Proposal for a ABM Research Grant

-Draft-

Modelling the Development and Evolution of Business Relations and Networks as Complex Adaptive Systems using Agent-Based Models

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1 Project Outline

A synthesis of existing and current techniques in computer intensive simulation and statistical network analysis is proposed in order to address the lack of data and theory about the development of business relationships and networks over time. While there is a considerable body of literature on the static analysis of networks in marketing, large scale longitudinal data is hardly available and as a consequence our theory and knowledge about the development of business networks is only rudimentary.

Admittedly, convention suggests a straight forward way to remedy this deficit: Collect data and run an exploratory analysis. But practical constraints render this approach highly problematic. The costs and efforts of a simple static analysis of business networks are already quite high, so that they can only be overcome by joint efforts (e.g. Axelsson & Easton (1992)). Extending such an approach to a longitudinal study appears to be cumbersome at best, demanding high stakes with only a vague and uncertain promise of success. Certainly, it is beyond the scope of a single, three-year research project.

As alternative solution, I intend to build an agent-based computer simulation which captures the crucial traits of organizational interaction in the context of a business network. The simulation will provide comprehensive data about the system's development over time will be analysed with tools of statistical network analysis, at a level of detail exceeding the prospects for any empirical study. The results can be used to sharpen our intuitions about the development of complex network structures and provide a conceptual basis for subsequent empirical studies. Concretely, this research project will provide a classification scheme for the dynamics which can be expected in systems structurally similar to that of business networks. It will provide helpful insights likewise to academics and managers.

2 Networks

The analysis of networks has been drawing considerable public attention through recent years, receiving a tremendous boost with the emergence of the so-called Web 2.0 and social networking sites such as Facebook or LinkedIn. Remarkably enough, academic research has preceded the recent hype by decades: Early traces of the scientific analysis of social networks lead back to the 1930's, referring to contributions by Jacob L. Moreno and W. Lloyd Warner (Freeman, 2004). In the 1960's various research groups appeared who dedicated their efforts to the examination of social networks. Famous results of that time are Stanley Milgram's theory about *six degrees of separation* (Milgram, 1967) and the conceptualization of the *strength of weak ties* (Granovetter, 1973).

Recently, many stochastic and mathematical models have gained popularity. A main discovery was that patterns frequently found in real life networks can be reproduced on the basis of rather simple rules. Small-world networks show that networks with short average paths between any two members can be easily constructed by adding just a small number of cross-group connections to an initially barely connected ring of neighbours (Watts, 1999). Scale-free networks exhibit a distribution of connections which can be described as a power law function (Barabási & Albert, 1999). A characteristic which has since been attested to social, biological as well as computer networks.

These developments have not left the domain of marketing unaffected. Iacobucci (1996) collects a series of articles which analyse the relevance and effects of network structures in the field of marketing. She gives a very simple definition of the subject: A network describes a collection of actors (which can be persons, departments, firms, countries, and other entities) and their "structural connections" (in her words: familial, social, communicative, financial, strategic, business alliances, etc.). Following this very generic characterization, we encounter a potential case for network analysis, whenever interaction between actors occurs. In fact, the idea is so general, only a few constituents of marketing, of human life in general might escape it. Iacobucci summarizes this rather charmingly in the syllogism (Iacobucci, 1996, p. xii):

· Much of marketing is relational.

· Networks are an excellent means of studying relational phenomena.

∴ Networks are an excellent means to study much of marketing.

The above notion is certainly very compendious, and it may appear to be harmless and unproblematic as it only reflects generic everyday views. But the subject network analysis is far more controversial, as it challenges wide spread positivist notions of science. In the same volume, Galaskiewicz (1996, p. 20-21) specifies the nature of social network analysis in greater detail. He argues that social relationships can be aggregated into something which is more than the sum of the parts. The combination of many dyadic social relationships establish a new, meaningful social fact, which is worthy of study on its own right. Additionally, he reminds us to be aware that this is not trivial. It presumes that some social entity can exist without the actors who are part of that entity agreeing on its boundaries, recognizing it as a meaningful reality, or even realizing that the entity exists.

