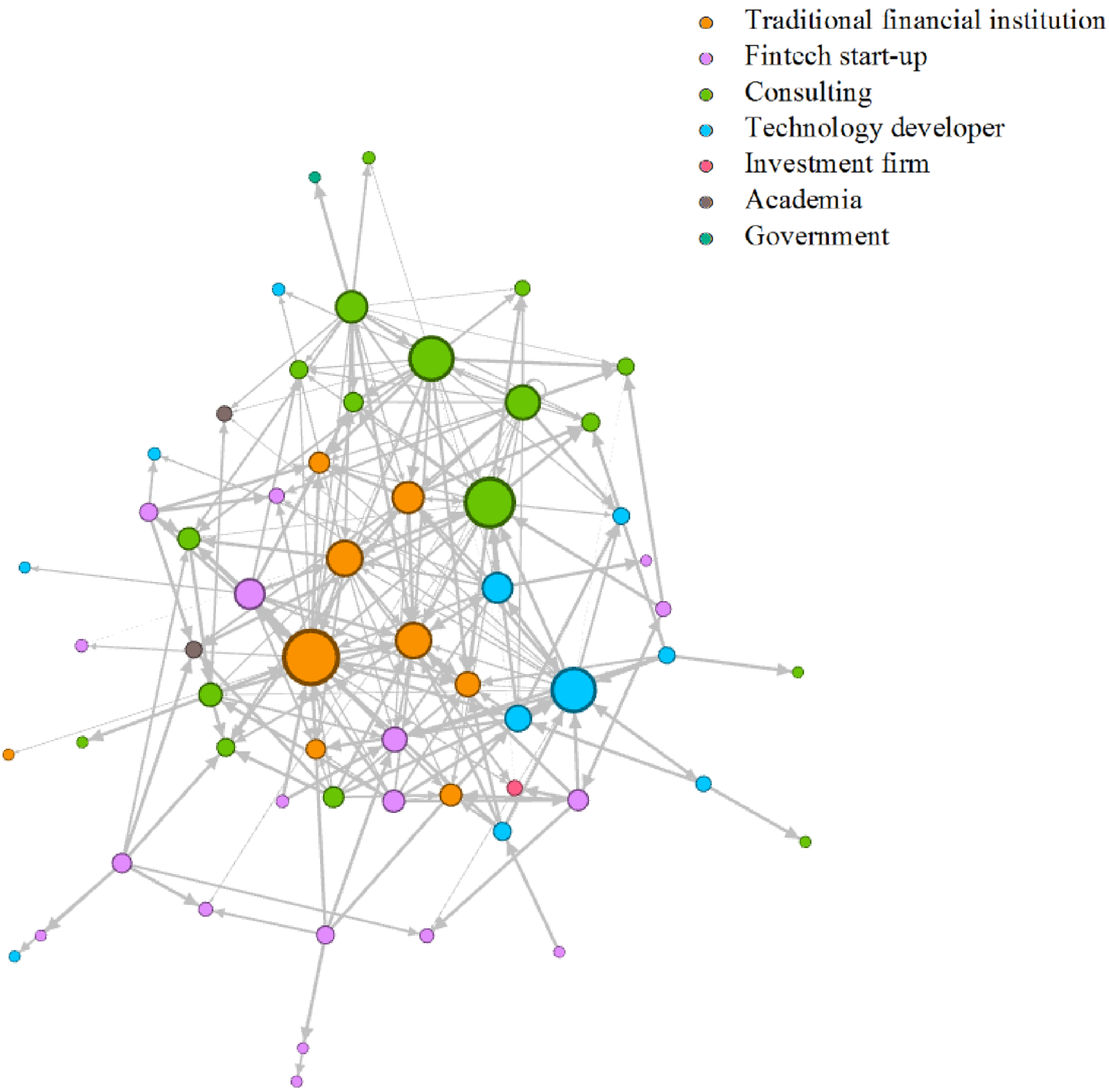


Figure 5 Regional cluster network

Figure 5 shows the regional cluster network as weighted and directed. The node colour represents the member's fintech category affiliation, while the node size corresponds to the node's betweenness centrality score. The thickness of a tie corresponds to the relation's assigned weight, while the direction of the relation is represented by the direction of the arrow.

Figure 5: The regional cluster network based on betweenness centrality and fintech category

