Developing Agent-Based Models of Business Relations and Networks as Complex Adaptive Systems

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Abstract

Business relationships are dynamic, embedded in a larger network of interconnected relationships and they change over time. Current research and theory in marketing give very limited attention the issue of dynamics and change in marketing systems. The dominant variance-based and cross-sectional approaches cannot capture the development of relationships over time; narrative and longitudinal research are usually so data intensive that they have to focus on the development of one relationship, or the interactions between a very small number of them.

From the perspective of complexity theory, business relations and networks can be seen as examples of complex adaptive systems in which the structure and patterns observed on the aggregated, collective level emerge from local, micro interactions over time in a self-organizing manner. Such systems can be modelled and studied using agent-based modelling methods. In order to advance our understanding of the dynamics of business relationships and networks, I propose to build computer models of the key mechanisms that drive the systems’ development.

These mechanisms can be identified in the existing literature, as they are the causal drivers implicit in many existing theories. However, even though we may be able to identify these mechanisms individually, the complexity of their actions and interactions is too high to understand them without assistance.

This report outlines the theoretical basis to develop and evaluate computer simulations of business relationships and networks, in order to better understand the consequences of the mechanisms involved in driving their development. The models to be developed are not meant to capture all the processes and mechanisms of real world business systems, as this would make them just as complicated as reality. Instead, the aim is to simplify and model basic mechanisms and processes underlying the formation and dynamics of business relations and networks, and gain a better and deeper understanding of the way they work and interact. This approach will also yield implications for theory development and future empirical research, as well as implications for managers and policy makers.
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1. Introduction

Business networks contain firms, banks, government agencies and other types of organizations that are linked, directly and indirectly, by interactions, ranging from trade to ownership, R&D alliances, or credit-debt relationships. The importance of such networks is becoming ever more evident. The global financial crisis showed how tightly interwoven and vulnerable the global banking and finance sector has become, and many industries show a trend towards the formation of competing, collaborative and strategic networks (Achrol & Kotler, 1999).

A review of relationship and network research in marketing in the 20th Century (Wilkinson, 2001) and others have pointed to the relatively underdeveloped nature of research regarding the dynamics and evolution of relations and networks. Most research is comparative static in nature and based on surveys of existing relations. Previous research on dynamics and change includes descriptive accounts of patterns of change, case studies of actual relation and network development and some general theories regarding the nature and processes of change. But there are no well developed models of the dynamics.

One way to advance our understanding of the dynamics and evolution of business relations and networks is through building simulation models drawing on recent developments in agent-based modelling (ABM) methods. Such methods are used increasingly to study the behaviour and dynamics of complex systems in various disciplines including economics, management, sociology, biology and engineering; but as of yet have not been used much in marketing.

Business relations and networks are examples of complex adaptive systems, in which the structure and patterns observed on the aggregated, collective level emerge from local, micro interactions over time in a self-organizing manner. Such systems can be modelled and studied using ABM techniques. The models are designed, calibrated and tested based on existing understanding and research regarding the processes and mechanisms involved. The purpose of this research project is to develop and evaluate such models, in order to better understand the consequences of the mechanisms involved in driving change and evolution of relations and networks, and how these mechanisms interact. The models to be developed are not meant to capture all the processes and mechanisms characterizing real world business systems, as this would make them as complicated as reality! Instead, the aim is to simplify and model basic mechanisms and processes underlying the formation and dynamics of business relations and networks, and gain a better and deeper understanding of the way they work and interact. This approach will also yield implications for theory development and future empirical research, as well as implications for managers and policy makers.

In order to give an overview of the envisioned endeavour, this report is structured as follows:
The next section describes the nature and role of business relations and networks in marketing, pointing to the relative lack of research concerning the dynamics and evolution of such systems in the discipline. This leads to a more general review of existing theories and research about the dynamics and evolution of business relations and networks in.

The review is basis for identifying key processes and mechanisms that must be incorporated in any comprehensive model. Section 4 summarises the main characteristics and role of simulation as a way of doing science, focusing in particular on agent-based simulation and modelling, which is distinguished from other types of simulations. Section 5 reviews existing computer simulations and models concerning aspects of relations and networks across a number of disciplines, including models of relations and networks in business, economic, social, biological, technical and abstract systems, in order to identify how the different types of mechanisms and processes have been and can be modelled. This review also indicates where additional modelling efforts are required to capture relevant mechanisms and processes.

Finally we describe our approach to model building which involves starting with simple or toy models of key mechanisms, investigating their behaviour and then combining them in a modular fashion into more comprehensive models. As part of this we describe some preliminary models that have been developed or are in the process of being implemented. This report concludes by outlining the future steps of model building and evaluation.
2. The Networks Perspective in Marketing

A firm, clearly, is not an island; it is embedded in a set of ongoing business, professional and personal relations that shape and are shaped by its actions and responses.

(Wilkinson, 2008, p. 1)

In recent years many scholars have paid attention to relational aspects in the discipline of marketing, including concepts like relationship marketing, supply chain management, customer relationship marketing, networking, partnering, strategic alliances, collaborative strategies, co-opetition, co-creation of value and the like. Our research focuses on relations in a particular context, the nature, role and development of relations between firms in business networks. Wilkinson (2008) offers the definition of a relationship as an interconnected set of transactions over time, involving at least two people. In this section I summarise existing research and theory in marketing concerning the nature and role of business relations and networks. I start with the work of the Industrial Marketing and Purchasing Group, because they took a leading role in the development of a network perspective business marketing.

2.1. Industrial Marketing and Purchasing Group

The IMP group has been among the main driving forces in the development of a relationship and network view in marketing and business. And it has been doing so for more than three decades. I begin by outlining their view of markets-as-networks, before reviewing other related research in this area.

Through a series of case studies and international collaborative surveys of domestic and international relations and networks in business markets, they have developed a rich set of concepts to highlight, describe and understand business relations and networks in marketing. From their perspective, all firms are involved in relations internally and with other firms and organizations. These relations are interconnected, embedded in networks of relations. Business is to a large extent conducted in the context of ongoing business relations with customer organizations, suppliers, distributors, technology partners, complementors, government organizations and others, some of which may have lasted many years. Through business relations and networks key resources are accessed, co-created, combined and used, including products and services, information and material resources. They are also the means by which value is created and delivered to customers.
Early developments began in Europe in the 1970s, led by researchers who were dissatisfied with the dominant marketing paradigm of the time, which focused on consumer goods and adopted a more stimulus-response, arms-length approach to the customer with the seller as the active party (Wilkinson, 2001). Their perception was that buyers in industrial markets are just as active as the sellers, as they seek out solutions for particular problems or invite tenders (McLoughlin & Horan, 2002). Instead of an anonymous mass market, the dominant form of business in industrial markets involves only a small number of often known organizations, where adaptations between buyers and sellers are common (Håkansson, 1982; Turnbull & Valla, 1986; Hallén et al., 1991).

It became apparent through their research that business relationships do not exist in isolation but are embedded in a wider network of interdependent relationships. A network of interconnected relationships were found to influence individual relationships and firm behaviour and performance in various ways. This lead to a broader network focus and the notion of markets-as-networks (Mattsson, 1997). Connections between relations became a central issue, as well as the structure and operation of the business network as a whole (e.g. Anderson et al., 1994).

In principle, the chain of connectedness is without limits and can span over several relationships that are (indirectly) connected. So the connectedness is not only important between relationships of a given company but between relationships of different companies. […] Generalized connectedness of business relationships implies existence of an aggregated structure, a form of organization that we have chosen to qualify as a network.

(Håkansson & Snehota, 1995, p. 19)

The market-as-networks view has two distinctive characteristics regarding the use and understanding of the term “network”. First, networks are not seen as a governance structure in the sense of a structure imposed or a technique followed by a dominant organization, in order to control and organize the other members of its network, as implied in other uses of the term (e.g. Coviello et al., 2002). Rather, the network is a way to understand the generalized connectedness that links organizations via relationships directly and indirectly. Networks are not under the control of individual firms, though some may exert more influence than others. Moreover, it has been argued that the multiple interactions and feedback effects in networks leads to a complexity that makes it very difficult to predict the effects of deliberate manipulations and attempts of network management by individual actors (Wilkinson & Young, 2002, 2005, e.g.) Second, networks are not seen as a-priori structures imposed on organizations, but
are seen as formed through the actions and interactions over time of actors involved, conti-
ually being made and remade (or not) through ongoing structuring and restructuring processes (McLoughlin & Horan, 2002).

Figure 1: Business relationships as elements of a network structure; from Hakansson and Sne-

The focus of IMP thinking is on business markets and may be distinguished from alternative views of relationship marketing that focus on the business strategies of firms in consumer markets. Mattsson (1997) distinguishes three levels of analysis. First and lowest, the micro-
level of dyadic relationships, second, the meso-level which describes subsets of a network or net, which refers to the relations in which a focal firm is directly involved, and third, the macro-level which considers the overall networks. Relationship marketing focuses attention on the first and second levels only and views the relations as more the subject of seller control and management (e.g. Sheth & Parvatiyar, 1999; Payne & Frow, 2005)

Another core element of the markets-as-networks framework is the understanding that time plays a central role in explaining and understanding exchange. First, buyers and sellers ac-
tively take into account what has happened before (shadow of the past) and they also form plans and have expectations of what is likely to happen in the future (shadow of the future), both of which affect their decisions in the present (Araujo, 1999). Second, relationships are seen as inherently dynamic as they are formed through the economic and social interactions taking place among firms over time. Third, relations are connected to other relations leading to flow on effects, adaptations and feedback effects in the larger network of which relations are a part.