The importance of networks in the social sciences is even more strongly emphasized by Granovetter (1985): While network analysis in the above sense might still pass as an interesting, but not fundamental supplement to main stream social sciences, he argues that the understanding of an actor's environment is a necessary requirement to understand this actor's behaviour. It is impossible to understand an actors' behaviour without understanding the relational context in which it operates, and this is the myriad social relationships that natural persons as well as corporate actors are embedded in.

The vantages of business networks have been discussed widely in the marketing and management literature. Commonly they are seen as an alternative mode of organization, bridging the gap between integration and free market solutions. Competitive advantages can be realized in business networks, combining economies of scale, specialization and reduced transaction costs (Jarillo, 1988). A central assumption in these approaches is the existence of a powerful hub, a member of the network who controls its structure and functions.

Wilkinson (2006) questions the practicability of such central coordination. It might well be the case that individual firms attempt to organize and direct the networks of which they are a part. But he reasons that it is nearly impossible to predict all effects which an action can have on the system. Deliberate manipulations of the network's structure will only add to its complexity. All firms in a network are more or less interdependent, therefore all of them have some degree of power and influence.

> [...] interactions produce, reproduce or change the parts, the firms and other organizations involved in business markets and the way they are interconnected. In an important sense people and firms do not manage these interactions and networks of interactions within and across firm boundaries - the interactions "manage" them. (Wilkinson, 2006, p. 458)

Wilkinson's position is deeply rooted in the tradition of the Industrial Marketing and Purchasing (IMP) group, which has emphasized the importance of networks especially in the field of industrial marketing for more than 30 years. McLoughlin & Horan (2002) picture the historical development of this approach: During the early beginnings the group's major concern was the study of trade between two active partners, including dimensions such as the strength and duration of a business relationship, as well as the impact of negotiations on several organizational levels. They also accounted for dynamical aspects in such a relationship, admitting that its nature is likely to be changed by the parties involved, for reasons of economy, security, quality assurance, or technological advantage. The foundations for this approach are outlined in Håkansson & Östberg (1975) and Håkansson, Johanson and Wootz (1976).

On this basis, as series of comparative national studies was conducted, spreading the IMP thought all over Europe. The results supported Håkansson's initial standpoint: Industrial marketing was found to be highly interactive and to a large extend based on dynamically developing long-term relationships. Axelsson & Easton (1992) give a comprehensive summary of their results. An extended and more carefully articulated version of this concept can be found in Håkansson & Snehota (1995).

A distinguishing feature of the IMP tradition is that it does not consider a network as an imposed structure of some sort of dominant organization. Instead, the network defines a point of view to capture the multitude of direct and indirect relationships between firms and companies. The governance itself is achieved through relationships, linking organizations, and the network is the way to understand the overall system of interconnected relationships. Networks are formed through the enactment of selective ties and relationships between otherwise autonomous actors. The IMP group explicitly assumes that both buyers and sellers are active participants in the exchange process, which implies that partners in trade are aware of their shared history and have individual expectations about future outcomes. Accordingly the entire analysis has to take into account that there is a temporal dimension to motivate and understand exchanges (Araujo, 1999).

Wilkinson (2001) describes the current state of research very pointedly: The methods currently available allow us in principle to unpack any given business network's structure, classify its constituents and identify the efficiencies underlying the division of tasks and activities within and between firms. Accordingly, we can study the economies of specialization and aggregation, motivating the relations which form the network. But this only describes the networks for a set point in time, assuming an inherent disposition to change. As I have argued, the value of such an analysis is limited. Static models are a widely accepted method in the social sciences. But this is more due to the lack of data for dynamic analysis then a conceptual prerequisite.

3 Complex Adaptive Systems

In the proposed research project, I want to focus explicitly on the dynamics networks and develop a tool to gain an intuition about the regularities which govern the development of business networks as a whole. The core idea is that the network can be seen as a complex adaptive system which customarily is analysed by means of computer simulations.

The term complex adaptive systems (CAS) was coined at the interdisciplinary Santa Fe Institute, by John H. Holland, Murray Gell-Mann and others (Holland, 1998). In general we speak of a system if a phenomenon can be analysed on different levels, such as the micro/unit-level and the aggregated or macro-level. Crucial for *complex* systems is that the rules which govern the behaviour on any of these levels are qualitatively different from the rules on other levels (Viscek, 2002). The behaviour on the aggregated level is more than just a simple sum of its parts.

