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Interlocking Directorates Networks and Young Firms' Performance: Social Capital in the Entrepreneurial Environment

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Abstract

There is voluminous research on the relationship between interlocking directorates networks and firm performance. However, empirical studies on this topic remain inconclusive. One issue identified by scholars is related to the scope of studies, as interlocking directorates literature has focused exclusively on mature and large companies. This research contributes by considering firm age as a moderator of the mentioned relationship. We utilize a seven-year panel dataset of the entire Professional, Scientific & Technical Activities sector in Norway, examining inter-industry network originating from a census dataset of all registered companies. The findings indicate that there is a negative moderating effect of firm age on the interlock-performance relationship. We find that young companies benefit more from participating in an interlocking directorates network than established firms. In addition, we consider two types of inter-board connections, ties to young companies and ties to established companies, in terms of their impact on firm performance. We find that young firms extract more benefits from both types of connections. As such, we argue that social capital, through interlocking directorates, can help young companies to overcome liabilities that are associated with an early organizational age.

Keywords

social capital; social network theory; interlocking directorates; board interlocks; young firms; firm age; firm performance; social network analysis; panel data analysis

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1 Introduction

Interlocking directorates occur “when a person is on the board of directors of two or more corporations”. It has been studied in a variety of contexts in the strategic management literature (Fich & White, 2005, p. 175). Despite an over forty-year period of extensive research, no consensus has been reached regarding the impact of board interlocks on firm performance (Peng, Multu, Sauerwald, Au & Wang, 2015). This master thesis addresses this inconclusiveness by distinguishing between the performance implications for young and established companies - building on the network-based theory of social capital and interlocking directorates research.

Social capital refers to “the aggregate of resources embedded within, available through, and derived from the network of relationships possessed by an individual or organization” (Inkpen & Tsang, 2005, p. 151). While there are different dimensions of social capital which can add value to an organization in distinct ways - our focus lies on the structural dimension, representing the patterns of relationships between the actors in the network (Inkpen & Tsang, 2005). In our context, this structural dimension refers to network resources embedded in the inter-board connections, represented by the locational advantage in our social structure, the interlocking directorates network. Thus, we follow the network-based theory of social capital introduced by Lin (1999), according to which social capital is “conceived as an investment in embedded resources in social networks” (Lin, 2005, p. 17).

To address the influence of board interlocks on performance, multiple theoretical perspectives have been applied - however, many take a dyadic view of the company and failing to acknowledge that companies are embedded in networks of relationships (Yeo, Pochet & Alcouffe, 2003; Haniffa & Hudaib, 2006; Davis & Cobb, 2010; Cai & Sevilir, 2012; Peng et al., 2015; Lamb & Roundy, 2016). In contrast, recognizes the social context in which firms are located - the interlocking directorates network in this case (Gulati, Dialdin & Wang, 2002).

Empirical findings on the relationship of social networks and firm performance remain inconclusive (Peng et al., 2015, p. 258; Baum, Calabrese & Silverman, 2000). While some scholars emphasize the negative consequences of networks on firm performance (Nohria & Garcia-Pont, 1991; Ingram & Baum, 1997; Gulati et al., 2002), the majority of social network academics view networks as a source of opportunities and resources - positively impacting performance (Baum & Oliver, 1991; Ingram & Inman, 1996; Khanna & Palepu, 1999; Gulati et al., 2002). In the context of interlocking directorates research, the same inconclusiveness is observed in empirical studies. While some academic scholars find positive, negative and no effects of board interlocks on firm performance (Mizruchi, 1996; Dalton, Daily, Ellstrand & Johnson, 1998; Peng et al., 2015), others find that the importance of interlocking directorates is diminishing in recent years (Chu & Davis, 2016). This ambiguity resulted in criticism of the research investigating the interlock-performance relationship (Peng et al., 2015).

One of the main issues is centered around the fact that the majority of research is focused on large and mature companies (Johannson, Dahlander & Wallin, 2008). However, young companies usually have specific characteristics, distinguishing them from established organizations: Young enterprises have higher failure rates, explained by a lack of stable relationships with partners and restricted access to resources - often addressed as liability of newness and supported by multiple studies (Stinchcombe, 1965; Freeman, Carroll & Hannan, 1983; Brüderl & Schüssler, 1990). In the context of our study, the participation of young firms in interlocking directorates networks can be seen as means of overcoming this liability through securing necessary resources embedded in these networks (Baum et al., 2000). For example, opening opportunities to enhance legitimacy, gain access to financing, information, expertise, and advice (Mizruchi & Stearns, 1988; Westphal, 1999; Hillman, Keim & Luce, 2001; Horton, Millo & Serafeim, 2012). These opportunities are particularly significant for younger enterprises due to the liability described above and can further improve their performance, while established companies usually have already gained substantial resources and expertise.

Considering the above, our motivation is to resolve the ambiguity in the academic literature on the interlock-performance relationship by investigating differing effects of social capital through interlocking directorates on the performance of young and established companies. Thus, we aim to contribute to the academic literature by considering the organizational age as a factor influencing the interlock-performance relationship. Accordingly, our research question is the following:

To what extent does social capital through interlocking directorates impact the performance of young and established firms?

This master thesis is structured as follows. First, the relevant literature is reviewed - creating a theoretical foundation for the development of the hypotheses. This is followed by the methodological section of the paper, including the research strategy, data-, variables- and social network description, as well as an overview of the regression model. Next, the findings are introduced, which is followed by a theoretical discussion of the results. Finally, the theoretical, managerial and methodological implications are considered - as well as the limitations of our study, directions for future research and a conclusion. An additional part of our thesis (Chapter 7) is related to our methodology and presents a detailed discussion on the correspondence between global and local betweenness centrality measures.

2 Theoretical Background & Hypotheses

The thorough theoretical review below sheds light on the mechanisms underlying the relationship between participation in the interlocking directorates network and firm performance – and aims to resolve the ambiguity in the academic literature outlined in the introduction.

2.1 Social Capital Theory

An underlying aspect of our study is why and how board interconnections add value to firms, participating in a network of relationships. The social capital theory gained increasing popularity by explaining the implications of membership in social structures, such as board interlocks - emphasizing the benefits that organizations can extract from these structures (Nahapiet & Ghoshal, 1998; Koka & Prescott, 2002).

Social Capital. The term social capital is rooted in social sciences and emerged in various forms and contexts (Becker, 1964; Jacobs, 1965; Bourdieu, 1986; Coleman, 1988; Putnam, 1993; Nahapiet & Ghoshal, 1998; Koka & Prescott, 2002). Although this diversity resulted in a lack of consensus on the definition of social capital, scholars agree on the central premise that "social capital represents the ability of actors to secure benefits by virtue of membership in social networks or other social structures" (Inkpen & Tsang, 2005, p. 150; Nahapiet & Ghoshal, 1998). Lin (1999, p. 31) describes these benefits as 1) providing essential information, 2) making actors more influential among others, 3) serving as "individual's social credentials", and 4) reinforcing "identity and recognition".

In organizational research, social capital explores topics, such as relationships between organizations and the market, as well as relations inside and outside the firm (Baker, 1990; Burt, 1992; Putnam, 1993; Tsai & Ghoshal, 1998; Inkpen & Tsang, 2005). On this level, social capital can be defined as "*the aggregate of resources embedded within, available through, and derived from the network of relationships possessed by an individual or organization*" (Inkpen & Tsang, 2005, p. 151). As such, the concept is a prominent approach to characterize interfirm ties, such as interlocking directorates (Inkpen & Tsang, 2005).

Social Capital Dimensions. Social capital includes different facets of the social context, making it a "multidimensional construct that can contribute in many ways to the creation of new value for an organization" (Tsai, 2000, p. 927). There are three widely acknowledged social capital dimensions, representing different sources of value for a company: 1) *Structural*, 2) *relational*, and 3) *cognitive* (Tsai & Ghoshal 1998; Nahapiet & Ghoshal, 1998).

The structural (and relational) dimension of social capital is based on Granovetter's (1985) concepts of structural and relational embeddedness (Lindenberg, 1996; Nahapiet & Ghoshal, 1998; Tsai & Ghoshal, 1998). Following this, the *structural dimension* refers to the pattern of relations between actors in the network, where the location (e.g., in terms of network ties or network configuration) provides certain advantages, such as access to information or resources (Wasserman & Faust, 1994; Nahapiet & Ghoshal, 1998; Inkpen & Tsang, 2005). In contrast, the *relational dimension* is focused on the relational outcomes of interactions, such as trustworthiness, while the *cognitive dimension* refers to network resources "providing shared representation, interpretations, and systems of meaning among parties" (Nahapiet & Ghoshal, 1998, p. 244; Coleman, 1988; Putnam, 1993; Tsai & Ghoshal, 1998; Nahapiet & Ghoshal, 1998; Inkpen & Tsang, 2005).

While there is usually a distinction between these dimensions regarding their impact, some scholars view the relational and cognitive dimensions as consequences of the structural dimension - as it considers the network as a whole (Simsek, Lubatkin & Floyd, 2003). In this context, creating clarity on the implications of the structural dimension is an essential step for further studies on the implication of relational and cognitive aspects. Therefore, our focus lies on the structural dimension of social capital - allowing us to explore the implications of the firm's position in an overall network of inter-board connections.

2.2 Social Network Theory

It is evident from the previous section that social capital embedded in inter-organizational ties, such as board interlocks, can add value to organizations in multiple ways. However, the social capital concept is often not studied independently, but commonly viewed in the context of social network theory - both in terms of theoretical reasoning and operationalization of the concept. Since board interlocks span a network of relationships, we follow a network-based theory of social capital (Lin, 1999). According to Lin (2005, p. 17), "conceived as an investment in embedded resources in social networks, social capital focuses on resources (e.g., wealth, power and reputation) of ties that an actor, an individual or collectivity, can access for attaining certain goals".

Social Networks. The social network phenomenon has an interdisciplinary foundation, with a variety of methodological approaches (Heider, 1946; Moreno, 1953; Granovetter 1985; Powell, 1990; Burt, 1992; Wasserman & Faust, 1994; Uzzi, 1997). Laumann, Galaskiewicz & Marsden (1978, p. 548) define social networks as a "*set of nodes (e.g., persons, organizations) linked by a set of social relationships (e.g., friendship, transfer of funds, overlapping membership) of a specified type*". The central premise behind the theory is that an "action does not take place in a barren social context but is instead embedded in a social network of relationships" (Gulati et al., 2002, p. 281). On an organizational level, scholars investigate how companies are interconnected with other companies - constituting a social network of organizations (Walker, 1988; Powell, 1990; Mizruchi, 1992). These interconnections include, for example, strategic alliances, the relationships between suppliers and trade association members, as well as board interlocks (Gulati et al., 2002).

The focal organizational network of our study stems from board interconnections of organizations, commonly addressed as an interlocking directorates network. This network is associated with a specific set of characteristics - as it constitutes a so-called *two-mode* network (Shleifer & Vishny, 1997; Lamb & Roundy, 2016). As opposed to one-mode networks, which are "consisting of nodes of the same kind, representing actors of the same type or category" (Sankar, Asokan & Kumar, 2015, p. 115), actors in two-mode networks (also referred to as *affiliation networks*, *dual networks*, *hyper networks* or *bipartite networks*) have an additional property. Through this property, actors can participate in activities – and become members of certain collectives (Breiger, 1974; McPherson, 1982; Wasserman & Faust, 1994; Faust, 1997). As a consequence, these collectives also have linkages between each other - tied by participants that have multiple memberships. In our case, organizations (collectives) are linked through joint membership of board directors (actors).

The social network theory maintains that organizational networks have three dimensions - namely, network centrality, the structural configuration of ties and partner profiles (Gulati et al., 2002). These dimensions have a different influence on the value companies obtain from this network. The focus of our research is the value associated with *the centrality dimension*, being one of the key measures of a firm's network and reflecting the extent to which the location of an actor is pivotal compared to other actors in the network (Gulati et al., 2002). In this way, we operationalize the structural dimension of social capital. In the context of our study, a central position allows organizations to access more and better resources embedded in the interlocking directorates network (Peng et al., 2015).

Social Networks and Firm Performance. Arguably, a better ability to extract resources from the network is connected to better firm performance (Peng et al., 2015). However, looking into the general social network theory, it is evident that networks can provide both opportunities and constraints for actors (Ingram & Inman, 1996; Ingram & Baum, 1997; Powell, Koput, Smith-Doerr & Owen-Smith, 1999). As Gulati et al. (2002, p. 286) put it: "Networks giveth; networks taketh away".

On the one hand, the opportunities include sharing of various resources, such as financial, institutional, knowledge and informational - which can improve firm outcomes, such as performance, learning, and innovation capabilities (Baum & Oliver, 1991; Ingram & Inman, 1996; Khanna & Palepu, 1999). For example, network ties can serve as a mean for "disseminating both existing and newly acquired knowledge so that all members can quickly access it" (Gulati et al., 2002, p. 287). In the context of social capital theory and interlocking directorates, social capital represents the ability of actors (organizations in our case) to extract the benefits from the directorates network through gaining access to the resources described above. Furthermore, firms that are more central in the network may have a better possibility to access "resources and opportunities" in form of informational, control or learning benefits - improving the firms' performance (Peng et al., 2015, p. 265; Gulati, 1999; Yang, Lin & Peng, 2011).

On the other hand, network membership can prevent companies from exploring new partnership opportunities, locking them into existing relationships and limiting their adaptability (Nohria & Garcia-Pont, 1991; Ingram & Baum, 1997; Gulati et al., 2002). Also, being network members, companies can be exposed to "the risk of unwittingly transferring valuable knowledge and proprietary information to competitor firms in the network" (Gulati et al., 2002; p. 287). Finally, network membership may imply adherence to certain norms or practices, which may not always be suitable for every company in the network (Ingram & Baum, 1997). This implies that social capital, represented by the ability to extract resources embedded in an interlocking directorates network, and further, centrality in this network, can negatively affect a company's outcomes.

A multitude of empirical studies has addressed the relationship between network participation and firm performance, with ambivalent results (Peng et al., 2015). Several studies suggest that social networks have a positive effect on performance (e.g., Baum et al., 2000; Koka & Prescott, 2002) - whereas others find adverse effects on performance or effects depending on the context, such as industry characteristics (e.g., Gargiulo & Benassi, 2000; Rowley, Behrens & Krackhardt, 2000; Peng et al., 2015). Considering the centrality dimension of the network, empirical studies found both positive and negative results for companies from being central in the network (Kilduff & Krackhardt, 1994; Tsai, 2001; Labianca & Brass, 2006; Yang et al., 2011; Larcker, So & Wang, 2013; Peng et al., 2015).

Concluding, there is no agreement in the literature on the effects of network participation on firm performance, but rather an indication that the relationship is dependent on the context. Thus, a closer investigation of our focal organizational network is necessary to gain a deeper understanding of the phenomenon and its impact on firm performance.

2.3 Interlocking Directorates

Interlocking Directorates. A board interlock occurs “when a person is on the board of directors of two or more corporations, providing a link or interlock between them” (Fich & White, 2005, p. 175). The interest in interlocking directorates originated at the beginning of the 20th century, and since then this social structure became one of the most studied in organizational research (Jeidel, 1905; Mills, 1956; Porter, 1956; Koening & Gogel, 1981; Davis & Greve, 1997). Mizruchi’s (1996) review of the board interlock literature fueled academic interest, leading to an “explosion of research on the topic” (Lamb & Roundy, 2016, p. 1517). The phenomenon has been studied from a variety of theoretical perspectives, such as the resource-based view, the resource dependence view and the institutional theory (Pfeffer & Salancik, 1978; Barney, 1991; Mizruchi, 1996; Hillman & Dalziel, 2003; Zona, Gomez-Mejia & Withers, 2018). However, all these theories view companies as atomistic entities, failing to acknowledge that companies are embedded in networks of relationships (Gulati et al., 2000). Social network research incorporates arguments of these theories and extends their logic by recognizing the social context in which firms are located - the interlocking directorates network in this case (Gulati et al., 2002).

As an example, the formation of board interlocks is explained by the resource dependence theory as a way to "gain access to critical resources" for organizations that share interdependencies (Zona et al., 2018, p. 593; Pfeffer & Salancik, 1978); by the institutional theory - as a mean of gaining legitimacy (Mizruchi, 1996; Lamb & Roundy, 2016); and by the resource-based view - as a way to secure directors as "valuable, unique and hard-to-imitate managerial resources" (Peng et al., 2015, p. 263; Barney, 1991). In contrast, *social network theorists* recognized the social context - arguing that networks shape "the flow of valuable information about new tie opportunities" (Gulati et al., 2002, p. 282; Burt, 1992). The rationale behind the formation of these ties is gaining access to the valuable resources embedded in the social structures, otherwise unavailable outside the network - e.g., critical resources and legitimacy described in other theories (Lamb & Roundy, 2016).

Interlocking Directorates and Firm Performance. Multiple theories have been applied to explain the interlock-performance relationship, the majority of which take a dyadic view of the company - as described before. For instance, the resource dependence theory is mainly associated with the positive impact of board interlocks on firm performance - as interlocks help firms to obtain critical resources and information (Pfeffer & Salancik, 1978; Lamb & Roundy, 2016). By contrast, the agency theory posits that "interlocks impair monitoring, raising agency costs and depressing performance" (Zona et al., 2018, p. 4). *Social network theory* integrated the social context into the interlock-performance relationship research. Accordingly, firms that are embedded in an interlocking directorates network can use the advantages of social capital that are not available to the companies outside the network - as such, participation in the network can enhance firm performance (Peng et al., 2015, p. 265; Gulati, 1999; Yang et al., 2011). This participation, in turn, can facilitate information flows, providing influence over critical actors in the network, and social credentials in the form of additional resources (Lin, 1999). However, network participation can also have negative consequences for firm performance, inhibiting the adaptability and locking firms in the existing relationships - as introduced in the previous section (Nohria & Garcia-Pont; 1991; Ingram & Baum, 1997; Gulati et al., 2002). Accordingly, the social network theory implies that the participation in the interlocking directorates network bears forces for both performance increases and decreases.

Looking at the empirical evidence on the impact of board interlocks on firm performance, it also remains ambiguous. Scholars find positive, negative and no interlock-performance relationships (Mizruchi, 1996; Dalton et al., 1998; Peng et al., 2015). For example, different researchers in Canada, Belgium, and China found a strong positive connection between board interlocks and performance (Carrington, 1981; Cuyvers & Meeusen, 1985; Keister, 1998; Peng et al., 2015). At the same time, Fligstein & Brantley (1992) found that the fewer interlocks the company has, the better the performance. Chu and Davis (2016) add another element to the discussion, finding that the importance of interlocking directorates is diminishing – as the demand for well-connected directors in large US corporations is declining. As Peng et al. (2015, p. 258) put it, "the question whether board interlocks matter for firm performance . . . continues to beg for an answer".

Caveats of Interlock-Performance Relationship Research. The inconclusiveness in empirical findings resulted in sharp criticism of the research investigating the impact of board interlocks on firm performance (e.g., Johansson et al., 2008; Peng et al., 2015). Many issues highlighted in the literature are related to methodological approaches. First, the prevalence of cross-sectional studies over longitudinal undermines the opportunity to observe how the dynamics in board interlock networks affect performance. This issue becomes even more significant with the uncertainty of the causal order of the interlock-performance relationship highlighted by Mizruchi (1996), which cannot be easily resolved with cross-sectional research design (Johansson et al., 2008; Zona et al., 2018). Second, as firm performance is influenced by a variety of factors, the effects of interlocks can be not significant enough (Peng et al., 2015). These problems will be addressed in the methodology part of our thesis.

Apart from the methodological concern, a major issue that the literature fails to address is that interlocking directorates go beyond only large established companies, such as Fortune 500 (Johansson et al., 2008; Chu & Davis, 2016). This includes both considering ties to young companies and exploring the impact of board interlocks on young companies' performance itself, which creates interest to explore whether the importance of the board interlocks for firm performance may be dependent on the organizational characteristics, such as stage of development (Daily & Dalton, 1992; Johansson et al., 2008;). Therefore, we aim to investigate *the difference in the interlock-performance relationship between young and* *established companies* in order to resolve the ambiguity surrounding the interlock-performance research.

2.4 Connecting the Nodes: Hypotheses Development

We investigate the social capital embedded in interlocking directorates networks and reflected in the centrality of firms in these (structural dimension of social capital). Guided by our research question, we explore the impact of a central position in the interlocking directorates network on firm performance. As previous empirical studies on this topic yielded ambiguous results, we aim to address a potentially overlooked firm characteristic that might explain this inconclusiveness on the interlock-performance relationship. Specifically, most studies were focused on mature and large organizations. However, it is plausible that the age of a company might affect this relationship, as young companies significantly differ from others (Stinchcombe, 1965; Baum et al., 2000; Shane, 2001).

To begin with, failure rates for young companies are observed to be much higher than for established companies (Baum et al., 2000). Stinchcombe (1965) proposes that new firms fail more frequently since these have not developed effective work roles, stable relationships inside the organization and with partners, and do not possess - or have access to - sufficient resources and expertise. Indeed, Shane (2001) highlighted that the success of new companies often depends on the availability of broad market and industry knowledge. This is commonly referred to as the liability of newness and supported by multiple studies (Stinchcombe, 1965; Freeman et al., 1983; Brüderl & Schüssler, 1990). Notably, the liability of newness usually coexists with the liability of smallness, as younger organizations often tend to be smaller - facing higher risks (Brüderl & Schüssler, 1990; Yamakawa, Yang & Lin, 2011).

