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ORIGINAL PAPER

DOES BEING CENTRAL IN FORMAL NETWORK IMPROVE TRUST PROJECTION? A SOCIAL NETWORK ANALYSIS OF SUPPLY NETWORK STRUCTURE

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ABSTRACT. **Background:** This research attempts to extend the understanding and application of embeddedeness theory beyond the general network structure. Previous research on network analysis largely focused on the context of the decentralized network structure and how it impacts on the performance of the network member. However, each member of a supply network is embedded in a centralized network structure. The focal firm often plays the commanding role in such structure. Thus, the supply network is a centralized network because of the existence of the focal firm. The existence of the focal firm may influence the impact of firm performance, particularly on the generation of relational capital. Hence, the objective of this research is to determine how formality derives from the centralization of the supply network and influences trust projection in the supply network structure so that it is possible to organize supply network resources to their optimum capacity.

Methods: Basing on the previously applied approach of Social Network Analysis from the sociology research field, we adopted the Social Network Analysis methodology to collect data on supply network connectivity or relations. Using an Exponential Random Graph Model [ERGM], we developed a random search algorithm for network relational capital optimization. Exponential Random Graph Modeling [ERGM] is a statistical method for modeling the generative processes that create social networks. In ERGM, the log-odds of a tie between members of a dyad of nodes or actors in the network are essentially modeled using an exponential form analogous to logistic regressions.

Results: The findings of this study indicate that centrality negatively influences trust projection in the supply network. Hence, a firm embedded in upstream supply network benefits differently in terms of relational capital through the different degree of embeddedness. The firm's resources should be re-aligned to match the benefits of the different network structural positions.

Conclusion: The results of the statistical network analysis reveal interesting findings in terms of prominent structural forms and the impact of involvement or embeddedness in the formal of a supply network. What this means is that the more embedded a firm is in the upstream supply network based on the formal contract tie, the less the likelihood that it will be perceived as trustworthy by other network members. Consequently, this tells us that firms' embbededness in a centralized network structure which is based on a formal contract ties have a negative impact on the firms' level of trust perception.

Key words: network analysis, information sharing, social capital resources.

INTRODUCTION

This research aims to extend the understanding and application of the embeddedness theory by determining the impact of firms' embeddedness in a centralized network structure such as a supply network. More specifically, this research investigates the implications of a firm's embeddedness or involvement in a centralized upstream supply chain network structure on relational capital outcomes.

There is an extensive amount of literature in the field of operation and supply chain

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management indicating that the supply chain network and, more particularly, the upstream supply chain network, has become more complex [Bozarth, Warsing et al. 2009, Li, Yang et al. 2010, Sivadasan, Smart et al. 2010]. Scholars have also concluded that the inter-firm relationship is one of the drivers of upstream supply chain network complexity and deeper understanding is needed to elucidate and comprehend the complexity of these inter-firm relationships [Choi, Krause 2006, Li, Yang et al. 2010].

Issues regarding inter-firm relations have increased concerns related to the problem of supply chain complexity [Bode, Wagner 2015, Dubey, Gunasekaran et al. 2017]. Beyond the direct implications, it has far-reaching consequences for firms in a supply chain network, which originated from disrupted interactions and communications. One disruption to the communications and interaction system could cause butterfly [or ripple] effects [Lee, Padmanabhan et al. 1997] that can create havoc throughout the network.

The literature on operation and supply chain management indicates that there has been extensive research carried out concerning complexity in the supply chain. Many early scholars in operations and supply chain management have adopted both a system perspective [Anderson 1999] and a complex adaptive system perspective [Gell-Mann 1995] in order to comprehend, describe and understand complexity in the supply chain network [Lee, Padmanabhan et al. 1997, Pathak, Day et al. 2007, Osman 2018]. The literature also indicates that there has been a great advance in the drivers of complexity [Wilding 1998, Choi, Kim 2008, Bozarth, Warsing et al. 2009]. However, the focus of these studies has been largely on the attributes of the system elements, but less on the relations between the firm's organizations [the terms organizations and firms are used interchangeably throughout this thesis] that formed the basic, important components of an integrated network of firms [Borgatti, Li 2009, Kim, Choi et al. 2010, Kim, Chen et al. 2015].

Furthermore, network scholars and organizational study scholars have not only advanced the motivation and drivers of firms' embeddedness in network relationships, but also the impact of firms' embeddedness on the network relationships [Borgatti, Jones et al. 1998, Cross, Borgatti et al. 2002, Cousins, Handfield et al. 2006, Borgatti, Li 2009]. It was argued that a decentralized, integrated network of firms generates social capital or relational capital that can be an important source of competitive advantage to related firms when facing complexity in the market environment [Zaheer, Bell 2005, Polyviou, Croxton et al. 2019]. One important stream of embeddednesss research is that relational capital such as trust has emerged from recurrent commercial transactions and the inter-weaving of commercial transactions with webs of social exchanges in a decentralized network structure [Gulati 1998, Nayak, Bhatnagar et al. 2018, Schell, Hiepler et al. 2018]. In this business environment, firms depend upon these relational capital items to coordinate and safeguard their interests against unintended and opportunistic acts from other network members.