Adaptivity is merely a means to an end. Following the characterization of Gross & Blasius (2008), adaptivity can be seen as a mechanism that frequently induces complexity. Basically, adaptivity describes a feedback mechanism between different levels of a system. Changes on one level of the system effect the structure of another, which can lead to a recurring cycle of action and adaption on both levels.

As illustrative example Gross & Blasius (2008) use a system of roads: If traffic congestions are common on a given road, this is likely to lead to new roads being built, in order to unburden the first. The structure of the whole system changes and on the micro level, traffic will adapt to the changes, making use of the new roads. This adapted behavior might again lead to new congestions at unexpected points, like feeder roads or hubs. We see that there is a direct feedback mechanism which connects the micro state (traffic flow) and macro topology (roads) of the network, top-down as well as bottom-up.

Furthermore Gross & Blasius (2008) specify certain dynamical phenomena which are commonly observed in adaptive systems: They show robust dynamical self-organization and it has often been observed that different classes of nodes emerge spontaneously from initially inhomogeneous populations. Most importantly adaptive systems express complex mutual dynamics in state and topology, so adaptivity can be seen as an important antecedent to complexity.

The phenomenon of complexity has been of interest in many disciplines from physics to linguistics, but so far this has not led to a unifying theory. Viscek (2002) argues that the rising interest in complexity is symptomatic for an ongoing shift of the focus of research:

> In the past, mankind has learned to understand reality through simplification and analysis. [...] This is the world of Newtonian mechanics, and it ignores a huge number of other, simultaneously acting factors. [...] In complex systems, we accept that processes that occur simultaneously on different scales or levels are important, and the intricate behavior of the whole system depends on its

units in a nontrivial way. Here, the description of the entire system's behavior requires a qualitatively new theory, because the laws that describe its behavior are qualitatively different from those that govern its individual units.

3.1 Dynamic Business Networks

I propose to examine business networks in the light of complex adaptive systems. In this, I mainly follow the rationale provided by Wilkinson (2006). As the previous description suggests, business networks might well be characterized as complex systems: We can assume there are rules which govern the behaviour of singular units of the network - this has been the rationale for decades of research in economics, marketing, management and related fields. It seems reasonable to assume that the rules which govern the behaviour of individual players are not same as the rules which govern the network structure. While e.g. the maximization of profit is commonly assumed to be a key variable which determines the former, the numerous interactions and interdependencies on the aggregated level seem reason enough to preclude such a simple explanation in the latter.

Furthermore, it is reasonable to assume that this complexity is to great extent the result of a feedback mechanism between the operating companies and the structure they are embedded in. Companies create the network's connections bottom-up, in a self-organizing way, but the structure of the network affects the behaviour of the parties involved. Companies usually interact with companies of which they are at least aware of, have existing relationships or previously dealt with. Yet again, connections can also be changed, old connections can be ended, new acquaintances can be made. This constitutes a complete feedback loop from units to structure and from structure to units. The network emerges, influences micro behaviour, but it is not fixed and affected by the the processes on the micro-level.

In conclusion it appears reasonable to claim, business networks have the nature of adaptive systems as well. Business networks are complex adaptive systems.

Comprehensive examinations of static networks can give us an overview of a networks structure, and focussed studies of the development of dyadic relationships can give us a limited insight in the dynamics of some parts of the network, but neither can provide a general overview of the entire system's interdependent dynamics. In order to gain insights into the development of entire business networks, I want to employ tools which have proven promising in dealing with complexity: computer simulations.

3.2 Analysis of Complexity

Complex systems are characterized in particular by their non-linear behaviour, which makes them generally hard to trace down with common linear tools of analysis. As an alternative solution Miller & Page (2007) illustrate the merits of computer simulations in this area, highlighting especially agent-based models as feasible means to explore complex adaptive phenomena. Admittedly, this approach is still rather uncommon in the field of marketing, therefore I will use this section to give a brief introduction, before I outline the approach which I intend to pursue.

The literature on complex systems usually focusses on so-called *attractor states*: The system can be in a state of transfixed stability, complete chaos or in between in a dynamic equilibrium. In such an equilibrium, the dynamics continue, but they exhibit patterns and statistical regularities. The latter is naturally the most interesting case, as it allows for the next step: inferring the regularities of the system in focus. It is then the scientists' concern to analyse the given attractor states and determine the conditions which lead to their emergence; be it the chaotic attractor in which the system is in a constant flux with no discernible pattern, or a more structured attractor (Kauffman, 1992; Morgan, 1997; Holland, 1998).