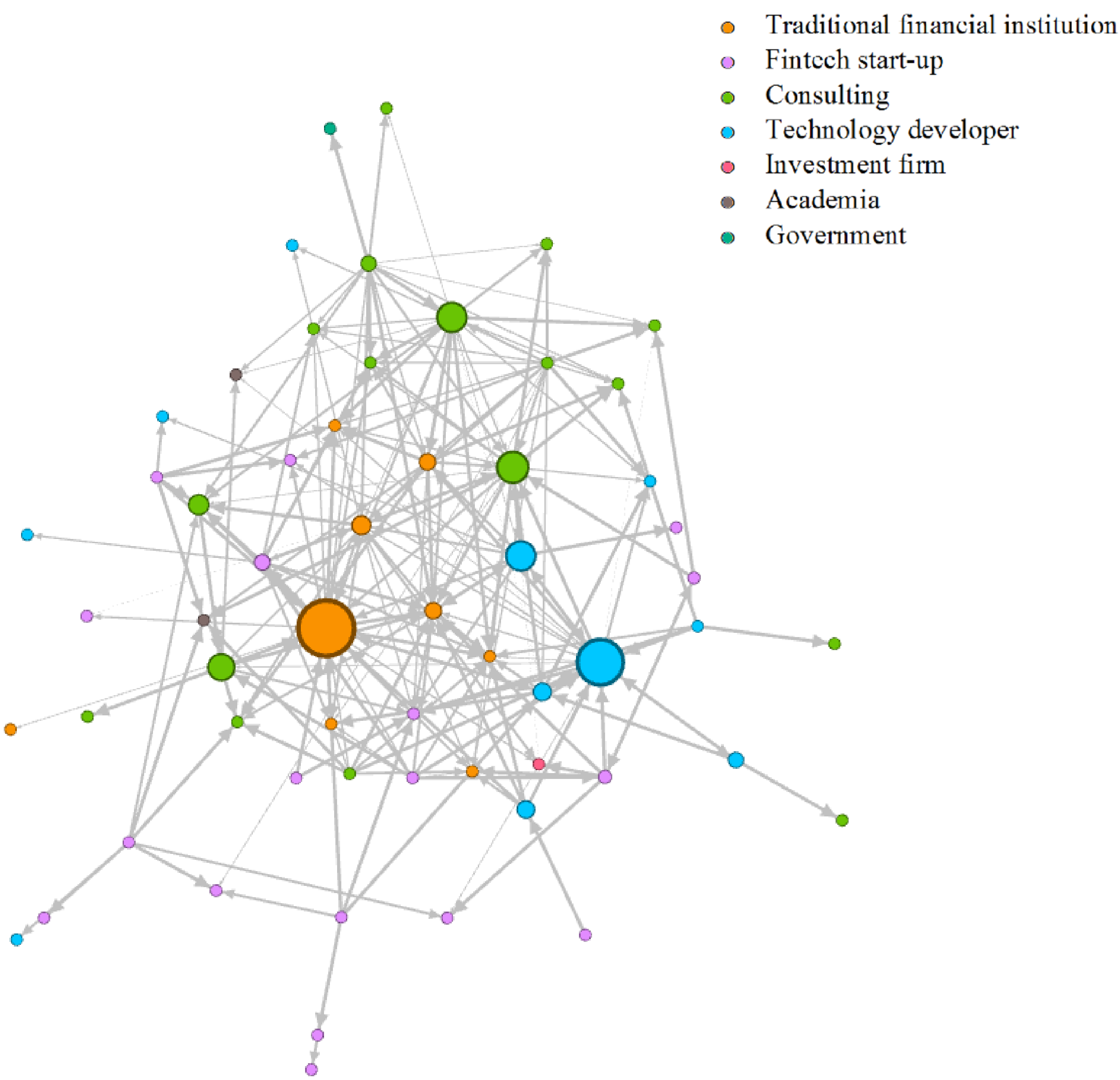


Figure 6 Regional cluster network

Figure 6 shows the regional cluster network as weighted and directed. The green nodes are NCE FI members with a Burt's constraint score (BCS) below 0.15. The red nodes are cluster members with a BCS above 0.15. The thickness of a tie corresponds to the relation's assigned weight, while the direction of the relation is represented by the direction of the arrow.