The IMP group conceptualises the dimensions of relations in terms of four interconnected elements - actors, activities, resources and ideas. Actors are the individuals and organizations involved in a relationship. They perceive and respond to each other both professionally and socially. So-called actor bonds describe the perception of identities in relation to each other,
and to third parties, they influence how actors interpret situations and how they respond to them. They include dimensions such as power-dependence, trust, commitment, antagonism and cooperativeness. Actor bonds arise between actors over time, and are adapted mutually, changing their strength and nature, giving rise to a relationship atmosphere. Activity links refer to all the activities undertaken within and between firms, including economic, technical, administrative or operational activities. These, too, are subject to mutual adaptations as the relationship progresses over time. Individual companies have access to a certain set of resources. Through relationships, resource ties can be established that allow companies to access each other’s resources, as they carry out their activities. Adaptations, transformations and the creation of new resources occur (Håkansson & Snehota, 1995). As a fourth dimension, ideas or schemas were introduced by Welch & Wilkinson (2002), after they realized that meanings, logics, norms, paradigms, cognitive maps, ideologies, mental models etc., in short, ideas were another dimension in relationships not included in the first three. Others have suggested the concept of network pictures to refer to the way firms perceive the network, which is a similar notion (Ford et al., 2003). These elements of shared cognition interact with the other three dimensions in shaping the development of a relationship. Table 1 summarizes these four elements and matches them to the three levels of analysis in the IMP framework.

### 2.2. Other Research and Theory about Business Relations and Networks

Various other streams of research have analysed aspects of business relations and networks. Wilkinson (2001) traces the developments in this area throughout the entire last century. Wroe Alderson was the first to develop and integrative socio-economic theory of marketing systems, combining concepts from economics, especially transaction cost theory, and behavioural dimensions (Alderson, 1950). McCammon Jr. (1963) brought together research and concepts from various behavioural sciences to conceptualize the processes of change taking place in channel systems. McCammon Jr. & Little (1965) added political and social dimensions to a

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<th>Company structure</th>
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<th>Network structure</th>
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<td>Schema</td>
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Table 1: The AARI Scheme of Analysis; from Welch and Wilkinson (2002)
framework of channel behaviour. Both of these describe how non-economic relations among organizations have an impact on exchange relations. This led on to research focusing on the behavioural dimensions of relations, particular in marketing channels, which are a form of network. The watershed book was Stern’s edited collection of essays and published papers in 1969.

The issue of channel control and power gained much attention from the late 1960s on. Power, conflict and communication were identified as key dimensions of relations among firms (Stern, 1969; Bucklin, 1970). Stern introduced theories from sociology, social psychology and politics to the area of channel networks and triggered a series of empirical studies to test the resulting theories and hypotheses. In these early years, the main research focus lay on the concepts of power-dependence and conflict (Gaski, 1984). Most of these early studies were based on surveys, often by mail, perhaps preceded by some exploratory interviews to develop the research instruments.

Along with advances in measurement methodologies and modelling (e.g. structural equation modelling) researchers began to investigate the connections between a wider range of constructs. Many dimensions of interfirm relations could now be measured on scales with acceptable psychometric properties, and in parallel, theory was developed that integrated them into more comprehensive models of relationships (e.g. Anderson & Narus, 1990). Many new dimensions were examined in a short period of time, so that (Wilkinson, 2001, p. 33) poignantly describes this stage of research as the *dimension a month club*. From the dominant focus on power-dependence the number of studied dimensions expanded to include satisfaction (e.g. Ruerkert & Churchill, 1984) and fairness (e.g. Anderson & Narus, 1990), continuity (e.g. Ganesan, 1994), communication (e.g. Mohr et al., 1996), formalization and centralization (e.g. Anderson & Narus, 1990), cooperation (e.g. Anderson & Narus, 1990; Heide & John, 1990; Dant & Schul, 1992; Morgan & Hunt, 1994; Andaleeb, 1995; Mohr et al., 1996), trust (e.g. Moorman et al., 1992; Anderson & Barton, 1989; Anderson & Narus, 1990; Bucklin & Sengupta, 1993; Scheer & Stern, 1992; Dant & Schul, 1992; Ganesan, 1994; Morgan & Hunt, 1994; Kumar et al., 1995; Doney & Cannon, 1997) and commitment (e.g. Anderson & Barton, 1989; Anderson & Weitz, 1992; Heide & John, 1990; Morgan & Hunt, 1994; Gundlach et al., 1995; Kumar et al., 1995; Geyskens et al., 1996; Mohr et al., 1996).

In addition, dimensions of the environments in which relationships exist were conceptualized and examined in greater detail (e.g. Achrol & Stern, 1988; Dwyer & Oh, 1987; Webster, 1992; Achrol & Kotler, 1999). Attention was paid to the ways companies act in, and deal with, networks of relations. Theoretical foundations were laid by Anderson et al. (1994); Achrol (1997); Achrol & Kotler (1999); Håkansson & Snehota (1995) and Iacobucci (1996). These
led to several models of how to assess relationship portfolios (e.g. Turnbull et al., 1996; Olsen & Ellram, 1997), or the creation of value in a network (e.g. Anderson et al., 1994; Ghosh & John, 1999). Several empirical studies examined the interplay of network dimensions. Studies were conducted for example concerning the connections between relations (e.g. Blankenburg-Holm et al., 1996, 1999) or firms’ network competence (Ritter, 1999).

Most of this research focuses on the interplay of only a few dimensions at a time. Iacobucci & Hibbard (1999) undertook a meta-analysis to consolidate key elements of this plethora of research into one comprehensive overview. Figure 2 summarizes their findings.

In addition to the study of individual dimensions of relations and their links and antecedents, typologies of relationships were derived on the basis of combinations of several underlying dimensions. Cannon & Perreault Jr. (1999) used the dimensions information exchange, operational linkages, legal bonds, cooperation and specific investments by buyers as well as by sellers to find clusters of relationships that resemble each other in these dimensions on the basis of more than 400 buyer-seller relationships. These relationship types showed distinct characteristics along the dimensions availability of alternatives, supply market dynamism, importance and complexity of supply. This led to the identification of eight different relationship types (see Figure 3). Other empirically determined typologies have been reported based on measures of relationship atmosphere, including Young & Wilkinson (1998); Bensaou (1999);
An important theoretical development was the linking of transaction cost analysis (TCA) to the study of relations and networks. Transaction costs are the costs required to organize a transaction, e.g., costs of drafting and negotiating contracts or costs of monitoring and enforcing agreements, which affects the efficiency of different forms of economic organization including within and between firms.

2.3. Lack of Research on Dynamics and Change in Marketing

Most of the research above is comparative-static in nature, relying on cross-sectional data and statistical methods that do not account for temporal developments. Dwyer et al. (1987) called attention to transitions in business relationships as well as their evolution. Nevertheless, almost twenty years later the lack of empirical research was still noted:

Empirical research in relationship management has tended to take a snapshot of a relationship at a given time and attempt to project its trajectory, despite agreement among researchers that a longitudinal perspective focused on process models advances the implications for practice.
Most recently, Dagnino et al. (2008) point out that the existing research on interfirm relations and networks is mainly static, urging researchers to enhance their efforts to understand the dynamics of interfirm relationships. Among the

IMP theory is essentially of a dynamic nature, being based on the interactions taking place between market participants over time and the way this shapes structure and atmosphere. And as noted before, many studies in this tradition rely on narratives methods, focusing on in-depth descriptions of the development of only one, or a small number of, interconnected relationships. Welch et al. (1996, 1998) investigate the effects of network development and facilitation, and Alajoutsijärvi et al. (1999) investigates the relevance of focal nets of cooperation, tracing the developments in three international companies over a period of 30 years. Others not associated with IMP have also reported studies of the evolution of relations. For example, Narayandas & Rangan (2004) compare relationships that are characterized by various degrees of initial power asymmetry and investigate developments regarding interpersonal trust and interorganizational commitment. Buttriss (2009) examines coevolutionary learning and innovation processes as a company explores and adopts e-business solutions, and Huang (2010) the development of various aspects of trust in a relationship.

Stage models are one way researchers have portrayed change in relationships. In these models a pre-determined sequence of stages is proposed to describe the development of business relationships. Such models attempt to capture the essentials of rich process data in simpler accounts of stepwise developments or typical activities. For example, Ford (1980) portrays a business relationship analogously to a life-cycle, categorizing the five stages of a relationship: First, in the pre-relationship stage new potential partners are evaluated. Second in the early stage, negotiation and sample deliveries take place. Third contracts are signed and deliveries are made in the developmental stage. Four, the long term stage is entered after several major purchases. And fifth, in the final stage the relation becomes institutionalized. He identifies critical events that the members of a relationship encounter and defines stages accordingly. Similarly the stage model developed by Wilson (1995) defines stages of partner selection, defining purpose, setting relationship boundaries, creating relationship value and relationship maintenance. The motivation of this model is to provide a framework that allows for constructs to go through active and latent phases of the relationship development. Wilson (1995) maintains that trust is only of importance during the first two stages of a relationship’s development. Dwyer et al. (1987) develop a stage model of a relationship development process. Their stages follow a marriage metaphor, which leads from stages of awareness, exploration, expansion, commitment and dissolution. They also include subprocesses such as attraction,
communication and bargaining, as well as norm and expectation development.