Despite recently increased efforts, the scientific exploration of complex phenomena is still at an early stage of development thus mostly of exploratory nature. A commonly applied tool in the analysis of complexity are computer simulations, especially agent-based modelling. Generally, these models simulate a simplified micro structure of a complex system, together with mechanisms which allow the formation of the macro level, solely on the basis of low-level interactions. This construct is then used to explore emergent effects on the entire system, giving the researcher the opportunity to study the system even *beyond the often highly accidental set of entities that nature happened to leave around for us to study* (Langton, 1996, p. iv).

Gilbert & Troitzsch (2005) provide an overview of this emerging field of science. Their perspective is that simulation is a particular way to build a model, "a well-recognized way of understanding the world". In general terms a model is a simplification of some other structure or system, it is smaller, less detailed, less complex, or all of that together. The goal of simulation is to create a model of the phenomenon of interest which is simpler to study than the target itself. They argue that simulation is akin to experimental methodology: The most common approach is to set up a simulation model and then execute it many times, varying the conditions in which it runs and thus exploring the effects of different parameters. The crucial difference between simulation and experiments though, is that in an experiment the actual object of interest is controlled whereas in a simulation one is experimenting with a synthetic model rather than the phenomenon itself. Simulations give the researcher a large extent of control: Parameters and initial conditions can be varied systematically and their behaviour can be monitored down to the last detail. This combination qualifies simulations prominently for the analysis of complex systems which would otherwise be impenetrable with our present means of analysis. The rationale behind this approach is that the conclusions drawn about the model will to some degree also apply to the real life system because the two are *sufficiently similar*.

During the last decades, this approach has also found many applications in the social sciences, ranging from anthropology to economics (Kohler & Gumerman, 2000; Tesfatsion & Judd, 2006). The Journal of Artificial Societies and Social Simulation provides a centralized and well renowned portal for academic discussion, and slowly but steadily simulation-based publications appear in first tier journals, e.g. LeBaron & Tesfatsion (2008) and other journals devote entire special issues to the subject (e.g. Computational Economics (2001), The Journal of Economic Dynamics and Control (2004)).

Regarding business networks, several approaches have already been undertaken to study them with the aid of simulation: Wilkinson, Wiley and Lin (2000) use the N-K model of Kauffman (1992, 1995) to simulate the effects of the structural balance assumption, which means that triples of players attempt to exclusively like or dislike each other, but want to avoid the intermixture of these states in their triadic relationships. Wilkinson, Young and Ladley (2007) use a self-learning algorithm to assess the evolution of cooperation in Prisoner's Dilemma setups, comparing the effects of individual versus group selection.

My simulation is supposed to cover a middle ground, following the multi-agent approach. I intend to construct agents which can imitate key features of business behaviour. They act and interact autonomously, following their own objectives on the basis of individual "knowledge" about the world. While they are not as simple as the cells in the N-K model, they will not be able to develop new rules of behaviour on their own. Except for the agents' actual interactions, all mechanisms and parameters in the simulation will be known and the system's development can be monitored down to the last detail. On the basis of micro-interactions which resemble the real-life processes closely enough, I intend to use this rich source of data and control to gain insights into the development of business network, which can otherwise not be attained.

4 Methodology

Agent-based modelling is a subclass of simulation techniques which have gained in importance in the social sciences in recent years. Multi-agent systems were developed in the early 1990s, borrowing techniques from nonlinear dynamics and artificial intelligence. According to Gilbert & Troitzsch (2005), especially their promise of simulating autonomous individuals as well as their interactions strongly increased the interest in simulation as a scientific method. A distinctive feature of agent-based models is that they are "bottom-up": The agents interact "intelligently" with their environment on basis of internal states and processes. On the basis of these interactive, yet autonomous micro processes the researcher expects to examine emergent behaviour on the aggregated system level. The term emergence is commonly used to describe macro behaviour which arises not from superposition, but from interaction at the micro level (Marks, 2007).