Figure 6: The regional cluster network based on Burt's centrality score

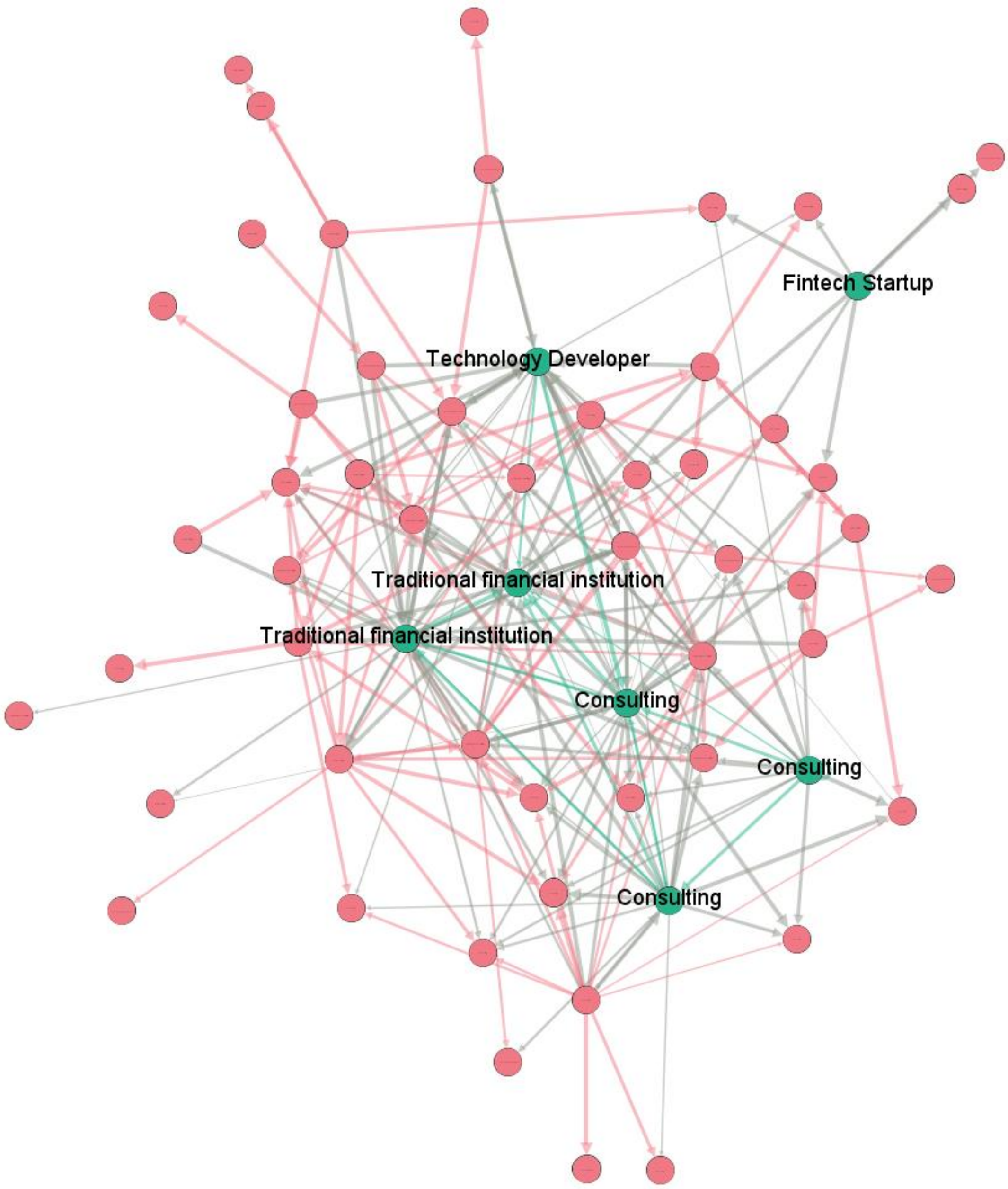


Figure 7 Regional cluster network

Figure 7 shows the regional cluster network as weighted and directed. The more intense green the node colour is, the more the actor stated that it benefits from being a member of NCE Finance Innovation with regards to fintech innovation (second survey question in part three). The node's size corresponds to the actor's betweenness centrality. The thickness of a tie corresponds to the relation's assigned weight, while the direction of the relation is represented by the direction of the arrow.

Figure 7: The regional cluster network based on betweenness centrality and innovation benefit