Clearly, complexity in the upstream supply chain network arising from the extensive inter-firm relations offers a unique source of competitive advantage that can be accessed by the embedded firms in the integrated network structure.

However, a supply chain network or, more particularly, an upstream supply chain network is a centralized network structure because of the existence of a focal firm which is involved in administering and managing transactions in the upstream supply chain network [Giannoccaro 2018, Lin, Su et al. 2018]. This important structural characteristic might have an implication for the firm's relational capital outcomes. Thus, this research is an examination of the impact of a firm's network involvement or its embeddedness in a complex upstream supply chain network on relational capital outcomes trust. Using social network analysis methodology, this research collects data on network ties from firms involve in maritime industry in South East Asia region. Network data were analysed using the Exponential Random Graph Model. Findings indicate that centralizing the structure of the supply network affects relational capital development among the supply network members. Research limitations and future research directions were also presented. The following sections of the article will discuss the literature that indicates the importance and this research, followed by a methodology section. The findings of the data analysis are presented next and the significance of the findings discussed.

LITERATURE REVIEW

Embeddedness theory posits that firms' embeddedness in the network not only increases economic performance, but also enhances the relational capital, which often translates into an economic payoff [Uzzi 1996]. Pierre Bourdieu [2010] defines relational capital as outcomes which have emerged from inter-firm relations. This definition stresses the benefits of network embeddedness. Through relational capital, firms gain direct access to economic resources or align themselves with firms that provide the resources [Nahapiet, Ghoshal 1998].

Starovic and Marr [2003] consider relational capital to include customer satisfaction and interactions with other firms by employees, distribution channels, supplier channels and franchising channels respectively. This is the information accumulated by the firm as a result of its interactions with other parties and the potential of future information arising from these exchanges.

A firm's embeddedness in networks facilitates the creation of relational capital [Putnam 1993, Lee, Tuselmann et al. 2019]. Burt [2001] added that values of relational capital create business opportunities for the related parties. Relational capital such as trust provides firms with values like solidarity, especially when interactions are fixated and regulated based on rules and reciprocity.

Trust emerges as connectivity increases among the organizations in the network. For example, Uzzi [1997] shows how firms have embedded ties with each other in addition to the arm's-length relationship. Uzzi [1997] refers to the arm's-length relationship as an opportunistic relationship, while embedded ties induce cooperation, and coordination among network organizations. Others further emphasized three features of embedded ties, which include fine grained information exchange, joint problem-solving and trust [Powell 2003, Lee, Tuselmann et al. 2019]. The findings of Lee, Tuselmann et al. [2019], Powell [2003] and Uzzi [1997] all point to the competitive advantage for organizations in a network form of relationships.

In social network terminology, affiliation with other organizations with high network centrality not only provides peripheral organizations with access to capital, these ties also provide other organizations with reputational spill-over benefits. Network centrality refers to an organization's position in the network relative to others [Scott 1988]. As one of the most important properties of network structure, network centrality evaluates an actor's status, prominence and power [Knoke, Kuklinski 1982]. Knoke and Kuklinski [1982] further stated that actors who are the most important or prominent in the network are usually located in the most central positions within the network. Being central means the actors or organizations are connected to almost all other actors in the network. The connections can be in the form of formal ties, which include contractual relationships. Exchange of resources occurs between actors that are tied together either formally or informally.

Thus, extensive contacts or associations with the central organizations in the network increase the availability of information and inflate the reputational spill over benefits [Luoma-aho 2007, Yan, Zhang et al. 2019]. Hence, the embeddedness in the exchange network not only begets tangible returns, it also warrants the accumulation of other intangible ones such as relational capital outcomes.

However, many of these inter-organizational network outcomes studies have focused on the decentralized network structure [Uzzi 1996, Uzzi 1997, Nahapiet, Ghoshal

1998, Li, Yang et al. 2010, Yan, Zhang et al. 2019]. Little to no research has paid attention to firms' embeddedness in centralized networks with focal firms, such as in the upstream supply chain network. There is a clear difference in terms of the network structure [Giannoccaro 2018]. In the supply network, it is argued that an upstream supply network is likely to be a centralized network structure [Choi, Kim 2008, Kim, Choi et al. 2010]. Thus, it is not certain what the effects of firms' embeddedness in such a centralized network structure are on network relational capital outcomes as per a decentralized network structure. One important element that may influence diverse relational capital effects is the nature of the network governance between a decentralized network and a centralized network structure. A centralized coordination approach often involves a lead firm or a focal firm or manufacturer that would manage the transactions of materials and other webs of social exchanges. This is the case that this research intends to investigate.

The basic idea behind a centralized network structure is that an administrative entity will function as the manager or administrator of the network and its activities. Although network members still interact with one another, the existence of the focal actor or firm determined that the network model is centralized [Giannoccaro 2018]. The focal firm plays a key role in coordinating and sustaining the network.

However, because the focal firm is the most powerful firm in the network structure [and often the firm with the most investment compared to other network members], this may generate a Machiavellian image on this focal firm. The literature has indicated some trade-offs, such as a reduced level of commitments and reduced horizontal connections among firms in the network structure.