Computer simulations have been used in marketing research and simple computer models of channel systems were already developed in the 1960s, to portray and study the dynamics of the interaction among activities and how this affected performance. Among them are Forrester’s (1961) models of industrial dynamics and models of market processes by Balderston & Hoggatt (1962). Also Bowersox (1972) developed logistics simulation models to understand the dynamics of physical distribution systems. But these models were system dynamics models in which the dynamics of a system is played out under different starting conditions with a fixed structure and parameter values. They do not model changes in structure and organization.

More recently, simulations have been built in terms of NK models, in order to understand the interaction between exchanges in connected relations and the evolution network structure (e.g. Easton et al., 1997, 1999; Wilkinson et al., 2001; Easton et al., 2008). Here N refers to the total number of actors in the network. K refers to the number of connections every actor holds to other actors. Through these connections actors mutually affect their activity on the basis of Boolean rules. The effects of actors and transactions on each other are interpreted in marketing terms and the dynamics and resulting steady state network structures are identified and examined under different conditions. More general models of network relations in channels and the way intermediaries arise have been proposed by Wilkinson (1990). Other simulations have focused on competitive interactions and dynamics including links to chaos theory Hibbert & Wilkinson (1994) and evolving competitive strategies Midgley et al. (1997). Recently Folgesvold & Prenkert (2009) report a simulation model of the fishing industry structure in Norway.

2.4. Theories of Organisation Change in other Disciplines

Additional theories and research regarding organization change (OC) exist in other business disciplines. These are relevant because business relations and networks are forms of organization. Change in this area is often described in one of two different ways: 1) an observed difference over time in an organizational entity on selected dimensions; 2) a narrative describing a sequence of events on how development and change unfold (Poole et al., 2000).

There is an extensive body of theory that has been developed around the subject of change processes. Challenged by the dynamic nature of the subject matter, fundamental ontological questions have been addressed in greater detail in OC theory than in marketing. The perspective on change is essentially influenced by the view of organizations as consisting of things or processes (Tsoukas & Chia, 2002). This distinction goes far beyond organizational studies, and can be traced back to antiquity and the differing philosophies of Democritus and Hera-
clitus (Rescher, 1996). In Democritus’ atomistic world-view, nature is composed of stable material substance or things. The identity or substance of things does not change, only their development and adaptation in relation to other dimensions and properties, like their positioning in space and time. Contrarily, Heraclitus saw nature as a constellation of processes. Enduring things or substances are produced by varied and fluctuating activities. “Process is fundamental: The river is not an object but an ever-changing flow; the sun is not a thing, but a flaming fire. Everything in nature is a matter of process, of activity, of change” (Rescher, 1996, p. 10).

Both perspectives have their proponents in the field of organization studies. On one side Heath & Sitkin (2001) argue that organizations should be studied as social entities, rather than as social processes, pointing to subjects such as identity, structure, culture, and performance that are central to successful organizational enterprise. Processes are important, but ultimately reducible to the action of things. On the other side researchers such as Tsoukas & Chia (2002) describes change as the basic constituent of organizations. In this view, organizations are only reifications of a set of processes that maintain the organization by continuously structuring it and maintaining its boundaries, opposed by other processes that are continuously breaking down the organization and its boundaries. In this view stability and change have the same explanation: If the processes that shape the organization so that it can be reified as the same thing by some observer(s), we speak of stability; change occurs when the processes operate so that the reification is perceived as changing. In both instances, the judgements made by observer’s decide between stability or change, they are not real things (Rescher, 1996). From this perspective Weick (1979) and Tsoukas (2005) argue that the term “organization” is a vacuous, often misleading, reified conception of social action. Organization behaviour can only be understood through processes, such as acts and interactions, movement and change, attributions and justifications, sense-making and sense-giving; substances, entities, and things are secondary conceptual abstractions.

These two perspectives can be seen as complementary, each providing a different - but only partial - understanding of OC. Van de Ven & Poole (2005) develop a typology of approaches for studying OC that accounts for the two competing ontologies, as well as two diverging epistemologies, that rely on what they call either variance- or process methods. Seeing business relationships and networks as inherently dynamic phenomena, that can be understood from an atomistic, as well as a process-oriented perspective, the next section will review Van de Ven and Poole’s typology and see how existent approaches can be classified.

Van de Ven & Poole (2005) make an important distinction between variance theory (Mohr, 1982) methodology, which statistically explains the variance in a dependent variable with a set
of independent variables, and process theory which seeks for explanation in terms of temporal order and the sequence of events presented as a story or historical narrative (Abbott, 1988; Pentland, 1999; Poole et al., 2000; Tsoukas, 2005). Due to the different understanding of what constitutes an explanation, the ways required to generate an explanation differ greatly as well.

Variance methods are typical of much research in marketing, including the dimensions or variables describing different aspects of relations and networks and how they are correlated. Variables are used to identify and measure important aspects or attributes of the subject as variables and derives explanations in the form of causal statements or models that incorporate these variables. However, variance-based methods do not provide direct tests of the existence or relevance of the causalities proposed (Poole et al., 2000) Variance theory relies on the general linear model that is the basis for most statistical methods, such as regression, and factor analysis, ANOVA and structural equation modelling, adequate data is generated through experimental and mostly cross-sectional survey research designs (Van de Ven & Poole, 2005).

Process methods observe temporal progressions, but they generate explanations beyond surface description, identifying generative mechanisms that cause observed events to happen and accounting for the specific circumstances or contingencies that these causal mechanisms operate in (Harre & Madden, 1975; Tsoukas, 1989). The explanations in process theories may incorporate several different types of effects, such as critical events or turning points, different time scales, and causal factors that influence the sequencing of events (Van de Ven & Poole, 2005). A variety of approaches are associated with process methods, including direct observation, archival analysis, or multiple case studies over time. Process methods may derive theory from observation, test hypothesized models of change process, or use abduction or retrodiction (Peirce, 1955). In-depth studies of processes may employ two or even all three of these approaches (Van de Ven & Grazman, 1999; Bartel & Garud, 2004, e.g.), and both qualitative and quantitative approaches are used in process research (Langley, 1999; Poole et al., 2000). The limitations of process methods lie in the richness and complexity of the required analyses. Large amounts of multifaceted data have to be collected and analysed which can be very labour-intensive. Rich accounts of multiple interwoven themes make deriving parsimonious theories a challenging endeavour (Langley, 1999), so that the researcher is in danger of what Pettigrew (1990) termed 'data asphyxiation’. In other words the scope of process methods is limited by the intensity of the process of analysis.

An overview of the distinctive characteristics of variance and process approaches is given in Table 2, which originally appeared in Poole et al. (2000, p. 36).

Combining the two ontological perspectives (atomistic and process views) and the two dis-
Table 2: Comparison of Variance and Process Approaches, from Poole et al. (2000, p. 36)

<table>
<thead>
<tr>
<th>Variance Approach</th>
<th>Process Approach</th>
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<tbody>
<tr>
<td>Fixed entities with varying attributes</td>
<td>Entities participate in events and may change over time</td>
</tr>
<tr>
<td>Explanations based on necessary and sufficient causality</td>
<td>Explanations based on necessary causality</td>
</tr>
<tr>
<td>Explanations based on efficient causality</td>
<td>Explanations based on final, formal, and efficient causality</td>
</tr>
<tr>
<td>Generality depends on uniformity across contexts</td>
<td>Generality depends on versatility across cases</td>
</tr>
<tr>
<td>Time ordering among independent variables is immaterial</td>
<td>Time ordering of independent events is critical</td>
</tr>
<tr>
<td>Emphasis on immediate causation</td>
<td>Explanations are layered and incorporate both immediate and distal causation</td>
</tr>
<tr>
<td>Attributes have a single meaning over time</td>
<td>Entities, attributes, events may change in meaning over time</td>
</tr>
</tbody>
</table>

Distinct epistemologies (variance and process methods) Van de Ven & Poole (2005) derive a typology of alternative approaches for studying organizational change. Ontology and epistemology are independent dimensions to characterize ways in which research is conducted, so that there are examples where process methods are used to understand how change occurs in a world that consists of things, and variance methods have been used to characterize processes. Considering the fundamental nature of these dimensions, it is appropriate to analyse research regarding business relationships and networks in the light of said typology, as summarized in table 3. Approaches I and II refer to variance and process methods, respectively, that could be used to study a business relation or network that is viewed as a entity with an enduring identity. Approaches III and IV adopt variance and process methods, respectively, to study relationships as processes. Each approach has its own strengths and weaknesses, in addressing various research questions about change. In the following, existing research approaches on business relationships will be discussed in terms of this typology.
**Ontology:**
An relationship is represented as being:

<table>
<thead>
<tr>
<th>An entity (a ’thing’)</th>
<th>A process</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Variance method</strong></td>
<td><strong>Approach I</strong> Variance studies in business relationships by causal analysis if independent variables that explain the state of dependent variables</td>
</tr>
<tr>
<td><strong>Process narratives</strong></td>
<td><strong>Approach II</strong> Process studies of change in relationships as entities, narrative sequences of events, stages or cycles of change in the development of an entity</td>
</tr>
</tbody>
</table>

Table 3: A Typology of Approaches for Studying Business Relationships, adapted from Van de Ven & Poole (2005, p. 1387)
Approach I: Variance Study of Business Relationships as Entities

Approach I studies business relationships as entities with certain characteristics using variance methodology. Most behavioural studies, as well as studies that assess the antecedents and consequences of transaction cost theory follow Approach I. This approach measures characteristics of relationships and uses statistical techniques to assess how they relate to each other. It can be used to study covariation between dimensions.