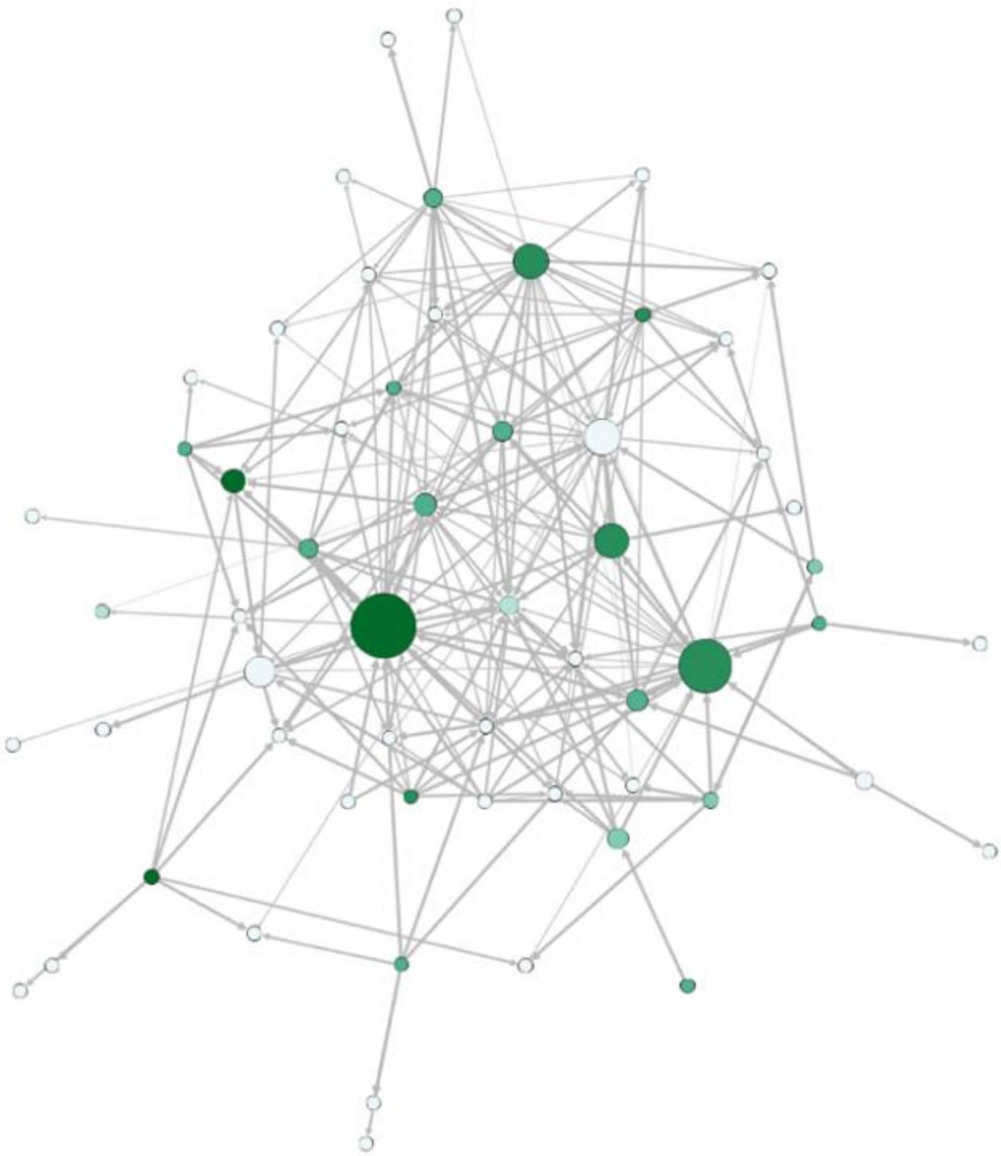


Figure 8 Regional cluster network

Figure 8 shows the regional cluster network as weighted and directed. The more intense red the node colour is, the more the actor stated that it benefits from being a member of NCE Finance Innovation with regards to fintech innovation (second survey question in part three). The node size corresponds to the actor's out-degree centrality score. The thickness of a tie corresponds to the relation's assigned weight, while the direction of the relation is represented by the direction of the arrow.

Figure 8: The regional cluster network based on out-degree centrality and innovation benefit