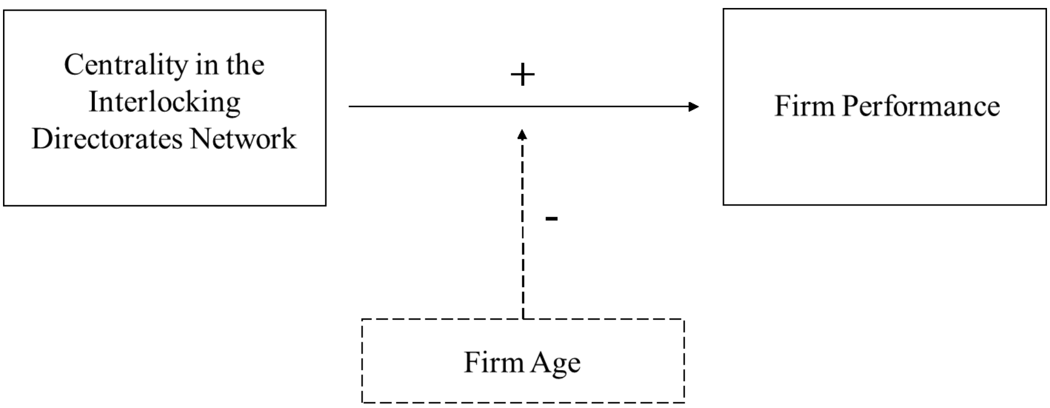
Following the argumentation from social network theory and social capital theory, interlocking directorates networks provide the opportunity to secure necessary supplies and information embedded in the network through establishing interfirm ties (Gulati & Gargiulo, 1999; Dahlin, Pesämaa & Öberg, 2016). Prior research found that inter-board connections can enhance the legitimacy, access to financing and provide information, expertise, and advice - which, in turn, improve firm performance (Mizruchi & Stearns, 1988; Westphal, 1999; Hillman et al., 2001; Horton et al., 2012). For younger enterprises, this represents a way to mitigate the adverse effects of liabilities of newness (and smallness) (Johansson et al., 2008).

Following the reasoning of Baum et al. (2000), the participation in an interlocking directorates network can be, particularly beneficial to young firms - enabling to build relationships and gain access to resources - overcoming the liability of newness (and smallness). Regarding the centrality dimension of the interlocking directorates network, a more pivotal position may enhance young firms' performance even more through providing "better and more resources and opportunities" (Peng et al., 2015, p. 265; Yang et al., 2011). In the same manner, the outlined opportunities from centrality in an interlocking directorates network can also be extracted by established companies. However, this type of firms usually already has substantial resources, partnership relations, and expertise (Brüderl & Schüssler, 1990).

At the same time, based on the social network theory, the interlocking directorates network can constrain companies and negatively affect performance - through locking firms into existing partnerships and inhibiting their adaptability and agility (Gulati et al., 2002). With increasing age, firms fine-tune resources and repeat routines, which initially enhanced performance can result in competency traps and core-rigidity for mature players (Levitt & March, 1988; Leonard-Barton, 1995). This organizational inertia can, thus, make older organizations more prone to the negative forces of the interlocking directorates network (Hannan & Freeman, 1984; Yamakawa et al., 2011). In contrast, young companies are new to the network and agiler, and, therefore, less affected by the network constraints.

Accordingly, the positive impact of a central position in an interlocking directorates network on performance may be more significant for younger enterprises and may decline with the increase of the organizational age (Figure 1).

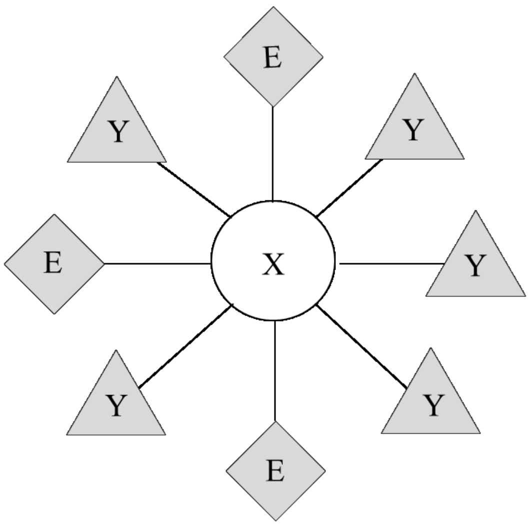
Figure 1. Theoretical Model for Hypothesis 1



***Hypothesis 1**: Firm age negatively moderates a positive impact of centrality in an interlocking directorates network on firm performance, such that the higher the firm age, the lower the impact.*

On a more granular level, it is interesting to consider the nature of ties connecting a given company to others - as it may further affect the magnitude of value the firm extracts from this network. As the focus of this study is organizational age, it is relevant to not only examine the age of the firm itself - but also the age of the companies that a firm is connected to. For this purpose, we distinguish between two groups of firms a company can be connected to: Young and established companies. The ties to young and established companies can bring different types of value to an organization - which was also explored by Shan, Walker & Kogut (1994) and Yamakawa et al. (2011). In the context of centrality in board interlocks, Figure 2 illustrates the distinction between these two types (in terms of degree centrality, represented by the number of direct ties). For the remainder of the thesis, we will refer to these as centrality among young firms and centrality among established firms (see Figure 2).

Figure 2. Representation of Different Ties in the Context of Our Study



Note: The figure represents an example of types of direct ties a company can have to other companies. Firm *X* denotes some firm from the interlocking directorates network (it can be either a young or an established firm); triangles marked *Y* represent young companies, while diamonds marked *E* represent established companies. In this case, the focal firm *X* has 3 ties to established firms and 5 ties to young firms. Notably, considering centrality among young firms, we only take into account the ties to young firms. Considering centrality among established firms, we only take into account the ties to established firms.

Looking into the effect of connections to established companies, it is evident that mature enterprises are usually more resource-rich players, with significant experience, reputation and established relationships, representing network resources in the context of the social network theory (Tushman & Anderson, 1986; Pisano, 1991; Shan et al., 1994; Stuart, Hoang & Hybels, 1999). As such, the lack of internal resources makes it necessary for young firms to "cooperate with older firms to access complementary assets such as financial capital, marketing, and distribution capabilities and increase their legitimacy and reputation" (Yamakawa et al., 2011, p. 289). However, as the liability of newness (and smallness) disappears with the increase in the organizational age, mature companies have a lower necessity to obtain these resources from the network through creating ties with established companies. Accordingly, the positive impact of a central position among established firms in the interlocking directorates network on performance may be more significant for younger enterprises, which typically lack financial, informational and relational supplies, related to liabilities of newness. At the same time, this positive impact may decline with the increase of organizational maturity, as these liabilities vanish - see the second column of Table 1.

Hypothesis 2a*: Firm age negatively moderates a positive impact of centrality among established companies in an interlocking directorates network on firm performance, such that the higher the firm age, the lower the impact.*

Considering the connections to young firms, these ties may benefit companies in terms of access to innovation capabilities, learning and knowledge exchange (Shan et al., 1994; Powell & Grodal, 2005). Despite the lack of internal resources associated with younger firms, these companies usually pioneer the technological innovations having a more significant impact on the sector development than older firms (Sørensen & Stuart, 2000; Yamakawa et al., 2011). As such, inter-board connections with younger companies can be seen as a mean to improve firm performance by overcoming inertial forces that "limit firms' ability to absorb and act on knowledge developed beyond their boundaries" and prevents established firms from adaptation to changes in environmental conditions (Yamakawa et al., 2011, p. 189; Hill & Rothaermal, 2003). Accordingly, the positive impact of a central position among young firms on performance may be more significant for established enterprises, which are usually less agile and are more prone to inertial forces. At the same time, this impact may be lower for young companies – see the first column of Table 1 (Johansson et al., 2008).

Hypothesis 2b*: Firm age positively moderates a positive impact of centrality among young companies in an interlocking directorates network on firm performance, such that the higher the firm age, the higher the impact.*

Summarizing the argumentation from the last two hypotheses, we expect that interlocks between young and established firms will yield better benefits for both parties, in contrast to inter-board ties between the same group of organizations (see Table 1). This is also in line with a study on innovation outcomes by Shan et al. (1994), who found that the cooperative agreements between established and young companies have a positive effect on both.

Table 1. Representation of Hypothesis 2a and 2b

	Centrality Among Young Firms	Centrality Among Established Firms
Young Firm	+	++
Established Firm	++	+

Note: +/++ denotes the extent of the positive impact of centrality among young firms/centrality among established firms on firm performance. While + represent a positive impact, ++ denotes a stronger positive impact.

3 Methodology

3.1 Research Strategy and Design

The interlock-performance relationship is a mature topic in the academic literature with established concepts and research instruments (Mizruchi, 1996; Au, Peng & Wang, 2000; Phan, Lee & Lau, 2003; Peng et al., 2015; Zona et al., 2018). Thus, a *quantitative study* enables us to test hypotheses that were deduced based on the extensive theoretical foundation. Further, we identified a *longitudinal research design* as the most appropriate approach for reasons described in the methodology part below.

3.2 Data Description

The basis for our analysis is a national census of organizations and individuals in Norway, including observations for a period of seven years, from 2009 to 2015. The data on all variables for the specified period is obtained from Statistics Norway accessed through the facilities of BI Norwegian Business School. This constitutes a panel dataset. Particularly, the data is unbalanced, due to newly founded firms that entered the organizational landscape within this period, and failing organizations that disappeared (Wooldridge, 2012). Notably, the setting of our analysis, Norway, has a high level of technological readiness, and a sophisticated business environment - representing a suitable setting for our study.

The choice of *census data* (population study) is central to our social network analysis and generation of the independent variables. While many studies on various types of social networks have an intra-industry focus, ignoring inter-industry connections, we intend to contribute by considering an entire directorates network (e.g., Powell et al., 1999; Baum et al., 2000). Thus, all companies that existed from 2009 to 2015 are included in the calculation of variables associated with the network. Companies with one board member or less were excluded to avoid considering non-functioning and extremely small enterprises. The social network will be described in more detail in the next sections.

To test our hypotheses, we narrowed the scope of our regression analysis based on NACE industry classification to one sector - namely, *Professional, Scientific & Technical Activities* - for the following reasons. First, narrowing the research to one sector decreases the risk of misinterpretations of results due to inter-industry variation. As highlighted by Huber & Van de Ven (1995, p. 302), focusing on a single industry allows for analyzing companies that are subject to "a uniform set of exogenous changes". Second, the Professional, Scientific & Technical Activities sector offers a suitable environment for our research. Previous studies, focused on interfirm relations, indicated that industries with high rates of innovation and a significant entrepreneurial sector, also showed a higher frequency of interfirm relations as means of learning, access to knowledge and skills (e.g., Shan et al., 1994).

In addition, we focus on two types of organizations in our research, *young companies* and *established companies*. For our analysis, we define a company as young, if it is between two and six years old (following other studies, such as Baum et al. (2000), von Gelderen, Frese, & Thurik (2000), Baum & Silverman (2004), and Johannson et al. (2008)), while all others are viewed as established companies. This distinction is necessary for generating some of the independent variables introduced in the next section. Notably, observations will only be considered for companies that are at least two years old, in order to eliminate the volatility of the early stages of development of an enterprise (Stinchcombe, 1965; Fichman & Levinthal, 1991; Baum, 1996; Baum et al., 2000). Apart from this, the companies that had no connections in the network, as well as extremely connected firms, were excluded from the analysis. This is a crucial step in order to avoid significant outliers, which may distort the analysis results (Wooldridge, 2012).

As a result, we obtained a final sample of firms that existed for the period 2009-2015 in Professional, Scientific & Technical Activities sector, thereby comprising an unbalanced dataset with 26,649 firm-year observations. The distribution of companies by organizational age is presented in Table 2. Notably, all the variables were standardized.

Table 2. Distribution of Firms by Organizational Age in the Sample

Year	Established Firms	Young Firms	All Firms
2009	2,361	1,187	3,548
2010	2,357	1,179	3,536
2011	2,567	1,149	3,716
2012	2,651	1,155	3,806
2013	2,755	1,170	3,925
2014	2,878	1,137	4,015
2015	2,952	1,151	4,103
Total	18,521	8,128	26,649

3.3 Variables Description

Dependent Variables. As we aim to compare the effects of interlocks on young and established companies' performance, it is important to choose performance measures that are comparable among these enterprises on different stages of development. We chose three dependent variables that reflect various aspects of firm performance to test our hypotheses, following Venkatraman and Ramanujam (1986) and Murphy, Trailer and Hill's (1996) suggestion to avoid limiting the research to only one performance dimension. An explicit specification of the dimensions aids the proper interpretation of the results in the model and enables a more accurate comparison between young and established companies' performance (Murphy et al., 1996). Company performance is evaluated as *return on assets* (ROA), following former studies on board interlocks (Mizruchi, 1996; Peng et al., 2015; Sanchez & Barroso-Castro, 2015; Zona et al., 2018). This measure reflects 'efficiency' dimension of firm performance - and is "the most commonly used performance measure in strategy research" (Zona et al., 2018, p. 13; Murphy et al., 1996). Further, *revenue growth* and *employee growth* were selected as measures that reflect 'growth' dimension of firm performance, following previous organizational research (Murphy et al., 1996; Baum et al., 2000; Baum & Silverman, 2004; Peng et al., 2015; Zona et al., 2018). Notably, all dependent variables were winsorized at 1%- and 99%-level in order to minimize the influence of outliers (this data transformation was also used for some of the control variables - see below). Additionally, the variables have been scaled by 100 to enable better legibility of the estimation results.

Notably, we consider that the effects of the variables on firm performance are non-immediate (Peng et al., 2015; Sánchez & Barroso-Castro, 2015; Zona et al., 2018). Therefore, we use a one-year lag of all independent and control variables. In addition, all dependent variables, as well as control variables based on accounting data, were inflation-adjusted (using the Consumer Price Index) in order to allow comparability between the time periods. The descriptive statistics of all variables and the correlation matrix is displayed in Appendix B.

Social Network Analysis and Independent Variables. We focus on the effects of a central position in the network on firm performance, which makes it necessary to utilize social network analysis methods to obtain our independent variables - centralities.

An interlocking directorates network is considered to be a so-called *affiliation network*, consisting of two elements: Actors and events. These networks are also referred to as *two-mode* networks, since "the affiliation relation relates each actor to a subset of events, and relates each event to a subset of actors" (Faust, 1997, p. 157). In our case, we obtained the information on interlocking directorates from a role database of all individuals in Norway, which includes a list of board directors (actors) for each company (event). Notably, our definition of board director includes CEOs, as they are often a central part of the board (Vo, 2010). Since we are interested in the interfirm relations that the actors span through their joint participation in an event, the database was transformed to an edgelist - a two-column list with company-to-company connections based on common board directors (ties). Based on the edgelist, we created a *one-mode network* with all connections between companies. The network is *nondirectional* (source and destination are not defined) and *unweighted* (strength of the relationship is not defined). Due to the extraordinary size of our network, conventional analysis tools for social network analysis are reaching their limits (e.g., UCINET and Gephi) - therefore, all network calculations and transformations were performed using *Python* and its dedicated *NetworkX library*.

The created network served as an input for the calculation of our independent variables - centralities. The concept of centrality, representing "importance or visibility of actors within a network", received wide acceptance in the social network research (Faust, 1997, p. 160). The most prominent centrality measures were introduced by Freeman (1978) - these are degree-, closeness-, and betweenness centrality. While degree centrality is measured by the number of direct contacts of a node in a network, being an indicator of immediate connectivity, closeness centrality includes direct and indirect links, measuring how close one node is to all other nodes in a network (Faust, 1997; Sankar et al., 2015; Peng et al., 2015). Betweenness centrality is the extent to which a node is part of the shortest path between other nodes (geodesic) - and measures “the ability of a node to control the flow of information through it” (Sankar et al., 2015, p. 117). For a detailed overview of centrality measures refer to Appendix A.

These measures have been routinely used to analyze various types of social networks (Faust, 1997). Notably, the majority of empirical network studies are based on small-scale network (less than 500 nodes) (Everett & Borgatti, 2005). However, with the technological advancements paving the way to collect data on larger networks, it became “apparent that many of the tools developed for analyzing networks are not scalable” - and as the network size increases the computation complexity increases as well (Everett & Borgatti, 2005, p. 32). This is the case in our research, as we consider the entire interlocking directorates network, with more than 100,000 nodes in some years, making it almost impossible to calculate betweenness centrality and “meaningless” to compute closeness centrality (Everett & Borgatti, 2005, p. 32; Marsden, 2002). This problem became the subject of many methodological studies, proposing various algorithms for approximation of betweenness centrality, while closeness centrality is usually disregarded for large networks (Brandes, 2001; Marsden, 2002; Everett & Borgatti, 2005; Geisberger, Sanders & Schultes, 2008; Chan, Leung & Liò, 2009).

A prominent approach for social network scholars is based on an egocentric design “that obtains information about only that portion of a network in the immediate locality of a given node” (Marsden, 2002, p. 408; Freeman, 1978). This method yields certain advantages for researchers, such as more efficient computation without the need for so-called sociocentric network data (information about the whole network). We acknowledge the discussion in the academic literature on the correspondence between global and local betweenness centralities as well as their correlation with degree centrality (Mardsen, 2002; Everett & Borgatti, 2005). We, therefore, dedicate Chapter 7 to analyze and discuss the implications of employing egocentric betweenness centrality. In addition, a more detailed description of sociocentric and egocentric centrality measures is provided in Appendix A.

Taking into account the arguments presented, we measure the centrality in our directorates network using four independent variables, namely: *Degree centrality* (representing direct connections to all companies), *degree centrality among established companies* (representing direct connections to established companies), *degree centrality among young companies* (representing direct connections to young companies) and *ego betweenness centrality* for a node's second-order zone (betweenness centrality calculated on ego network with radius of two). The degree centrality variables were transformed using the logarithm function in order to deal with the extreme right skewness of the variable distribution (this data transformation was also used for some of the control variables - see below) (Wooldridge, 2012).

Interaction Effects. As highlighted in the previous section, we aim to explore the differences in an interlock-performance relationship in relation to the maturity of the organization. To test these hypotheses, we use four interaction effects as independent variables, namely: 1) The interaction term of *firm age and degree centrality*, 2) the interaction term of *firm age and degree centrality among established companies*, 3) the interaction term of *firm age and degree centrality among young companies*, and 4) the interaction term of *firm age and ego betweenness centrality*.

Control Variables. Since our dependent variable, firm performance, is viewed as a rather complex concept in the literature, it is beyond the bounds of possibility to control for all its possible determinants (Zona et al., 2018). Therefore, a *one-year lagged dependent variable* is included in order to account for "possible omitted variables outside those explicitly included in regressions" (Zona et al., 2018, p. 15; Greene, 2000; Sánchez & Barroso-Castro, 2015). In addition, as human capital is recognized as one of the strong determinants of firm performance, we control for its effects by including *management (CEO) tenure* and *number of employees* (both variables were transformed using the logarithm function, while the latter was also winsorized at 99%-level) - based on a meta-analysis of the human capital-performance relationship (Crook, Todd, Combs, Woehr & Ketchen, 2011). Further, we employ commonly used control variables in the board interlocks and organizational research - namely, *firm size*, represented by the logarithm of total assets, *firm age* and *board size* (Baum et al., 2000; Peng et al., 2015; Zona et al., 2018;). To control for other differences in firm performance that may stem from the variability of financial condition, we include *current ratio* (calculated as firm's current assets divided by its current liabilities and also winsorized at 1%- and 99%-level) and *debt ratio* (calculated as firm's total liabilities divided by its total equity). Finally, *year dummies* are included to account for temporal effects, such as general economic shifts (Wooldridge, 2012; Sánchez & Barroso-Castro, 2015).

3.4 Social Network Description

In the following section, we briefly describe our interlocking directorates network in order to contextualize this study and specifically our independent variables.

As mentioned above, we consider the entire directorates network with all companies registered by Statistics Norway. From Appendix C, it is evident that there was a considerable growth of 28% in the overall number of enterprises in the network over the seven-year period (which also caused the increase of the number of directors and number of interlocks). Regarding the network structure, the number of components also increased significantly over the years, as well as the size of the largest component - which connected almost 80% of firms in 2015 (92,915 firms). Also, the average clustering coefficient remained steady at a 0.6 level over the period. In practical terms, this implies that the firms that a company is connected to, are also highly likely to be interconnected with each other. This high coefficient might be explained by the fact that our network was derived from a two-mode network: If there is a board member associated with a number of companies, the network will contain all possible ties between these companies. This also implies that interlocking directorates networks generally have strong clustering tendencies due to the nature of affiliation networks. Further, the density measure is rather low - which is expected since we investigate a large social network, with approximately 100,000 firms in every year. Looking into the degree distribution, the majority of nodes have a low degree (which equals to 1 or 2), while only a few have a high degree, representing a scale-free nature, and following a power-law distribution of $P(k) \sim k^{-a}$ - see Appendix C (Barabási & Albert, 1999; Holme & Kim, 2002). Concluding on the overall network structure, it shows indications of a scale-free nature, as well as high clustering tendencies, as observed in many real-world networks (Holme & Kim, 2002).

A comparison of the firm centrality measures in the entire network and in the Professional, Scientific & Technical Activities sector for the year 2015 is presented in Table 3. For data on all years refer to Appendix C. Considering the whole network, the average degree centrality increased slightly over the seven-year period, from 13.8 to 14.2 (direct connections to other actors in the network). At the same time, the average degree centrality among young companies dropped by approximately 35%, while the average degree centrality among established companies rose by 37%. Notably, the same tendencies are observed in the Professional, Scientific & Technical Activities sector. These changes in the centrality measures signify structural shifts in our network, which can be connected to the decrease in the number of young firms and the increase in the number of established companies over the period of study. Finally, ego betweenness centrality was slightly higher in the observed sector than in the entire network - while its values in both cases changed marginally over the period of study.