Poole et al. (2000) point out that activities or changes can at best indirectly be studied using variance methods, as it requires researchers to abstract variables from the process data. Variance methods are not dynamic and unable to capture processes, for example how certain characteristics of a relationship develop or how different types of relationships come to exist. Furthermore there are several assumptions underlying this methodology that make it difficult to rely on it with respect to dynamic subjects like business relationships (Abbott, 1988): First, this approach assumes that the same causal factors operate homogeneously across all cases, which ignores the possibilities of multiple causes or changes in causal factors over time. Second, it assumes that the entities under examination are fixed, which does not apply to firms that can reorganize, merge or split, or change the actors in particular roles, relevant to the relationship under analysis. Third, the degree to which variance based-methods can account for contextual and historical influences is limited, because of the usual focus on main effects and the exclusion of interaction and order effects. And fourth, variance methods assume independent cases, which is problematic in a network of interconnected relationships that influence each other. In sum, variance-based approaches work well for comparisons among variables of entities or relationships, but they are limited when it comes to explain development and change over time.

Process-Based Studies (Approaches II and III)

Both, Approach II and III adopt process methodology. While the former studies how business relationships as entities develop, the latter assumes that the world is composed of processes, and tries to understand what they are, and how they interact as the relationship unfolds over time. Typical questions for Approach III are: how do processes of sense-making, conflict resolution, protests, or making a living unfold over time? In Approach II, developments are conceptualized as a succession of events, stages, cycles, or states, but they are always attributed to an entity, a person, a thing or 'the relationship' as an entity. In the interpretation of developments, substance has priority over process. Also, Approach II relies on the observer’s judgements regarding the significance of events (Poole et al., 2000). As mentioned before,
typical process methodologies are narratives, such as case studies or descriptive characterisations of relationship histories, and stage models, which attempt to capture the essentials of rich process data in a simpler account of stepwise development or typical activities. Then it depends on the ontological perspective whether these approaches fall into categories II or III. Examples are many studies in the IMP tradition, focusing on in-depth descriptions of the development of only one, or a small number of, interconnected relationships. Furthermore, above mentioned stage models fall into this category.

As mentioned earlier, process methods are much more labour and data intensive than variance methods, so that their scope and applicability is limited. It may be possible to investigate the development of a few relationships, or their underlying processes, in detail, over an extended period of time, but the study of the development of an entire business network is certainly beyond the reach of these methods. However, the concepts of explanation and generalization are not the same in this type of research. No attempts are made to study representative cases or samples of cases. Instead the aim is to identify key underlying mechanisms which are potentially relevant in all cases and which may or may not be triggered in a given case situation. Analytical and theoretical rather than statistical generalisation is the focus. This is discussed further in a following section on the nature and study of causal mechanisms.

**Approach IV: Variance Study of Relationships as Processes**

Approach IV presumes a process ontology and applies a variance perspective to the study of it. Van de Ven & Poole (2005) emphasize the difference between Approaches IV and II: “the latter define variables that describe states changed as part of the process, whereas Approach IV studies define variables that describe the nature of the process (e.g. the speed at which it operates)” (p. 1392) In Approach IV a variety of quantitative process analysis techniques can be used, including Markov analysis, multivariate time series techniques, event history analysis, and nonlinear systems analysis. Their aim is to uncover and test for properties of series of events and the mechanisms that drive the process. In using quantitative analysis the rigor and system of variance research can be introduced to the study of processes (Van de Ven & Poole, 2005).

Generally, two different varieties of Approach IV can be distinguished: One based on empirical investigation about the structure of an evolving process, the other using mathematical models and simulation techniques gain an understanding of processes.

Empirical investigations have to define variables that capture characteristics of processes and then codes events to assign values to these variables. The resulting time series can then be analysed with regard to the sequence, pattern, or structure of the unfolding process. There do
not appear to be any empirical studies in the area of business relationships and networks that
follow Approach IV. Examples given by Van de Ven & Poole (2005) look at characteristics
of processes such as their rate of change, their complexity, or modes of structuration (e.g.
DeSanctis & Poole, 1994, and concepts of faithful appropriation) or appropriation style (Poole
et al., 2000).

Mathematical and simulation models become of interest, when the system or organization
in question exhibits non-linear dynamic characteristics. It is these types of models that are
of central interest in this project. Such systems have more structure than completely random
(white noise) time series, but also, they are not so well behaved that they can be captured by
periodic or stable equilibriums. Van de Ven & Poole (2005) suggest that non-linear dynamic
patterns arise from underlying causal factors acting interdependently in a non-linear fashion.
To understand such behaviour, the authors refer to the theory of complex adaptive systems
(CAS) which they describe as “currently, the most influential model for explaining nonlinear
dynamic systems” (Van de Ven & Poole, 2005, p. 1392-3). In a nutshell, CAS deals with
self-organization and local action and their aggregate system outcomes. CAS and its potential
contributions will be discussed in greater detail in the following section.

Mathematical and simulation models that follow Approach IV formalize theories about pro-
cesses and can help us derive implications of processes that cannot adequately be described
verbally even solved mathematically. Van de Ven & Poole (2005) draw an analogy to calculus
which represents physical motion and change “in ways that transcend verbal expression” (p.
1393). Many processes in the real world are so complex that would be impossible for the the-
orists to think them through with qualitative methods. Mathematical and simulation process
models simplify these real world processes. The models make these processes accessible to
quantitative means of analysis, so that we can gain an understanding of how the processes
work.

The purpose of our research is to build simulation models of this type. In the following sec-
tion we discuss the nature and role of causal mechanisms in understanding change processes
because these are central to the development of this type of simulation model. After that we
discuss the nature and role of simulation models in more detail, especially agent based models,
and how they are built and tested before describing how they may be used to build models of
the dynamics and evolution of business relations and networks.
3. Mechanisms

The previous section indicated that process-based approaches to understanding change focus on identifying underlying causal mechanisms that drive processes of change. This is different from variance based cross-sectional comparative static models that are more commonly the focus of research and modelling in marketing. Mechanisms, as I will show, also play an important part in the development of simulation models of the dynamics and evolution of business relations and networks. In this section I review the concept of mechanisms and how they relate to understanding and modelling change processes.

The term mechanism is often loosely used and can be confusing. Campbell (2005) describes mechanisms as the processes that account for causal relationships among variables, Elster (1989) uses a metaphor to describe mechanisms as the nuts, bolts, cogs, and wheels that link causes with effects. Bunge (1997, p. 414), sees mechanisms “as a real process in a concrete systems, such that it is capable of bringing about, or preventing, some change in the system as a whole”. A richer definition is given by Hedström (2005):

Mechanisms [...] consist of entities (with their properties) and the activities that these entities engage in, either by themselves or in concert with other entities [...] a constellation of entities and activities that are organized such that they regularly bring about a particular type of outcome.

(Hedström, 2005, p. 25)

There are many other definitions of mechanisms in the literature using examples and terminology from various disciplines, and no attempt is made here to summarize this discussion in detail. Instead a few essential features of mechanisms will be highlighted: First, mechanisms emanate from actors, their functional roles and their activities. Actors have specific properties such as structure, attributes, orientations and locations. On basis of these properties, actors are able to engage in activities, actions and interactions (Machamer et al., 2000). However, the same entities and activities, in a different spatial and temporal arrangement could yield different mechanisms (Craver, 2001). Second, mechanisms are a continuous process, embodied in a sequence of prototypical events, capable of causing or preventing changes in a system Bunge (1997). The effects of any given event are determined by the context of its occurrence, its timing and its relation to other events. Third, mechanisms are not independent of each other. Observable changes are usually brought about by various mechanisms, working together and counteracting one another (Gambetta, 1998).
Mechanisms are often left implicit in our causal explanations of events, especially if we are focusing on the behaviour of variables rather than actors. Thus we may say that a manager’s trust in another firm depends on how reliable or benevolent a firm has acted in the past. This implies that if the other firm’s behaviour in terms of reliability and benevolence changed, it could affect the amount of trust the manager has in the firm. A variable-based model does not specify the processes involved here: Which differences are perceived by the manager as evidence of better behaviour? How does s/he learn about them? How accurate are perceptions likely to be due to thresholds of awareness and attention, bounded rationality and selective perception processes? How do changes in perception cause changes in trust - is it a simple addition as suggested in some models of behaviour, or a more complex psychological sense-making process? What are the consequences of changes in the amount of trust, and how do they come about? Mechanisms are everywhere, but identifying them is not something we are trained to do. The physical sciences and engineering are much more concerned with mechanisms as they try to understand how things work and to apply this knowledge to make other things. Instead of analysis their focus is on synthesis.