An early, yet popular, agent-based model is Sugarscape by Epstein & Axtell (1996). It explores the evolution of a society of ant-like agents, on a grid of inhomogeneous food sources. Although there have been elaborate refinements applied to the model, in order to explore more intricate details of the population, one emergent property of the simple baseline variant was that an initially uniform distribution of "wealth" quickly changes to a strongly skewed distribution, reflecting the agents' level of fitness.

Terna (2001) clarifies the distinctive features of agent-based approaches compared to other scientific schools of thought: Opposed to organicism, agent-based models assume that there are relatively simple structures at the agents' level which are able to reproduce the complexity of reality. Contrasting to methodological individualism, ABM does not attempt to reproduce the complexity of the system directly in the agents, the agents are simpler not overburdened with knowledge and abilities. The focus of agent-based models lies on the interactions which generate complexity. All in agreement with the central thesis in Epstein & Axtell

(1996): simple entities, interacting through simple, local rules can produce very complicated behaviour.

4.1 Epistemological Status

But what can we learn from computer simulations? Or to phrase this question more elaborately: What is the epistemological status of results stemming from computer simulation studies? Many scholars have debated about this issue, paying tribute to the facts that all results are based on artificial data, created in a computer, on the basis of more or less arbitrary rules, with the explicit purpose of leading to emergent results that cannot be traced back to the original rules by common linear, analytic means.

On this background Axelrod (1997) coined the famous expression *simulation is a third way of doing science*. It is a combination of both classical ways of learning about the world: Deduction and induction. Simulations are strictly deductive in the sense that they take their initial setup, agent design, parameters, a set of random numbers (if necessary) and calculate the final outcome through mathematical operations. Only if we make changes to this set of explicit assumptions (especially using another random seed), will we receive different results. But unlike deduction, simulations do not derive theorems. Simulations generate data which can then be analysed inductively, generally using the same tools which are usually applied in the analysis of empirical data. The crucial difference to induction is that the modeller knows exactly on which set of rules each of his results are based. Axelrod (1997, p. 25) continues:

> While induction can be used to find patterns in data, and deduction can be used to find consequences of assumptions, simulation modelling can be used as an aid intuition. Simulation is a way of doing thought experiments. While the assumptions may be simple, the consequences may not be at all obvious.

Epstein (2006) uses the concept of *explanatory candidacy* to illustrate this topic: There can be several theories and models which explain a given phenomenon. A simulation which reproduces that specific regularity provides us with *an* explanation. In general, simulation does not provide the means to guarantee that this is the only, or even true, explanation. Explanatory candidates can be seen on a level similar to hypotheses, both can be falsified by means of statistical tests - but the computer-assisted and logically correct deduction process in simulations can at least guarantee that the falsification will not just uncover human error in the reasoning process.

Unfortunately, the conjunctive nature of simulation models complicates this procedure: If a model does not exhibit the desired behaviour, only the conjunction of all parameters and configurations can be discarded. But the modeller faces a high-dimensional space of conditions, with no guarantee of continuity, and possibly a large number of non-linear interactions among elements. Generally, this problem is addressed by extensive numbers of simulation runs, exploring the parameter space on the basis of efficient experimental designs and optimization techniques.

Considering the scarcity of longitudinal data about the development of business networks, I think such a computer assisted thought experiment provides a feasible alternative to gain some primary insights into their development over time. We can refine our intuition about the phenomenon and use the simulation's insights as a guideline for subsequent empirical studies.

4.2 Validation

A heavily debated issue in the simulation community is the appropriate way to validate a simulation model. As of now, no undisputed concept has been found. Validation can be seen as the assessment of similarity between the simulation and the real phenomenon. In the classical sense, a model's structural validity is provided if *it truly reflects the way in which the real system operates to produce this behaviour* (Zeigler, 1976). But many scholars argue that this classical concept is not an adequate measure for validity of simulations. Küppers & Lenhard (2005) reason, that the goal of simulation is not to analyse the real system, but to imitate it, and learn from this imitation because we have more extensive control over it. Therefore the assessment of validity of a simulation needs to be adjusted.