Table 3. Network Measures in the Entire Network and in the Professional, Scientific & Technical Activities Sector, 2015

Measure	Entire Network	Professional, Scientific & Technical Activities Sector
Number of firms	120,220	4,103
Average degree centrality	14.247	10.009
Average degree centrality among young firms	3.510	2.484
Average degree centrality among established firms	9.084	6.447
Average ego betweenness centrality	0.106	0.156

Note: Entire Network denotes the measures for the entire interlocking directorates network, not limited to firms considered in the regression models, while the Professional, Scientific & Technical Activities sector is limited to firms in our regression sample. The data for all years is presented in Appendix C.

3.5 Regression Model

A central concern for our study is the model choice and specification since the literature on the interlock-performance relationship has highlighted its *endogenous nature* (Mizruchi, 1996; Peng et al. 2015; Sanchez & Barroso-Castro, 2015; Zona et al., 2018). This has been disregarded by many previous studies and may also explain the ambiguity of empirical findings (Mizruchi, 1996). In a regression model, endogenous relationships of variables can result in an *endogeneity bias*, meaning that the independent variables are likely to correlate with the error term and, thus, are not strictly exogenous (Wooldridge, 2012). This can cause inconsistent estimates, misleading conclusions and interpretations (Ullah, Akhtar & Zaefarian, 2018). The problem is not exclusive to the interlock-performance literature – Antonakis, Bendahan, Jacquart, and Lalive (2010, p. 1086) concluded that scholars fail to address "up to 90% of design and estimation conditions that make causal claims invalid", based on a review of 110 articles from top-tier journals.

This causality problem cannot be adequately resolved with cross-sectional research design, calling for a longitudinal approach - panel data in our case. However, there are a number of typical problems associated with panel data analysis, which the selected regression model should be able to withstand. Specifically, researchers usually face the issue of unobserved heterogeneity - arising from fixed firm effects in the model, so-called "unobserved, time-constant factors" - see Appendix D (Wooldridge, 2012, p. 460). These unobserved effects usually impact the dependent variable and are correlated with the explanatory variables - which is likely to cause an estimation bias and rules out the use of traditional methods, such as Ordinary Least Squares (OLS) (Roodman, 2006). The problem is commonly addressed by the application of standard panel data models, such as fixed effects estimation (Wooldridge, 2001). Importantly, the fixed effects model comes with the standard assumption that all covariates are strictly exogenous, which is crucial for the estimator's consistency. However, in our study, the explanatory variables associated with board interlocks are not considered strictly exogenous - prohibiting the use of a fixed effects method. As highlighted above, we predict interlocks to affect firm performance, but it could be the opposite - that prior performance affects interlocks and firm's position in the network.

In addition, as outlined in the previous section, a lagged dependent variable is included as a control variable, constructing *dynamic panel data (DPD)*. Thus, another issue with using fixed effects is the so-called "dynamic panel bias", when the lagged dependent variables are likely to be correlated with the unobserved firm effects in panel data (Roodman, 2006, p. 17; Nickell, 1981). This bias can give rise to endogeneity problems, which become even more significant in "small T, large N" contexts and further contribute to the inconsistency of fixed effects estimators (Roodman, 2006, p. 17; Sánchez & Barroso-Castro, 2015; Zona et al., 2018).

The highlighted issues can be addressed by using *DPD estimation techniques* by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998). The scholars proposed DPD estimators in the context of the *Generalized Method of Moments (GMM)* - see Appendix D. Specifically, the key aspect of these DPD estimators is the assumption that the necessary instruments for endogenous variables are 'internal' - that is, lagged levels of the instrumented regressors. The method approaches the endogeneity problem, caused by reverse causality and dynamic panel bias mentioned above, by obtaining instrumental variables from the dataset itself. Also, the estimators account for "time-invariant firm characteristics by using first differences to transform regressors and removing any fixed firm-specific effect" (Zona et al., 2018, p. 16). As a result, the use of this method will ensure the consistency and reliability of the estimates. Accordingly, we use DPD estimators in the context of GMM to estimate the following dynamic panel data model:

$$y_{it} = \gamma y_{i,t-1} + \beta' x_{i,t-1} + \alpha_i + \varepsilon_i \text{ for } i = 1,\dots, N \text{ and } t = 1,\dots, T \qquad (1)$$

where y_{it} denotes the dependent variable (firm performance); $y_{i,t-1}$ denotes the first lag of the dependent variable (previous year's firm performance); $x_{i,t-1}$ represents all independent and control variables lagged by one year relative to the dependent variable; α_i and ε_i represent unobserved fixed effects and the error term respectively.

We use the *Arellano-Bover/Blundell-Bond estimator,* also known as *System GMM,* with a *two-step estimation procedure*, using the second lag of endogenous variables. This approach expands the popular Arellano-Bond estimator for DPD models "by making an additional assumption, that first differences of instrument variables are uncorrelated with the fixed effects"- allowing the inclusion of more instruments, and thereby increasing efficiency (Roodman, 2006, p. 1). Additionally, we use a *two-step estimation*, in which "the standard covariance matrix is robust to panel-specific autocorrelation and heteroskedasticity" (Mileva, 2007, p. 6; Roodman, 2006). However, the two-step approach "can produce standard errors that are downward biased", which motivated the use of the *two-step robust option* in our model in order to eliminate the downward bias of the standard errors - known as Windmeijer (2005) finite-sample correction (Roodman, 2006, p. 10). Finally, we implement the *equation(level)* option on year dummies, indicating that we use these only as instruments in the level equation, following the guidance of Roodman (2006) and Baum (2013). For a more thorough explanation of the GMM estimators, refer to Appendix D.

4 Findings

Table 4 reports the regression results, used to investigate the hypotheses. Notably, the base model, without the interaction terms, is displayed in Appendix E. Prior to the analysis it is essential to consider the role of the lagged dependent variable in the regression. Precisely, the lagged dependent variable captures a significant share of variance to be explained by other independent and control variables - often making their coefficients nonsignificant (Achen, 2000; Zona et al., 2018). Thus, following Zona et al. (2018) we consider a significance on a 5% level as strong support for our hypotheses. Descriptive statistics and the correlation matrix are presented in Appendix B.

In order to test the validity of the model specification, the Hansen test of overidentifying restrictions was performed, which shows whether the instruments used are valid (Roodman, 2006). It is evident from Table 4 that the Hansen test statistics are not significant in any of the models - suggesting that the instruments employed are appropriate and not correlated with the error term. In addition, we used Arellano-Bond tests of autocorrelation to detect whether "the lagged instruments are rendered invalid as a result of autocorrelation" (Zona et al., 2018, p. 16; Roodman, 2006). In Table 4, AR(2) statistics are not significant for the models with the dependent variables revenue growth and employee growth - supporting the null hypothesis that there is no second-order serial correlation of the error term. However, in Model 1 and Model 4, with the dependent variable ROA, AR(2) statistics are significant, suggesting that our instruments (second lags of endogenous variables) are invalid (Roodman, 2006). Therefore, we employ deeper lags of the instrumented variables in order to improve the validity of the instruments (lag limits option set from the second lag and further). We confirm that there is no autocorrelation using AR(3) statistics – see Table 4. Finally, Wald χ^2 tests, indicating the overall fit of the regression model, are highly significant in all models (Roodman, 2006).

In Table 4, Models 1-3 report results for Hypothesis 1, which suggests that the organizational age is a negative moderator of the positive impact of centrality on firm performance. Centrality in these models is represented by the two measures: Degree- and ego betweenness centrality. While degree centrality is positive and highly significant in all models (Model 1: β = 6.022, Model 2: β = 0.224, Model 3: β = 23.13; $p < 0.001$), the two-way interaction term of this centrality and firm age is negative and also highly significant (Model 1: β = -0.451, Model 2: β = -0.014, Model 3: β = -1.689; $p < 0.001$). Further, a Wald test supports the significance of the interaction term in Models 2-3, while in Model 1 it does not. Apart from this, ego betweenness centrality and its two-way interaction term with firm age are not significant in any of the Models 1-3. Overall, the results provide support for Hypothesis 1, based on the degree centrality measure. Accordingly, for young companies, a high degree centrality (many direct connections to other actors) in an interlocking directorates network will increase firm performance - positively affecting the growth dimension of performance, namely revenue and employee growth. However, with the increase of firm age (when the company is considered as an established player), the positive impact of centrality on firm performance will diminish – which can even become negative. Notably, there is no indication of the effect of centrality represented through ego betweenness centrality (meaning that the company is located on the shortest path between other actors in its second-order zone) on firm performance. In addition, there is no indication of an impact of degree centrality on the efficiency dimension of firm performance, represented by ROA.

Models 4-6 are used to investigate the Hypotheses 2a and 2b. Hypothesis 2a suggests that the positive influence of connections to established companies in the network on firm performance will be negatively moderated by firm age. Conversely, Hypothesis 2b proposes that the positive influence of connections to young companies in the network on firm performance will be positively moderated by firm age. To test these hypotheses, we include a degree centrality among established companies (direct ties with companies of age six years and older), degree centrality among young companies (direct ties with companies of age between two and six years) and their two-way interaction terms with firm age.

From Model 4 in Table 4, it is evident that degree centrality among established companies is positive and highly significant (β = 5.097, $p < 0.001$), however, its interaction term with firm age is not significant - failing to support Hypothesis 2a. At the same time, in Model 5 and Model 6 the two-way interactions of degree centrality among established companies and firm age are negative and significant (Model 5: β = -0.015, Model 6: β = -1.013; $p < 0.05$) while the main effects of degree centrality among established companies are positive and also significant (Model 5: β = 0.266, $p < 0.001$; Model 6: β = 14.45, $p < 0.05$) - providing strong support for Hypothesis 2a. The significance of the interaction terms is also supported by a Wald test. Accordingly, young companies that have a higher degree centrality among established companies will have a higher firm performance, in terms of growth. However, the increase of the firm age will decrease this positive effect – making the overall effect negative at certain level of firm age.

Apart from this, the main effects of degree centrality among young companies are positive and significant in Models 5-6, while in Model 4 the variable is not significant. Following this, in Models 4-6 the two-way interaction terms of degree centrality among young companies and firm age are negative and significant (Model 4: $\beta = -0.395$, $p < 0.001$; Model 5: $\beta = -0.016$, $p < 0.1$; Model 6: $\beta = -0.938$, $p < 0.05$) - the opposite of our expectations. Further, a Wald test supports the significance of the interaction term only in Model 6, while in Models 4-5 the significance of the two-way interactions is not supported. Thus, Hypothesis 2b is not supported. However, Models 6, in which both the main effect and interaction term are significant, yields interesting results. Specifically, it appears that for young companies, an increase in the direct ties to other young companies (higher degree centrality among young firms) increase their firm performance in terms of employee growth. Nevertheless, the higher the firm age (established companies), the lower the positive impact. Similarly to the previous results, this effect can turn negative at a certain organizational age.

In all models where the coefficients are significant, there appears to be a certain threshold for the negative impact of firm age on the relationship of the degree centrality variables and firm performance, particularly for revenue and employee growth. This firm age threshold varies between 13.75 years (Model 3 - Hypothesis 1) to 17.75 years (Model 5 - Hypothesis 2a) in our models – obtained by examining the main effect and the respective two-way interaction effect coefficients, *ceteris paribus*. Thus, when a company reaches this age the overall impact of centrality in an interlocking directorates network becomes negative.

Notably, the analyses replicated in other industries yielded similar results, providing support for our findings - see Appendix F.

Table 4. Regression Results – Firm Performance

Variables	(1) ROA+	(2) Revenue Growth	(3) Employee Growth	(4) ROA+	(5) Revenue Growth	(6) Employee Growth
ROA	37.100**			49.710**		
	(17.490)			(20.500)		
Revenue Growth		24.680*			9.566	
		(14.200)			(14.050)	
Employee Growth			11.960			20.500
			(13.390)			(15.070)
Degree Centrality	6.022***	0.224***	23.230***			
	(1.633)	(0.075)	(4.721)			
Ego Betweenness Centrality	-6.415	-0.115	11.490			
	(5.336)	(0.249)	(17.900)			
Firm Age * Degree Centrality	-0.451***	-0.014**	-1.689***			
	(0.124)	(0.005)	(0.345)			
Firm Age * Ego Betweenness Cent.	0.457	0.006	-0.440			
	(0.347)	(0.016)	(1.188)			
Degree Centrality (E)				5.097***	0.266***	14.450**
				(1.826)	(0.097)	(5.976)
Degree Centrality (Y)				-0.914	0.189*	14.400**
				(1.683)	(0.113)	(6.043)
Firm Age * Degree Centrality (E)				0.098	-0.015**	-1.013**
				(0.142)	(0.007)	(0.395)
Firm Age * Degree Centrality (Y)				-0.395***	-0.016*	-0.938**
				(0.126)	(0.009)	(0.455)
Firm Age	0.764***	0.019**	2.603***	0.609**	0.035***	2.447***
	(0.223)	(0.009)	(0.565)	(0.311)	(0.014)	(0.789)
Firm Size	-1.200***	-0.038***	-0.740**	-1.194***	-0.023**	-1.055***
	(0.191)	(0.011)	(0.311)	(0.178)	(0.012)	(0.361)
Management Tenure	0.191	0.001	-0.0454	0.049	-0.006	0.270
	(0.198)	(0.005)	(0.363)	(0.259)	(0.007)	(0.458)
Board Size	-0.893**	-0.008	-2.266***	-0.738*	-0.027**	-1.681**
	(0.409)	(0.012)	(0.714)	(0.403)	(0.013)	(0.692)
Number of Employees	1.733***	0.015		1.653***	0.011	
	(0.196)	(0.012)		(0.298)	(0.016)	
Current Ratio	-0.005	0.006**	-0.019	-0.002	0.006*	-0.028**
	(0.008)	(0.003)	(0.013)	(0.008)	(0.004)	(0.011)
Debt Ratio	-0.002*	0.000	0.018***	-0.001*	0.000	0.019***
	(0.001)	(0.000)	(0.006)	(0.001)	(0.000)	(0.006)
Observations	18.494	13.316	13.917	11,750	8.339	8.821
Year Effects	Included	Included	Included	Included	Included	Included
Hansen Test	22.281	30.363	41.967	15.484	31.411	28.834
AR(2)	1.806*	1.288	1.485	1.931*	0.876	0.949
AR(3)	-1.164	-	-	-0.888	-	-
Wald-Chi2	413.79***	173.51***	145.77***	1,257.08***	82.32***	121.39***

Note: All independent and control variables are lagged by one year. Standard errors are robust and indicated in brackets. Dependent variables are standardized. Degree Centrality (Y) denotes the degree centrality among young companies, Degree Centrality (E) denotes degree centrality among established companies.
+ Includes deeper lags of instrumented variable due to indication of autocorrelation in AR(2) test
* p<0.1, ** p<0.05, *** p<0.01

5 Discussion

This paper investigates the extent to which social capital through interlocking directorates impacts the performance of young and established firms. Connecting the network-based theory of social capital and board interlock research, we aim to resolve the ambiguity in the academic literature on the interlock-performance relationship. Our motivation was to gain new insights into this relationship through the inclusion of a firm characteristic, namely organizational age, as a moderator.

First, we hypothesized that there is a positive influence of a central position in the interlocking directorates network on firm performance, negatively moderated by firm age - such that the older the company, the smaller is the impact. Our empirical findings strongly support our expectations. Specifically, a pivotal position in the interlocking directorates network enhances the performance. However, this effect diminishes with an increasing firm age.

In the context of the network-based theory of social capital, this positive effect can be linked to the ability of actors to extract benefits from participation in a social structure, in our case an interlocking directorates network (Nahapiet & Ghoshal, 1998; Lin, 1999; Koka & Prescott, 2002; Inkpen & Tsang, 2005). On a more granular level, this implies that actors can gain access to various kinds of resources and opportunities, such as informational, financial and learning benefits, through a locational advantage (referring to the structural dimension of social capital, represented by centrality) (Tsai & Ghoshal, 1998; Gulati et al., 2002; Peng et al., 2015). However, we found that the value extracted from the actor's position in the network also depends on a specific firm trait - the organizational age. As outlined in the literature review, this can be connected to Stinchcombe's (1965) theory about the liability of newness (and smallness). In detail, younger enterprises suffer from a lack of resources, market and industry knowledge, and solid partnerships, which encourages them to seek ways to overcome these liabilities (Stinchcombe, 1965). Thus, one possible way for young firms is to participate in an interlocking directorates network.

While for established companies it is still important to have access to the mentioned resources and opportunities, for younger firms centrality in the network plays a more important role according to our findings. A possible explanation for this is that board interlock networks only provide benefits to a certain extent. While many connections to other companies through board interlocks assist young firms in alleviating the burdens of these liabilities, more mature firms have already reached a certain resource level, market legitimacy, and industry knowledge (Shan et al. 1994; Kor & Misangyi, 2008). Thus, centrality in an interlocking directorates network may bring a limited marginal utility to these firms. Notably, our findings suggest that at a certain level of organizational age the impact of a central position can even turn negative. Although the literature that describes the negative effects of network participation (Nohria & Garcia-Pont, 1991; Ingram & Baum, 1997; Gulati et al., 2002) is not directly considering organizational maturity as a factor, inertia associated with increasing organizational age (Hannan & Freeman, 1984) may be a factor that gives rise to these arguments. Central mature organizations may be more likely to be locked in existing relationships and lack adaptability - which may negatively affect performance, in line with the constraints highlighted in the social network theory. Repeating Gulati et al. (2002, p. 286): “Networks giveth; networks taketh away”.

On a deeper level of analysis, the centrality dimension of the network is represented by the number of direct connections to other actors (degree centrality) and the extent to which the firm is located on the shortest path between others (ego betweenness centrality) (Faust, 1997). While a strong effect of degree centrality was found, no evidence of an impact of ego betweenness was revealed. In the context of the network-based theory of social capital, it implies that firms are likely to extract the benefits from network participation (e.g., gaining access to resources and opportunities) through establishing more direct connections. However, controlling the flow of information between other companies (having high ego betweenness centrality) does not lead to the same effect.

In the broader context of social capital, this has specific implications for the theoretical discussion: Our findings indicate that social capital in terms of locational advantages (structural dimension) does not benefit all organizations in the same way. Instead, this impact on firm performance depends on organizational age. The outlined findings are particularly interesting in the context of the general social network research. As described in the literature review, a substantial part of the academic scholars highlights the benefits of network membership (Baum & Oliver, 1991; Ingram & Inman, 1996; Khanna & Palepu, 1999), and further the locational advantage in the network (Gulati, 1999; Yang et al., 2011; Peng et al., 2015). However, fewer studies consider the constraints of social capital rooted in the network (Granovetter, 1985; Burt, 1992; Uzzi, 1997; Powell et al., 1999). For instance, Powell et al. (1999) found that there are limits to the rewards actors can extract from being central in a network - and at certain levels of centrality, these start to diminish. Our research adds another aspect of network constraints to the discussion by finding decreasing returns from network centrality with increasing firm age.

The second part of this study is dedicated to the impact of different types of connections on firm performance. Specifically, we investigated whether the firm's position among established and young companies impacts the value extracted from the network differently. To begin with, we expected that the positive influence of centrality among mature companies on performance is negatively moderated by the organizational age. Another expectation was that the positive impact of centrality among young companies on performance is positively moderated by firm age. Thus, we hypothesized that the interlocks between young and established companies yield the most benefits from network resources to both parties (similar studies were conducted by Shan et al. (1994) and Yamakawa et al. (2011)). Our findings support that being central among established companies yields higher returns from the network for younger companies (significant results in two out of three models). However, contrary to our hypothesis, the results suggest that a central location among young firms provides less value for established and more for young companies (significant results in one out of three models - less support for this result). Overall, the findings imply that young companies benefit more from both types of network centralities in an interlocking directorates network than established companies.

In the context of the network-based theory of social capital, this implies that, in both cases, young companies extract more benefits from the locational advantage than mature firms. This contrasts our argumentation on how established firms may benefit from young firm connections in terms of access to innovation and knowledge as means of counteracting inertial forces (Shan et al., 1994; Johannson et al., 2008). Instead, it appears that the returns from network centrality among both young and established companies are diminishing with an increasing organizational age. In line with the previous argumentation, the negative impact of the network participation reflected in the lack of adaptability may inhibit the ability of mature players to extract benefits from either type of relationships with other actors (in our case with young and established firms). In contrast, struggling to overcome the liabilities of newness (and smallness) and improve performance, young players may build relations (inter-board connections) with both resource-rich mature players as well as other innovative and creative young firms.

Concluding, social capital seems to be more impactful for younger firms than for established firms in the context of interlocking directorates. With this research, we propose organizational age as a moderator of the interlock-performance relationship - introducing an explanation for the inconclusive results in the previous empirical findings.

6 Implications & Conclusion

6.1 Theoretical, Managerial & Methodological Implications

Theoretical Implications. There is an ongoing discussion on the impact of board interlocks on firm performance. In this thesis, we find evidence that organizational age has a strong influence on this relationship. This implies that firm characteristics that are associated with different stages of development influence the impact of having a central position in an interlocking directorates network on performance. Translating these findings into the domain of social capital, specifically its structural dimension, it can be argued that there is no optimal structural position for all organizations in a social network, but rather that the position needs to be fitted to the companies' stage of development to provide optimal organizational benefits. Thus, the consideration of the liability of newness (and smallness) becomes an important factor in the context of studying interlocking directorates networks and their connection to firm performance.

Considering the impact of ties to different groups of companies on firm performance, our study adds a new aspect to the academic discussion. Previous research described and found that relations between young and established firms are more advantageous than ties between the same group of organizations (Shan et al., 1994; Yamakawa et al., 2011). However, our findings suggest that in interlocking directorates networks mature organizations are not able to extract more benefits from the collaboration with young partners. This may indicate that older companies become constrained by organizational inertia that gives rise to adverse effects of the interlocking directorates network (as described before).

Overall, in context of opportunities and constraints that the social network theory literature highlights, we discover that old companies are rather connected to the constraining elements, compared to young firms which are rather connected to the opportunities - both theoretically and empirically.