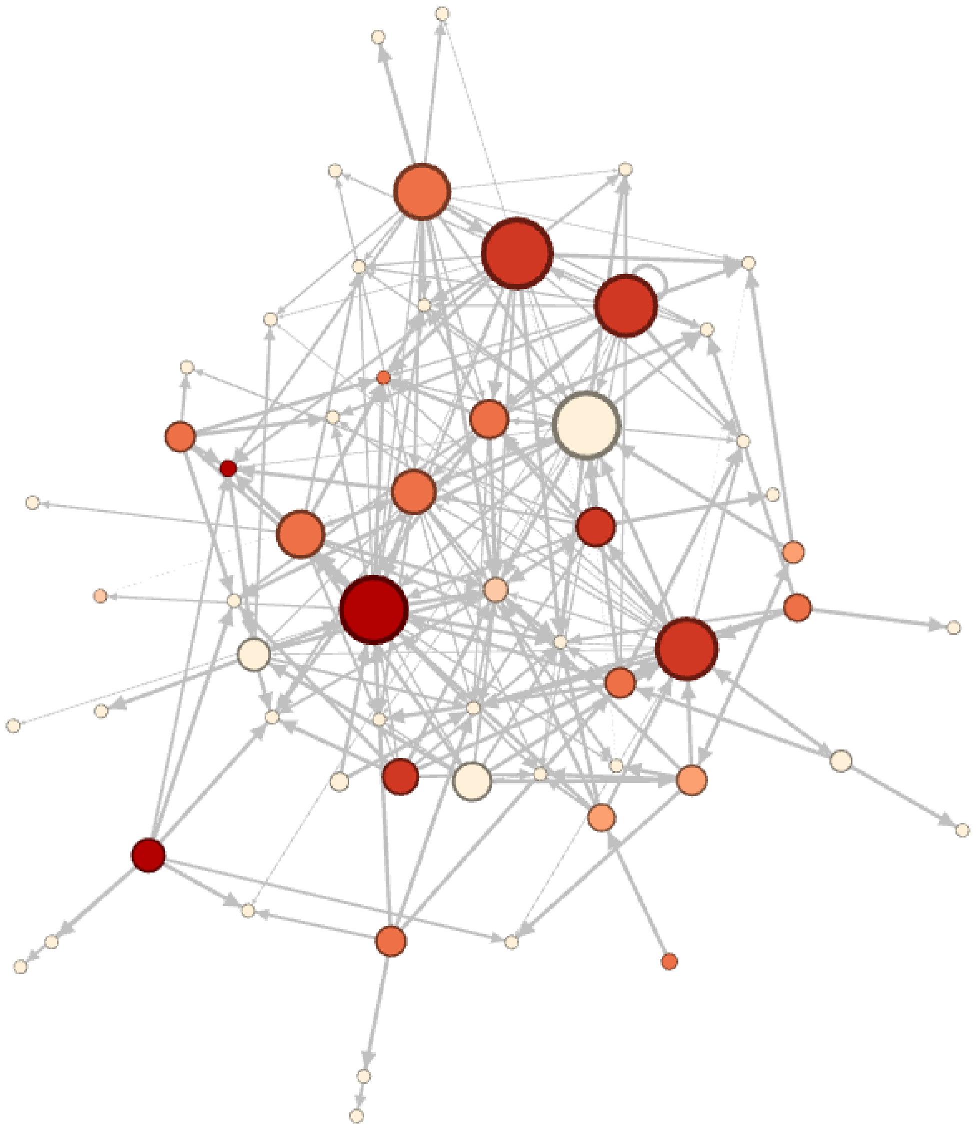


Figure 9 Histogram of degree distribution

Figure 9: Histogram of NCE FI members' degree centrality distribution

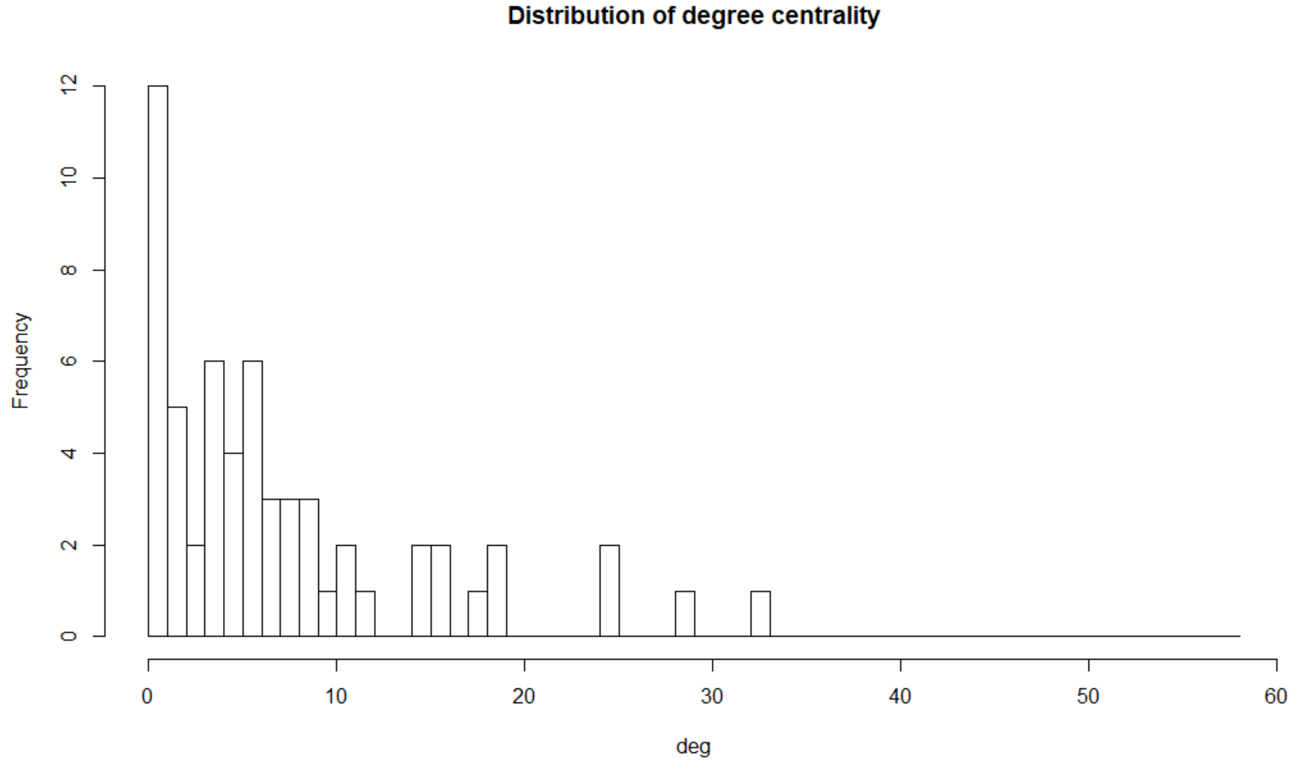
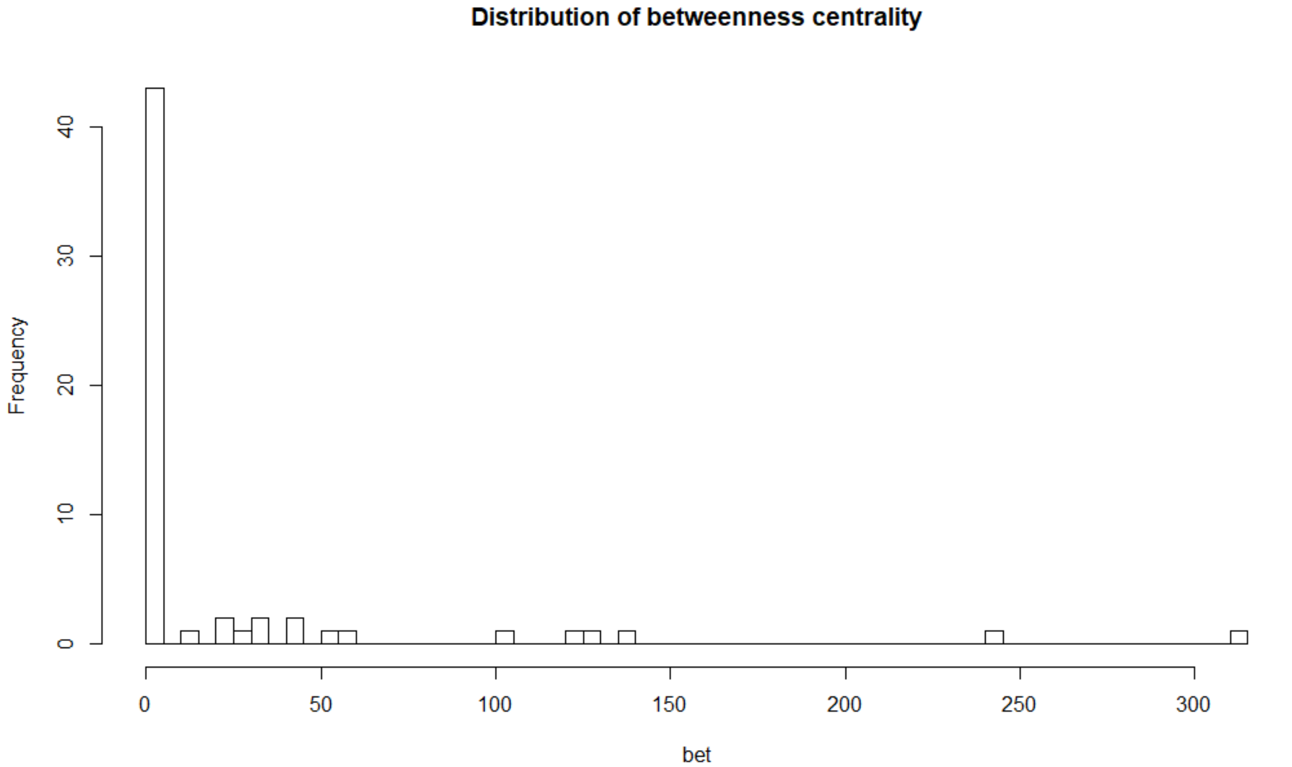