One recurring thought is that the validity of simulations cannot be assessed on a theoretical basis, it needs to be tested empirically, on the basis of data. Marks (2007) provides a basis for a more formalized assessment of simulation validity. On the basis of set theory, he compares the set of empirically observed behaviour to the set of behaviour displayed by the simulation. But, he argues, we must judge validity with respect to a simulation's goal. Depending on whether this goal is exploration, prediction or explanation, the desirable relation between simulation behaviour and empirical data differs. Generally speaking he says *a good simulation is one that achieves its aim.*

Conceptually, my proposed aim is the exploration of an empirical phenomenon, namely the development of business relationships. According to Marks (2007) exploratory simulation studies try to answer questions like: Under what conditions does it change to another general form of behaviour? Just what ranges of behaviour can the system generate? How sensitive is the model behaviour (and hopefully the real-world behaviour) to changes in the behaviour of a single actor, or of all actors, or of the limits of interactions between players? In his framework the appropriate relation of an exploratory simulation's results to real life data is the so-called *incomplete case*: With a given parameter constellation the simulation should only exhibit a certain subset of the empirically observed behaviour. In this sense, the representation of the real world is incomplete. The idea of an exploratory model is then to change the underlying assumptions (i.e. parameters), and examine how and when the simulation's macro-behaviour changes, like *a searchlight might pick out objects of interest flying across the night sky* (Marks, 2007, p. 276).

From a theory perspective, simulations do not require a realistic agent design, whatever leads to the desired behaviour provides a possible explanation. Considering the scarcity of longitudinal data on business networks, it appears to be feasible though, to build agents whose behaviour can also, to some degree be validated on the micro level, so that it is easier to relate values of simulations parameters to certain conditions in real life. The main criterion for micro validation would then be how closely the simulated agents imitate real actors' behaviour. To some extent, it might be possible to assess this micro validity quantitatively but I expect to draw on theory driven and qualitative validation methods to the largest extent.

Macro-validation certainly is a necessary requirement and particularly difficult under the given circumstances. Lacking the data, it is not possible to validate the network's dynamics - but static characteristics of the network's topology can be compared with those of previously conducted empirical examinations of real-life business networks. The minimum requirement for this approach is to find an existing case which has been described in detail at two points in time. The case could be drawn e.g. from the IMP group's existing collection of studies, but a suitable case has yet to be determined. Then the simulation can be assessed by determining whether there are settings under which the simulated network reproduces all of the empirically observed states in succession.

Parallel to the simulation's macro-validation, this approach offers the opportunity to conduct an explanatory analysis for the specific real life case. It would then be my goal to determine all sets of parameters which produce the target behaviour, which necessitates to explore the model's entire parameter space. The resulting overview of possible explanations will also provide a means to assess the robustness of a given phenomenon.

This approach is in agreement with the recommendations for explanatory simulations in Moss & Edmonds (2005). They classify the various levels of agreement of simulation with empirical data:

- *Level 0:* The model is a caricature of reality, as established through the use of simple graphical devices.
- *Level 1:* The model is in qualitative agreement with empirical macro-structures (e.g. distributional properties of the agent population)
- *Level 2:* The model produces quantitative agreement with empirical macro-structures, established through statistical estimation routines
- *Level 3:* The model exhibits quantitative agreement with empirical micro-structures, determined from cross-sectional and longitudinal analysis.

Nevertheless, they emphasize, there will always be an element of surprise owed to emergent nature of the processes, so that commonly only *stylized facts* (Kaldor, 1961) can be used to assess the qualitative agreement with empirical macro-structures.

4.3 Network Statistics

At this stage of research, I cannot say concretely which measures will be used to describe and explore the network. The clear vantage of simulation studies is the sweeping abundance of data, so it is appropriate to postpone this decision, at least until a suitable empirical case has been determined. The constructs reported therein will necessarily be included in the statistics monitored in the simulation. The following outlines summarise tentative tools and techniques which capture important characteristics of networks. As the relative scarcity of dynamical network data goes along with only few measures which assess the dynamics in networks directly, we will have to rely on time series of repeatedly applied, static network statistics:

- *Clustering Coefficient:* It reflects how often the members of the network are connected to "friends of friends", i.e. the relative amount of connected triads in the network. (Watts & Strogatz, 1998).
- *Average Path Length:* Measures the minimum number of players between any pair of members of the network. It is a measure of the efficiency of information or mass transport on a network (Albert & Barabási, 2002).
- *Partitioning:* Statistical clustering algorithms are used to divide the network into segments which represent "natural subsets". These are players well connected among themselves, but at the same time relatively well separated from the others. Girvan & Newman (2002) successfully used this approach to detect community structures in social networks.
- *Degree Distribution:* The degree of a member in the network is the number if his relationships to other members. Accordingly, the degree distribution is the empirical distribution of numbers of connections. Degree distributions are very common measures in network analysis, especially after researchers found out, that many real-life networks' degree distributions have a power-law tail (Albert, Jeong and Barabási, 1999).
- *Centrality:* Measures of centrality can be used to assess the relative importance of players in the network. Betweenness centrality summarizes the extent to which a player is located "between" other pairs of players (Freeman, 1979). The distribution of centrality measures gives a global overview of the network.
- *Network Regression:* One of the more advanced tools in network analysis is network regression. Summarizing all dyadic relations in a network in an adjacency matrix, this approach reconstitutes this matrix as a combination of simpler, archetypical matrices, analogous to classical regression techniques. This approach allows for various hypothesis tests and might offer a way for more rigorous structural analysis (Butts, 2008).
- *Longitudinal Network Models:* The only approach which is aimed explicitly at the dynamics in a network is introduced by Snijders (2005). It represents the evolution of a network as the result of many Markov processes over time. Its actor-oriented variant assumes that the members of the network change their relationships in order to optimize myopic stochastic objective functions. The model estimates these functions' parameters.

4.4 Related Agent-Based Models

There are some agent-based simulation models assessing social behaviour conditional on underlying network structures. While the concrete implementation of my model is still open to debate, I intend to draw as much as possible previously examined mechanisms.

Wilhite (2006) examines the performance of simple barter economies on the basis of different, but fixed network structures. The members of these economies start with an inhomogeneous endowment of two goods and trade with each other consecutively, maximizing a given utility function. The results show, that the network topology is affecting the outcomes significantly. For example, Barabási and Albert's (1999) scale-fee networks prove to be highly efficient performance in all categories under examination. Wilhite (2001, p.62) argues this is an evolutionary advantage of this particular structure *so that natural selection might pick small-world networks as efficient structures when search and negotiation accounts for a non-trivial portion of transaction costs.* Certainly it would be interesting to check this proposition in a more realistic simulation, such as the approach envisioned here.

Other papers examine the impact of network structures on cooperation in the game theoretic framework. The Iterated Prisoner's Dilemma serves as a basis for simulations e.g. in Ashlock *et al.* (1996) and Hanaki *et al.* (2007). The former uses a threshold model of expected payoffs which allows agents to select with whom they will cooperate. Their findings show, that the emergence of cooperative behaviour is faster in a setting where choice and refusal of partners is possible than without. In fact, when partners are chosen randomly and no refusal is allowed, many simulations never reached full cooperation.

Hanaki *et al.* (2007) extend this approach, studying the coevolution of individual behaviours as well as the interaction structures. They retain the existing network structure and allow the agents to make only one change to their network of relationships at a time. The agent may either terminate a relationship on the basis of myopic cost benefit considerations, or it may propose to create a new relationship, which has to meet the consent of the potential partner. The study examines the effects of two opposing forces in the selection of potential partners: The tridaic closure bias (Rapoport, 1963) reflects the tendency to connect to a friend of a friend. Sheer randomness on the other hand pairs agents drawn from a uniform distribution. For random pairings, the simulation includes a so-called trust parameter. Interestingly enough, their results show, that triadic closure has a negative effect on the average global fraction of cooperators. On the other hand, suspicion i.e. low levels of trust towards potential cooperation partners enhances cooperation. Additionally, their results suggest that the scarcity of a network also has a positive effect on cooperation. The level of cooperation was found to be higher in networks with only few connections.

To my knowledge, Hanaki *et al.* (2007) provides the only attempt simulate the endogenous development of network structures explicitly. But in comparison to their approach, I intend to simulate a model of exchange, not an abstract Prisoner's Dilemma.

