Market Organisation - Relevance of Structural Embeddedness of Economic Transactions in Networks

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Abstract

This paper deals with research questions about the social and structural embeddedness of interorganizational networks. Social Network Analysis have proven capable of not only dealing with attributive data but also with interdependent relational data of actors within a network. Social network analysis provides with the class of p* models a tool with which multiplex and interdependent relations and attributes can be handled. The outcome of p* models may help to demonstrate that the market organisation of an industry can be understood in terms of structural regularities in a specific multiplex exchange system, especially in regard to social aspects, which are assumed to be important for the resource exchanges among industry members.

Keywords: *Social Network Analysis, Interorganizational Relations, Structural Embeddedness, p* Model, Networks.*

Introduction

Although the concept of network organisation has already been taken into consideration by the managerial literature and despite the fact that the relevance of network organisation as an organisational form of economic transactions is increasing, there are only few quantitative analyses dealing explicitly with the structure and impact of information linkages as well as social networks on pure “business networks”. Before proving the relevance of structural properties of networks for economic performance, one has to ascertain the interdependencies between network resources and identified structures. After identifying the theoretical background and entity of investigation considering interorganizational networks in the second paragraph, the concept of structural embeddedness is described. In order to go beyond metaphorical descriptions, social network analysis, especially the family of exponential random graph models (p* models) is introduced. Linking the existent feasibilities of analysing relational data with inferential statistics, possible interpretations with regard to interorganizational network aspects will be given.

Interorganizational networks

In publications of interorganizational relationships the term network is common, but mainly used in a metaphorical sense (Ghoshal, 1987; Böttcher, 1996). Since the basic article of Williamson (1975) literature stresses the advantage of economic transactions in business

networks, either as loosely coupled systems or as hybrid organisation forms, in opposition to the classical organisation forms market and hierarchy. In general network organizations are assumed to be more flexible and stable regarding environmental changes than traditional forms of organizations (Sydow, 1992; Powell; 1990, Jarillo; 1993).
The article concentrates on interorganizational relationships between firms within an entire industry und follows the definition of Sydow/Windeler (1994, p. 79) that regards a business network as a form of organizing economic activities realizing competitive advantages, which are marked by complex-reciprocal, more cooperative than competitive and relatively stable relations between legally independent, but often economically dependent firms.

Table1: Research questions at different levels of network and relationship management

Level of observation		Description	Research question
1	Industries as networks	Networks as dominant organizational form within an entire industry. Often networks are not visible, but the understanding of function, principles, and processes are essential for one's own positioning in the industry.	Is there any competition on the network level? How could networks and competition on the network level be analysed? How could networks be identified? Which are the boundaries of networks?
2	Business Networks	Firms form observable or implicitly important networks. The position in networks and daily tasks of managing complex, interorganizational processes have an impact on the performance of the enterprises.	How networks are created and managed? Which types of networks are important (supplier- , buyer-, alliance-, virtual networks etc.)? Are there specific management implications?
3	Portfolio of relations	Firms maintain an increasing number of supply chain relationships. Prioritization of relationships and detecting interdependencies is a challenging task.	How can important external relationships be identified? In which way could an optimal portfolio of relation be established? In which way should different types of relationships be managed?
4	Relationships	Firms are increasingly dependent on external resources and on the commitment of supply chain partners. That is why relationship management is important.	Are interorganizational relations manageable in a traditional sense? Which are the frontiers of interorganizational management?

Source: Möller/Halinen (1999, p. 414).

In general interorganizational networks could be defined as one more governance structure of economic transactions (Williamson, 1975; Hamilton/Rauch, 2001; see for an overview Oliver/ Ebers, 1998).
Often, the rational for choosing one of the two traditional forms of organisations is related either to the determinants of the resource-based view or to transaction cost analysis. Observing hybrid organisations in reality do not must question these approaches in organizational theory.

Actually, they have to be extended to the fact of informal organizations, so that beside the rational, economic factors of explanation there are arguments to add a social perspective (Gassenheimer, 1998; Anderson et al. 1994). Informal organization can be interpreted as social exchange. Blau (1964) defines social exchange as “voluntary actions of individuals that are motivated by the returns they are expected to bring from others” and which are “contingent on rewarding reactions from others.”