The commitments of network actors and horizontal connections between the network actors are important factors towards generating relational capital. Thus, the existence of a centralized firm may mean that network members may experience lower levels of relational capital as the outcome of a reduction in commitments from network actors and a reduction in horizontal connections [Wegner, Faccin et al. 2018].

Network centralization reduces horizontal connections that are important for the creation of relational capital. As relational capital emerges through informal, horizontal connections between firms in the network, the introduction of a central focal firm may reduce the generation of relational capital or centralize relational capital upon the focal firm alone [Lincoln, Sargent 2018].

Applying this argument to the centralized upstream supply chain network structure, the level of relational capital experience by network members may be reduced, because their levels of embeddedness are suppressed by the central focal firms in the lean relationships.

However, the literature has also indicated that a history of successful collaboration between firms can help maintain the level of relational capital between network actors. Thus, the relational capital outcomes that have forged successful collaboration activities within or outside the network's particular network boundary may be resilient in the eyes of certain network actors. Despite the reduction of embeddedness, some network members will still be perceived as more trustworthy by other network members.

In summary, as indicated earlier, the upstream supply chain network is a centralized network structure within the focal firm, i.e. the main manufacturer managing and administering the transactions between the firms in the supply base or the upstream supply chain network. To the extent that negative and positive effects influence the centralized network governance, a perplexing issue may also emerge regarding the impact of firm embeddedness in a centralized upstream supply chain network structure. It is not clear whether embeddedness in the centralized upstream supply chain network will improve a firm's level of relational capital, or, conversely, whether centralized network governance will impede the generation of the relational capital outcomes. This perplexity raises the following question regarding the impact of a firm's embeddedness or involvement in the centralized upstream supply chain network structure: Is the embeddedness of firms in the centralized upstream supply chain network related to their respective relational capital outcome?

NETWORK DEGREE CENTRALITY AND TRUST

Idris and Saridakis [2018] proposed classifying network ties through the increasing formality of the ties. Poppo and Zenger [2002] found that governance of inter-firm relationships involves formal and informal coordination. Under formal coordination or inter-firm relations, Cousins, Handfield et al. [2006] argue that long-term resource dependencies between firms or organizations are forged to ensure future commitments and cooperation. Examples of this formal coordination include inter-firm relations such as contract ties and joint planning programs [Poppo, Zenger 2002, Idris, Saridakis 2018]. Thus, in this study, the researcher argues that contract ties constitute networks among firms in the centralized upstream supply chain network structure. Wasserman and Galaskiewicz [1994] stated that a network is made up of a finite set of actors and relations. The authors added that the relations between the actors defined the actors of the network. In the contract tie networks, actors are the firms. Similarly, the relations are specifically contracts which all exist in the upstream supply chain. An important characteristic of the formal inter-firm relation is the existence of a hierarchical or a top-down approach to the governance of the inter-firm network. Through the hierarchical or top-down approach, governance benefits such as administration and control are realized through the centrality of ties [Powell 2003].

Centrality relates to the coreness of a firm's position in a network of inter-firm relationships [Freeman 1979]. What is meant by coreness the central location of the firms in the network. In this study, the researcher adopted network centrality measures through which to illustrate firms' centrality in the centralized upstream supply chain network structure, i.e. degree centrality index. Degree centrality measures the number of other firms in the centralized upstream supply chain network to which a firm is tied. Extensive interactions generate trust among firms. For example, Eccles [1981] found that extensive interactions among a network of homebuilder firms also create trust among network members. The authors found that exchanges of information among the contractors regarding materials' prices create stronger inter-firm relationships and thereby facilitate the creation of trust. Similarly, in order to obtain information regarding a potential partner before collaboration activities can be carried out, firms resort to trusted firms for information. The trust between the firms is the result of multiple exchanges in the past. In the same vein, it is argued that years of inter-firm relationships generate trust among them. Extensive interactions are a catalyst for trust in networks of inter-firm relations [Wegner, Faccin et al. 2018, Lee, Tuselmann et al. 2019, Polyviou, Croxton et al. 2019].

Thus, the literature indicates that firms in a network having an extensive relationship with other firms in the network may be perceived as trustworthy by others. Since extensive relationships in network analysis can be pictured based on the level of firms' coreness in the network structure, this thesis hypothesizes that firms that are more embedded in the centralized upstream supply network following their central position in formal contract ties may experience greater trust.

RESEARCH METHODOLOGY

Social network analysis is a powerful methodology for describing and analysing the inter-relationship of nodes within a particular network [Knoke, Kuklinski 1982]. The relations can represent, for instance, communication, workflow, information sharing or the exchange of goods among actors representing individuals, organizations or even nations [Knoke, Kuklinski 1982, Borgatti and Li 2009]. Nodes within a network can be individuals, a group of individuals, such as a department within an organization, or even an organization itself within a larger network such as the supply chain. Given the flexibility defining these nodes, SNA can be effectively used to study both the organizational and inter-organizational phenomena [Borgatti, Li 2009]. At the organizational level, the network describes the relationship among individuals or groups within organizations, while at the inter-organizational level, SNA concerned the interrelationship or organizations within horizontal and vertical network [Lazzarini, Chaddad et al. 2001].