Managerial Implications. For managerial implications, it is essential to consider the different dimensions of firm performance (efficiency and growth). According to our study, the locational advantage in the network was found to be significant for growth only. This signifies that young companies should consider how to become a pivotal actor in the network, since this can assist in achieving revenue- and employee growth, however, not efficiency (ROA) improvement, and in this regard the profitability. As organizational age increases, companies may consider different means for performance improvement discussed in the strategic management literature (e.g., strategic alliances), since centrality in the interlocking directorates network appears to have a limited impact (Stuart, 2000; Zollo et al., 2002; Lavie, 2007; Sampson, 2007). Reassessing the costs and benefits of engaging in board interlocks might be worthwhile, as the organization matures.

Additionally, both types of interconnections studied in this thesis appear to be more important for younger companies than for established ones. However, it is still important to consider that ties to established and young firms provide different kinds of network resources and, thus, add value to an organization in a different way. Young players should, therefore, align their policy of inter-board connections with the strategic goals established by the management. With increasing age, however, firms should not consider ties of any kind in the interlocking directorates network as means for performance improvement, since benefits appear to diminish. This implies that inter-board connections from established companies to young firms provide neither growth nor efficiency benefits per se.

Methodological Implications. Besides managerial and theoretical contributions, we also make two methodological contributions to the area of board interlock research. First, our study outlines the benefits and follows the approach of considering the entirety of a network for obtaining network measures, not setting network boundaries on industry or company size (e.g., listed firms) - as followed by merely every study on this topic. While we acknowledge the issue of data availability and collection, this approach ensures that important inter-industry ties will not be omitted - or many connections to young companies will be ignored.

Second, we contribute by highlighting the endogeneity issue associated with the interlock-performance relationship. This issue has been discussed multiple times in the interlock literature but is rarely adequately addressed (Mizruchi, 1996; Peng et al., 2015). We recommend a (longitudinal) panel data approach, instrumenting endogenous variables with time lags as a remedy (following Arellano and Bond's (1991) estimation technique, using the GMM framework). While this increases the complexity of the analysis, it is a crucial step for ensuring the validity of the overall model and results. Notably, this part does not include contributions made in the extended methodological discussion (Chapter 7).

6.2 Limitations

While our study makes important theoretical, managerial and methodological contributions, it also comes with certain limitations. First, our *sampling frame and the context* of our study should be taken into account. Specifically, our research is limited to a specific country, Norway, and industry, Professional, Scientific & Technical Activities - which can potentially inhibit the generalizability of the results. As an example, our social network analysis and centrality measures are contained in the Norwegian business environment - not accounting for international ties of companies. In addition, since we examine the network during a limited period, from 2009 to 2015, we do not consider the evolution of the network, which could be beneficial for a deeper understanding of the interlock-performance relationship.

Second, aiming to compare the influence of board interlocks on companies' performance, we employ the same measures for all companies, following the relevant literature. However, by contrast to established companies, *young companies have specific characteristics* commonly reflected in their performance, also often dependent on their phase of development - such as the absence of abnormal revenue growth and profit (do Carmo Silva, 2015). Although our study attempts to reduce such concerns through various data transformations and cutting - this problem might still limit the comparability between young and old companies and increase volatility of observations.

Third, a common limitation for studies investigating the interlock-performance relationship is the *endogeneity problem* (Mizruchi, 1996; Peng et al., 2015). In our research, we accounted for this issue by using advanced statistical methods as well as lagging all independent and control variables. However, further studies may be needed to "confront a challenging causal ordering problem" (Peng et al., 2015, p. 264).

Finally, we assume linearity of the interlock-performance relationship in our study. However, there is the possibility that at a certain level, the positive influence of the interlocks on performance could become negative - constructing a curvilinear relationship (inverted U-shape) (Sánchez & Barroso-Castro, 2015).

6.3 Directions for Future Research

Apart from the limitations, our study also provides a number of fruitful directions for future research. First, our focus on firm characteristics that can have a substantial effect on the interlock-performance relationship might offer new avenues for future studies. In this thesis, we have explored the impact of the organizational age. However, identifying how this impact changes with the inclusion of additional firm attributes (e.g., resource intensity) is necessary to gain a deeper understanding of the interlock-performance relationship (Zona et al., 2018; Sánchez & Barroso-Castro, 2015). Additionally, it would be interesting to investigate under which circumstances the relationship between centrality in the interlocking directorates network and firm performance disappears or potentially becomes negative.

Future research may also take into account other dimensions of firm performance, such as profit, liquidity, market share, or leverage - as highlighted by Murphy et al. (1996). This might provide more profound insights into how to utilize interlocks in order to enhance various aspects of performance, achieving differing strategic goals.

Another possible line of investigation is to consider not only firm, but also industry characteristics in the context of the interlock-performance relationship. Specifically, the impact of centrality in the interlocking directorates networks, as well as the moderating influence of firm age, might differ in various settings. Thus, future research might aim to answer the following questions: In which industries does centrality in the interlocking directorates network have the highest impact for young firms, and in which settings is there no impact? In which sectors are ties from young to established companies most important (e.g., asset intensive or knowledge intensive industries)?

Finally, we analyze the impact of only one dimension of social capital, namely the structural dimension, while we do not account for the influence of other social capital facets on firm performance, such as trustworthiness of the network actors (relational dimension). We focused on the locational advantages of actors, however, as theorized by many academic scholars, tie strength may be an additional important factor that impacts how much value an organization may extract from the network (Moran, 2005; Levin, Walter, Appleyard & Cross, 2016). Thus, in the context of our research, an interesting avenue for future studies might be to investigate whether centrality in the interlocking directorates network yields more advantages when the actors' ties are stronger - and how results shift with changes of organizational and industry characteristics (outlined above).

6.4 Conclusion

This thesis addressed the controversial topic of the interlock-performance relationship in the literature. While there are contradicting theoretical arguments and ambiguous empirical results on this topic – we aimed to shed light on the effects on companies with different organizational age. Connecting the network-based theory of social capital and board interlock research, we investigated the extent to which social capital through interlocking directorates impacts the performance of young and established firms. The results support our hypothesis that a central position in an interlocking directorates network (which represents the structural dimension of social capital) improves the performance of young firms, which, however, decreases with the organizational age. At the same time, organizational inertia stimulating the negative effects of the network participation inhibits the ability of mature companies to extract benefits from either type of relationships with other actors (in our case with young and established firms). In addition to the theoretical findings, we contribute with a refined methodological approach to address the theoretical and methodological challenges that come with the topic.

Networks giveth to the young, networks taketh from the old.

7 Extended Methodological Discussion

The motivation for this chapter is to explore the correspondence between sociocentric (global) and egocentric (local) betweenness centralities - complementing the methodology chapter of our thesis.

7.1 Introduction

As introduced in our methodology, we employ a local betweenness measure for the purpose of our study, also referred to as egocentric betweenness centrality - due to the computational complexity of calculating global betweenness centrality in a large social network (Everett & Borgatti 2005, Marsden 2002). The approach of using ego betweenness is based on previous empirical network studies by Marsden (2002) and network simulations by Everett and Borgatti (2005), finding that ego betweenness serves as a proxy for global betweenness. These findings have been further supported by several additional studies (e.g., Schrott, 2004). Notably, all of these consider ego betweenness as the betweenness measure of a subset G_i of the entire graph *G,* centered around the node *i*, such that the subset G_i includes node *i* and all nodes *j* that have a path length to node *i* of $d(N_i, N_j)=1$. This is also referred to as the *first-order zone* of an egocentric network (Wasserman & Faust, 1994, Marsden, 2002).

Based on these findings, we decided to employ an ego betweenness centrality for studying the interlocking directorates network. However, with the extension of considering the *second-order zone* egocentric network for our betweenness measure calculation, where subset G_i includes node *i* and all nodes *j* that have a maximum path length to *i* of $d(N_i, N_j)<=2$. This approach has been chosen on the foundation of strategic management studies, researching the local social networks based on a network's second-order zone (Uehara, 1994; Dahlin et al., 2016). This is also supported by methodological papers, such as Chen, Lü, Shang, Zhang, and Zhou (2012) - which suggested exploration of “the nearest and the next-nearest neighbors of a node” as a trade-off between considering too limited information (e.g., with the first-order zone) and running into computational difficulties (e.g., with higher-order zone) (Zhao, Liu, Wang & Li, 2017, p. 11).

Multiple studies have found a strong, positive correlation between degree centrality and sociocentric betweenness centrality (Valente, Coronges, Lakon & Costenbader, 2008; Meghanathan & He, 2016) - and if ego betweenness centrality is a good proxy for sociocentric betweenness centrality, we would expect a certain extent of positive correlation between degree and ego betweenness centrality. However, in the exploratory phase of our data analysis, we made an interesting discovery: The correlation between these two measures is low in our empirical data (0.08 in the Professional, Scientific & Technical Activities sector). Naturally, this spiked our interest, and resulted in three central questions that we aim to address in this methodological discussion:

1. *How closely do sociocentric and egocentric betweenness centrality correspond?*
2. *Under which conditions do these measures differ?*
3. *What are the implications of using these betweenness measures, if there is a systematic difference between them?*

This chapter is structured as follows: First, the terminology and definitions of the egocentric network area are introduced. Second, previous studies on the relationship of ego betweenness and global betweenness centralities are dissected, specifically focusing on their methodological approach. Third, a random network simulation is performed, replicating different network structures, and analyzing the correlation between ego-betweenness, global betweenness and degree centrality. Finally, the network simulation results are discussed in the light of the questions highlighted above, and implications for future studies are provided.

7.2 Egocentric Networks Terminology

Egocentric network research has gained traction in recent years - but there is arguably still a limited understanding of the relationship between sociocentric networks and the egocentric networks that they contain. However, this understanding becomes more critical with increased interest in large social networks, especially where global network data is difficult to obtain (Borgatti, Everett & Johnson, 2018). As guidance through this methodological discussion, the key terminology for this chapter is presented in Table 5.

Table 5. Egocentric Networks Terminology

Term	Definition
Sociocentric Vs. Egocentric Network	*Sociocentric network* includes “relationships among all nodes within a bounded social network”, while *egocentric network* includes “only that portion of a network in the immediate locality of a given node” (Marsden, 2002, p. 408).
Ego	*Ego* represents the “focal” actor in an egocentric network, with “a set of alters [other actors in an egocentric network] who have ties to an ego” as well as ties to each other (Wassermann & Faust, 1994, p. 53).
***K*th-Order Zone**	The egocentric network can have different radiuses (*k*), which represents “the minimum eccentricity over all the actors of the network” (eccentricity is defined as “an actor’s largest geodesic distance”) (Izquierdo & Hanneman, 2006, p. 14). The radius sets the boundaries for the egocentric network – *kth-order zone*.
Sociocentric Vs. Egocentric Betweenness Centrality	Betweenness centrality is the extent to which a node is part of the shortest path between other nodes (Sankar et al., 2015). *Sociocentric betweenness centrality* is calculated as the sum of the proportion of all geodesics that pass through a particular node (Wassermann & Faust, 1994). The main difference of *egocentric betweenness centrality* from sociocentric is that the maximal length of the geodesics in the ego network will vary according to the radius (*k*th-order zone) defined by a researcher (Marsden, 2002).

Notably, in the context of this discussion, we consider networks to be unweighted and undirected, following Marsden (2002) and Everett and Borgatti (2005).

7.3 Previous Studies on Sociocentric and Egocentric Betweenness

Two pivotal studies have addressed the relationship between sociocentric betweenness and egocentric betweenness centrality: Marsden (2002) and Everett and Borgatti (2005).

Marsden (2002) addressed the relationship between sociocentric and egocentric network centralities in an empirical analysis of 17 network datasets, with a network size from 14 to 217 nodes. The study concludes that ego betweenness is a reliable substitute for sociocentric betweenness. However, in a further discussion, the author acknowledges that the measures may not correspond under certain conditions, providing examples of nodes that are referred as ‘hubs’ (those nodes that connect with many peripheral actors) and ‘bridges’ (those nodes that connect with few central actors) (Mizruchi, Mariolis, Schwartz & Mintz, 1986; Marsden, 2002). Specifically, nodes with high hub centrality usually have low sociocentric and high egocentric centrality, while nodes with high bridge centrality usually have high sociocentric and low egocentric centrality - which leads to a low correlation between the sociocentric and egocentric centrality measures (Mizruchi et al., 1986; Marsden, 2002).

Everett and Borgatti (2005) show that there is no formal connection between the two measures by outlining a theoretical network structure with no direct link between sociocentric and egocentric betweenness measures. However, they acknowledge that the outlined cases are rare – and proceed with a random network simulation based on Erdős–Rényi graphs (tie formation between every possible node-pair in a network is determined by a fixed probability of connection *p*). The authors use different *p* (from 0.1 to 0.6) and different network sizes (from 25 to 500). The simulation shows a strong correlation between sociocentric and egocentric betweenness (higher than 0.85) in all cases – with a decreasing standard deviation with increasing network sizes (Everett & Borgatti, 2005).

While these studies provide evidence for a strong positive relationship of sociocentric and egocentric betweenness centrality, two points have to be noted:

1) The empirical study by Marsden (2002) is based on rather small networks (no more than 300 nodes) that does not account for the implications of large social networks that became popular in recent years.

2) Everett and Borgatti (2005) network simulation is based on a simple random graph generation model (Erdős–Rényi graph, also known as Bernoulli graph) that does not represent most real-world network structures. While the network simulation apparently addresses the potential influence of isolates by choosing high probabilities of tie formation (network simulations configurations do not surpass the disconnectedness threshold of $p<log(n)/n$*), it substantially increases the density and average degree, while ignoring clustering and scale-free properties (see below) (Jackson, 2008).*

Summarizing, the points above are highlighting a lack of generalizability of Marsden (2002) and Everett and Borgatti's (2005) findings on the correlation of sociocentric and egocentric betweenness.

Beyond the First-Order Zone. The study of ego betweenness centrality is exclusively limited to first-order-zone ego networks (as addressed in the introduction) and their approximation of sociocentric betweenness centrality measures. However, considering a higher-order-zone ego network might be a reasonable approach to follow. Arguably, the motivation for the use of higher-order zones is not directly linked to the goal of approximating sociocentric betweenness centrality, but rather to the theoretical rationale that an actor's ability to control information that flows through large geodesics (shortest path length between two nodes) becomes irrelevant, since the value of information might decrease with every contact point (e.g., following the rationale of Katz (1953) on influence of nodes, by penalizing distant neighbours in a network). Similarly, it might seem reasonable to consider information that flows from nodes that are outside the network of direct connections (first-order zone) (Chen et al. , 2012; Zhao et al., 2017). This motivates the consideration of higher-order zones for an egocentric network design. We, therefore, extend the studies of Marsden (2002) and Everett and Borgatti (2005) in this methodological discussion.

7.4 Network Simulation

We aim to address the limitations of previous studies by taking a more holistic approach to a network simulation. First, we simulate networks with real-world network structures and consider ego networks beyond the first-order-zone definition, including second- and third-order-zone ego-networks.

Network Generation Algorithm. As introduced above, real-world networks have specific properties that have been observed in many settings: Clustering and a scale-free nature (Newman, 2001; Clauset, Shalizi & Newman, 2009). Since we aim to achieve results that are relevant for research on naturally occurring networks, it is vital that we consider these in our network simulations.

A scale-free nature refers to the fact that many real-world network's degree distributions follow a power-law distribution of $P(k)\sim k^{-a}$, meaning that there are very few actors with a high centrality and many actors with a very low centrality (Barabási & Albert, 1999; Clauset et al., 2009). In network generation algorithms, this property is connected to the preferential attachment paradigm, suggesting that "networks are built by adding nodes and links successively" (Jacob & Mörters, 2015, p. 632). This is replicated through a so-called Preferential Attachment (PA) method - modelling that the probability to be connected to a node with high degree centrality is higher than to be connected to a node with a low degree centrality (Barabási & Albert, 1999; Holme & Kim, 2002). While this achieves similar degree distribution of real-world networks - the local network structures of generated networks still differ significantly to observed networks, due to clustering (Jacob & Mörters, 2015).

Clustering refers to the phenomenon that networks show multiple tightly-knit groups. From the perspective of sociology, this is commonly explained by the homophily phenomenon, stating that actors have a "hidden variable" that incentivizes tie formation in the case of similarity (Jacob & Mörters, 2015, p. 633; McPherson, Smith-Lovin & Cook, 2001). In the context of network generation, there are various approaches to replicating clustering property in random networks (e.g., Watts & Strogatz (1998)).

There is a multitude of network generation models that integrate the scale-free nature and clustering property (e.g., Flaxman, Frieze & Vera, 2006; Aiello, Bonato, Cooper, Janssen & Pralat, 2009). For the purpose of our network simulation, we employ Holme and Kim's (2002) model. The model is based on a PA method described above, paired with a Triad Formation (TF) extension, such that new tie formation is more likely to occur with neighbors of nodes that you are already connected with. This model allows for a tunable clustering in the random graph model.

Methodology - Simulation. In total, 50,400 network simulations were performed using Python's NetworkX library. All networks were generated based on the Holme and Kim (2002) algorithm introduced above, which accounts for real-world social network properties through PA (scale-free nature) and TF (clustering property). The simulation iterates through different graph generation settings, namely the number of random ties added to each new node (*n*), probability of adding a triangle after adding a random tie (*tr*) as well as the network size (*s*).

Based on the generated networks, degree centrality, sociocentric betweenness centrality, as well as ego betweenness centrality based on first-, second- and third-order-zone ego networks are calculated. Subsequently, the correlation between these measures is observed. Figures 3-5 on the following pages plot the different correlation coefficients for selected network generation combinations (*tr*, *n*, *s*), based on ego networks. Notably, the plotted correlation coefficients are the mean correlations based on 100 simulations for each setting. Additionally, network diameter and density are obtained for all simulated networks. The diameter represents the geodesic between the two most distant network actors, while density is the proportion of actual ties to all possible ties in the network (Wasserman & Faust, 1994).

7.5 Findings

This methodological discussion aims to explore to what extent sociocentric and egocentric betweenness centrality correspond. A central finding in our simulation is that the correlation between sociocentric and egocentric betweenness vary significantly with the change of parameters of the network - opposing the findings of Marsden (2002) and Everett and Borgatti (2005). At the same time, in all combinations of parameters, the correlation between degree and sociocentric betweenness centrality is close to 1, in line with previous studies on centrality correlations (Valente et al., 2008; Meghanathan & He, 2016).

We make three observations that are present in all simulated networks (Figures 3-5). First, the correlation between sociocentric and egocentric betweenness is monotonously decreasing with an increase in network size, *ceteris paribus*, in some cases approximating to 0. This opposes the findings of both Marsden (2002) and Everett and Borgatti (2005), reporting strong correlation in all observed and simulated networks. Second, increasing the clustering property in the simulated networks (through increased *tr*) always increases the correlation coefficients between sociocentric and egocentric betweenness, *ceteris paribus*. Third, increasing the density (through increased initial ties *n*) leads to a decay in the correlation between sociocentric and egocentric betweenness (especially in larger networks), *ceteris paribus* (except third-order-zone ego networks).

Focusing on first-order-zone ego betweenness measures, we observe that there is a substantial correlation with sociocentric betweenness (partly supporting findings of Marsen (2002) and Everett and Borgatti (2005)) - however, with increasing density and decreasing clustering properties[1], these correlations appears to approximate zero (see Figure 3). Interestingly, this behavior changes in ego networks with higher-order zones. In second-order-zone ego networks, the decay in the correlations is more evident than in first-order zones, especially when the network size increases. Moreover, we observe a threshold in the network size, after which the correlations rapidly drop from close to one to almost zero, observed in the dense second-order zone ego networks. In third-order zone ego networks, sociocentric and egocentric betweenness measures increasingly correlate, even in larger networks, which is observed in more dense networks (high initial nodes *n*).

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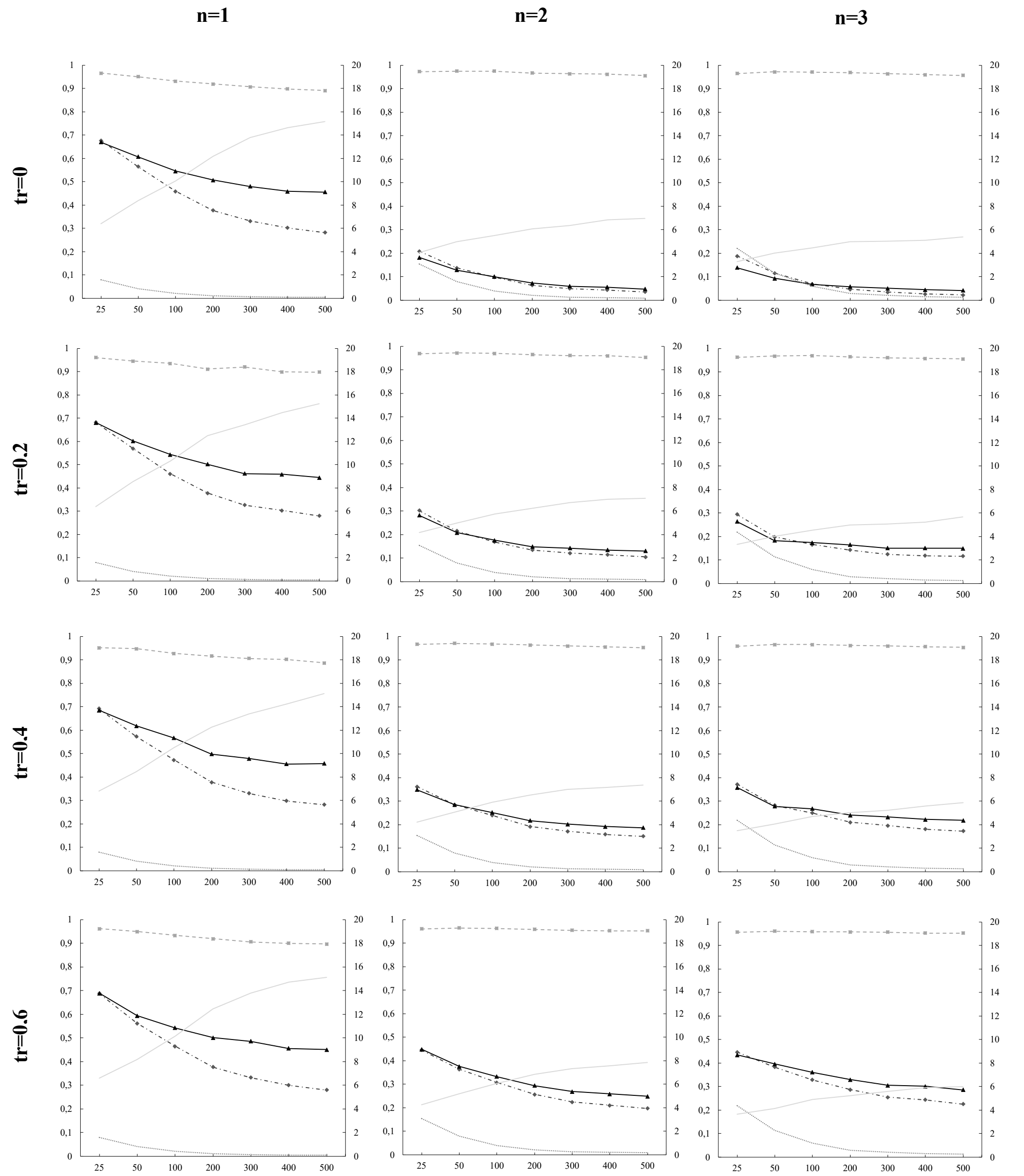
[1] Notably, real-world networks rarely have extremely high density and a low clustering property (e.g., McPherson et al., 2001).