The term of social embeddedness is common in literature observing economic and social dimensions of relationships simultaneously. It follows the idea that commercial transactions take place due to social relations and create economic opportunities, which are difficult to establish via markets, contracts, or vertical integration (Uzzi, 1996). Social embeddedness of economic transactions can be understood as linking the perspective of “under-socialized” neoclassical theory on the one side and the “over-socialized” perspective of Sociology on the other side and thereby improving both concepts.

In addition to the central work of Coleman (1988), Granovetter (1985) argues that neoclassical as well as sociological theory has as basic foundation the atomistic action of individuals and does not consider the social organization of human activity. Recent literature in economics distinguish not only between a social and economic dimension of individual action but also add a strategic and institutional point of view (Gilbert, 2003; Dacin et al., 1999; Fonti, 2003).

Apart from economic relations or market organization, the social dimension can be added by introducing the constructs trust and reputation as well as dyadic social relationships between members of enterprises. Studies like those of Heide (1990), Wathne (2004), Nooteboom (1997), Zaheer (1998) or Claro (2003) have proven that these constructs have a significant impact on the performance of enterprises. These research foci can be classified into the Möller/ Halinen’s systematic of research of (1999), which differentiates between four types of research questions observing interorganizational networks (see table 1): identification of relevant competitors and customers in industries to level 1, strategic aspects of enterprise development to level 2, supplier-buyer relationships to level 3, and relationship-marketing to level 4.

Structural embeddedness

The findings of the mentioned studies above are derived from traditional attributive analyses via multi-item questions. The respondents should answer the constructs (trust, reputation, information etc.) either having an aggregate of its relationships in mind or focusing to one, e.g. the most important relationship. In extension to the traditional analyses considering aggregated attributive data or pseudo-relational data that is accustomed to the research question in focus, a structural perspective of relationships can be added. Although the importance of the social dimension as determinant of economic action has already been mentioned in economics e. g. by Sweezy (1949) or Williamson (1975), the impact of social and economic structure on economic action has recently been treated under the concepts of social capital or structural embeddedness (Dasgupta/Serageldin, 1999; Burt et al., 1983, 1992; Coleman, 1990; Granovetter, 1985).

In addition to the dyadic perspective, the simultaneous observation of several buyer-supplier relationships leads to the concept of structural embeddedness. The interesting point of view is the hypothesis that not only economic and social relations are dependent on each other but also the relations among an entire group of firms, e.g. an industry. That means, the quality of social relationships between enterprise A and B could have an influence on the economic form of interaction between enterprise A and C. Granovetter (1985) stated: “Structural embeddedness is a function of how many participants interact with one another, how likely future interactions are among participants, and how likely are to talk about these interactions.” Within the framework of interorganizational networks Nahapiet/Ghoshal (1998, p. 243) define embeddedness as „the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit. Social capital thus comprises both the network and the assets that may be mobilized through the network.” The fact of multiple, simultaneous and interdependent relations (between and within the social and economic dimension) is discussed as multiplexity. In observing different kinds of relationships, e.g. within a supplier-buyer relationship we focus on a multi-relational perspective – in assuming that these different relationships could be dependent on each other refers to the construct of multiplexity.

Multiplexity shows to which degree two actors are linked directly or indirectly by more than one type of relationship (Wasserman/Faust, 1998; Contractor/Lorange, 2003). It is regarded as a factor that improves the capability of managing organizational crises. The different types and structures of a set of relationships (direct, indirect, social, and/or economic) are able to compensate deficiencies of formal organizations and conciliate sensible information in critical situations (Lewicki/Bunker, 1996; Sydow, 2002). Further multiplex interpersonal and interorganizational relations are regarded as self-enhancing and create new relationships (Boissevain, 1974).

Feld (1997) defines structural embeddedness by considering explicitly multiplex relations: „The structural embeddedness of a relationship between two individuals is defined as the extent to which these individuals relate to the same others. [. . .] Structural embeddedness presumably arises from sharing one or more foci of activity with one another, and thereby developing common relationships with others from those activities.” So, the term “social” can be interpreted first as the kind of content, which specifies the relationship A has to B, e. g. friendship, and second it can be interpreted as the interdependencies of attributes and relations of A to C influencing the relation of A to B.