Unlike the traditional multivariate analysis performed in logistics and supply chain management research, which focus on individuals or organizations as the unit of analysis, SNA has an added advantage. SNA also focuses on the patterning of relationships among actors in the network. Several literature sources state that in social network analysis an actor e.g. individuals, or group of individuals and an organization or group of organizations, is seen as embedded in a larger network structure that both constrains and liberates [Granovetter 1985, Baum, Oliver 1992, Romo, Schwartz 1995, Choi, Kim 2008]. The analysis of such network embeddedness can result in potential findings that could not be obtained with conventional survey and case study methodology [Knoke, Kuklinski 1982, Diani 2002]. For instance, SNA allows for the uncovering of the informal relationship and formal relationship that employees within an organization or inter organizations had established with one another. These relationships, particularly informal relationships, often cut across formal functional boundaries and reporting channels, and help meet difficult deadlines and perform challenging tasks [Krackhardt 1999, Rowley, Behrens et al. 2000, Moran 2005].

For this study, the supply network of a small maritime industry seemed to be an ideal setting. A supply network in the maritime industry is a material-intensive enterprise. Much of the activities and activities are highly dynamic and are widely dispersed throughout the network. Materials and information are transferred through interactions among different buyer-supplier organizations. Because buyer-supplier organizations in the supply network operate in an environment of a high degree of complexity [Bozarth, Warsing et al. 2009] and uncertainty [Wilding 1998], these buyer-supplier organizations seek an edge through connections or interactions with the members of the network. Lambert and Cooper [2000] stated that the key to these issues is the on-going relationship with the other partners. They stress the importance of investigating the relationships suppliers and customers have with competitors ["non-member process links"] using other theoretical perspectives. This model begs the question of who manages whom, who coordinates what, and how coordination and integration are maintained.

A survey was used to collect majority of the information needed for this study. Surveys and questionnaires are traditional tools to help network researchers to obtain data on inter-organizational relation-ships [Wasserman, Galaskiewicz 1994]. Leading network researchers such as Galaskiewicz [2011] and Borgatti and Li [2009] established the credibility of this technique for collecting network data on inter-organizational transactions such as information transfer, resource transfer and joint activities. A survey is suitable for this type of study, because it allows the researcher to tap into the participants' subjective perceptions of interactions rather than objectively measure interactions, which in many situations are hard to gain access to for confidentiality reasons [Diani 2002].

The network survey questionnaire entitled "Structural Embeddedness and Organizational Performance" is comprised of 13 main questions, including the demographics section. The network questionnaire is designed so that it is contained within A4 pages with no blank spaces. It is prefaced by an introductory preamble at the top of page one asking for the respondents' participation and signed by the author. In order to make the network questionnaire as easy as possible, it is broken up into the sections. In addition, some necessary questions such as the network ties questions are preceded by instructions on how to answer the questions. The survey instrument is divided into several sections consisting of 3 types of questions. The first type of question seeks general demographic information from the respondents with regard to the firms that they are serving. This set of questions also provides the descriptive statistics of the responding firms. Information acquired through this type of question consists of material regarding the firms' address, and total number of employees or staff, as well as the number of years in operation. The second category of questions investigates the network ties between the firms in the centralized upstream supply network. In this section, the survey shows a table with the names of all the firms listed in the first column of the table. Based on this, the respondents were asked to indicate by making a tick in the table the list of firms that they have been in communication with for the certain types of relationships listed in the last six months. These ties are important in order to understand both formal and informal relationships between organisations (Choi, Hong, 2002, Corteville, Sun, 2009, Provan, Milward, 1995). The types of ties investigated were contracts and information-sharing ties. The contractual tie questions show how formally linked one firm is with another in the upstream supply network. The survey instrument asked the key informants to indicate on the roster the list of firms with which they have formal service contracts relating to the supply of materials. The firms can be in tier two, supplying materials to the tier one supplier, who in turn supplies the focal firm with the materials necessary for the production of RHIB.

DATA ANALYSIS

Many leading network scholars have claimed that traditional statistical analysis disregards the possibility of relations between the individual nodes or actors through the assumption of independence of observation [Robins, Pattison et al. 2009, Bamber, Jiang et al. 2010, Shumate, Palazzolo 2010, Lusher, Robins et al. 2012], when in fact, in social networks, the node and actor are an interdependent, related unit of analysis [Knoke, Kuklinski 1982]. It is for this interdependency and relatedness argument that a special class of statistical models is preferred when investigating social relations, in particular, the Exponential Random Graph Model [ERGM] [Shumate, Palazzolo 2010].

Exponential Random Graph Modeling [ERGM] is a statistical method for modeling the generative processes that create the social networks [Handcock et al. 2004]. In ERGM, the log-odds of a tie between members of a dyad of nodes or actors in the network are essentially modeled using an exponential form analogous to logistic regressions. One of the advantages of ERGM is that it allows the researchers to model the structural elements of the network as covariates [Robins, Pattison et al. 2007].