Figure 10 Histogram of betweenness centrality distribution

Figure 10: Histogram of NCE FI members' betweenness centrality distribution



Appendix C: The survey

0% Fullføringsgrad av spørreundersøkelsen 100%

NHH

Vennligst skriv inn ditt ***unike respondentnummer*** *(tre siffer)*, som du fikk oppgitt i invitasjonen på e-post:

Praktisk informasjon

Undersøkelsen tar ca. 10-15 minutter å besvare.

Undersøkelsen er svært enkel å besvare og går ut på at du lister opp de aktører du (top-of-mind) mener representerer de viktigste relasjonene for din bedrift. Det kreves ingen informasjon utover din egen kunnskap for å besvare undersøkelsen.

Anonymitet og konfidensialitet

Alle opplysninger i undersøkelsen vil bli behandlet strengt konfidensielt. I alle analyser og publikasjoner vil data bli anonymisert og aggregert, slik at det vil være umulig å identifisere enkeltbedrifter eller tilbakeføre opplysninger til den enkelte bedrift. Studien er godkjent av Personvernombudet for forskning, Norsk Samfunnsvitenskapelig Datatjeneste.

Som et preventivt tiltak for å unngå tredjepersonsopplysninger ber vi deg om å ikke oppgi navn på enkeltpersoner i de åpne tekstfeltene.

Ved å besvare undersøkelsen samtykker du i at data blir lagret og brukt til forskningsformål (og ingenting annet).

→

0% Fullføringsgrad av spørreundersøkelsen 100%

NHH

Del 1: Ditt virksomhetsnettverk

I denne delen av undersøkelsen blir du bedt om å **identifisere og rangere de (maks 10) mest sentrale virksomhetene i din bedrifts nettverk**, innenfor spesifikke nettverkskategorier.

Disse innebærer din bedrift sine viktigste **innovasjonssamarbeidspartnere, leverandører, kunder, konkurrenter og finansieringspartnere.** Du kan liste opp de samme selskapene innenfor flere kategorier (en leverandør kan for eksempel også være en samarbeidspartner innenfor innovasjon).

Disse innebærer din bedrift sine viktigste **innovasjonssamarbeidspartnere, leverandører, kunder, konkurrenter og finansieringspartnere.** Du kan liste opp de samme selskapene innenfor flere kategorier (en leverandør kan for eksempel også være en samarbeidspartner innenfor innovasjon).