Social Network Analysis

The tools and methods of Social Network Analysis have proven capable of dealing not only with attributive data but also with interdependent relational data of actors within a network (Wasserman/Faust 1998; Kilduff/Tsai, 2003; Jansen, 2003). Social systems could be defined through the entities or actors of the systems (persons or organisations) and by the relationships between them, which could be e.g. information, friendship, support, or economic transfer relations, so that systems form a specific social structure (Pappi, 1987). Conceptually, entities are represented by nodes and the relationships by edges and can be graphically represented by a network. For example, firms within an entire industry are entities represented by nodes, to which attributive data (size, sales volume, number of staff etc.) can be attached. Relations between the firms such as e.g. degree of cooperation, spatial proximity, or equity participation are represented by edges.

The social network perspective considers the actors not to be independent entities but takes into account that actors are dependent on relationships with other actors or to attributes of

actors with whom they are linked. The network structure constraints and offers opportunities for the individual action of each entity within the social system (Wassermann/Faust, 1998, p. 4f.)).
Additionally to the common descriptive way of analysing networks on the individual level of entities, the level of subgroups of the network and on entire networks, the class of p* models provides the possibility of treating research questions in a statistical manner in a framework of social network analysis (Pattison/Wasserman, 1999; Wasserman/Robins, 2005).

p* models

p* models are special applications of exponential random graph models and interorganizational analyses have already been undertaken e.g. by Lazega (1999) or (2003). They allow statistical inferential investigation beyond the descriptive way of social network analysis. The idea of this class of models is to model interdependencies among the variables, so that it is possible to map the outcomes of structural embeddedness.
The main modelling aim is to inspect whether there are significantly more or less structural characteristics of interest in the observed network than expected by chance. Reflecting the possible influence of attributive as well as relational data models shall incorporate both effects and provide tests for the importance of one against the other. p* models create a randomized distribution of possible network relation given a set of fixed actors on which basis statistical inference with regard to the observed network can be done. Fitting p* models mean to find the best estimate parameters for the distribution of randomized networks, using the observed network as a guide. The models represent every relationship as a stochastic function of the attributive and structural characters of actors or networks. The enhanced multivariate p* models allow to explore regularities in the interplay of exchanges and transfers of each kind of resource (trust, information etc.) among the firms in terms of local dyadic and triadic characteristics (Wasserman/Robins, 2005; Snijders et al., 2004).
Pattison (2003) explicitly points out to differentiate between the methodological and the substantive modelling step because of the nature of deducing results modeling interdependent data by using p* models (see below). From a methodological point of view one has to define two network tie variables that are conditionally dependent given the values of all other tie variables and from the substantive point of view, one has to specify what the assumptions about dependence are? The methodological and substantive aspects are linked together by the idea that network ties and structure are the essence of (un-)observed processes that are assumed to be local and interactive. As one can not naturally claim these processes to be strict and deterministic, the stochastic generation of the network distribution integrates both regularities and irregularities of the assumed network structure. Thus, stochastic model formulation in which local interactions are permitted and assumptions about "locality" are explicit regularities, allows one to identify relevant structural properties by estimation of model parameters.

Referring to presenting the technical aspects of p* models, Robins et al. (2005) suggest a five-step procedure of constructing exponential random graph models:

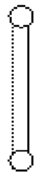
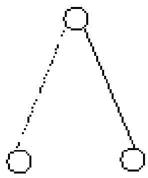
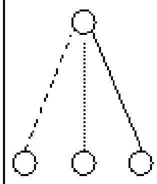
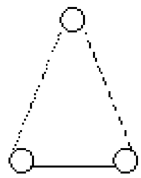
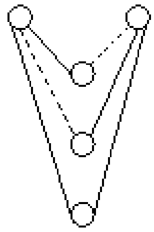
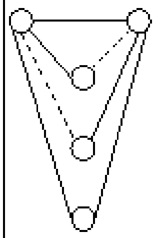
1. Each possible tie in a network expressed by matrix X has to be regarded as a random variable. Variables between actors *i* and *j* are modelled by X = [*Xij*], with *Xij* = 1 if *i* has a tie to *j* and 0 otherwise. The observed matrix of X is denoted by x = [x_{ij}]. X may be a directed or non-directed network that means in the former case we differ between the cases *Xij* and *Xji*.

2. Implementing substantive hypotheses special attention should be paid to dependence graphs as a certain way of statistical implementation. The interdependencies are indicated by a dependence Graph *D*, where an edge $D_{Xij\ Xkl}$ between two nodes X_{ji} and X_{kl} of the dependence graph signifies that two corresponding ties *ji* and *kl* are assumed to be dependent, conditional on all other ties in the network (Pattison, 1999).