Based on previous research and theory, five general types of mechanisms may be identified that underlie the development of business relationships and networks. The mechanisms are distinguished in terms of the type of processes they seek to explain, and they comprise various sub-mechanisms deemed to be relevant. Nevertheless, the same kind of mechanism may be relevant to more than one type of process, such as various psychological mechanisms, that may be the drivers of human action in various different situations. In the following I review 1) mechanisms related to specialization and division of labour, 2) business mating mechanisms that influence that formation of relations, 3) business dancing mechanisms that determine the interactions in established relations, 4) mechanisms connecting relations to an interconnected business network, and 5) environmental mechanisms that influence relations from outside.

3.1. Mechanisms Related to Specialization and Division of Labour

Firms in business networks are heterogeneous, networks comprise competing and complementary firms, including buyers and sellers, intermediaries, producers, suppliers, service suppliers etc. Firms specialise in particular assortments of activities that match their capabilities, skills resources and capacity and offer value to other firms in exchange for value they receive in return. Relations arise to link organisations specialising in different functions in value chains in which they are perceived to have comparative advantage. The existence of relations involves
trading off the economies available from different types of specialisation between firms and the costs of linking and coordinating such specialist firms i.e. transaction costs. For individual firms this represents the classic make or buy decision - to do the work required themselves or outsource it. The processes of insourcing and outsourcing involve decision-making and evaluation processes, whereby firms compare the perceived costs and benefits of alternative potential suppliers in their consideration set.

Many theories about the nature and value of business relationships are based on theories regarding the economies of specialisation, theories of comparative advantage and transaction cost theory. There are two types of costs involved carrying out economic activities, production and transaction costs. Both types of costs are subject to efficiencies of various ways of aggregation (Williamson, 1981): 1) Aggregating more of the same activity (economies of scale), 2) aggregating activities with common inputs (economies of scope), and 3) aggregating complementary activities (administrative efficiencies). The following economic mechanisms have been identified to affect production and transaction cost functions, clarifying the these economies can be attained (Dixon & Wilkinson, 1986). First, all these cases the efficiencies may be attainable through more efficient use of factor inputs in the production process. Following the principle of multiples (Florence, 1933), factor inputs, including people, machines and land come in fixed, inseparable quantities. Aggregated operation allow firms to combine specialist inputs with different operating scales more efficiently. Second, the principle of massed reserves or pooled risk (Florence, 1933) states that widening the customer base can lower the ratio of inventory costs, bad debts and other costs to total costs. Fluctuations in demand and debts across customers become more likely to cancel each other out, which reduces risk and increases planning reliability. Third, the principle of bulk transactions (Florence, 1933) extends above mechanisms to transactions. They, too, can be aggregated, allowing for economies of scope and scale. Last, economies of reduced contacts can be attained, through the activity of intermediaries in a market the number of transactions and their associated costs can be reduced (Hall, 1949).

On the basis of these determinants of economic action, opportunities exist for various types of specialists to emerge at different stages of value chains, including marketing intermediaries. They specialise in particular activities on behalf of other firms e.g. wholesalers, component suppliers, transport agencies, system suppliers. They specialize in particular activities and aggregate them by serving more than client, customer or partner.
3.2. Business Mating Mechanisms: The formation of Relations and Networks

Mechanisms related to business mating concern how firms encounter and get to know each other and how they choose and refuse and get chosen as potential relationship partners. This could vary from random processes to ones that are predominantly influenced by past interactions, predispositions and communication networks and perceived degree of comparative advantage. Research suggests that people and firms tend to form relations with those they have had dealings with in the past, those that are similar to them in the way they operate and those offering complementary resources. Similarities in the business environment faced and market position with respect to innovativeness and technology are important for later relationships performance (Wilkinson et al., 2005).

Once a suitable partner is found, the potential mechanisms by which businesses can coordinate their behaviour are manifold. During the formation phase, prospective partners negotiate the terms that govern their future collaboration. Transaction costs, including those associated with adaptation, performance evaluation and safeguarding affect the kind relationship governance structure established at the outset, which varies from arms length market trading, through more cooperative relations to hierarchical (ownership) governance (Rindfleisch & Heide, 1997). The structures set at the beginning will set the rules and boundaries for most of the following activities but they may change over time as conditions change (see next section). Apart from contractual provisions, equity arrangements (Osborn & Baughn, 1990) or less formal mechanisms, such as information sharing and joint planning provide further ways to align both partners’ contributions (Palay, 1984; Noordewier et al., 1990).

In industrial sourcing decisions, uncertainty and risk are relatively high for the buyer and this is usually reflected in the negotiated cooperation agreements. Orders involving large quantities of technically complex products that can only be acquired from a small number of alternative suppliers are particularly problematic. The choice of governance mechanisms is not unilateral but a joint decision that is influenced by social norms (e.g. trust), power and dependence and the availability of alternatives. (Bergen et al., 1992) The relative power of channel partners has been shown to affect prices as well as the division of surpluses (Mallen, 1967).

3.3. Business Dancing Mechanisms: Interacting in Relations

Once the terms of trade and relational governance are settled the relationship will evolve over time as the result of consecutive interactions. Long-term exchange relations involve economic
as well as social and personal interactions through which people and firms learn about each other, adapt to each other and gain and lose resources and benefits. Firms may use various types of strategies in deciding how to interact and adapt them over time based on the experience and outcomes occurring. This means we need to model learning and adapting processes as well as communication and exchange processes. Relationship termination and decline processes are also relevant and will partly depend on what is happening in other connected relations and the more general environment (see following sections).

The development of a productive relationship takes time, effort and money, investments in the relationship are undertaken by both sides. It usually requires adaptations of resources, activities, ideas/plans and actor bonds on an ongoing basis. On the one hand adaptations, investments and specialization can make a relationship more efficient, to some degree more flexible and more competitive, as a “relationship atmosphere” develops between the actors involved (Håkansson, 1982). On the other hand, these investments can be highly specific, useful only within the relationship, i.e. asset specificity exists. This asset specificity increases switching costs and leads to lock-in effects and greater potential damage from opportunism (Williamson, 1975).

The management of relationships involves also a strategic dimension. As relationships develop, costs and benefits change over time, and firms may become aware of better alternatives and experience changes regarding their attractiveness to other firms. A firm’s scale and scope changes as a result of their performance over time as well as through changes in market conditions (Dixon & Wilkinson, 1986). Also, it has been found that it is possible to develop partners in relationships, unprofitable customers can be turned into profitable ones in the long run, thus it can be worthwhile to maintain relationships with currently unprofitable customers (Elsner et al., 2004). Expectations about the future can affect decisions in the present (Axelrod, 1984).

3.4. Mechanisms Connecting Relations

Relationships exist not in isolation but they are interconnected to an entire network. They influence each other. IMP researchers have led the way in studying connected relations and we have some idea of the different types of impacts and functions of connected relations (e.g. Anderson et al., 1994; Blankenburg-Holm et al., 1996; Wiley et al., 2009). But these are the results of various kinds of underlying mechanisms, including the way exchange in one relation depends on exchange taking place or not in another relation at the same time or in advance of the focal exchange (Easton et al., 1997, 1999, 2008), as well as communication, innovation and learning processes and technological processes.

There are several mechanisms that indicate how relationships interconnect and interfere
with each other. A firm’s resources are limited and the demands of different partners might be diverging, so that a firm has to decide how to serve incompatible requests (Turnbull et al., 1996). Firms also compare performance in one relation with others and this affects switching decisions and satisfaction in relations. Furthermore, the same two companies can have different types of relations to each other at the same time, as buyers and sellers simultaneously. Bergen et al. (1992) found that firms act on the basis of reciprocity, giving preference to a supplier who is also a customer for the firm’s products.

The behaviour in a network comprises also a strategic dimension. Considering importance and difficulty of a purchase, firms can attempt to manage their portfolio of relations to gain a competitively advantageous network position, e.g. regarding the access to resources or customers (Olsen & Ellram, 1997). Bridging positions can be attractive for intermediaries. Balderston (1958) developed an early model to demonstrate the resulting interaction between economies of specialization and competition. A single intermediary in a market would be a monopolist earning supernormal profits, which would attract additional intermediaries to set up. Depending on cost structures, the number of buyers and sellers in a market and the way they allocate their business among intermediaries, the number of intermediaries that can enter the market is limited. Intermediaries reduce the absolute number of transactions and make each one bulkier, as they handle products on behalf of several buyers and sellers. This can reduce costs for communication, transport, payment and contract negotiation per transaction. But this is to some extent offset because trading is now indirect through the intermediary, which means it requires two transaction to link a seller and buyer not one when they deal direct.

3.5. Environmental Mechanisms and their Impact

Any business network operates in a context that includes other industries and networks, markets and the general macro environment. It is not the purpose of the models, which I want to develop, to model the environment as such, as this would make our task too comprehensive. But we can include aspects of the environment and how it changes over time. This includes the speed and variability of change and feedback effects that may arise from actions taking place in a focal network. For example in a comprehensive agent-based model of the development, evolution and demise of the Anasazi Indian tribe in America, the modellers were able to include the known history of weather patterns and the physical geography of the environment into their model (Axtell et al., 2002). In a similar way a generic model of business relations and networks can be adapted and recalibrated to fit better with particular business contexts and environments to examine how it performs and why.
Business relations operate in a physical space and with a given social and economic infrastructure. Social norms and laws set boundaries to the activities that can be performed, and the available infrastructure affects transaction costs, logistics, communication and other activities in the relation. Theories of retail gravitation Reilly (1931), for example, posit that intermediaries arise mid-distance between larger hubs.