Virksomhetene som du lister opp kan være private og offentlige virksomheter, utdanningsinstitusjoner, eller andre typer organisasjoner.

Det er viktig å påpeke at du som respondent ikke trenger å bruke tid på å innhente informasjon, eller tenke særlig lenge på hvert spørsmål. Svarene skal heller være basert på din oppfatning («top of mind») av hvilke virksomheter som du mener bør være inkludert under hvert spørsmål og hvordan du mener disse bør være rangert.

← →

0% Fullføringsgrad av spørreundersøkelsen 100%

NHH

1. Innovasjonssamarbeidspartnere

Vennligst skriv inn de (maks 10) mest sentrale **innovasjonssamarbeidspartnerene** til virksomheten din i de tomme tekstfeltene under, i rangert rekkefølge. Den viktigste samarbeidspartneren skal være øverst på linje nummer 1, den nest viktigste samarbeidspartneren på linje nummer 2 og så videre.

Med innovasjonssamarbeidspartnere mener vi private og offentlige virksomheter, utdanningsinstitusjoner, eller andre typer organisasjoner som din bedrift samarbeider med når det gjelder innovasjon. Dette inkluderer for eksempel samarbeid rundt utvikling av nye produkter og tjenester, forbedring av eksisterende produkter og tjenester, samt samarbeid for å løse relevante bransjespesifikke problemstillinger.

1
2
3
4
5
6
7
8
9
10

← →

0% Fullføringsgrad av spørreundersøkelsen 100%

NHH

2. Leverandører

Vennligst skriv inn de (maks 10) mest sentrale **leverandørene** til virksomheten din i de tomme tekstfeltene under, i rangert rekkefølge. Den viktigste leverandøren skal være øverst på linje nummer 1, den nest viktigste leverandøren på linje nummer 2 og så videre.

Med leverandører mener vi selskaper som leverer viktige innsatsfaktorer til ditt selskap i form av teknologi (for eksempel software), fysiske innsatsfaktorer (for eksempel hardware), eller kunnskap (konsulenter) og så videre.

1
2
3
4
5
6
7
8
9
10

← →

0% Fullføringsgrad av spørreundersøkelsen 100%

NHH

3. Kunder (B2B)

Vennligst skriv inn de (maks 10) mest sentrale **kundene (B2B)** til virksomheten din i de tomme tekstfeltene under, i rangert rekkefølge. Den viktigste kunden skal være øverst på linje nummer 1, den nest viktigste kunden på linje nummer 2 og så videre.

Med kunder (B2B, eller "business to business") mener vi private og offentlige virksomheter som kjøper (eller mottar) din bedrifts produkter og tjenester.

1
2
3
4
5
6
7
8
9
10

← →

0% Fullføringsgrad av spørreundersøkelsen 100%

NHH

4. Konkurrenter

Vennligst skriv inn de (maks 10) mest sentrale **konkurrentene** til virksomheten din i de tomme tekstfeltene under, i rangert rekkefølge. Den viktigste konkurrenten skal være øverst på linje nummer 1, den nest viktigste konkurrenten på linje nummer 2 og så videre.

Med konkurrenter menes andre virksomheter som i større eller mindre grad konkurrerer om markedsandeler i markeder som din virksomhet opererer i.

1
2
3
4
5
6
7
8
9
10

← →

0% Fullføringsgrad av spørreundersøkelsen 100%

NHH

5. Finansieringspartnere

Vennligst skriv inn de (maks 10) mest sentrale **finansieringspartnerene** til virksomheten din i de tomme tekstfeltene under, i rangert rekkefølge. Den viktigste finansieringspartneren skal være øverst på linje nummer 1, den nest viktigste finansieringspartneren på linje nummer 2 og så videre.

Med finansieringspartnere mener vi private og offentlige virksomheter ditt selskap mottar lån og eller annen type finansiell støtte fra, samt investeringspartnere (selskaper din virksomhet foretar investeringer sammen med).

1
2
3
4
5
6
7
8
9
10

← →

0% Fullføringsgrad av spørreundersøkelsen 100%

NHH

Er din virksomhet medlem av NCE Finance Innovation Cluster?

Ja

Nei

← →

0% Fullføringsgrad av spørreundersøkelsen 100%

NHH

Del 2: Ditt virksomhetsnettverk i NCE Finance Innovation Cluster

I denne delen av undersøkelsen skal du identifisere og rangere de maks (10) viktigste virksomhetene innenfor de samme kategoriene som i forrige del av undersøkelsen (Del 1). Forskjellen fra forrige del er at virksomhetene du skal velge mellom og rangere er medlemmer av NCE Finance Innovation Cluster.

← →

0% Fullføringsgrad av spørreundersøkelsen 100%

NHH

1. Innovasjonssamarbeidspartnerene i NCE Finance Innovation Cluster

Vennligst velg de (maks 10) mest sentrale **innovasjonssamarbeidspartnerene** til virksomheten din fra nedtrekksmenyene på hver linje. Den viktigste samarbeidspartneren skal være øverst på linje nummer 1, den nest viktigste samarbeidspartneren på linje nummer 2 og så videre.