Models distinguish whether possible ties between actors depend on the fact that they share a dyad, whether they share an actor or whether they depend on a tie between a different pair of actors not directly involved. Each of the dependencies can be accomplished by the influence of actor attributes on the probability of tie formation. Dyadic precondition and dependence for tie formation can be modelled and estimated by Bernoulli graphs or dyad-independent random graphs (Koehly, 2005). More complex modelling of actor and tie sharing preconditions of the probability of tie formation can be done by markovian random graphs. Assuming markovian dependence means in general that the probability of a tie between actors *i* and *j* is dependent on another tie linked to the tie in question through actor *i* or *j*.

Table 2 shows markovian dependence structures for non-directed local structures, whereas extended examples of interpretations are presented in table 3. The descriptions of dependence structures are ones common in social network analysis and p* modelling. Nodes are represented by circles, ties between actors by the edges and different types of lines symbolize different types of relationships, referring to multiplexity. The graphs have to be interpreted as follows: Node at the top is fix whereas the nodes at the bottom are either dependent on another tie or attribute incorporate by the node at the top. Especially the k-triangle graph enables one to test for clusters within a network and different actors, whilst the normal triangle only tests for transitivity among three actors. The k-independent graph has to be seen as a precondition for k-triangles, so that one is able to look for high connectivity among network actors based only on independent indirect ties or based on dependent direct ties.

Table 2: Overview of Non-Directed Dependence Structures of p* models

Descrip-tion:	Density	Two-star or two path	Three-star	Triangle	k-independent two paths	k-triangles
Graphical Represen-tation:						
Interpre-tation:	Multi-plexity	Interlocking or Association	Attractiveness or Popularity	Exchange or Transitivity	Independency	Transitivity

The inclusion of local structures based on substantial interpretations can be seen as a strength of p* models because of the paucity of network models that incorporate effects, such as transitivity, generalized exchange or popularity (Newman, 2003).
3. After having specified the interdependencies through a markovian dependence graph, a mathematical representation in order to model the dependence graph as a probabilistic distribution is given by Besag (1974). He uses the Hammersley-Clifford theorem that considers local dependence structures and leads to the following term:

$$p(X = x) = \frac{\exp(\theta' z(x))}{\kappa(\theta)} \qquad (1)$$

where *z* is a collection of *r* explanatory variables (network statistics calculated on *x*), is a collection of *r* parameters that are to be estimated and *k* is a normalizing constant that ensures the probability sums to 1. So, the formula derives a probability for the observed network x over the distribution of randomized networks X by taking into consideration the assumptions of interdependencies exp(´*z(x)*). Thus, the Hammersley-Clifford theorem derives a probabilistic distribution for each actor by including all other other variables.

4. One has to impose homogeneity constraints to reduce the number of parameters and thereby define the model clearly. Moreover, parameters for each actor’s local structures should be estimated, so that in fact exponential random graph models imply homogeneity constraints over the whole network. A homogeneity assumption of isomorphic network configurations can be specified: parameters are equated if the configurations are the same when we ignore the labels on the nodes, so that configurations of actors are said to be isomorphic. A second assumption of constraint could be to confine certain network structures to a limited group of nodes, e.g. to define them through common actor attributes or a priori assumptions.

5. The estimation of the described model has been improved recently. Starting with pseudo-likelihood estimation procedure, which has proven to be degenerate in some cases by Handcock (2003), an acceptable procedure is given by Mont Carlo maximum likelihood estimation. (Snijders et al., 2002, 2005; Handcock et al. 2004). It should be noted that the engaged estimation procedures are not logistic regression. Therefore, it is crucial to remember the idea of p* models: comparing the estimated parameters based on probabilistic distribution, which is influenced by the count statistics of a network as structural interdependencies, allow us to make some statistical inference about the underlying structure of a given network.

There are two preferable programs on which exponential random graph models can be imposed and estimated: SIENA and Statnet. The former one is a desktop oriented program included in the Stocnet package (Boer et al., 2003) and follows the suggested estimation algorithms of Snijders (2002, 2005). The latter one is a software package based on the open source software R (Handcock et al., 2005) and can be adapted to the researcher’s needs.