5 Research Activities and Schedule

In light of the preceding considerations, simulations appear to be a feasible tool to investigate the dynamics of business networks. But additional literature research will be necessary to provide concrete ways of implementation and to narrow down the scope of examined research questions. In addition to gaining a broader overview over the existing concepts and theories about business relationships and networks in marketing, sociology and management research, it will be necessary to provide the following model constituents:

- Concrete, detailed and iterated case studies suitable for macro validation
- Studies and theories about the dimensions influencing the formation and development of business relationships. Tentatively these are trust and expectation (Jarillo, 1988),
- Models which suggest concrete implementations of these dimensions and especially their interactions.
- Readily implemented exchange simulations which can be extended by the above mentioned dimensions and mechanisms for network formations

Tentatively, the agents' trade behaviour will be modelled through a satisficing process, which depends on existing trade relationships, expectations and trust. Expectations will be formed through the outcomes of direct trades as well as the results of indirect trades with members of an agent's trust network. Trust relations will be formed through a friend-of-friend mechanism, mimicking the triadic closure bias. Initial configurations can either be provided manually, in order to investigate a concrete setting or randomized, or with the help of a random network generator (Albert & Barabási, 2002).

Generally, it would be preferable to dock to an existing agent-based exchange model, replicate its code and compare the results, both, in terms of a replication study and to check for the correct implementation of my model. Only in the subsequent step explicit dimensions and mechanisms to enforce the formation of business relationships will be added, making use of the modular nature of agent-based simulation (Gilbert & Troitzsch, 2005). Gilbert (2004, p. 9) agrees with this concept:

> Often, an effective strategy is to start from a very simple model, which is easy to specify and implement. When one understands this simple model and its dynamics, it can be extended to encompass more features and more complexity. The baseline model can be designed to be the equivalent of a null hypothesis in statistical analysis: a model that is not expected to show the phenomenon in question. Then, if an addition to the baseline model is made and the model behaves differently, one can be sure that it is the addition that has the effect.

A suitable simulation has yet to be determined.

The overall aim of my research project is to describe the dynamics in simulated business networks, leading to the identification of patterns in some or all of the network's dimensions which can be used as a basis for a classification of dynamics. Optimally, the classification can be traced back to the simulation's initial conditions, providing the grounds for causal explanations of the simulation's development. Future research could then use these results and test these new found interrelations empirically.

Additionally, the approach outlined above entails a preceding stage of hypothesis testing. Empirically or theoretically motivated dimensions and mechanisms will provide the necessary micro foundations of the simulation. Accordingly, their implementation, parametrization and interaction will already be subject to testing during the macro-validation phase. Especially the nature of their interactions will be among the hypotheses to test. As outlined above, this stage of analysis will examine whether empirical findings can be reproduced by the simulation, based on at least two assessments of the same real-life business network at different points in time. The model specification itself constitutes a conjunctive hypothesis which is put to test: Can a system of the given composition produce macro behaviour which is in agreement with empirical findings?

The collection of parameter sets which lead to that specific type of macro-behaviour will then be assessed for suitability as explanations for the real life phenomenon and a robustness analysis of the observed outcome outcome can be conducted. This approach will provide explanatory candidates for the empirical reference case and these explanations can in turn be contrasted to any existing explanations of the empirical analysis.

Only when this step of macro validation shows that the simulation replicates stylized empirical findings under reasonable settings, will it be used to explore the possible range of dynamics of a business network. In the next stage the simulation's parameter space will be systematically traversed and the resulting behaviour on the aggregate network level classified.

The proposed approach is exploratory in nature and it is targeted at a field where only small, scattered attempts of study have been undertaken so far. It is not aimed at an exhaustive explanation of the dynamics in business networks, but I expect to find regularities in the simulated data, which can be used to generate hypotheses about the nature of existing networks and give us an intuition on what future empirical research can be targeted.

The outstanding literature review will take approximately two months time, followed by a programming stage of three and model assurance phase of two months. In order to meet this schedule, it will be necessary to hire an external programmer. The simulation and statistical analysis will then be conducted in three months time, and another two months will be necessary to prepare manuscripts for submission.

The results will be summarized in manuscripts for publication in academic journals of several disciplines. Conceptual considerations and abstract results will be relevant to modellers and network analysts, concrete managerial implications will be submitted to journals in marketing and management science.

Assuming that business networks actually exist, i.e. that they are to some degree entities, not just a figure of speech, it seems to be worthwhile to devote some efforts on the exploration of their inherent dynamics.

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