Figure 3. Correlation Coefficients of Centrality Measures based on First-Order-Zone Ego Network Simulations

First-Order Zone Ego Betweenness

The *left-hand y-axis* indicates *correlation coefficients* and *density*; the *right-hand y-axis* refers to *the network diameter*. The *x-axis* indicates the *network size*.



Note: Correlation coefficients between sociocentric betweenness (SB), ego betweenness (EB), and degree centrality are based on random network simulations using the Holme and Kim (2002) algorithm. Ego betweenness centrality calculation is based on first-order zone egocentric networks.

In the network generations, *n* denotes the number of random ties added to each new node and *tr* denotes the probability of adding a triangle after adding a random tie. *Diameter* represents the geodesic between the two most distant network actors, while *density* is the proportion of actual ties to all possible ties in the network. The correlation coefficients, as well as density and diameter, are means, based on 100 network simulation for each random graph setting. Notably, the x-axis is non-linear.

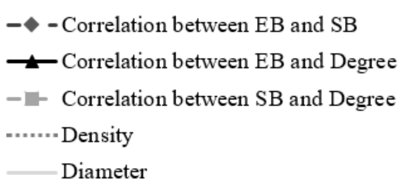
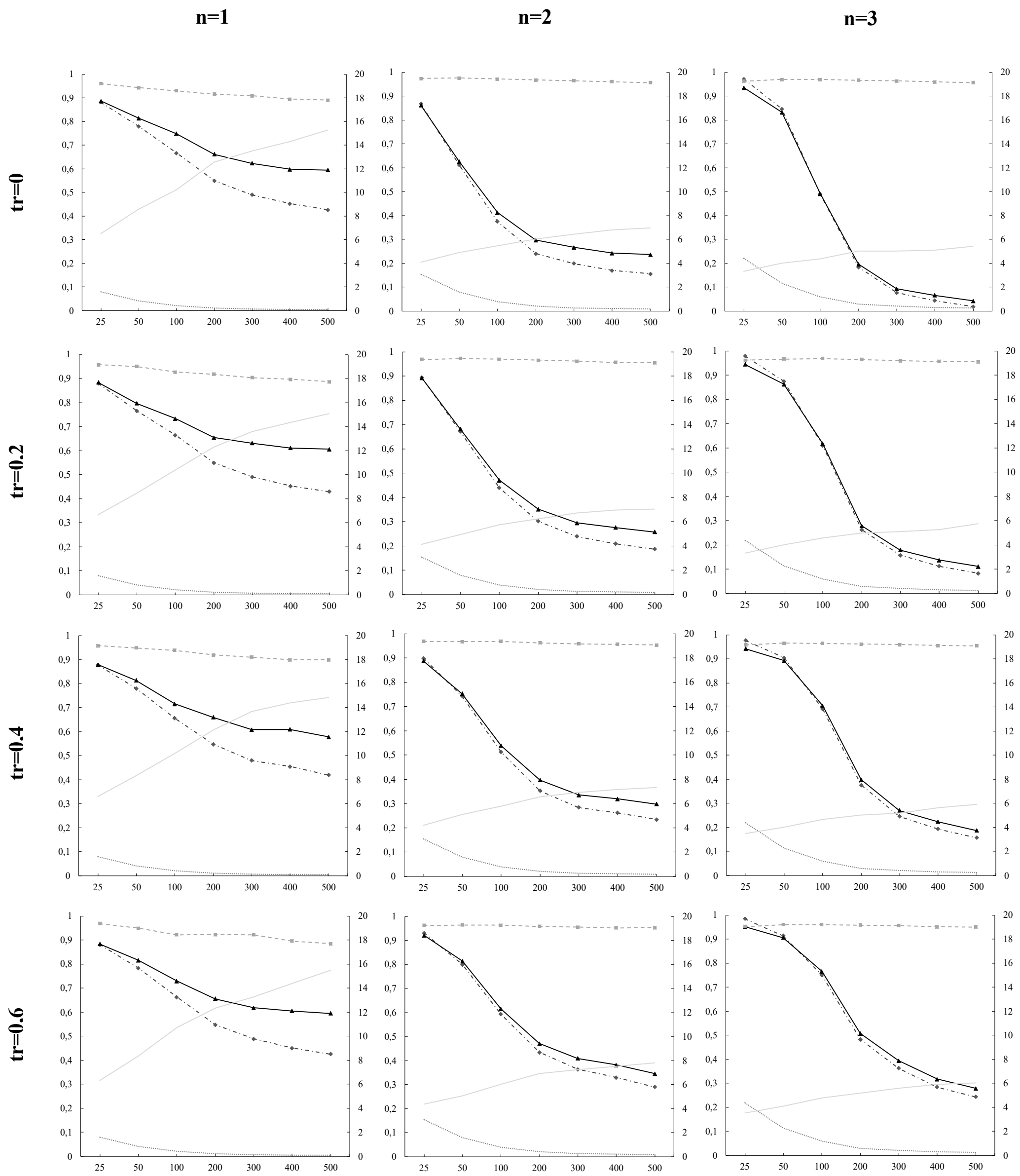


Figure 4. Correlation Coefficients of Centrality Measures based on Second-Order-Zone Ego Network Simulations

Second-Order Zone Ego Betweenness

The *left-hand y-axis* indicates *correlation coefficients* and *density*; the *right-hand y-axis* refers to *the network diameter*. The *x-axis* indicates the *network size*.



Note: Correlation coefficients between sociocentric betweenness (SB), ego betweenness (EB), and degree centrality are based on random network simulations using the Holme and Kim (2002) algorithm. Ego betweenness centrality calculation is based on second-order zone egocentric networks.

In the network generations, *n* denotes the number of random ties added to each new node and *tr* denotes the probability of adding a triangle after adding a random tie. *Diameter* represents the geodesic between the two most distant network actors, while *density* is the proportion of actual ties to all possible ties in the network. The correlation coefficients, as well as density and diameter, are means, based on 100 network simulation for each random graph setting. Notably, the x-axis is non-linear.

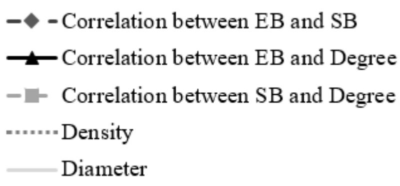
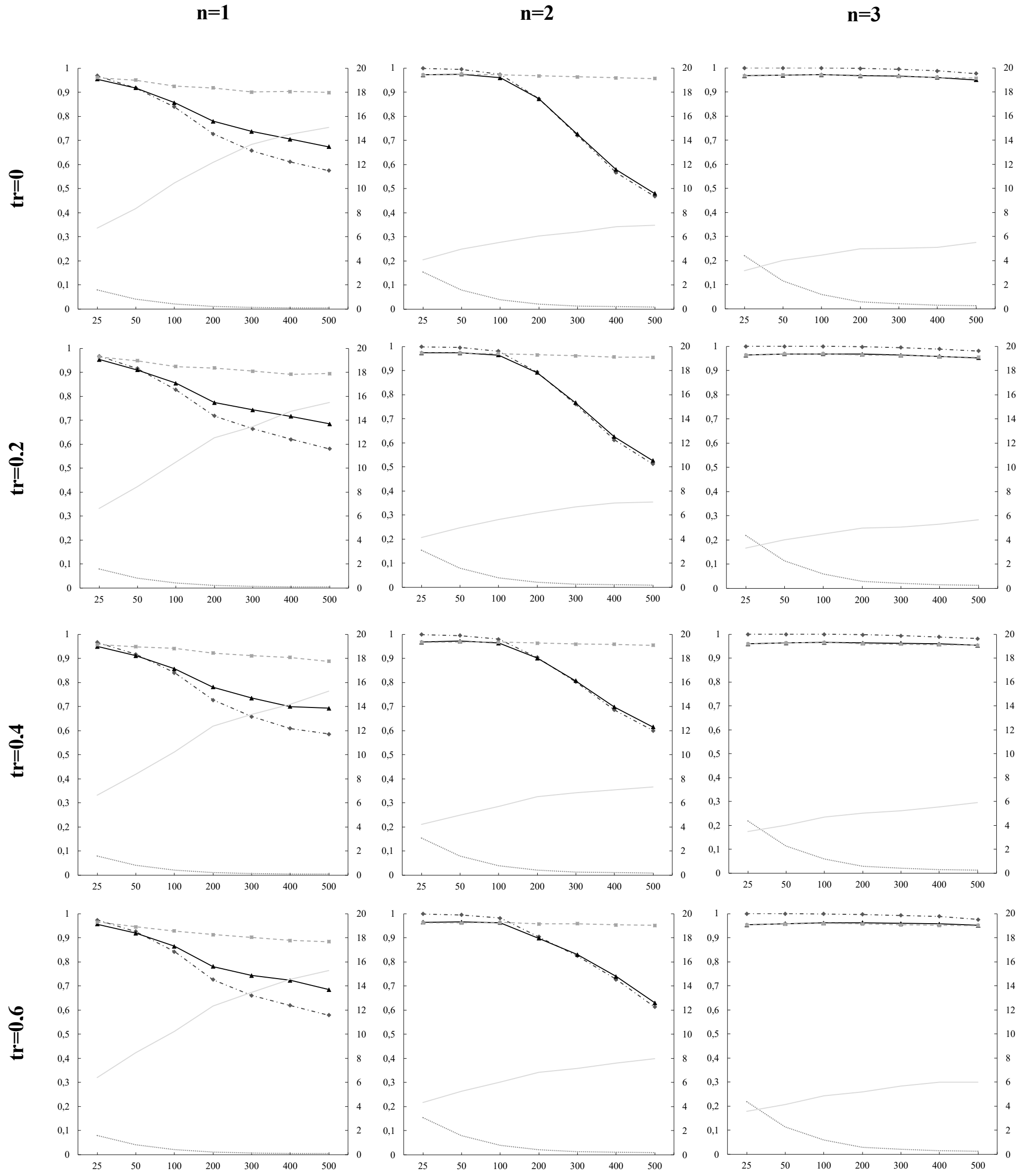


Figure 5. Correlation Coefficients of Centrality Measures based on Third-Order-Zone Ego Network Simulations

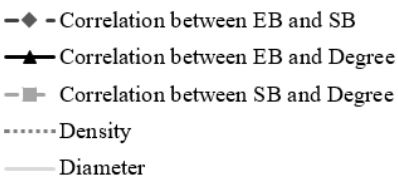
Third-Order Zone Ego Betweenness

The *left-hand y-axis* indicates *correlation coefficients* and *density*; the *right-hand y-axis* refers to *the network diameter*. The *x-axis* indicates the *network size*.



Note: Correlation coefficients between sociocentric betweenness (SB), ego betweenness (EB), and degree centrality are based on random network simulations using the Holme and Kim (2002) algorithm. Ego betweenness centrality calculation is based on third-order zone egocentric networks.

In the network generations, *n* denotes the number of random ties added to each new node and *tr* denotes the probability of adding a triangle after adding a random tie. *Diameter* represents the geodesic between the two most distant network actors, while *density* is the proportion of actual ties to all possible ties in the network. The correlation coefficients, as well as density and diameter, are means, based on 100 network simulation for each random graph setting. Notably, the x-axis is non-linear.



7.6 Discussion

Our findings have certain implications for our initial questions introduced before. To start with, we observe that sociocentric and egocentric betweenness centrality corresponds only under certain conditions, even if only considering ego networks with first-order zones: There are systematic changes in the correlation coefficients when adjusting clustering properties, network density, and network size. Accordingly, we argue that there can be local network structures, which substantially differ from their sociocentric network. As a result, this affects the validity of ego betweenness as a proxy for sociocentric betweenness centrality in certain networks. By contrast, degree centrality is highly correlated with global betweenness centrality in all networks (see Figures 3-5), indicating that degree centrality can be a better proxy for sociocentric betweenness centrality than egocentric betweenness.

With our second question, we aim to explore under which circumstances sociocentric and egocentric betweenness centrality differ. We propose that the validity of using ego betweenness centrality as a proxy for sociocentric betweenness centrality relates to the extent to which the ego network captures the sociocentric network. In small networks, the correlations between sociocentric and egocentric betweenness centralities are high, since the ego network captures large parts of the global network (indicated by the fact that increasing clustering has a positive impact on the correlation). This, however, seems to disappear, when considering larger networks and lower clustering. If one expands the definition of ego networks to higher-orders, the ego network captures more of the original network - especially observed when looking at networks of high density (correlation approximates 1). An interesting observation in favor of this argument is that there is a threshold in network size in the second-order-zone ego networks (Figure 4). This supports the fact that there is strong correspondence in the two measures as long as a particular part of the network is captured - and extremely low correspondence after a certain cutoff point in network size.

Overall, under the condition that sociocentric and egocentric measures correspond, it is more reasonable to take sociocentric betweenness centrality since the egocentric measure captures large parts of the same network (especially in higher-order zones). This is usually the case for smaller networks. However, the network sizes in studies have been rapidly increasing in recent years. In these large networks, egocentric betweenness centrality may not be a good proxy for sociocentric betweenness as the ego network captures only some part of the whole network. Instead, egocentric betweenness can be a measure of the ability of a node to control information in its nearest neighborhood. Therefore, we argue that it can still be reasonable to use egocentric betweenness centrality for large networks, not as a proxy for the sociocentric measure but as a measure of local control of information flows. In this context, using first-order-zone ego networks can be one alternative. However, including higher-order-zone ego networks can add more value by not only considering direct connections, but also the indirect links (as pointed out by Chen et al. (2012) and Zhao et al. (2017)). An example can be the Facebook network. In this case, egocentric betweenness would be a weak proxy for sociocentric betweenness according to our findings, but instead would be a measure of the ability to control information in the nearest neighborhood of a certain individual (node).

Addressing the third question of this study, we argue that it is critical to research not only global network structures but also local networks that these contain. Putting this in the context of betweenness centrality concept, actors can be of high importance in terms of controlling the local network information flows, while others have the same role for controlling global network information flows - which correspond to substantially different roles. This can also be connected to the studies by Mizruchi et al. (1986) and Marsden (2002), describing ‘bridge’ and ‘hub’ actors - for which sociocentric and egocentric betweenness centralities do not correspond as their global and local structures appear to be significantly different.

7.7 Conclusion

This methodological discussion aimed at investigating the correspondence of sociocentric and egocentric betweenness centralities. Although scholars claim that ego betweenness can be seen as an appropriate substitute for global betweenness for large social networks (Marsden, 2002; Everett & Borgatti, 2005), we found that the correlation between these measures can vary significantly with network properties and size. This adds a new and interesting aspect to the social network analysis literature. Many social network studies address the issue of sociocentric betweenness centrality approximation, with an egocentric network design (Brandes, 2001; Marsden, 2002; Everett & Borgatti, 2005; Geisberger et al., 2008; Chan et al., 2009). However, few authors, especially in social sciences, actually address the applicability of ego betweenness centrality and consider alternatives. We argue that the academic discussion should revolve less around the *approximation of sociocentric betweenness measure with ego betweenness centrality* and more on *the applicability and the rationale of the ego betweenness measure*. This is connected to the fundamental question of how egocentric network structures look like in large social networks (Carnovale & Yeniyurt, 2015).

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Appendices

Appendix A - Centrality Measures in Social Networks

Centrality is one of the most frequently used measures in social network research and is a network's essential structural characteristic (Faust, 1997; Wasserman & Faust, 1994). Freeman (1978) introduced the most prominent concepts to the literature – namely, degree-, closeness- and betweenness centrality. Initially, these measures were defined for sociocentric network data "that provide information on relationships among all nodes within a bounded social network" (Marsden, 2002, p. 408). However, as more and more studies aimed to explore larger networks, and significant difficulties in the implementation of the sociocentric design started to dominate – an egocentric design became an efficient alternative to the global network study (these concepts are described in more detail in the methodology discussion in Chapter 7). Consequently, we will hereby introduce these measures in the sociocentric and egocentric context.

Degree centrality corresponds to the degree of a node, measuring the number of ties to other actors in the network (Freeman, 1978; Wasserman & Faust, 1994). According to Freeman (1978, p. 221), degree centrality "is viewed as important as an index of its potential communicational activity". For a sociocentric social network, the measure is computed as follows (Wasserman & Faust, 1994):

$$C_D(n_i) = d(n_i) = \sum_j x_{ij} = \sum_j x_{ji}$$

where n_i denotes node i; $C_D(n_i)$ denotes degree centrality; $d(n_i)$ represents the degree of the node i (number of edges involving node i); $\sum_j x_{ij}$ denotes the number of connections of node i to other nodes in an undirected graph ($\sum_j x_{ij} = \sum_j x_{ji}$). It should be noted that sociocentric and egocentric measures of degree centrality are identical as it includes only the direct connections of a given node i (which remain the same in an egocentric design) (Marsden, 2002).

Closeness centrality is focused on how close the actor is to others in the network, measured as the sum of shortest path (also referred to as geodesics) distances from one actor to all other actors (Wasserman & Faust, 1994; Bavelas, 1950; Harary, 1959; Beauchamp, 1965; Rogers, 1974; Freeman, 1978). Freeman (1978) argues that closeness centrality indicates the node's ability to undertake independent actions in the network, being closer to others. The sociocentric closeness centrality is measured as follows (Wasserman & Faust, 1994):

$$C_C(n_i) = \frac{g-1}{\sum_{j=1}^{g} d(n_i,n_j)}$$

where n_i denotes node i; $C_C(n_i)$ denotes closeness centrality; while $d(n_i, n_j)$ represents the number of ties in the geodesics connecting actors i and j, $\sum_{j=1}^{g} d(n_i, n_j)$ is the total distance from i to all other actors; g denotes the number of nodes in the network, and g-1 represents standardization by the sum of minimum possible distances. Notably, as closeness centrality $C_C(n_i)$ attempts to measure the connections of a given node i to all other nodes, it "is simply not applicable to ego networks" - since an egocentric network is defined by the maximum length of geodesics (Everett & Borgatti, 2005, p. 32).

Betweenness centrality signifies whether the actor is located between other actors on their shortest paths in the network and can be measured as the probability that one actor is "involved in the communication" between other actors (Wasserman & Faust, 1994, p. 190; Freeman, 1978). Freeman (1978, p. 224) highlights that betweenness centrality can be viewed as an indicator of the potential "for control of communication" by a given node. For sociocentric networks, betweenness centrality can be calculated as follows (Wasserman & Faust, 1994):

$$C_B(n_i) = \sum_{j<k} \frac{g_{jk}(n_i)}{g_{jk}}$$

where n_i denotes node i; $C_B(n_i)$ denotes betweenness centrality; while g_{jk} represents the number of geodesics linking actors j and k, $g_{jk}(n_i)$ is the number of geodesics linking actors j and k, passing through actor i. For large networks, betweenness centrality is characterized by computational complexity (Marsden, 2002; Everett & Borgatti, 2005). The computation of betweenness centrality $C_B(n_i)$ for ego network, however, is considered easier and corresponds "imperfectly to the sociocentric version" (Marsden, 2002, p. 410). The main difference between the two network designs is that the maximal length of the geodesics in the ego network will vary according to the radius (*kth-order zone*) defined by a researcher – e.g., an ego network based on node's i second-order zone (with a radius of 2) will yield maximum geodesics of length 4.