Various characteristics of the goods and services involved also shape production and transaction cost functions. Aspinvall (1956) emphasises the importance of heterogeneity for the costs of promoting and distributing goods. Their replacement rate, gross margin, customizations for the customer, durability, and search time may differ and suitable marketing measures have to be adapted accordingly which affect cost functions. Technology is also an important environmental condition, as this affects how quickly costs fall in relation to changes in scale and scope and how activities are interconnected, such as whether they are complementary or competing (Dixon & Wilkinson, 1986).

The environment of a business relationship is not static, but highly volatile in some industries. Partners have to respond to technological changes, changes in regulations and in their competitive surroundings. Such developments might render the outcomes of an existing contract suboptimal and partners have to adjust or change partners. Only to some degree can an uncertain future be anticipated in contracts and partners have to respond on the basis of implicit or explicit rules, to gain benefits from each other (Rindfleisch & Heide, 1997).
4. Complex Adaptive Systems

Our intent is to consider business relationships and networks from the perspective of complexity theory. In this, we mainly follow the rationale provided in Wilkinson (2006), which will be summarized briefly, after an introduction of the core constituents of complexity theory.

First of all, it is necessary to say, that there is not one clear-cut definition of the term “complexity”. A unifying trait of the many analyses and theories dealing with complexity is that they attempt to understand nontrivial emergent and self-organizing phenomena (Mitchell, 2009, p. 13).

A comprehensive discussion of all the aspects and variants of complexity theory is beyond the scope of this proposal and can be found in many popular science books (e.g. Waldrop, 1992; Bossomaier & Green, 1998; Wolfram, 2002; Mitchell, 2009). Usually, complexity is attributed to so-called complex adaptive systems (CAS), where a system, as defined by (Viscek, 2002), is an entity that can be analysed on multiple levels, such as a micro/unit level and an aggregated, macro level. Mitchell (2009, p. 13) defines CAS as systems “in which large networks of components with no central control and simple rules of operation give rise to complex collective behavior, sophisticated information processing, and adaption via learning or evolution”. Or to put it in other words: The main characteristic of a complex system is that the laws which describe its behavior are qualitatively different for different levels (Viscek, 2002, p. 131).

In many systems it has been observed that in a bottom up self-organising way, order emerges from the micro interactions among system members, even though no central actor is in charge, coordinating their activities. Furthermore, many of these systems show a top down feedback effect through which the macro state of the system on a large scale influences the individuals’ micro interactions, e.g. when inflation figures feedback to affect individual purchase decisions. Figure 4 schematically illustrates such feedback effects on the basis of an economic system.

There are many different types of CAS, including business and economic systems, social systems, traffic systems, biological and ecological systems (e.g. ant colonies, the immune system, the brain) and the world wide web. All these systems can be analysed on different scales, such as micro- and macro-level, or individual and collective. The ant colony consists of ants, the brains of which are made of neurons and the world wide web is an interconnected collection of web pages. These systems are of interest because they exhibit non-trivial emergent behaviour on the aggregated level: Ant colonies build nests, and coordinate maintenance work, supply procurement and foraging; the human brain is capable of producing something as complex as a free will and a personality and the world wide web provides a formidable
channel of information propagation. Furthermore, at the micro-level, the individual behaviour is relatively simple and, what is more interesting, it does not straight-forwardly explain how the complex behaviour on the macro-level arises. Ants have been found to communicate via pheromones and indirectly through locally changing their environment (stigmerty), but without a central planner, it is hard to imagine how the large collective can actually build and sustain itself. Sometimes the appearance of order and patterns misleads us to the assumption that someone or something has planned or coordinated it. Complexity theory deals with cases where this is not necessarily the case. A single neuron is not much more than an electronic relay, which translates input signals into output signals. Individual web pages cannot do much more than provide content and link to other pages. The complexity of the collective arises not in the individual constituents, but it emerges through the interactions between them (Mitchell, 2009). These interactive dynamics make the system’s behaviour highly nonlinear, such that small changes can have disproportionately large effects, and the equations of motion, necessary to describe the system’s development become far to difficult to analytically tractable.

Non adaptive systems with fixed rules of behaviour and interaction, such as physical and mechanical systems, are complicated and complex but are not CAS. The importance of feedback effects between their levels is not seen as a core mechanism to induce complexity (Gross & Blasius, 2008). Examples of merely complex systems are hurricanes and turbulent rushing
rivers (Mitchell, 2009). However, these will not be in focus here.

To sum up, the essential characteristics of complex adaptive systems are:

- Complex systems have multiple levels of operation, such as micro to macro.
- Non-trivial patterns and behaviours emerge on higher levels of analysis.
- Individual behaviour can be described be relatively simple behavioural rules.
- Collective behaviour arises from numerous interaction among individuals.
- Analysis of individual behaviour in isolation does not tell us how collective behaviour arises.
- Individual behaviour can only be fully understood in the context of the collective.
- There is no centralized coordination.
- The systems are dynamic, they learn and adapt.

Business relations and networks have these characteristics. Large scale order emerges from the local interactions taking place within and between firms and other organizations over time, in a self-organizing way. While individual firms may have unequal power and influence over others, no single firm is in charge of a relation or network.

Some researchers even proclaim a shift of scientific paradigms has taken place with the advent of complexity theory and CAS. The many interconnected relationships form an overarching structure: the business network. There is no obvious network leader to orchestrate the interactions, nonetheless, the network as a whole works: It produces goods and services, organizes procurement and supply, finance as well as research and development. The overall structure and behaviour of the network arises in a self-organizing bottom-up manner. In comparison to the complexity of the overall system, the businesses’ behaviour is relatively simple, they rely on limited, local information and interact only with a limited number of partners. Such insights are not really new, as the following quote from an early journal of marketing paper makes clear. But we can do something more about studying and modelling it.

[A] market changes day to day through the very fact that goods are bought and sold. While evaluation is taking place within a marketing structure, the structure itself is being rendered weaker or stronger, and the changes in organization which follow will have an impact on tomorrow’s evaluations. Marketing theory will not provide an adequate approach if it ignores this interaction between the system and the processes which take place within it.
In the following, the use and value of computer simulation, with focus on applications in the social sciences will be discussed. Among the many variants of computer simulations, agent-based modelling (ABM) has become established as the main tool to explore social, interactive phenomena and CAS. The nature of ABM will be described and how it contrasts with other simulation techniques, how it has been used so far and how it is possible to formulate and analyse theories about dynamic interactive systems, such as business relations and networks with the aid of ABM.

4.1. Computer Simulations in the Social Sciences

The non-linear, adaptive interaction in most complex systems usually cannot be readily captured by analytical expressions, therefore computer simulations are used as a means of analysis. Essentially, they provide numerical solutions to highly complex, non-linear mathematical problems. Gilbert & Troitzsch (2005, p.2) describe simulations as a particular type of modelling: Models are simplifications of the real world, which are less detailed and/or less complex than the original. Also, simulations are formal models (Diesing, 1971), only that they are expressed primarily in the language of computer code (Cioffi-Revilla, 2010). Necessarily this representation makes them much more precise than a theory in words alone and makes simulations a useful method of theory development and analysis (Gilbert & Troitzsch, 2005, p.3) Simulations, like classical statistical models, have inputs and outputs. The inputs are used to match the simulation with a particular situation, and the outputs are the results derived on the basis of deterministic rules during a simulation run.

In contrast to many mathematical models, simulation models are not so strongly simplified that they become analytically tractable. Commonly there is not one closed set of equations that can be manipulated algebraically to predict the outcomes of the simulated system under different conditions (Gilbert & Troitzsch, 2005). However their outcomes can be determined numerically. Simulations can be seen as imitations of generative mechanisms for highly non-linear, dynamic behaviour (Küppers & Lenhard, 2005) which make them appropriate tools to explore CAS (Gilbert & Troitzsch, 2005).

Generally, a simulation is a collection of formalized mathematical rules, applied to a clearly defined set of (possibly random) inputs. These rules transform the inputs into outputs deterministically. Through systematic examination of the space of possible input values, a mapping of the respective outcomes can be calculated. Commonly, statistical techniques, such as regression analysis are used to gain a simplified understanding how the outcomes relate to the
inputs, providing a so-called metamodel. For the special case of agent-based modelling, this approach was formalized by Leombruni & Richiardi (2005) and will be presented in greater detail in section 4.3.2.

4.2. Purposes of Social Simulation

What can we learn from computer simulations? Many scholars have debated this issue, paying tribute to the fact that all results of a simulation are based on artificial data, created in a computer, on the basis of more or less comprehensible rules, with the explicit purpose of leading to emergent results that cannot be traced back to the original rules by common linear, analytic means.

Axelrod (1997) suggests that “Simulation is a third way of doing science”. Simulation 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, rules, parameters, a set of random numbers or other starting conditions (as appropriate) and calculate the final outcome through mathematical operations. Only if we make changes to this set of explicit assumptions (including the use of different starting conditions and/or random seeds), will we get different results. But unlike deduction, simulations do not prove theorems. Simulations generate data and this data can then be analysed inductively, using the same tools that can be applied to empirical data. The crucial difference to induction is that the modeller knows exactly on which set of rules each of his results is based. Axelrod (1997) 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 to intuition. Simulation is a way of doing thought experiments. While the assumptions may be simple, the consequences may not be at all obvious.