In ERGM, a tie can be modeled as a function of node and edge variances. ERGM are sometimes known in the social network literature as P-star [P*] models [Robins et al., 2007]. The purpose of ERGM is to simulate the probability distribution function of a given class of graphs. The stochastic process giving rise to the observed network is modeled as a function of network configurations. However, on networks, even a small one, the number of possible configurations of ties is rather large. Because of this, the probability distribution of the network structural elements must be estimated. The estimation is done using the Markov Chain Monte Carlo [MCMC] method to sample the distribution of the structural features of interest among networks having the same number of nodes as the observed network. With the outcome information, the coefficients can be estimated using the Maximum Likelihood Estimates [MLE] methods [Robins et al., 2007].

In general, the analysis technique performed in this section is known as the generative model [Robins et al. 2007]. This technique provides a full stochastic representation of the process of the network formation, which allows the dependence among the observation to become the focus of the models. An ERGM model allows the researcher to control the impacts of higher order structures with lower ones. Exponential random graph models [ERGM] have the following form:

$$P_r\,(Y = y\,) = \;1/k]\,\exp\left(\sum nA(g)\,A(y)\right) \qquad (1)$$

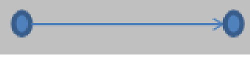
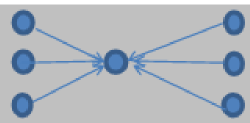
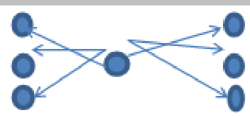
where:
- The summation is over all configurations A;
- ηA is the parameter corresponding to configuration A [and is non-zero only if all pairs of variables in A are assumed to be conditionally dependent];
- gA[y] is the network statistic corresponding to configuration A; gA[y] = 1 if the configuration is observed in the network y, and is 0 otherwise.

All ERGM models are in the form of equation (1), which describes a general probability distribution of graphs on n nodes. The probability of observing any particular graph y in this distribution is given by the equation, and this probability is dependent both on the statistics gA(y) in the network y and on the various non-zero parameters ηA for all configurations A in the model. Configurations might include reciprocated ties, transitive triads and so on [Robins et al., 2007]. Hence, the model enables us to examine a variety of possible structural regularities [Handcock et al., 2004]. The probability of observing the graph is dependent on the presence of various structural characteristics introduced in the model. It is worth stressing that a model for the network y consists of n (n – 1) possible network ties. In this study the total research population is comprised of 37 firms. Thus, the total number of possible ties under investigation is 37(37-1) = 1332. The total tie is large enough to provide valid statistical inference of the results. The model specification for the trust networks is briefly described as follows. For the ERGM analysis to take place, the researcher adopted the PNet program to run the network data set of each of the ties in the network and the prevailing structural embeddedness variables (i.e. degree centrality) as the model parameters.

The generative models analysis presented here was conducted using the PNet program [Wang, Robins et al. 2006]. Overall, in this section of the data analysis, the covariates of the thesis are modelled in two different ways. The first method is to model the impact of each covariate on the log-odds on the different type of ties under consideration [formal contract ties and informal information sharing ties]. The second method involves modelling the impact of the structural embeddedness parameter in the different types of network generated from the network survey questionnaire. The model's network effects are tested for fit using the Monte Carlo Maximum Likelihood Estimates [MCMCMLE] estimation techniques and calculate the estimated coefficient using the PNET package.

Network effects in ERGM refer to the associations between social network ties and the actor attributes of the particular network [Robins, Pattison et al. 2007]. An example of network effects include the tendency of dyadic ties to be mutual i.e. Actor A likes Actor B and Actor B likes Actor A in return. However, there are also other effects that incorporate nodes or actors' attributes that may help explain the forming of ties between the network members. For instance, a highly popular node or actor of the network may be attributed to the actor's level of education or the actor's age. In the ERG model, a number of effects can be included in the model by the researcher just as adding variables into a regression analysis to determine the explanatory power of particular variable/s. As the ERG model is statistical, it is possible to determine whether certain network effects occur at levels greater or less than chance. The complexities of social relations suggest that there are many interdependent network effects that are occurring at the same time within the network. ERGM provides the means to explore these network effects together, manage the different attributes and explore the network complexity as a whole [Lusher 2011]. This study applied these capabilities of ERGM analysis to answer the arguments of this study hypothesis.

The network effects are divided into pure structural effects. Pure structural effects are the self-organizing characteristics of a social network that do not rely on the characteristics or the attributes of the individual nodes or actors [Robins, Elliott et al. 2001, Wang, Robins et al. 2006, Wang, Robins et al. 2006, Lusher, Robins et al. 2012]. For instance, the fact that people would shake hands with others regardless of the attributes of these other individuals is a form of pure structural effects which indicate mutuality or reciprocity of ties. Transitive relation is another form of structural effects. Transitive pure structural effects relate to a condition whereby a friend of a friend is a friend. Transitive pure structural effects are also known specifically in ERGM as triadic parameter effects [further discussion in Table 1]. In principle, pure structural effects explain the conditions where the presence of one or more ties leads to the formation of other social ties.