Appendix B - Correlation Matrix & Descriptive Statistics

Table B1. Correlation Matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
1. ROA													
2. Revenue Growth	0.11*												
3. Employee Growth	0.06*	0.27*											
4. Degree Centrality	-0.04*	0.01	-0.02*										
5. Betweenness Centrality	-0.04*	0.01	0.01	0.08*									
6. Degree Centrality (E)	-0.05*	0.03*	-0.00	0.80*	0.02*								
7. Degree Centrality (Y)	-0.03*	-0.00	-0.04*	0.95*	0.10*	0.63*							
8. Firm Age	0.07*	-0.09*	-0.10*	0.04*	0.05*	-0.06*	0.10*						
9. Firm Size	0.04*	-0.04*	-0.07*	0.34*	0.11*	0.24*	0.34*	0.27*					
10. Management Tenure	0.10*	-0.05*	-0.03*	-0.07*	-0.04*	-0.08*	-0.04*	0.26*	0.01				
11. Board Size	-0.02*	-0.01	-0.01	0.24*	0.43*	0.15*	0.26*	0.12*	0.38*	-0.08*			
12. Number of Employees	0.04*	-0.09*	-0.19*	0.19*	0.09*	0.11*	0.21*	0.24*	0.63*	-0.03*	0.36*		
13. Current Ratio	-0.01	0.03*	-0.01	0.02*	0.00	0.01	0.02*	0.02*	0.05*	0.02*	0.01	-0.04*	
14. Debt Ratio	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.01	0.01	-0.00	0.02*	-0.01	0.01	0.00

Notes: The asterisks indicate significant correlation coefficients (* p<0.05). Degree Centrality (E)/(Y) denote degree centrality among established/young companies. The matrix is calculated for the year 2015, while all independent and control variables are lagged one year relative to the dependent variables

Table B2. Descriptive Statistics: Means, Standard Deviations and Variable Description

Variable	M	SD	Variable Description
ROA	1.20	8.51	Standardized; winsorized at 1%- and 99%-level; scaled by 100
Revenue Growth	-0.78	0.46	Standardized; winsorized at 1%- and 99%-level; scaled by 100
Employee Growth	-4.15	32.59	Standardized; winsorized at 1%- and 99%-level; scaled by 100
Degree Centrality	2.39	0.91	Transformed using the logarithm function; observations with values that are equal to 0 or higher than 200 were dropped
Ego Betweenness Centrality	0.17	0.20	No transformations made
Degree Centrality (Y)	1.85	1.05	Transformed using the logarithm function
Degree Centrality (E)	1.01	0.88	Transformed using the logarithm function
Firm Age	12.89	5.88	No transformations made
Firm Size	16.58	1.75	Represented by a logarithm of total assets
Management Tenure	0.01	1.07	Standardized; transformed using the logarithm function
Board Size	0.30	1.04	Standardized
Number of Employees	0.38	1.03	Standardized; transformed using the logarithm function; winsorized at 99%-level
Current Ratio	1.90	9.00	Winsorized at 1%- and 99%-level
Debt Ratio	0.35	8.00	No transformations made

Note: Degree Centrality (Y)/(E) denote degree centrality among young/established firms. M denotes mean. SD denotes standard deviation. All variables based on accounting data were inflation-adjusted (using CPI).

Appendix C - Social Network Description

Network Properties. Understanding the structural properties of the entire network is essential to analyze the structural properties of the actors. As part of the analysis, we obtained multiple measures for the interlocking directorates networks of 2009-2015, the methodology chapter of this thesis. An overview of all measures is provided in Table C1 below.

The *number of firms* relate to all firms that span the network. This includes all companies that are registered in Norway in the respective years, only excluding companies with one board member or less.

The *number of directors* includes the entirety of board members associated with Norwegian firms.

Board interlocks, also commonly addressed as the number of ties/number of edges in the social network literature, refers to the aggregate number of connections between firms that are present in the network. As introduced before, the membership of an individual in the board of two distinct companies forms a tie between these firms, which is ultimately spanning the network that is the subject of our analysis (Faust, 1997). Notably, this number does not consider multiple ties between the same company pair but considers them as a single connection.

Average degree refers to the average number of board interlocks (number of ties to other companies) a company has.

Average degree among young firms relates to the average number of board interlocks a company has with young firms (number of ties to young firms), independent from its own type.

Average degree among established firms relates to the average number of board interlocks a company has with established firms (number of ties to established companies), independent from its own type.

Average ego betweenness refers to the average ego betweenness centrality, which is defined in the methodology chapter.

Number of components. Our interlocking directorates networks are disconnected, meaning that it is “partitioned into two or more subsets in which there are no paths between the nodes in different subsets.” (Wassermann & Faust, 1994, p. 109). These subsets are also referred to as components. Hence, these measures indicate the total number of subsets in the network. Notably, these subsets include isolates, components of size one (no board interlock).

Size of the largest component. Referring to the definition above, this measure represents the number of firms that are contained in the largest subset of the network (largest component).

Density considers the proportion of ties that are present in the network to all possible ties that a graph can have. The density Δ can be expressed as

$$\Delta = \frac{2L}{g(g-1)}$$

where *L* denoted the number of ties (board interlocks) in the network, and *g* denotes the number of nodes (firms) in the network (Wassermann & Faust, 1994).

Average clustering coefficient addresses to which extent nodes (firms) tend to cluster together. The average clustering coefficient can be expressed as

$$\overline{C} = \frac{1}{n}\sum_{i=1}^{n} C_i$$

where

$$C_i = \frac{2L_i}{k_i(k_i-1)}$$

with k_i denoting the degree (board interlocks) of the node (firm) i and L_i denoting the number of ties (board interlocks) between the neighbours k_i of node (firm) i (Watts & Strogatz, 1998).

Table C1. Overview of Interlocking Directorates Networks Properties, 2009-2015

	2009	2010	2011	2012	2013	2014	2015
Number of firms	93,703	94,950	104,877	107,685	110,864	115,010	120,220
Number of directors	234,746	236,578	264,441	271,364	277,871	285,643	294,810
Board interlocks	644,313	651,000	737,197	768,151	802,954	832,815	856,414
Average degree	13.752	13.712	14.058	14.266	14.485	14.482	14.247
Average degree to young firms	5.464	5.612	5.193	4.815	4.200	3.691	3.510
Average degree to established firms	6.621	6.770	7.443	7.961	8.697	9.123	9.084
Average ego betweenness	0.105	0.105	0.112	0.110	0.109	0.107	0.106
Number of components	7,144	7,249	7,446	7,914	8,225	8,843	9,457
Size of largest component	73,180	74,092	83,604	84,902	87,218	89,556	92,915
Transitivity	0.717	0.714	0.734	0.735	0.727	0.733	0.712
Density	0.000147	0.000144	0.000134	0.000132	0.000131	0.000126	0.000119
Average Clustering Coefficient	0.6129	0.6151	0.6034	0.6044	0.6046	0.6059	0.6058

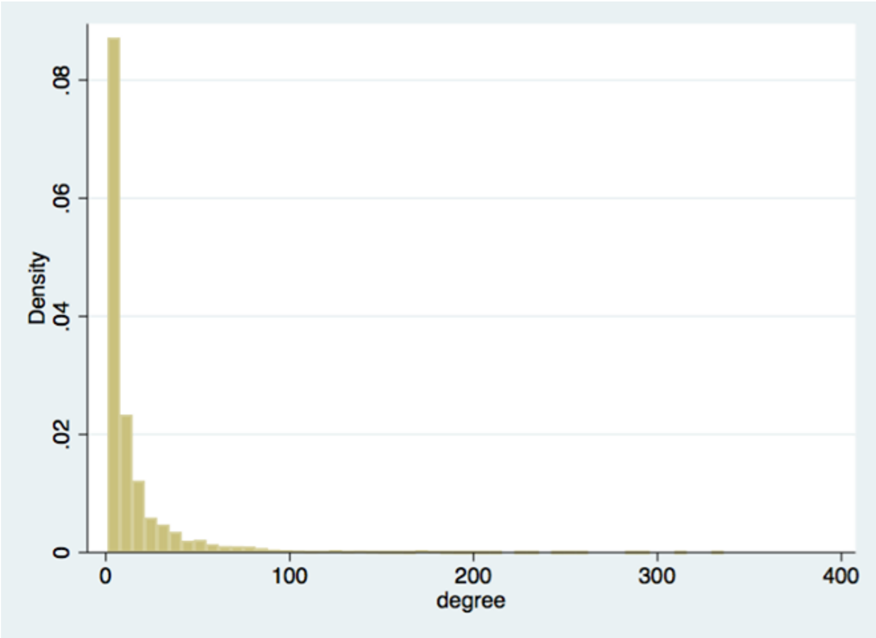
Note: Considering the entire interlocking directorates networks, not limited to firms considered in the regression models. Notably, the table is based on the raw network data, which is calculated from the edgelist of firms participating in the network. This implies that isolates are not considered in these statistics. Isolates were added at a later stage by merging the data with other variables and dropping observations with missing data.

Table C2. Interlocking Directorates Network Measures in the Entire Network and in the Professional, Scientific & Technical Activities Sector, 2009-2015

Measure	2009		2010		2011		2012		2013		2014		2015	
	Entire	PST	Entire	PST	Entire	PST	Entire	PST	Entire	PST	Entire	PST	Entire	PST
Number of firms	93,703	3,548	94,950	3,536	104,877	3,716	107,685	3,806	110,864	3,925	115,010	4,015	120,220	4,103
Average degree centrality	13.752	9.578	13.712	9.684	14.058	9.872	14.266	9.956	14.485	10.000	14.482	9.933	14.247	10.009
Average degree centrality am. young firms	5.464	3.552	5.612	3.700	5.193	3.434	4.815	3.221	4.200	2.827	3.691	2.534	3.510	2.484
Average degree centrality am. established firms	6.621	4.844	6.770	5.000	7.443	5.447	7.961	5.653	8.697	6.052	9.123	6.319	9.084	6.447
Average ego betweenness centrality	0.105	0.151	0.105	0.156	0.112	0.164	0.110	0.161	0.109	0.159	0.107	0.158	0.106	0.156

Note: Entire denotes the measures for the entire interlocking directorates network, not limited to firms considered in the regression models, while PST denotes the measures for the Professional, Scientific & Technical Activities sector, limited to firms in our regression sample.

Figure C1. Degree Centrality Distribution



Note: The figure represents the degree distribution of the entire interlocking directorates network in 2015. Other years show similar results.

Figure C2. Numerical Summary Statistics of Degree Centrality Variable

degree

	Percentiles	Smallest		
1%	1	1		
5%	1	1		
10%	1	1	Obs	120,220
25%	2	1	Sum of Wgt.	120,220
50%	5		Mean	14.24745
		Largest	Std. Dev.	23.94419
75%	15	290		
90%	37	290	Variance	573.3245
95%	59	315	Skewness	3.760946
99%	128	336	Kurtosis	21.46958

Note: The figure represents the degree distribution of the entire interlocking directorates network in 2015. Other years show similar results.

Appendix D - Generalized Method of Moments

Introduction to Generalized Method of Moments (GMM). The *Generalized Method of Moments (GMM)* was first proposed by Hansen (1982) and, since then, has gained high popularity in the econometrics literature, becoming a Nobel Prize-winning technique in 2013 (Hall, 2005). Notably, the GMM is the generalization of the classical technique known since the work of Pearson (1893) as the *Method of Moments (MM)*. The traditional MM is the basis for many parameter estimation techniques, utilizing the sample moments in order to estimate the unknown parameters of interest (Zsohar, 2010; Wooldridge, 2001). A comprehensive definition of the MM estimator is provided by Zsohar (2010, p. 153):

> "Suppose that we have an observed sample $\{x_i: i = 1, 2,\dots, n\}$ from which we want to estimate an unknown parameter vector $\theta \in R^p$ with true value θ_0. Let $f(x_i, \theta)$ be a continuous and continuously differentiable $R^p \rightarrow R^q$ function of θ, and let $E[f(x_i, \theta)]$ exist and be finite for all i and θ. Then the population moment conditions are that $E[f(x_i, \theta_0)] = 0$. The corresponding sample moments are given by
>
> $$f_n(\theta_0) = \frac{1}{n}\sum_{i=1}^{n} f(x_i, \theta).$$
>
> The method of moments estimator of θ_0 based on the population moments $E[f(x_i, \theta)]$ is the solution to the system of equations $f_n(\theta) = 0$."

The GMM technique extends this classical theory by allowing to incorporate more moment conditions q than parameters p, which prevents the researcher from losing any information by disregarding $q - p$ moments (Zsohar, 2010; Wooldridge, 2001). Zsohar (2010, p. 156) defines the GMM estimator as follows:

> "Suppose that the conditions in Definition 1 [MM estimator definition above] are met and we have an observed sample $\{x_i: i = 1, 2,\dots, n\}$ from which we want to estimate an unknown parameter vector $\theta \in \Theta \subseteq R^p$ with true value θ_0. Let $E[f(x_i, \theta)]$ be a set of q population moments and $f_n(\theta)$ the corresponding sample counterparts. Define the criterion function $Q_n(\theta)$ as
>
> $$Q_n(\theta) = f_n(\theta)' W_n f_n(\theta),$$
>
> where W_n, the weighting matrix, converges to a positive definite matrix W as n grows large. Then the GMM estimator of θ_0 is given by
>
> $$\hat{\theta} = argmin\ Qn(\theta),\ \theta \in \Theta."$$

The introduction of GMM facilitated "the development of numerous statistical inference techniques based on GMM estimators", which have been applied in various areas and contexts (Hall, 2005, p. 1). One of the applications of GMM is on dynamic panel data models, containing a lagged dependent variable together with unobserved fixed effects (Wooldridge, 2001). As this is the case in our study, the dynamic panel data model and issues associated with this type of data (e.g., dynamic panel data bias and endogeneity problem) are introduced in the methodology chapter. The following section will provide a more detailed description of GMM estimators, focusing on dynamic panel data applications.

Difference & System GMM Estimators: Overview. One of the first standard methods for dynamic panel data models was Anderson and Hsiao's (1982) 2SLS estimator. The technique uses first-differencing to eliminate the fixed effects, and "lags two and beyond are used as instrumental variables for the differenced lagged dependent variable" (Wooldridge, 2001, p. 98). Notably, the Anderson and Hsiao (1982) estimator prevents the researcher from utilizing more lags of the endogenous variable, as "the longer the lags used, the smaller the sample, since observations for which lagged observations are unavailable are dropped" (Roodman, 2006, p. 23).

A remedy for this problem was proposed by Holtz-Eakin, Newey, and Rosen (1988) and then popularized by Arellano and Bond (1991), who introduced the *Difference GMM estimator* (also known as *Arellano and Bond estimator*). Specifically, within the GMM framework, Arellano and Bond (1991) "build a set of instruments from the second lag of *y* [dependent variable], one for each time period, and substitute zeros for missing observations, resulting in GMM-style instruments"- which allows the inclusion of all available lags as instruments (Roodman, 2006, p. 23). In other words, the estimator is a more efficient alternative to Anderson and Hsiao (1982) as it utilizes additional moment conditions, increasing the set of instruments (Behr, 2003).

Initially, Arellano and Bond (1991) argued for the use of differencing transformation of regressors in order to eliminate unobserved effects. However, studies by Arellano and Bover (1995) and Blundell and Bond (1998) found a potential limitation in the Arellano and Bond estimator. Particularly, the lags used in Difference GMM can often be weak instruments for a first-differenced variable, especially when a variable is "close to a random walk" (meaning that past levels provide almost no information about the future levels) (Roodman, 2006, p. 29). The authors, therefore, introduced a modification of the Arellano and Bond (1991) approach, with an additional assumption "that first differences of instrument variables are uncorrelated with the fixed effects" – which allows for the inclusion of new instruments (Roodman, 2006, p. 1). Specifically, the extended estimator includes not only lagged levels "as instruments for equations in first differences" but also lagged differences "as instruments for equations in levels" – the *System GMM estimator* (also known as *Arellano-Bover/Blundell-Bond estimator*) (Baltagi, 2005, p. 148). Further studies by Hahn (1999), Blundell, Bond and Windmeijer (2000), and Blundell and Bond (2000) confirm the "dramatic efficiency gains" of the System GMM estimator through the introduction of additional moment conditions (Baltagi, 2005, p. 148).

Difference & System GMM Estimators: Assumptions. Roodman (2006, p. 15) provides a comprehensive overview of the assumptions behind the Difference and System GMM estimators of Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998) – complementing the theoretical reasoning illustrated in the previous sections:

> "1. The process may be dynamic, with current realizations of the dependent variable influenced by past ones.
>
> 2. There may be arbitrarily distributed fixed individual effects. This argues against cross-section regressions, which must essentially assume fixed effects away, and in favor of a panel set-up, where variation over time can be used to identify parameters.
>
> 3. Some regressors may be endogenous.
>
> 4. The idiosyncratic disturbances (those apart from the fixed effects) may have individual-specific patterns of heteroskedasticity and serial correlation.
>
> 5. The idiosyncratic disturbances are uncorrelated across individuals.
>
> . . .
>
> 6. Some regressors may be predetermined but not strictly exogenous: independent of current disturbances, they may be influenced by past ones. The lagged dependent variable is an example.
>
> 7. The number of time periods of available data, T, may be small. (The panel is "small T, large N")
>
> . . .
>
> 8. The only available instruments are "internal" based on lags of theinstrumented variables."

Appendix E - Base Regression Model

Table E1. Regression Results for the Base Model – Firm Performance

Variables	(1) ROA⁺	(2) Revenue Growth	(3) Employee Growth⁺
ROA	61.840***		
	(10.970)		
Revenue Growth		27.560*	
		(14.120)	
Employee Growth			31.550**
			(13.500)
Degree Centrality	0.222	0.049**	1.463
	(0.451)	(0.022)	(1.721)
Ego Betweenness Centrality	-1.644	-0.029	14.060**
	(1.611)	(0.081)	(5.911)
Firm Age	0.069***	-0.002	-0.176
	(0.016)	(0.002)	(0.118)
Firm Size	-1.176***	-0.038***	-0.881**
	(0.173)	(0.012)	(0.395)
Management Tenure	-0.104	0.002	-0.043
	(0.140)	(0.005)	(0.379)
Board Size	-0.068	0.002	-1.499*
	(0.266)	(0.011)	(0.838)
Number of Employees	1.331***	0.012	
	(0.151)	(0.012)	
Current Ratio	-0.001	0.006**	-0.017
	(0.007)	(0.003)	(0.018)
Debt Ratio	-0.002*	0.000	0.018***
	(0.001)	(0.000)	(0.005)
Observations	18,494	13,316	18,494
Year Effects	Included	Included	Included
Hansen Test	41.684	56.561***	92.233***
AR(2)	3.273***	1.449	2.864***
AR(3)	-1.087	-	-0.217
Wald-Chi2	464.48***	69,119***	154.51***

Note: All independent and control variables are lagged by one year. Standard errors are robust and indicated in brackets. Dependent variables are standardized. Degree Centrality (Y)/(E) denote degree centrality among young/established firms.

⁺ Includes deeper lags of the instrumented variables, due to indications of autocorrelation in AR(2) test

* p<0.1; ** p<0.05; *** p<0.01

Appendix F - Regression Models in Other Industries

Table F1. Regression Results in the Manufacturing Industry – Firm Performance

Variables	(1) ROA+	(2) Revenue Growth	(3) Employee Growth	(4) ROA	(5) Revenue Growth	(6) Employee Growth
ROA	55.180***			74.070***		
	(12.060)			(12.810)		
Revenue Growth		6.460			4.145	
		(17.700)			(19.530)	
Employee Growth			19.000			34.840**
			(16.040)			(16.580)
Degree Centrality	4.004***	0.199***	19.270***			
	(1.102)	(0.047)	(3.204)			
Ego Betweenness Centrality	-0.386	-0.139	-18.320			
	(4.682)	(0.307)	(20.910)			
Firm Age * Degree Centrality	-0.252***	-0.012***	-1.305***			
	(0.073)	(0.003)	(0.214)			
Firm Age * Ego Betweenness Centrality	0.003	0.011	1.075			
	(0.299)	(0.018)	(1.298)			
Degree Centrality (Y)				1.119	0.177**	10.630**
				(1.227)	(0.080)	(4.831)
Degree Centrality (E)				2.096	0.214***	10.610**
				(1.365)	(0.074)	(5.127)
Firm Age * Degree Centrality (Y)				-0.116	-0.012**	-0.639**
				(0.084)	(0.005)	(0.317)
Firm Age * Degree Centrality (E)				-0.088	-0.014**	-0.861***
				(0.085)	(0.005)	(0.328)
Firm Age	0.557***	0.018***	2.074***	0.391*	0.034***	2.046***
	(0.157)	(0.006)	(0.412)	(0.200)	(0.010)	(0.616)
Firm Size	-0.460***	-0.003	-0.691***	-0.451***	-0.007	-1.031***
	(0.110)	(0.009)	(0.255)	(0.115)	(0.010)	(0.280)
Management Tenure	0.108	-0.009*	0.447	-0.104	-0.006	0.589
	(0.117)	(0.005)	(0.303)	(0.141)	(0.006)	(0.379)
Board Size	-0.169	-0.007	-0.557	0.0453	-0.006	-0.261
	(0.189)	(0.008)	(0.458)	(0.163)	(0.007)	(0.376)
Number of Employees	0.511***	-0.023**		0.358***	-0.022*	
	(0.111)	(0.010)		(0.117)	(0.012)	
Current Ratio	-0.094**	-0.005**	-0.051	-0.090**	-0.005**	-0.082
	(0.038)	(0.002)	(0.085)	(0.039)	(0.002)	(0.094)
Debt Ratio	-0.001	-0.001*	-0.002	0.001	-0.000	0.014
	(0.001)	(0.001)	(0.010)	(0.002)	(0.001)	(0.009)
Observations	20,420	15,705	15,992	20,420	15,705	15,992
Year Effects	Included	Included	Included	Included	Included	Included
Hansen Test	19.371	40.859*	29.490	33.510*	61.176***	50.383*
AR(2)	2.082**	0.869	1.249	1.245	0.292	1.719
AR(3)	-0,713	-	-	-	-	-
Wald-Chi2	764.25***	103.90***	885.41***	363.62***	115.52***	571.37***

Note: All independent and control variables are lagged by one year. Standard errors are robust and indicated in brackets. Dependent variables are standardized. Degree Centrality (Y)/(E) denote degree centrality among young/established firms; + Includes deeper lags of instrumented variable due to indication of autocorrelation in AR(2) test; * p<0.1, ** p<0.05, *** p<0.01