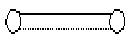
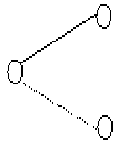
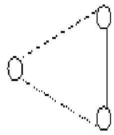
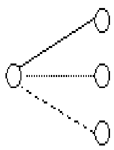
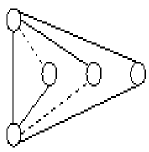
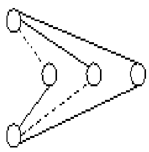
Conclusion

This paper deals with research questions on social and structural embeddedness of interorganizational networks. Especially, structural embeddedness can not be inspected without considering relational data and tools for considering interdependent data among the variables. Social network analysis offers the class of p* models a tool with which multiplex and interdependent relations and attributes can be handled. However, one has to pay attention to linking methodological and substantive modelling. With regard to the systematic of interorganizational network research of Möller/Halinen (1999), p* models can help to enlighten research questions: based on observed relationships between industry members, it is possible to unveil the functioning of competition and cooperation by observing special structures linking industry members directly or indirectly to each other. Further, it is possible to specify in detail the way economic transactions are embedded in social or other economic relations. So, management implications can be reflected out of the awareness which other industry members have an impact on the own e.g. buyer-supplier relationships.

That is why portfolio management of relationships and the management of single relations should be improved considering the fact that there could be third party effects or very isolated enterprises. If there is a high probability that a certain industry is influenced not only by functional (buyer-supplier relations) and structural (who is connected to whom) determinants but by social relations, it could be reasonable to invest in different information and influence channels. To which extent structural properties have an influence can be estimated via descriptive social network analysis and p* models by using the advantages of statistical inference.

The results of p* models may help to show that the market organisation of an industry can be understood in terms of structural regularities within a specific multiplex exchange system, especially in terms of social aspects, which are assumed to be important for the resource exchanges among industry members. In fact, researchers have now useful statistical inference tools to unveil to which extent economic transactions are organised in networks or in an atomistic, hierarchical respectively, manner.

Table 3: Examples of interpretations of independent variables of exponential random graph models in Social Network Analysis

Graphical Representation	Endogenous independent variable: same network	Exogenous independent variable: Other network	Exogenous independent variable: actor attributes
	Actor j has a tie to actor i. That is, they are more likely to be engaged in mutual collaboration rather than chain-of-command unidirectional interactions	If actor j has a tie to actor i, it is more likely that they are engaged in a second type of relationship as well.	If actor j has a tie to actor i and they both share a common attribute, they are more likely to engage in mutual collaboration.
	If actor j has a tie with actor k, it is more likely that actor j has a tie with actor i as well.	If actor j has a tie with actor k, it is more likely that actor j has a tie with actor i in a different type of relationship.	If actor j has a tie with actor k and they both share a common attribute, it is more likely that actor j has a tie with actor i as well.
	If actor j has a tie with actor k and actor i, it is more likely that actor j has a tie with actor l as well.	If actor j has a tie with actor k and actor i, it is more likely that actor j has a tie with actor l in a different type of relationship.	If actor j has a tie with actor k and actor i and all share a common attribute, it is more likely that actor j has a tie with actor as well.
	If actor j has a tie with actor k and actor i has a tie with actor k, it is more likely that actor k has a tie to i as well. That is, they are more likely to collaborate in embedded triangles than in mutually isolated dyads or unidirectional interactions.	If actor j has a tie with actor k and actor i has a tie with actor k, it is more likely that actor k has a tie to actor i in a different type of relationship. That is, they are more likely to collaborate in embedded triangles by generalized exchange through different types of relationship.	If actor j has a tie with actor k, actor i has a tie with actor k, and actors i, j, and k all share a common attribute, it is more likely that they collaborate in embedded triangles than in mutually isolated dyads.
	How many different triangles do actor i and j, connected by an edge, have together? That means that greater the number of triangles the more network partners they share.	How many different triangles do actor i and j, connected by an edge, have together, considering different network types? That means that greater the number of triangles the more network partner they share.	How many different triangles do actor i and j, connected by an edge and sharing a common attribute, have together? That means j and i share more network partners, which is caused by attributes of the actors.
	How many different two-paths connect two independent nodes?	How many different two-paths connect two independent nodes considering different network types as well?	How many different two-paths are connecting two independent nodes with the same attributes?

Source: own demonstration, following Contractor, N. (1999) and Snijders et al. (2004).

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