Parameter	Interpretation	Description	Explanation
Density Arc	Baseline tendency for a tie to occur		One firm nominating another firm
Reciprocity	Tendency for reciprocation		Mutual ties between two firms
Degree Based Popularity A-in-S	Tendency of Spread of in-degree distribution. Centrality, coreperiphery as a result of actor popularity		Indicative of presences of highly nominated firms within the network
Activity Based A-out-S	Tendency of Spread of out-degree distribution.		Indicative of the activity of firms to engage many others

Source: Robins et al.[2012]

Fig. 1. Summary of purely structural ERGM network effects

Figure 1 presents a list of purely structural network parameters which measure [and control for] endogenous, or self-organizing, structuring within the networks of this study and related to the study hypotheses, and consequently helping to answer the research question. The first column of Figure 1 lists the names of pure structural effects parameters [as well as the codes] relevant for this study. These parameters are selected based on the theoretical objectives of this thesis. The relevant parameter is the Arc parameter. The Arc is the baseline parameter in any network. It represents the tie that connects [minimum] two nodes into a dyad. Using the Arc parameter estimates, the researcher is able to determine the density or cohesiveness of the network under consideration [Wang, Robins et al. 2006]. The second groups of pure structural effects parameters are degree-based parameters. For the ERG models, this research include two degree-based pure structural parameters which represent degree centrality. The parameters are the popularity-based and the activity degree centrality parameters, coded as A-in-S and A-out-S respectively. The significance of these parameter estimates will help support the hypothesis in this study. The second column of Table 1 shows an interpretation of the parameters. What it means in the second column of Table 1 is the propensity of the structural parameters effects to take effects given the network size and number. For instance, an ERG model with positive and significant reciprocity estimates [details of determining the parameter significant is given in the following sections] indicates the high propensity for mutual ties to occur in the network given the network size and number of nodes. The third column of Table 1 describes the pure structural effects parameters in graphical formats. In column three, buyer-supplier organizations are represented by the blue nodes, while the lines between two nodes represent the ties that connect them. The lines also have arrows indicating the direction of the tie, either inward or outward. The final column discusses the meaning of the parameters from the supply chain perspectives. From the perspective of supply relationships, the Arc parameter refers to the tendency of the organizations to forge ties with other buyer-supplier organizations in the network given the size and number of the nodes in the network. Reciprocity relates to the presence of mutual ties between the buyer-supplier organizations in the trust network of the MMEA supply system. The popularity parameter [A-in-S] suggests that popular buyer-supplier organizations tend to receive more ties from shared alters and to communicate together. Activity spread [A-out-S] relates to the activity of organization to engage other buyer-supplier organizations in the network.

FINDINGS AND DISCUSSION

In this section, the researcher presents the ERGM analysis result in involving the network embeddedness measure a degree of centrality in the contract tie. To test for the trust network structural variations in a more systematic way, this thesis ran a series of ERG models, which allow the researcher to determine statistically whether certain configurations are more prevalent in the network than would occur by chance alone [Snijders, Pattison et al. 2006, Robins, Pattison et al. 2009]. Statistically, the researcher conducted the ERGM analysis with one main objective: to determine whether the significant structural parameters in the trust network reflect the parameters that represent embeddedness property i.e. degree-based parameters. This objective is achieved by analyzing the outcome of the Pure Structural Effect ERG models.

The ERGM analysis was conducted following Robins, Lewis et al.[2012], Lusher [2011] and Lusher, Robins et al.'s [2010] methods of analysis. Basically, in this section, we analyzed the network data based on an important principle parameter. In the initial analysis, we conducted the Pure Structural Parameter Effects model ERGM analysis to determine the relevant structural formation of the trust network. With this analysis, the researcher was able to determine the patterns of tie formation propensity.

It is important to note that throughout this statistical network modeling analysis there will only be only one Pure Structural Effects models with the relevant, converged, structural parameters. This Pure Structural Effects model is for the trust network alone.

In Model 1, this thesis runs a dyad-independence model in which we only test for the significance of the structural parameter. Model 1 will provide the general sense of how trust network ties are being formed.

The correct interpretation of the outcome parameters in the ERG models requires the investigation of three parameters features, which are the MLE [Maximum Likelihood Estimate], Magnitude or Effects, and the associated convergence t-statistics. The sign of the MLE [" +" or "-"] provides an indication of whether the particular network structure occurs more or less likely than predicted by chance. The Magnitude or Effects of the parameter assess the significance of the parameter in the model. If the Magnitude or Effects of the parameter estimates is greater than two times the standard error, it is considered significant and is denoted by an asterisk [*]. For a model to be considered well converged, the t-statistics must be near zero [generally less than 0.1 is an absolute value]. All of the parameters included in these study models are under the convergence threshold, indicating that the models fit the data well. This allows for the testing of hypotheses associated with the specific parameters. It is important to note that these ERG models are conditional, meaning that each subsequent parameter added into the models represent a mechanism that is operating over and above other mechanisms. The next section of this thesis discusses the analysis results of the ERG model for the trust network and embeddedness attributes based on degree centrality in contract ties.

The parameter estimates [MLE], Magnitude or Effects, and convergence t-statistics for the MMEA trust network are presented as follows:

Table 1 presents the attributes-based network effects and the structural parameters effects in the models.