Table F2. Regression Results in the Construction Industry – Firm Performance

Variables	(1) ROA	(2) Revenue Growth	(3) Employee Growth	(4) ROA⁺	(5) Revenue Growth	(6) Employee Growth
ROA	24.340*			36.720***		
	(14.770)			(13.450)		
Revenue Growth		3.364			-20.780	
		(12.790)			(15.670)	
Employee Growth			17.850			-18.790
			(12.280)			(14.490)
Degree Centrality	3.593***	0.237***	14.240***			
	(0.902)	(0.057)	(3.276)			
Ego Betweenness Centrality	0.993	-0.331	11.040			
	(4.944)	(0.278)	(20.980)			
Firm Age * Degree Centrality	-0.235***	-0.015***	-0.970***			
	(0.0647)	(0.004)	(0.235)			
Firm Age * Ego Betweenness Centrality	-0.141	0.021	-0.284			
	(0.337)	(0.018)	(1.338)			
Degree Centrality (Y)				3.438**	0.357***	17.040***
				(1.368)	(0.094)	(5.698)
Degree Centrality (E)				3.371***	0.172**	16.390***
				(0.994)	(0.076)	(4.506)
Firm Age * Degree Centrality (Y)				-0.209***	-0.011**	-1.126***
				(0.066)	(0.005)	(0.294)
Firm Age * Degree Centrality (E)				-0.251***	-0.024***	-1.130***
				(0.095)	(0.007)	(0.403)
Firm Age	0.400***	0.017***	1.200***	0.640***	0.039***	2.525***
	(0.094)	(0.006)	(0.319)	(0.154)	(0.011)	(0.605)
Firm Size	-0.746***	-0.028**	-1.507***	-0.876***	-0.017	-1.610***
	(0.202)	(0.013)	(0.350)	(0.182)	(0.015)	(0.462)
Management Tenure	0.246***	-0.008	-0.223	0.258**	-0.010	-0.011
	(0.089)	(0.005)	(0.298)	(0.118)	(0.007)	(0.358)
Board Size	-0.249*	-0.006	-1.320***	-0.199	-0.019**	-1.494***
	(0.137)	(0.008)	(0.458)	(0.128)	(0.009)	(0.496)
Number of Employees	0.507***	-0.019*		0.403***	-0.031**	
	(0.135)	(0.011)		(0.125)	(0.014)	
Current Ratio	-0.026	-0.005	-0.047	-0.025*	-0.006	-0.053
	(0.018)	(0.006)	(0.059)	(0.015)	(0.006)	(0.038)
Debt Ratio	0.003	0.001	-0.014	0.006**	0.000	-0.010
	(0.003)	(0.001)	(0.038)	(0.003)	(0.001)	(0.029)
Observations	21,554	16,494	16,767	12,279	9,315	9,552
Year Effects	Included	Included	Included	Included	Included	Included
Hansen Test	28.627*	45.107**	36.638	17.066	31.174	63.962***
AR(2)	1.258	1.325	1.478	2.194**	-0.219	-1.426
AR(3)	-	-	-	-0.684	-	-
Wald-Chi2	1,824***	233.64***	511.68***	148.13***	28,886***	254.55***

Note: All independent and control variables are lagged by one year. Standard errors are robust and indicated in brackets. Dependent variables are standardized. Degree Centrality (Y)/(E) denote degree centrality among young/established firms; ⁺ Includes deeper lags of instrumented variable due to indication of autocorrelation in AR(2) test; * p<0.1, ** p<0.05, *** p<0.01

Appendix G - Preliminary Thesis

BI Norwegian Business School - campus Oslo

GRA 19502

Master Thesis

Component of continuous assessment: Forprosjekt, Thesis MSc

Interlocking Directorates Network and Startup Performance: The Importance of Social Capital in the Entrepreneurial Environment

Navn: Jan Ohlenbusch, Krystyna Kakievska

Start: 01.01.2018 09.00

Finish: 15.01.2018 12.00

Preliminary Master Thesis Report

Interlocking Directorates Network and Startup Performance: The Importance of Social Capital in the Entrepreneurial Environment

Hand-in date:
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GRA19502 – Master Thesis

Programme:
Master of Science in Business – Major Strategy

Summary

This paper is a preliminary research report for our master thesis, aiming to investigate the effects of social capital through interlocking directorates on the performance of start-ups and established companies. It introduces the academic literature on the relevant topics, namely, social capital theory, social network theory, interlocking directorates, as well as the interlock-performance relationship. In addition, the report presents the research question, applicable research methods, and highlights potential limitations of the study. Further, ethical considerations and the project organization, timeline and milestones are outlined.

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1 Introduction

This paper is a preliminary report of our master thesis on the effects of social capital, through interlocking directorates, on the performance of start-ups and established companies.

The term social capital has emerged in various contexts, with scholars focusing on various levels of analysis, with a lack of consensus of an overarching definition (Lin, 1999; Koka & Prescott, 2002; Tsai & Ghoshal, 1998). For this study, we adapt the comprehensive definition of Inkpen & Tsang (2005, p.151) in their research on knowledge transfer in social networks, as “the aggregate of resources embedded within, available through, and derived from the network of relationships possessed by an individual or organization”. The academic literature identifies three main dimensions of social capital, namely, structural, relational and cognitive (Nahapiet & Ghoshal, 1998; Tsai & Ghoshal, 1998). While the relational and cognitive dimension focus on the relational outcomes of interactions; and shared representations and interpretation among actors, respectively - the structural dimension represents the patterns of relationships between the actors in the network (Nahapiet & Ghoshal, 1998; Inkpen & Tsang, 2005; Granovetter, 1992). The structural dimension focuses on the advantages that actors obtain from their location in the social structure, which will be the focus of our study.

The central premise behind the notion of social capital is that actors embedded in social networks can use the advantages of social capital not available to outside actors, such as access to information flows, influence and other social credentials (Lin, 1999; Lamb & Roundy, 2016). A significant body of research has investigated the “strategic use of social networks” and their impact on firm performance (Peng et al., 2015, p. 258; Baum et al., 2000). However, there is no consensus in the empirical findings between the link of social networks and firm performance (Peng et al., 2015).

One type of social networks are *interlocking directorates*, which has become an increasingly popular topic in the strategic management literature. Interlocking directorates, also addressed as *board interlocks,* occur “when a person is on the board of directors of two or more corporations, providing a link or interlock between them” (Fich & White, 2005, p. 175). The popularity of board interlocks resulted in a variety of perspectives on their antecedents, including access to critical resources, monitoring, gaining legitimacy and securing valuable human resources (Mizruchi, 1996; Lamb & Roundy, 2016). Further, many theoretical perspectives have been applied in order to assess the impact of interlocking directorates on firm performance, including the social network theory. However, the empirical evidence remains inconclusive, which resulted in strong criticism of the research investigating the interlock-performance relationship (Peng et al., 2015; Mizruchi, 1996). A main argument is centered around the lack of longitudinal studies - respecting the dynamic effects of board interlocks. Additionally, the causal order of the interlock-performance relationship and the complex nature of firm performance are highlighted as critical issues in the literature (Mizruchi, 1996; Peng et al., 2015; Johannson et al., 2008). Further, the majority of research is focused on established companies, ignoring varying effects of interlocks on different types of organizations.

Considering the effects of interlocks on performance it may be reasonable to distinguish between the impact for start-ups and well-established companies (Johannson et al., 2008). Young companies are seen to have higher failure rates, explained by a lack of stable relationships with partners and restricted access to resources - often addressed as liabilities of newness and/or smallness (Stinchcombe, 1965). Baum et al. (2000) argue that participation of young firms in these networks can help to overcome these liabilities, e.g. through building relationships and gaining access to resources. Furthermore, among all interorganizational relationships, board-interlocks are an alternative to other relationships such as alliances and joint ventures. Additionally, the effects of interlocks on start-up performance can be greater than on established companies, since start-ups are less associated with inertial effects stemming from complexity, diversity and operational forces of incumbents (Daily & Dalton, 1992; Johannson et al., 2008).

Taking into account the arguments presented above, our motivation is to address the theoretical challenges in the literature by investigating differing impacts of social capital through interlocking directorates on the performance of startups and established companies.

This preliminary report is structured as follows. First, the aim of the study and the research question are presented. Second, the existing literature on the topic is reviewed, and a hypothesis is developed. This is followed by the methodological section of the paper, including the research design, data & sample, research methods, and limitation of the study. Finally, ethical considerations are evaluated and an outline of the thesis project management and timeline is provided.

2 Research Question and Aim

Our research will focus on the influence of social capital through board interlocks on companies. The study aims to investigate the effects of the participation in interlocking directorates networks on the performance of startups and established companies, in order to identify differences in the impact on the respective types of companies. Accordingly, our research question is:

To what extent does social capital through interlocking directorates impact the performance of start-ups and established firms?

3 Literature Review

The following section provides an overview of the relevant literature, covering the following topics: 1) Social capital theory, 2) Social network theory, 3) Interlocking directorates, 4) Interlock-performance relationship. The literature review will result in the development of our hypothesis.

3.1 Social Capital Theory

Capital theory. The classical theory of capital has its roots in Marx's studies, conceptualizing capital as the surplus value captured by capitalists controlling the means of production (Carroll & Sapinski, 2011). Retaining the basic elements of capital, Marx's conception was further modified and refined by later academic scholars, resulting in neo-capital theories, such as the human capital theory and social capital theory (Schultz, 1961, Becker, 1964, Bourdieu, 1990, Lin, 1999, Coleman, 1988, Putnam, 1993). At present, mainly three different notions of capital can be considered as sources of value for an organization: Financial capital, human capital and social capital (Bosma et al., 2002, Fornoni et al., 2012). Financial capital is one of the most visible resources in an organization, and can be measured by financial indicators such as cash, bank deposits and investments (Cooper et al., 1994; Fornoni et al., 2012). By contrast, human capital is more complex and less visible. It can be defined as "the knowledge, skills, and abilities (...) embodied in people" (Crook et al., 2011, p. 444). Finally, social capital refers to "the relational resources attainable by individual actors through network of social relationships" (Tsai, 2000, p. 927). Since social capital is the focus of our research, the concept will be described in more detail in the following part.

Social capital theory. The social capital term in social sciences is rooted in community studies, which investigated the networks of personal relationships as a basis for "survival and functioning of city neighbourhoods" (Nahapiet & Ghoshal, 1998, p. 243; Jacobs, 1965). Therefore, the usage of the term in these early studies primarily emphasized the importance of social capital to the individuals (Loury, 1977; Coleman, 1988; Nahapiet & Ghoshal, 1998). Since then, the concept emerged in various forms and contexts, attracting considerable interest of the academic scholars for the past decades (Lin, 1999; Koka & Prescott, 2002). Specifically, the term was applied to a broader range of social phenomena in the business context, focusing on topics, such as relationships between organizations and the market, as well as, relations inside and outside the firm (Baker, 1990; Burt, 1992; Putnam, 1993; Inkpen & Tsang, 2005; Tsai & Ghoshal, 1998). Given the widespread acceptance of the concept, it is "inevitable that researchers extended the logic of social capital to the firm level" (Koka & Prescott, 2002, p. 796). Currently, the concept is gaining prominence in the strategic management literature as a basis for characterizing the set of relationships of a firm, namely, interfirm ties, which represent social capital (Inkpen & Tsang, 2005).

Given the differing perspectives on the concept, there is a lack of consensus in the literature on the precise definition of social capital. Bourdieu (1986) was one of the first researchers to provide a systematic analysis of the concept (Inkpen & Tsang, 2005). The scholar proposed a definition of social capital as "the aggregate of the actual or potential resources, which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance or recognition" (Bourdieu, 1986, p. 51). Further, academic scholars agreed on the central premise behind the social capital notion, specifically "that social capital represents the ability of actors to secure benefits by virtue of membership in social networks or other social structures" (Inkpen & Tsang, 2005, p.150; Nahapiet & Ghoshal, 1998). In other words, social capital in form of social ties in a network constitutes a valuable resource for its members.

At present, two main perspectives can be identified in the social capital literature relative to the level, on which the benefits are acquired (Leana & Van Buren, 1999; Lin, 1999; Inkpen & Tsang, 2005). On the one hand, theorists focus on the individual benefits from relational resources embedded in social networks, considering social capital a private good (e.g. Burt, 1997; Useem & Karabel, 1986). On the other hand, another group of scholars maintains that the benefits of social capital are available not only for those who create it, but also for group members (e.g. Bourdieu, 1986; Coleman, 1988; Putnam, 1993). In other words, they view social capital as a collective asset that "enhances group members' life chances" (Lin, 1999, p.32). Although two differing perspectives exist in the literature, in our research we will follow the comprehensive definition, which is based on the review of previous research and incorporates both views, provided by Inkpen & Tsang (2005, p.151): "the aggregate of resources embedded within, available through, and derived from the network of relationships possessed by an individual or organization". This definition illustrates the existence of two levels of social capital: Individual and organizational, which can often be interrelated (Inkpen & Tsang, 2005).

Another important aspect of social capital considered in the academic literature is that it has different attributes, as it includes many facets of the social context, such as "social ties, trusting relations, and value systems that facilitate actions of individuals located within the context" (Tsai & Ghoshal, 1998, p. 465). This makes it a "multidimensional construct that can contribute in many ways to the creation of new value for an organization" (Tsai, 2000, p. 927). Therefore, following the comprehensive reviews of the social capital literature by Nahapiet & Ghoshal (1998) and Tsai & Ghoshal (1998), three dimensions of social capital are widely acknowledged: 1) Structural, 2) relational, and 3) cognitive.

The structural and relational dimension of social capital can be based on Granovetter's (1992) overview of structural and relational embeddedness, following the relevant academic literature (Lindenberg, 1996; Nahapiet & Ghoshal, 1998; Tsai & Ghoshal, 1998). Specifically, structural embeddedness refers to "impersonal configuration of linkages between people or units" (Nahapiet & Ghoshal, 1998, p. 244). In other words, the structural dimension represents the pattern of relationships between actors in the network. The location in this social structure provides certain advantages for the actors, such as access to information or resources (Inkpen & Tsang, 2005). Among the prominent facets of the structural dimension are network ties, network configuration, and network stability (Wasserman & Faust, 1994; Nahapiet & Ghoshal, 1998; Inkpen & Tsang, 2005).

Relational embeddedness, as opposed to the structural, represents the kind of relationship developed through continuous interactions between actors (Granovetter, 1992; Nahapiet & Ghoshal, 1998). Thus, the relational dimension is more focused on the relational outcomes of the interactions, such as trust or trustworthiness of the network actors (Tsai & Ghoshal, 1998; Inkpen & Tsang, 2005). Indeed, according to Uzzi (1996), trust can be a governance mechanism for embedded relationships, constraining opportunistic behavior of parties involved.

Finally, the cognitive dimension of social capital refers to the network resources “providing shared representation, interpretations, and systems of meaning among parties” (Nahapiet & Ghoshal, 1998, p. 244). Specifically, this dimension can be represented by shared code, shared goal or shared culture, which, in turn, facilitates a common understanding and ways of acting in the social network (Inkpen & Tsang, 2005). An example can be a shared vision in the organization, through which this dimension is developed. This can enhance the interactions between different actors in the organizational network, which may benefit the whole organization as a result (Tsai & Ghoshal, 1998).

Since the focus of our research is the impact of the location of actors in the network on firm performance, the thesis is addressing the structural dimension of social capital.

3.2 Social Network Theory

Since social networks are viewed as a form of social capital, it becomes natural to explore the foundation of social network theory.

Network theory has a long history in academia and was studied in a variety of fields (Parkhe et al, 2006). While the notion of networks in the strategic management literature was not established until the late 1970s and early 1980s – networks were already studied in terms of sociology (Moreno, 1953), psychology (Heider, 1946) and cultural anthropology (Nadel, 1957). These studies created an interdisciplinary foundation and motivated further theoretical and empirical research (e.g. Powell, 1990; Burt, 1992; Nohria & Eccles, 1992 Granovetter 1985; Uzzi, 1997) – and the development of a variety of methodological approaches (e.g. Wasserman & Faust, 1994; Borgatti et al., 2009).

In organizational research, the field of network theory gained special prominence with the work Powell (1990) – highlighting, that organizations often appear in network forms, contrasting the traditional notion of hierarchy and markets in organizational governance. In the comprehensive overview of the network perspective of Gulati et al. (2017, p. 281), it is highlighted that central premise behind the theory is “that economic action does not take place in a barren social context but is instead embedded in a social network of relationships”. Laumann et al. (1978, p. 548) define a social network as a "set of nodes (e.g., persons, organizations) linked by a set of social relationships (e.g., friendship, transfer of funds, overlapping membership) of a specified type”. Originally, network research was focused on individuals and how their embeddedness affected their behaviour. Further, the rational was extended to the organizational level, considering how companies are interconnected with other companies - constituting a social network of organizations (Walker, 1988; Mizruchi, 1992). These interconnections include: “supplier relationships, resource flows, trade association memberships, interlocking directorates, relationships among individual employees, and prior strategic alliances” (Gulati et al., 2017, p. 281).

Considering the formation of organizational networks, many scholars have initially approached the creation of networks driven by the structure of the resource dependence, arguing that ties are formed between organizations that share interdependence (Gulati, 1995; Gulati & Gargiulo, 1999; Gulati et al, 2017). Thus, the environment was viewed as atomistic, in which the information about companies is readily available. However, network theorists extended this logic and focused on the social context, addressing prior interfirm ties and their influence on new tie creation (Burt, 1992).

The theory maintains that participation in the network provides both opportunities and constraints for actors (Ingram & Inman, 1996; Ingram & Baum, 1997). On the one hand, the opportunities include the sharing of various resources, such as financial, institutional, knowledge and informational - which can improve firm outcomes, such as performance, learning and innovation capabilities (Ingram & Inman. 1996; Khanna & Palepu, 1999; Baum & Oliver, 1991). On the other hand, network membership can prevent companies from exploring new opportunities limiting their adaptability - which can lead to negative performance consequences (Ingram & Baum, 1997). As Gulati et al. (2017, p. 286) put it: “Networks giveth; networks taketh away”.

The varying outcomes of network membership on firm performance are reflected in the empirical findings. Several studies suggest that social networks have a positive effect on performance (Baum et al., 2000; Koka & Prescott, 2002). Another group of scholars find negative effects on performance - or effects depending on the context, e.g. industry characteristics (Gargiulo & Benassi, 2000; Peng et al., 2015; Rowley et al., 2000).

Network characteristics can be analyzed in a variety of aspects, such as structural configuration, partner profiles and centrality in the network (Gulati et al., 2017). The focus of our research is the centrality dimension, being one of the key measures of a firm's network and reflecting the extent to which the location of an actor is pivotal compared to other actors in the network. A significant body of social network research argues that network centrality helps companies to reap the benefits from participation in the network. Indeed, firms that are more central in the network may have a better possibility to access "better and more resources and opportunities" - improving the firms' performance (Peng et al., 2015, p. 265; Yang et al., 2011; Farina, 2009).

As described by Sankar et al. (2015, p. 115), the majority of social networks are *one-mode networks*, "consisting of nodes of the same kind, representing actors of the same type or category". Another type of networks are *two-mode networks*, also referred to as *affiliation networks*, *dual networks, hypernetworks* or *bipartite networks*: By adding another property to actors, these can participate in activities – and become members of certain collectivities (Breiger, 1974; McPherson, 1982; Wasserman & Faust, 1994; Faust, 1997). As a consequence, these collectivities also have linkages between each other - tied by participants that have multiple memberships. An example of these are *interlocking directorate networks*, also addressed as *board interlocks*. A growing body of research in the strategic management literature employs social network analysis to understand the impact of these ties on organizational behavior and performance (Gulati et al., 2011).

3.3 Interlocking Directorates

Interlocking directorates are one of the most popular areas of study in the corporate governance literature, and a central topic within the strategic management literature (Lamb & Roundy, 2016; Shleifer & Vishny, 1997; Gulati & Westphal, 1999). According to Fich & White (2005, p. 175), interlocking directorates occur "when a person is on the board of directors of two or more corporations, providing a link or interlock between them". Thus, an interfirm relationship is formed between these enterprises (Zona et al., 2015).

The phenomenon of board interlocks appeared in the late nineteenth and early twentieth century in the environments of advanced capitalism (Caroll & Sapinski, 2011). The interest in interlocking directorates originated on a system-level, mainly addressing their effects on democracy, society and industry, starting with Jeidels's (1905) work on links between the biggest banks and the industry in Germany (Mills, 1956; Scott 1997). In addition, board interlocks were investigated in the US between 1910 and 1930, addressing the growing concerns about undermining effects of powerful banks on market competition (Caroll & Sapinski, 2011). Further, Mills (1956) and Porter (1956) developed the theory of power elite, highlighting how interlocks create "an elite that is autonomous from specific property interests" (Caroll & Sapinski, 2011, p. 181). In this context, a rising concentration of economic power within board interlocks was viewed as a threat to democracy. Notably, at this time, social network analysis was not established as a research method, but rather seen as a metaphor (Caroll & Sapinski, 2011).

Power structure research coined a shift in the board interlocks literature in the 1960s (Caroll & Sapinski, 2011). Scholars developed the elite cohesion theory using social network analysis as a method, emphasizing that potential differences in interest of individual companies are outweighed by "mechanisms of consensus formation that are embedded in social networks, such as those formed through interlocking directorates" (Burris, 2005, p. 250). Thus, interlocking directorates can be viewed as a fundament for elite consensus. For instance, Koening & Gogel (1981) argued that interlocking directorates are based on the personal networks of directors, usually having a common social background - and fostering elite cohesion.