(Axelrod, 1997, pp. 24-25)

The essential advantage of building explicit models is that all assumptions are laid out in detail, so that it is possible to study exactly what they entail. We can explore how the change of one assumption leads to a change in the final outcome, and how the effects of model assumptions affect each other. In the process of sensitivity analysis, one can sweep a huge range of parameters over a vast range of possible scenarios to identify the most salient uncertainties, regions of robustness, and important thresholds, in short map out the complete
phase space of the underlying equations of motion and adaption. Epstein (2008, sec. 1.9) provides a comprehensive list of possible applications for explicit models in general:

1. Prediction
2. Explanation (very distinct from predict)
3. Guide data collection
4. Illuminate core dynamics
5. Suggest dynamical analogies
6. Discover new questions
7. Promote a scientific habit of mind
8. Bound (bracket) outcomes to plausible ranges
9. Illuminate core uncertainties
10. Offer crisis options in near-real time
11. Demonstrate trade-offs / suggest efficiencies
12. Challenge the robustness of prevailing theory through perturbations
13. Expose prevailing wisdom as incompatible with available data
14. Train practitioners
15. Discipline the policy dialogue
16. Educate the general public
17. Reveal the apparently simple (complex) to be complex (simple)

Epstein is careful to distinguish between explanation and prediction. He specifies his notion of generative explanation, where macroscopic explananda (i.e. aggregate regularities, like wealth distributions, spatial settlement patterns, or epidemic dynamics) emerge from populations of heterogeneous software agents, which interact locally under plausible behavioural rules Epstein (2008).

Nevertheless there can be several alternative candidates to explain an explanandum, so while simulation may well provide us with an explanation, in general, simulation does not provide the means to guarantee that this is the only or true explanation. Epstein (2006) refers to this as explanatory candidacy. These 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.

The underlying notion of explanation is different to the more usual statistical one of reproducing covariance and correlation matrices. Herbert Simon (1968) argues that to grow is to explain. Simon sees explanations as simple interconnected mechanisms that can be shown to generate the most ‘striking’ patterns in empirical data. “To ’explain’ an empirical regularity is to discover a set of simple mechanisms that would produce the former in any system governed by the later” (Simon, 1968, p. 445).

Modelling can also serve as a guide for data collection (Epstein, 2008). It can be helpful to state the model and deduce its consequences in order to raise attention to data that has not been collected so far. Epstein refers to Maxwell’s electromagnetic theory as a prime example. Maxwell deduced the existence of radio waves from equations and only then set out to search and finally find them. Epstein states “Without models, in other words, it is not always clear what data to collect!” (Epstein, 2008, sec. 1.11) Theoretical approaches can help us find gaps in existing empirical work, what can be highly important especially in emerging areas such as the impact and dynamics of social networks.

From a philosophical standpoint, the merits of computer simulation models pose an interesting question. How can simulations have scientific value if they essentially just rearrange symbols in a predetermined, deterministic fashion and thus can never arrive at new knowledge? The design, premises and inputs of simulations are already known to the researcher, so the conclusions or outputs cannot possibly constitute a discovery. Endorsing the view of Di Paolo et al. (2000), computer simulations can be considered as opaque thought experiments.

Thomas Kuhn (1977, p. 261) outlines how thought experiments work: “thought experiments give the scientist access to information which is simultaneously at hand and yet somehow inaccessible to him”. Some facts, although they are known, are pushed to the periphery of scientific investigation, either because they are thought not to be relevant, or because their study would demand unavailable techniques. Computer simulations surpass the logically deductive capabilities of humans: We can use simulations to deduce consequences of a set of assumptions, and especially emergent properties of complex systems (Bedau, 1999). In situations in which our natural reasoning apparatus stumbles, Bedau portrays computer simulation as a “philosophical crutch”.

Simulations can be seen as computer assisted thought experiments, but the analogy between thought experiments as practised in an armchair and computer simulation modelling
is not complete. The conclusions of an armchair experiment follow logically and clearly, so that the experiment constitutes an explanation in itself. However, while simulation can be much more powerful and versatile, it is not understandable by simple inspection. Experiments must be run to understand the simulations mode of work, illuminate the causal relationships and interdependencies. This second, experimental step is what makes computer simulations “opaque” thought experiments (Di Paolo et al., 2000).

In order to actually gain insights from the analysis of a computer simulation one additional step is warranted: The understanding of what happens within the simulation, “must then be related to the corresponding theoretical terms which describe analogous phenomena in the natural world” (Di Paolo et al., 2000, p. 504). This step of re-translation can be trivial if observed patterns or mechanisms have corresponding counterparts in the existing theory, or it is possible that simulations uncover mechanisms that cannot be accommodated by existing theoretical frameworks. In both cases, the outcomes of computer simulations can inform the development of new theories and testable hypotheses, they can be the source of alternative explanations to observed phenomena and can point us to new fields of research altogether.

Di Paolo et al. (2000) map out the following three stages of simulation model analysis

**Exploratory phase** After the initial simulation model is built, explore different cases of interest, define relevant observables, record patterns, re-define observables or alter model if necessary.

**Experimental phase** Formulate hypotheses that organise observations, undertake crucial “experiments” to test these hypotheses, explain what goes on in the simulation in these terms.

**Explanatory phase** Relate the organisation of observations to the theories about natural phenomena and the hypotheses that motivated the construction of the model in the first place, make explicit the theoretical consequences.

### 4.3. Agent-Based Modelling

Agent-based modelling was developed in the 1990s as a sub-field of multi agent systems. Advances in software programming allowed programmers to build software agents, as self-contained programs that can control their own actions based on their perception of their operating environment (Huhns & Singh, 1998). Such agents are still used for example to collect information on web-pages on the internet. As a sub field of artificial intelligence, agents were also used to make computers solve problems without human interference.
According to Gilbert & Troitzsch (2005), it was the prospect of simulating the interactions of many autonomous individuals that strongly increased the interest in simulation as a tool for the social sciences. An agent is given a set of rules of behaviour that depend only in their internal states and on information from their immediate environment. Whole populations of agents can now be grown in that manner. All those agents have limited capacities to perceive their environment, some means of interaction and communication, a limited set of skills regarding the tasks they had to deal with, and several internal mechanism that coordinate all this. It is even possible to endow these agents with skills and characteristics heterogeneously. In a simulation run, the agents come to life, for example, they harvest food, metabolize, trade and may even die from exhaustion, if they do not manage to meet their needs with sufficient supplies (e.g. Sugarscape in Epstein & Axtell, 1996). It is possible to monitor all developments in the simulation, explore the agents’ interactions and the impacts they have on each other and the overall system. These simulations soon became known under the name agent-based modelling (ABM) (for reviews, see e.g. Tesfatsion & Judd, 2006).

Metaphors such as beliefs, intentions, desires or even emotions are used frequently to describe the agents’ actions. Wooldridge & Jennings (1995) outline the typical properties of computer agents:

**Autonomy:** Agents control their own actions as well as their internal state. Especially the user does not interfere with their decision making, after he specified its rules.

**Social Ability:** Agents interact with other agents, on the basis of a common language or actions.

**Reactivity:** Agents are able to perceive their environment, including other agents, and they are able to react on basis of these perceptions.

**Proactivity:** In addition to mere reactions to their environment, agents are also able to take the initiative, engaging in goal directed behaviour.

The aim of ABM is to capture and represent an interactive social system and it has frequently been used to study how macroscopic patterns and regularities observed in society, such as price equilibriums or the appearance of behavioural norms, can be generated from decentralized, local interactions between collections of agents (Ball, 2007). As such ABM is well suited to modelling complex adaptive systems.

ABM provides the tools to grow CAS in-silico, in a controlled, manipulatable and monitored environment, which allows us to study the emergence of complex behaviour in greatest
detail. Their micro-level structure is known and completely accessible; it can be manipulated and controlled in an experimental fashion, so that inside of the computer model even causal relationships regarding the system behaviour can be explored.

ABM simulations can account for much richer detail than analytical models. Agents can be heterogeneous, possessing different strengths or objectives; they have access to limited, mostly local, information and have only limited processing capacities. It is also possible to give agents capacities to learn, form experience or by copying others (Epstein, 2006). ABM can relax many assumptions made e.g. in neoclassical economic models like identical rationalizing agents, or populations with sizes of either one, two or an infinite number of agents (Ball, 2007). ABM extends the toolkit with which we attempt to model - to make sense - of your world.