Table 1. The attributes based network effects and the structural parameters effects in the models

Parameter	ML Estimates	Standard Error	Magnitude [MLE/Std Err]	Convergence *t*-ratio
***Model 1**: Pure Structural Effects [Embeddedness Based on Degree Centrality in Contract tie]*				
Arc	-1.101	0.082	13.33	0.014*
Reciprocity	1.478	0.401	3.69	0.048*
A-in-S	-1.350	0.429	3.14	0.014*
A-out-S	0.128	0.399	0.32	0.019

*A parameter estimates is considered significant when the absolute value of the ML is greater than twice the magnitude of standard error.

Model 1 were used to test embeddedness based on degree centrality in contract tie effects on the trust relationship. Model 1 is the Pure Structural Parameter Effects model for the trust network, which includes only the structural parameters. This model is used to show the propensity of ties structure to be formed in the trust network of the MMEA supply system. In Model 1, to obtain a converged Pure Structural Effects model for trust network, the following parameters are included conditionally until the model is converged i.e. until the t-statistics of each relevant parameter are less than 0.1. Consequently, the parameters that are included in the Pure Structural Effects model of the trust network are as follows: Reciprocity, A-in-S, and A-out-S. Structurally, these parameters reflect certain forms of ties structural formations in the trust network. Evidently, these parameters reflect centralization [A-in-S, A-out-S], [Wang, Robins et al. 2006, Robins, Pattison et al. 2009]. However, in this section of the analysis, greater attention will be given to the parameters that represent the degree-based or centrality parameters of the trust network, as these parameters reflect the core argument of the hypothesis. As this thesis argues in the hypothesis that embeddedness based on degree centrality would influence the trust level of the embedded buyer-supplier organizations, this thesis expects to find the presence of A-in-S and A-out-S parameters in the trust network. Quantitatively, it is expected that the centrality parameters estimates to be positive and significant in the models.

In Model 1, the Arc ML estimate is a significant and negative parameter [ML estimates = -1.101, SE =0.014], suggesting fewer trust relationships are expected in the MMEA supply system to be observed than would have been expected by chance. In other words, buyer-supplier organizations of the MMEA supply network forge trust relationships with only a few of the potential other buyer-supplier organizations in the network. This phenomenon is expected as trust relationships are built over time and rely on other endogenous variables, such as the size of the participating organizations and the length of the relationships [Doney, Cannon 1997, Laaksonen, Jarimo et al. 2009, Jiang, Chua et al. 2011]. Supplier size encompasses the firm's overall size and its market share position. Supplier size provides a signal to the buying firm that the selling firm can be trusted. Overall size and market share indicate that many other businesses trust this supplier enough to do business with it. This suggests that the supplier consistently delivers on its promises to others or it would not have been able to maintain its position in the industry. In addition, length of time represents an investment both parties make in the relationship. To the extent that buyers perceive such investments on the part of suppliers, they could calculate that a supplier would incur losses by acting in an opportunistic [i.e., untrustworthy] manner.

Furthermore, in Model1, the ERGM analysis provides interesting insights into the reciprocity in trust relationships of the MMEA buyer-supplier organizations. In Model1, for the purely structural parameter effects, we have significant and positive effects of reciprocity for trust relationship [MLE = 1.478, SE = 0.048]. Therefore, relative to chance and given the other effects in the models, buyer-supplier organizations are likely to nominate each other. Reciprocity is an important feature of many other social networks studies, and it is expected in trust relationships [Robins, Pattison et al. 2009, Bamber, Jiang et al. 2010, Lusher, Ackland 2010, Lusher, Robins et al. 2010, Lusher 2011, Lusher, Robins et al. 2012, Robins, Lewis et al. 2012]. What this means is that in the trust network of the MMEA supply system, the trust relationships are likely to be mutual, whereby if buyer-supplier organization A trusts B, it is highly likely that B will also trust A.

With regard to degree-based structural formations, two parameters, i.e. A-in-S and A-out-S are included in Model 1 to assess the presence of network centrality structural formation in the trust network. In Model 1, the A-in-S parameter is an indication of the presence of highly nominated buyer-supplier organizations within the trust network. Model 1 shows that the A-in-S parameter is significant but negative [MLE = -1.350, and SE = 0.014]. What can be taken from these parameter estimates is that in the trust network, controlling for other effects, although there is a significant parameter estimate for A-in-S, a negative MLE score indicates that it is unlikely that the trust ties relationship will be forged based on degree-based structural formation. In other words, in trust relationships or networks of the MMEA supply system, there is low propensity for buyer-supplier organizations to be embedded in a degree-based structure.

CONCLUSIONS

This research attempts to extend the understanding and application of the embeddedness theory by determining the impact of firms' embeddedness in a centralized network structure such as the supply network. Specifically, the question that this study attempt to answer looks at how the embeddedness of firms in the centralized upstream supply chain network is related to their respective relational capital outcome. The results of the statistical network analysis reveal some interesting findings and contribute partially towards the conclusions of this study. The researcher found interesting findings in terms of prominent structural forms and the impact of involvement or embeddedness in the formal of a supply network. The ERGM analysis revealed that there were significant negative effects of firms' embeddedness based on degree centrality in contract tie and trust, the Maximum Likelihood Estimate [MLE] is significant but negative when firms are highly embedded in the contract tie. What this means is that the more embedded a firm is in the upstream supply chain network based on the formal contract tie, the less the likelihood that it will be perceived as trustworthy by other network members. Consequently, this tells us that firms' embeddedness in a centralized network structure which is based on a formal contract ties have negative impacts on the firms' level of trust perception.