Since then, the interlocking directorates research has evolved, focusing on different levels of analysis, therefore, debates in the literature grew in the 1970s. Scott (1985) summarized these discussions by introducing two dimensions of studying interlocks - with an agent-system axis and an organization-individual axis - see Table 1. On a system level, the research was divided into an *intercorporate* approach, and a *class hegemony* approach. While the former viewed interlocks "as instrumental means in the accumulation and control of capital", the latter recognized interlocks as "channels of communication between individual directors, facilitating a common worldview among them" (Caroll & Sapinski, 2011, p. 183). In other words, these system level approaches describe the power structure as a development within which individual agents pursued their interest while contributing to common goals. By contrast, the agent-centered approaches view interlocks as properties of individuals (*social background approach*) or enterprises (*organizational approach*). Considering our study, we focus on the *organizational approach*, within which "interlocks become a characteristic of the firm that can be statistically related to performance or profitability" (Caroll & Sapinski, 2011, p. 182).

Table 1. Approaches to the study of interlocks

	Agent	**System**
Individuals	Social Background	Class Cohesion
Corporations	Organizational	Intercorporate

Source: Scott (1985)

The antecedents of interlocking directorates. The topic of board interlocks attracted interest of scholars from different fields, including finance, management and sociology - which resulted in a variety of theoretical perspectives on the foundational issues, such as the antecedents of interlocking directorates (Lamb & Roundy, 2016; Core et al., 1999; Gulati & Westphal, 1999; Mizruchi et al., 2006). Notably, the research of the causes of board interlocks can be broadly divided into the perspective of the firm and the perspective of the director (Lamb & Roundy, 2016). For the purposes of our research, we adopt the firm perspective and will, therefore, review the antecedents accordingly. In this section, we will focus on the main theories, explaining the rationale behind board interlocks.

One of the most commonly applied theories, explaining the board interlocks phenomenon, is the *resource dependence view*, which maintains that organization are dependent on external resources and need to reduce their environmental uncertainty and dependence (Pfeffer & Salancik, 1978). As such, board interlocks can be a tool, "enabling organizations to gain access to critical resources", such as access to valuable information, new practices and better terms of agreements (Zona et al., 2015, p. 593; Hillman & Dalziel, 2003; Mizruchi, 1996). Participation in interlocks is, thus, viewed as *cooptation* - absorbing disruptive elements into the enterprise (Selznik, 1949; Mizruchi, 1996). Following the resource dependence view, control over resources provides an opportunity for an organization to exercise power over a dependent firm (Mizruchi, 1996). Thus, one form of exercising this power can be a *monitoring* function that board representation implies, and interlocking directorates can be viewed as instruments of corporate control (Mizruchi, 1996). For example, financial institutions can use interlocks as means of controlling the firm's financials (Eisenhardt, 1989; Mizruchi, 1982). Notably, in a systematic review of the board interlocks research, Lamb & Roundy (2016) highlight resource-seeking and monitoring as increasingly prominent antecedents of the interlocks phenomenon in the academic literature.

Another important rationale for the formation of interlocking directorates is *legitimacy*, which implies inviting prestigious directors to improve reputation and acceptance of the company (Mizruchi, 1996). According to the *institutional theory*, “if an actor’s partner in a network form of organization possesses considerable legitimacy or status, then the actor may derive legitimacy or status through the affiliation” (Podolny & Page, 1998, p. 64; Peng et al., 2015). This is in line with Lamb & Roundy (2016), who view board interlocks as a mean of signaling - indicating the high quality of the firm to potential investors.

Additionally, interlocking directors can be viewed as “valuable, unique and hard-to-imitate managerial resources”, following the *resource-based view* (Peng et al., 2015, p. 263; Barney, 1991). This means that securing directors not only gives the company access to their skills, experience and expertise, but also prevents rivals from doing the same (Peng et al., 2015; Baum et al., 2000).

Recalling the overview of the *social network theory* in section 3.2, the logic of network formation can also be applied to interlocking directorates networks. The social network perspective suggests, that *prior interorganizational ties* influence the creation of new ties. According to Gulati et al. (2017), three means enable the formation of new connections: access (information about the partner’s capabilities and trustworthiness), timing (timely information about partners) and referrals (referring potential partners to existing partners) (Burt, 1992).

3.4 Interlock-Performance Relationship

According to Lamb & Roundy (2016), a common topic within the board interlock research is the outcomes of interlocking activities, among which the impact of these interorganizational relationships on firm performance is one of the most prominent areas of study.

Similarly to the research of the antecedents of board interlocks, many theoretical perspectives have been applied in order to explain the interlock-performance relationship, such as the resource dependence theory, agency theory, upper-echelon theory and social network theory (Lamb & Roundy, 2016; Peng et al., 2015; Davis & Cobb, 2010; Haniffa & Hudaib, 2006; Yeo et al., 2003; Cai & Sevilir, 2012). For example, the resource dependence theory is mainly associated with the positive impact of board interlocks on firm performance (Lamb & Roundy, 2016). The main argument is that interlocking directorates help firms to obtain critical resources and information, which creates a fundament for improving their performance (Davis & Cobb, 2010; Zona et al., 2015). These findings are also supported by the recent meta-analytic review of the resource dependence theory by Drees & Heugens (2013).

The *social network theory* has been widely applied in the research, focusing on the implications of the interlocks on firm performance (Lamb & Roundy, 2016). Following this perspective, firms that are embedded in an interlocking directorates network can use the advantages of social capital that are not available to the companies outside the network, as addressed in the previous section. Thus, participation in the network can enhance the firm performance - facilitating information flows, providing influence over critical actors in the network, and social credentials in form of additional resources (Lin, 1999).

Following the broader social network research introduced in section 3.2, the empirical evidence on the impact of board interlocks on firm performance also remain ambiguous, with scholars finding positive, negative and no interlock-performance relationships (Mizruchi, 1996; Peng et al., 2015; Dalton et al., 1998). This inconclusiveness resulted in strong criticism of the research investigating the impact of board interlocks on firm performance (Mizruchi, 1996; Peng et al., 2015). Specifically, the prevalence of cross-sectional studies over longitudinal undermines the opportunity to observe how the dynamics in board interlock networks affect performance. This issue becomes even more significant with the uncertainty of the causal order of the interlock-performance relationship, which cannot be easily resolved with cross-sectional research design (Mizruchi, 1996; Johansson et al., 2008). In addition, as firm performance is influenced by a variety of factors, the effects of interlocks can be not significant enough (Peng et al., 2015). Another problem is that the majority of academic research is focused on the large established companies, primarily from Fortune 500 companies (Johansson et al., 2008). However, the effects of board interlocks on performance may be different for established companies and startups.

Interlock-performance relationship in startups. As highlighted above, the relationship between interlocks and firm performance can vary between incumbents and young companies. As noted before by many scholars, failure rates for young companies are much higher than for established companies (Baum et al., 2000). This can be connected to Stinchcombe’s (1965) work, proposing that new firms fail more frequently, since these have not developed effective work roles, stable relationships with partners and do not possess - or have access to - sufficient resources. This is commonly referred to as the liability of newness and liability of smallness (Stinchcombe, 1965). Indeed, according to Shane (2001) the success of the new companies often depends on the availability of deep market and industry knowledge. Following Baum's et al. (2000) reasoning, the participation in a social network can be particularly beneficial to young firms - enabling to build relationships and gain access to resources of established companies - overcoming the liability of newness and smallness. There are different interorganizational relationships that help to mitigate the negative effects of liabilities, among which board interlocks can be viewed as an alternative to relationships such as alliances or joint ventures (Johansson et al., 2008). Indeed, prior research found, that inter-board connections can enhance the legitimacy, access to financing and provide information, expertise and advise - which is particularly important for start-ups (Hillman et al., 2001; Mizruchi & Stearns, 1988; Westphal, 1999; Horton et al., 2012). In addition, organizational systems and structures vary significantly between startups and established companies. While complexity, diversity and operating forces might impede impacts of board directors on firm performance - young companies are less associated with inertial effects (Johansson et al., 2008). Consequently, board directors might have a potentially stronger effect on firm performance of young firms, compared to established companies (Daily & Dalton, 1992; Eisenhardt & Schoonhooven, 1990).

Recalling the centrality arguments from section 3.2, a higher centrality in an interlocking directorates network is associated with greater opportunities to extract benefits from the network participation. Therefore, taking into account the arguments presented, we expect that a more central position in an interlocking directorates network has a greater positive effect on the performance of startups than on the performance of established companies.

Hypothesis:

A central position in an interlocking directorates network has a greater positive impact on startup performance than on established company performance.

4 Design and Methods

4.1 Research Design

The aim of our study is to evaluate the differences in the impact of social capital through interlocking directorates on the performance of startups and established companies. We intend to employ a quantitative study in order to measure the described effects, and will follow a deductive approach. We will utilize a longitudinal design, since it is the most appropriate approach for reasons described in the methodology part below.

4.2 Data & Sample

Our study is based on secondary data, which will be obtained from a database provided by our thesis supervisor. As will be further elaborated, the data is subject to access restrictions and, therefore, will be processed at the facilities of BI Norwegian Business School. The database is a registry of Norwegian companies - and contains information from 2000 to 2016, such as the financial performance, management and employee characteristics and list of board members.

An important characteristic of our research is the use of a total population sample, as our dataset will contain the entire population of Norwegian firms. This offers certain advantages for our study, as it lowers the risk of omitting important aspects in the analysis. However, the extent of our dataset poses some challenges. Specifically, the large number of observations prohibits the use of commonly used software, which will be discussed in the methods section.

We will focus our research on a single industry, namely the IT industry for the following reasons. First, narrowing the research to one sector decreases the risk of misinterpretations of results due to inter-industry variation. As highlighted by Huber & Van de Ven (1995, p. 302), focusing on a single industry allows for analyzing companies that are subject to “a uniform set of exogenous changes”. Second, the IT industry offers a suitable environment for our research. Previous studies, focused on inter-firm relations, indicated that industries with high rates of innovation and a significant entrepreneurial sector, also showed a higher frequency of interfirm relations (Walker et al., 1997; Kogut et al., 1995).

The sample will be a panel data set, containing observations for 7 years, from 2010 to 2016, which is a common time frame for similar studies (Zona et al., 2015; Johansson et al., 2008). Further, our study focuses on two types of organizations, namely startups and established companies. For our analysis, we consider a company as a startup, if it was founded between 2008 and 2014. However, observations will only be considered for companies that are at least 2 years old, in order to eliminate the volatility of the early phases of startups.

We chose Norway as the geographical location for our study for a number of reasons. A key aspect is the availability of an extensive database from official authorities and the disclosure of information for research purposes. Additionally, Norway represents one of the most advanced countries in the world, with a high level of technological readiness and a sophisticated entrepreneurial environment. This creates a suitable setting for our research.

4.3 Research Methods

The following section will introduce the dependent, independent and control variables that will be employed in the study, and describe the research methodology.

Dependent variables. Firm performance will be measured as return on assets (ROA), following former studies on board interlocks - and, being “the most commonly used performance measure in strategy research” (Zona et al., 2015, p.13; Mizruchi, 1996). Further, additional performance measures will be tested, namely return on equity (ROE) and number of patents granted, following previous research on performance in highly dynamic industries and board interlocks (Zona et al., 2015; Baum et al., 2000; Farina, 2009; Peng et al., 2015). Additionally, the effects of interlocks on performance are likely to be non-immediate (Peng et al., 2015; Zona et al., 2015; Bosma et al., 2002; Sánchez & Barroso-Castro, 2015). Therefore, we will use a 1-year lagged dependent variables (+1 year).

Independent variables. Centrality measures are one of the most frequently used measures in social network research (Faust, 1997; Wasserman & Faust, 1994; Borgatti et al., 2009). We will employ the three measures of centrality proposed by Freeman (1978), namely degree centrality, closeness centrality and betweenness centrality. In addition, we will include the commonly used eigenvector centrality (Faust, 1997). Degree centrality is measured by the number of contacts a node has with other nodes in a network, being an indicator of immediate connectivity (Faust, 1997; Sankar et al., 2015). Closeness centrality includes direct and indirect links, measuring how close one node is to all other nodes in a network (Peng et al., 2015). It is often used to measure “how long it will take for information to pass between a node and all other nodes" (Sankar et al., 2015, p.117). Betweenness centrality is the extent to which a node is part of the shortest path between other nodes - and measures "the ability of a node to control the flow of information through it" (Sankar et al., 2015, p.117). Eigenvector centrality is commonly added to these traditional measures in interlocking directorate research - and is highlighted as the most important for this purpose by many researchers (Mariolis, 1975; Mizruchi, 1982; Rosenthal et al., 1985; Faust, 1997). It measures the number of nodes to which one node is connected - and weights these nodes according to their centrality (Faust, 1997; Sankar et al., 2015).

Controls. We intend to align our control variables with the capital theories, presented in the literature review. Besides social capital represented by the independent variable, there is another important source of value for an organization, namely human capital (Fornoni et al., 2012). We intend to control for human capital effects by measuring education of employees and founders, as well as, management tenure. These measures are widely accepted according to a meta-analysis of the relationship between human capital and firm performance by Crook et al. (2011).

Following the research on board interlocks, we will include further control variables, such as firm size (number of employees) and board size (number of individuals on the board of directors) (Zona et al., 2015; Peng et al., 2015). Additionally, we include a year dummy variables to control for general economic trends (Wooldridge, 2015).

Methodology. Our method is divided into two main parts. First, a social network analysis will be performed to describe the structure of the network through centrality measures. Second, a regression will be employed to estimate the impact of the centralities on firm performance.

As stated before, board interlocks are considered to be a two-mode network, so-called affiliation network. However, our dataset will contain the list of board members (actors) for each company (event). Therefore, the data on board interlocks will be transformed into an affiliation network matrix, where rows represent all unique actors, and the columns represent all unique events. Since we are interested in the ties between companies, this matrix will be further transformed into an event overlap matrix, with columns and rows representing all unique companies and the cells indicating whether there are common board directors (ties) (Faust, 1997). Based on this matrix, we will obtain the centrality measures. Notably, these steps will be performed considering the entire population sample, including all industries, in order to include inter-industry ties in the centrality measures. Since our sample contains a sizable number of observations, accepted social network analysis tools, such as UCINET, will potentially reach their limits. Therefore, we will use Python, a more powerful tool, to perform our analysis using its dedicated NetworkX library.

Following this, the output of our social network analysis, specifically the centralities, will serve as the input (independent variables) for our statistical model.

Previous studies have highlighted the issue of an endogenous relationship between interlocks and performance (e.g. Zona et al., 2015; Peng et al. 2015; Mizruchi, 1996; Sanchez & Barroso-Castro, 2015). This problem has been addressed by using the Arellano-Bond model with the generalized method of moments (GMM) approach (Hansen, 1982; Arellano & Bond, 1991; Greene, 2000; Johansen et al., 2008; Sanchez & Barroso-Castro, 2015). This model uses dynamic panel estimators, common for situations with few time periods and many observations, as it is the case in our study (Roodman, 2006). GMM requires "using the lagged values of the original independent variables as instruments, thereby resolving the problem of endogeneity", as well as possible autocorrelation issues, due to the inclusion of lagged performance variables as controls (Hansen, 1982; Wooldridge, 2001; Zona et al., 2015). Additionally, multiple tests are required, due to the rather complex nature of our method, such as the Hansen test, to test the validity of our instruments; Wald chi-square statistics, testing the overall fit of the model - and the Arellano-Bond tests of autocorrelation (Roodman, 2006). We intend to use Stata for our analysis, using its *xtabond2* program, dedicated to dynamic panel data models using GMM (Roodman, 2006).

5 Limitations

The proposed research has certain limitations that have to be considered. First, the scope of our research is limited to a specific country, Norway, and industry, the IT industry - which can potentially limit the ability to generalize the results. The generalization problem can also arise due to the analysis of the impact of only one dimension of social capital, namely the structural dimension, while we do not account for the influence of other factors, such as trust (relational dimension) or common goals (cognitive dimension).

Second, we only concentrate on one type of interorganizational relationships, namely interlocking directorates. However, a network analysis might be enriched with more data on other types of relations, such as ownership-, supplier- and customer ties (Farina, 2009).

Third, since we examine the network during a limited period, we do not consider the evolution of the network, which could be beneficial for a deeper understanding of the interlock-performance relationship.

Fourth, by contrast to established companies, startups have specific characteristics, which are commonly reflected in performance measurements used in the literature. However, aiming to compare the two types of companies, we employ the same measures for all companies. Another argument concerning the nature of start-ups is that these companies might be in different phases of development, which might limit the comparability within this group - and increase volatility of observations.

Finally, our social network analysis and centrality measures are contained in the Norwegian business environment - not accounting for international ties of companies.

6 Ethical Considerations

An important aspect to address in every research are ethical considerations - identifying and specifying potential ethical dilemmas is an essential part of the research.

First, our research is based on the established research standards at BI Norwegian Business School, which follow the scientific and ethical guidelines by the Norwegian National Research Ethics Committee for Social Sciences and Humanities (NESH). As part of the educational institution, we comply with the ethical principles at BI, and have “an independent responsibility for conducting research activities within the current ethical framework” (BI Norwegian Business School, n.d.).

Second, our research is solely based on secondary data. Therefore, we will consider ethical issues related to our research and methodology, specifically, data management considerations. This refers to “the routine collection and storing of digital data and the practices of data sharing” (Bryman & Bell, 2015, p.146). In our case, we will obtain our database via our thesis supervisor at BI Norwegian Business School. The data is rendered anonymous and is highly confidential - and is subject to strict data access restrictions. Therefore, it is relevant to consider the

RESPECT project (n.d.), setting guidelines for European researchers regarding data protection issues. Accordingly, outlining the data processing operations prior to the actual analysis may help to identify potential legality issues, and is an essential element of our data management. One issue is already identified, specifically, that the data cannot be accessed and processed outside of Norway. Even though the research team is located in a different country, the data processing activities will be carried out in the facilities of BI Norwegian Business School during planned data analysis sessions - complying with the data access restrictions.

7 Project Management

Managing the research process is an essential aspect of accomplishing the master thesis. Recognizing the need of planning, organizing and controlling various tasks of our research project, we divide our work into three main phases. Our team consists of two members, which means that the participation of both during all phases of the research project is essential for dealing with the intensive workload. An overview of the project timeline is provided in Figure 1.

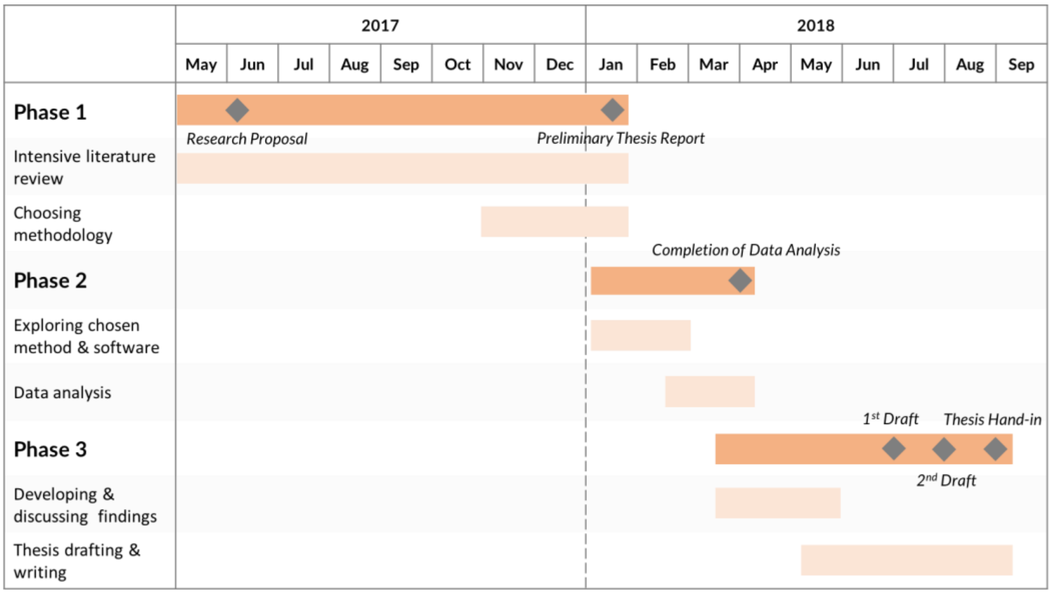
The first phase is centered around an in-depth literature review on the research topic. This phase started in May 2017, with the introduction to the chosen research topic and initial review of relevant academic findings, which resulted in the first important milestone of the project - the submission of the master thesis proposal on 24th of May, 2017. Further, this stage of the research continued with an intensive literature review. Based on this, the research method and variables were identified. Two major challenges were revealed in this process: First, the use of an advanced methodology (GMM) was deemed necessary, second, the nature of our extensive dataset requires the use of advanced analysis tools (Python, NetworkX library). The phase will finish with the submission of this preliminary report in January, 2018.

The second phase of the research is aimed to analyze the data, based on the research method and variables chosen during the first phase. An essential aspect of this phase is to become more familiar with 1) the methodology chosen and 2) the software employed. Since both team members are studying abroad during the first and second phase of the study, the data analysis itself will require a work trip in February 2018 to Oslo in order to meet the thesis advisor, and obtain the data needed. In addition, the data will be processed, and analyzed at the facilities of BI

Norwegian Business School using the chosen research tools. The phase is planned to last from January to March in 2018, ending with the completion of the data analysis.

The third phase is intended to develop the main findings, discuss the results and finalize the writing of the master thesis. Based on the data analysis and literature review, the research hypothesis developed earlier will be tested, results of the analysis and main findings will be described and discussed. The phase is estimated to last from April to August 2018, and includes three important milestones: 1) Completion of the first draft of master thesis on 1st of July, 2018; 2) Completion of the second draft of master thesis on 1st of August, 2018; and 3) Submission of the master thesis on 31st of August, 2018.

Figure 1. Project Timeline



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