Med innovasjonssamarbeidspartnere mener vi private og offentlige virksomheter, utdanningsinstitusjoner, eller andre typer organisasjoner som din bedrift samarbeider med når det gjelder innovasjon. Dette inkluderer for eksempel samarbeid rundt utvikling av nye produkter og tjenester, forbedring av eksisterende produkter og tjenester, samt samarbeid for å løse relevante bransjespesifikke problemstillinger.

	Rangering av viktigste Innovasjonssamarbeidspartnere
1	
2	
3	
4	
5	
6	
7	
8	
9	
10	

← →

0% Fullføringsgrad av spørreundersøkelsen 100%

NHH

2. Leverandører i NCE Finance Innovation Cluster

Vennligst velg de (maks 10) mest sentrale **leverandørene** til virksomheten din fra nedtrekksmenyene på hver linje. Den viktigste leverandøren skal være øverst på linje nummer 1, den nest viktigste leverandøren på linje nummer 2 og så videre.

Med leverandører mener vi selskaper som leverer viktige innsatsfaktorer til ditt selskap i form av teknologi (for eksempel software), fysiske innsatsfaktorer (for eksempel hardware), eller kunnskap (konsulenter) og så videre.

	Rangering av viktigste leverandører
1	
2	
3	
4	
5	
6	
7	
8	
9	
10	

← →

0% Fullføringsgrad av spørreundersøkelsen 100%

NHH

3. Kunder (B2B) i NCE Finance Innovation Cluster

Vennligst velg de (maks 10) mest sentrale **kundene (B2B)** til virksomheten din fra nedtrekksmenyene på hver linje. Den viktigste kunden skal være øverst på linje nummer 1, den nest viktigste kunden på linje nummer 2 og så videre.

Med kunder (B2B, eller "business to business") mener vi private og offentlige virksomheter som kjøper (eller mottar) din bedrifts produkter og tjenester.

	Rangering av viktigste kunder
1	
2	
3	
4	
5	
6	
7	
8	
9	
10	

← →

0% Fullføringsgrad av spørreundersøkelsen 100%

NHH

4. Konkurrenter

Vennligst velg de (maks 10) mest sentrale **konkurrentene** til virksomheten din fra nedtrekksmenyene på hver linje. Den viktigste konkurrenten skal være øverst på linje nummer 1, den nest viktigste konkurrenten på linje nummer 2 og så videre.

Med konkurrenter menes virksomheter som i større eller mindre grad konkurrerer med din virksomhet om markedsandeler i markeder som din virksomhet opererer i.

	Rangering av viktigste konkurrenter
1	
2	
3	
4	
5	
6	
7	
8	
9	
10	

←

→

0% Fullføringsgrad av spørreundersøkelsen 100%

NHH

5. Finansieringspartnere

Vennligst skriv inn de (maks 10) mest sentrale **finansieringspartnerene** til virksomheten din fra nedtrekksmenyene på hver linje. Den viktigste finansieringspartneren skal være øverst på linje nummer 1, den nest viktigste finansieringspartneren på linje nummer 2 og så videre.

Med finansieringspartnere mener vi private og offentlige virksomheter ditt selskap mottar lån og eller annen type finansiell støtte fra, samt investeringspartnere (selskaper din virksomhet foretar investeringer sammen med).

	Rangering av viktigste finansieringspartnere
1	
2	
3	
4	
5	
6	
7	
8	
9	
10	

← →

0% Fullføringsgrad av spørreundersøkelsen 100%

NHH

I denne delen ber vi deg svare på noen avsluttende spørsmål rundt din virksomhets medlemskap i NCE Finance Innovation Cluster.

Er virksomheten din fysisk representert på Fintech HUB-en i Media City, Bergen?

Ja

Nei

I hvilken grad anser du din virksomhet sitt medlemskap i NCE Finance Innovation Cluster som viktig for din bedrifts evne til å innovere innenfor Fintech?

I svært stor grad	I stor grad	I noen grad	I liten grad	I svært liten grad	Usikker

For å etablere et samarbeid med andre virksomheter i klyngen, hvor ofte går virksomheten din først gjennom NCE Finance Innovation Cluster?

- Alltid
- Som regel
- Av og til
- Aldri
- Usikker

Hvis det er noe ønsker å utdype i forbindelse med svarene du har oppgitt til nå, eller har andre kommentarer, vennligst benytt feltet under.

Ønsker du å motta fremtidige rapporter/publikasjoner basert på resultatene av dette prosjektet?

- Ja
- Nei

Ønsker du å bli invitert til et eksklusivt seminar i januar hvor de første forskningsresultatene legges frem?

Ja

Nei

←

→

0% Fullføringsgrad av spørreundersøkelsen 100%

NHH

Takk for at du tok deg tid til å ta denne spørreundersøkelsen.
Svaret ditt er registrert.

Nedenfor er en oppsummering av svarene dine

Last ned PDF