As a firm becomes more embedded in the upstream supply chain network structure, it will experience varying levels of relational capital depending on the type of activity that the firm is involved in. However, the same cannot be said when the type of network tie is rather formal and based on terms and regulations. The more embedded a firm is in the supply network based on its degree centrality network position, the less likelihood there is that the firm will be perceived as trustworthy by other firms embedded in a similar network structure. In other words, in a network of formal connectivity, putting oneself to the front by emphasizing on contracts terms will result in negative impact upon the firm level of trust.

This finding is in incongruence with Uzzi [1997] and Giannoccaro [2018]. The authors found that in inter-firm relationships, active relational governance such as information-sharing is associated with trust. An information sharing tie is not a form of a formal tie but rather an informal one. An important implication of this is that these findings provide support for the idea that firm commitment to contract activities could not enhances the perception of trust that the firm may receive from other network members.

This research is not without its limitations. Firstly, the scope of this study only focuses on the maritime industry. More works which focuses on other industries may reveal interesting new findings. Furthermore, it would also be valuable to view the dynamic of firms' relationships, for instance, to see how firms' relationships are linked to one another through time as industries, technology and other factors evolve. Because inter-organizational relationships are dynamic rather than static, their nature and form are expected to change over time. The ability to see which conditions would result in different outcomes would provide significant implications for the management of the firms' relationships and inter-organizational relationships in general, as well as to the general theory of embeddedness in explaining the implications of firm embeddedness and relational capital outcomes.

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CZY ZAJMOWANIE CENTRALNEJ POZYCJI W FORMALNEJ SIECI POPRAWIA ZDOBYCIE ZAUFANIA? ANALIZA SIECI SOCJALNYCH ISTNIEJĄCYCH W STRUKTURACH ŁAŃCUCHA DOSTAW

STRESZCZENIE. **Wstęp:** Praca ma celu rozszerzenie znaczenia i stosowania poza strukturę sieci teorii zależności aktywności ekonomicznych od czynników socjalnych. Wcześniejsze badania dotyczące analizy sieci w dużej mierze koncentrowały się na zagadnieniu decentralizacji struktury sieci i wpływu tego procesu na działanie poszczególnych jej członków. Niemniej każdy członek łańcucha dostaw jest elementem zcentralizowanej struktury sieci. Zcentralizowana firma odgrywa przywódcza rolę w całej takiej strukturze. Dlatego też łańcuch dostaw jest siecią zcentralizowaną z powodu istnienia firmy przywódczej. Istnieje takiego typu firmy w sieci ma wpływ na wyniki działalności.
Celem tej pracy jest określenie wpływu formalizmu, będącego wynikiem zcentralizowania łańcucha dostaw, ba poziom zaufania w obrębie tego łańcucha oraz możliwości organizacji wykorzystania zasobów tego łańcucha do uzyskania wykorzystania optimum zasobów.
Metody: W oparciu o wcześniej stosowane podejście używające analizy sieci socjalnych, zastosowano metodologię analizy sieci socjalnych do zgromadzenia danych dotyczących połączeń i relacji w obrębie łańcucha dostaw. Przy użyciu modelu Exponential Random Graph Model [ERGM] opracowano losowo szukający algorytm dla rozwiązywani problemu optymalizacji relacji sieci. Exponential Random Graph Modeling [ERGM] to metoda statystyczna służąca kształtowaniu procesów generatywnych, tworzących sieci socjalne. W metodzie tej, zarówno połączenia nieparzyste jak i dwójki węzłów sieci są modelowane poprzez użycie postaci wykładniczej analogicznej do regresji logistycznej.
Wyniki: Uzyskane wyniki badań wskazują, że centralizacja ma negatywny wpływ na poziom zaufania w łańcuchu dostaw. Firmy umieszczone w różnych częściach łańcucha dostaw zyskują w różny sposób z relacji socjalnych w obrębie tego łańcucha. Zasoby firmy musiałyby być przesunięte, aby uzyskiwać benefity wynikające z różnej pozycji w strukturze sieci.

Wnioski: Wyniki uzyskane na podstawie analizy statystycznej sieci wskazują na ciekawe zależności w obrębie strukturalnych form, mający wpływ na zaangażowanie w formalnej strukturze łańcucha dostaw. Im dana firma znajduje się wyżej w sieci łańcucha dostaw w odniesieniu do formalnych połączeń i relacji, tym jest mniejsze prawdopodobieństwa, że będzie traktowana z zaufaniem przez innych członków danej sieci. W konsekwencji, należy wysunąć wniosek, że ze wzrostem pozycji w zcentralizowanej sieci, zaufanie do danej firmy maleje.

Słowa kluczowe: analiza sieci, dzielenie się informacją, zasoby socjalne

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