ABM has been around for almost two decades now, and has grown from a niece interest to a recognized method in many fields. A broad selection of textbooks has become available (e.g. Gilbert & Troitzsch (2005), Tesfatsion & Judd (2006) and Edmonds et al. (2008)) and a collection of customized tools to set up a simulation (e.g. NetLogo, RePast, Swarm) even out the path for newcomers to the field. The Journal of Artificial Societies and Social Simulation provides a centralized portal for academic discussion, and simulation-based publications appear even in 1st tier journals, e.g. Midgley et al. (1997, 2007); Watts & Dodds (2007); LeBaron & Tesfatsion (2008). Other journals devote special issues or sections to the subject (e.g. The Journal of Economic Dynamics and Control, Computational Economics). Specific ABM simulations that have gained attention in recent years include the Agent-based Modeling of Electricity Systems (AMES) project, examining reliability of market performance measures in the US American electricity grid (Sun & Tesfatsion, 2007; Somani & Tesfatsion, 2008), and the Anasazi model which reproduced and explained spatial and demographic features of the development of an indian culture in Long House Valley in Arizona for a period of 500 years (Axtell et al., 2002). Procter & Gamble used ABM to optimize their production and supply chain strategies (Seibel & Kellam, 2003).

4.3.1. Other Types of Simulation Models

There are many different types of computer simulation. ABM’s distinctive features are their bottom-up, self-organizing structure, the agents’ autonomy, their interaction, reactivity as well as their goal-directed behaviour. The following approaches are also simulations used in the social sciences, but they differ in various aspects from ABM and should not be confused with them.

Cellular Automata are highly stylized versions of complex systems, trying to capture the
essence of interaction. They usually consist of a regular two-dimensional grid of cells, each of which can be in one of two states (e.g. on and off). All cells change their state in discrete time steps, following the same set of rules that determine the next state based on their own current state, and the state of their direct neighbours. These rules constitute idealized, deterministic interactions. Scientists investigate the interaction of initial conditions and dynamic rules on the aggregate system behaviours. Examples are Conway’s Game of Life (Gardner, 1970) and Schelling’s original model of segregation (Schelling, 1971). Although ABM and cellular automata follow essentially the same concepts, ABM has found by far more application in the social sciences. On one hand, this might be attributed to the permissibility of richer rules for interactions, on the other hand the interacting entities are not cells, but autonomous goal-oriented agents. (See e.g. Hegselmann et al., 1996; Hegselmann, 1996; Wolfram, 2002)

**Genetic Algorithms** have their origins in machine learning and optimization. They consist of a population of individuals who are confronted with a problem. They are equipped with several strategies to solve the problem and depending on their performance, they are assigned a fitness value. A new generation of individuals is then “bred” from the old group, whereas fitter individuals get to produce more offspring, strategies are copied, recombined and mutated. Mimicking natural selection, the population of individuals can find good solutions for the presented problem in an evolutionary manner, autonomously, without human assistance (Mitchell, 2009). Axelrod (1987) uses this approach to grow an optimal strategy for a Prisoner’s Dilemma. Compared to agent-based models, genetic algorithms focus much more on the process of learning and the final solution to the problem, while ABMs emphasize the agents’ interactions and dynamics.

**Monte Carlo Simulations** is a stochastic method to approximate the solution to a mathematical problem that is unfeasible or impossible to compute analytically. This approach requires the problem to be formalized and the availability of a suitable domain of input values. Repeatedly input values are drawn at random, the fixed algorithm is applied and the outcomes are recorded. The result is a distribution of outcomes which is considered as a stochastic approximation of an analytic solution to the original problem. The results provide probabilities for different outcomes (Vose, 2000). Markov-Chain Monte Carlo simulations are an extension of this approach which produce approximations of estimates of time series instead of distributions (Andrieu et al., 2003). While ABM experiments essentially use the same procedure to explore their input parameter space, the emphasis and elaboration of agent design and interactions in ABM is a distinctive
feature in comparison to Monte Carlo simulations. Monte Carlo simulations are usually not interpreted on a micro level.

**Microsimulation** models numerous individuals and simulates the development of their life, individually on the basis of stochastic processes. There is no interaction between the individuals, but the stochastic processes determine their chances of events such as marriage, childbirth, loss of employment, death, etc. The goal of this approach is to see how the simulated society develops over time - it has been used e.g. in Germany, Australia and Canada to devise policies for state pensions or graduate taxes (Orcutt (1986); Harding (1990), cited in Gilbert & Troitzsch (2005)).

**System Dynamics** are based on systems of difference and differential equations (Sterman, 2000; Forrester, 1980). These equations describe the macro level of the system directly, through internal feedback loops and time delays. The combinations of simple equations frequently result in complex non-linear dynamics, which have captured the interest of researchers for more than 50 years. Contrasting to agent-based simulation, system dynamics is restricted to the macro level of the target system as an “undifferentiated whole”, described by a multitude of attributes in the form of levels and rates (Gilbert & Troitzsch, 2005, p. 27). Most importantly, system dynamics are not designed to represent individuals and their actions.

### 4.3.2. Approaches to Modelling

ABM still is an emerging field of science and the debate about correct applications and what constitutes a useful model is still going on. Di Paolo et al. (2000) identify two opposing positions in the literature: At one extreme are **minimalists**, who see the value of simulations in the abstraction and simplification of real world phenomena, which allow us to understand mechanisms and dynamics through simulations, exactly because they are simpler than their real counterparts. At the other extreme are modellers who see value only in simulations that are **maximally faithful replicas** of the original systems, which then provide the added benefit of being under the total control of the modeller and available for all kinds of experiments and manipulations.

Maximally faithful replicas follow the view proposed by Maynard Smith (1974), that simulations strive for a maximum of detail, they are specific, gain validity and scientific worth to the extent that they accurately capture as much about a particular real system as possible. Only few ABM simulations are so advanced to fit this category. The Mason-Smithsonian Joint Project on Inner Asia (Cioffi-Revilla et al., 2007) is an interdisciplinary project to un-
nderstand the rise and fall of polities - national territorial societies with a system of government
over a very long time period, sufficiently long to examine the social effects of climate and
environmental change. Another candidate for this group is the project Agent-based Modeling of Electricity Systems (AMES) (Sun & Tesfatsion, 2007; Somani & Tesfatsion, 2008),
where strategically learning traders are put into a wholesale power market test-bed to assess
experimentally to which extent common market performance measures are informative for the
dynamic operation of restructured wholesale power markets. It is noteworthy to mention that
both projects are the results of the collaboration of several senior researchers and their teams,
across different institutions and both took several years to develop.

More common are minimalistic ABM simulations, such as Schelling’s (1971) segregation
model, Sugarscape (EpsteinAxtell1996) or Watts’ (2007) model of diffusion. According to
Bedau (1998, 1999), these simulation models provide explanations possessing both simplicity
and universality as their designers abstract away from the micro details in the real system.
Midgley et al. (2007) give another rationale why it might be preferable to design minimalist
simulations. The authors discuss their difficulties attempting to verify a model of only mod-
erate complexity, i.e. to ensure that the computer code actually does, what it is supposed to
do. Their conclusion is that a big model with many parameters, distributional assumptions,
and complex interactions also entails a large search space for verification and “the possibility
of building adequate confidence in the basic workings of the model is not that high” (Midgley
et al., 2007, p. 829). Therefore, they endorse an emphasis of minimalism in model design,
e.g. a focus one or two key aspects that will explain 80% of the variation of the phenomenon
in question. Quoting Einstein, make everything as simple as possible, but not simpler.

The boundaries between these two extremes are of course not set in stone. In a method-
ological paper on the management of the Mason-Smithsonian project Cioffi-Revilla (2010)
propose a stepwise approach for the development of large, detailed social simulations. In or-
der to arrive at a complex simulation, a succession of models with increasing complexity is
developed, which approximate the target system in a modular way.

Cioffi-Revilla (2010) draw on Imre Lakatos’ notion of a research programme where sci-
entists continuously add auxiliary hypotheses to a core model, to accommodate, and predict,
more empirical data. As an applied example the authors refer to Newton’s approach to me-
chanics and the law of gravity, which was developed as progressive sequence of theoretically
driven mathematical models. Newton started out with an initial simple, single, spherical,
and moonless Earth model to finally arrive at a planetary system model comprising the Sun,
multiple planets, moons, and elliptical orbits that approximated the real planetary system suf-
ficiently.
This stepwise approach has two interesting practical implications. First, Cioffi-Revilla (2010) emphasize that also Newton did not test his theory until he had reached a sufficiently complete model. He understood that the simpler models would fail empirical tests. Second, Newton did include selected features of the real world to guide the choice of assumptions he added to his model. The authors see this approach as a template for the development of complex simulation models and an analogous approach seems feasible to develop minimalist models into more complex ones, even without the aim of arriving at a maximally faithful replication of a real world system.

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.

(Gilbert, 2004, p. 9)

The interpretation of results of ABM simulations does not differ much from that of analytical, equation-based models. Leombruni & Richiardi (2005) show that simulations consist of a well-defined (although not concise) set of functions, which unambiguously define the macro-dynamics of the system. Moreover if the system arrives at an equilibrium, this can in theory be expressed as a function of the input parameters and initial conditions of the simulation.

At each time step $t$ of a simulation the state of an individual $i$, $i \in \{1, \ldots, n\}$, is described by a state variable $x_{i,t} \in \mathbb{R}^k$. The evolution of this state variable can in the most general case be dependent on individual-specific parameters $\alpha_i$ and on the current state of all other individuals but $i$: $x_{-i}$ and follow an individual-specific functional form $f_i(\cdot)$ which allows us to represent the behavioural rules for the individual as:

$$x_{i,t+1} = f_i(x_{i,t}, x_{-i,t}; \alpha_i) \quad (1)$$

The output of a simulation will be may be a macro-feature, representable by the statistic $Y$.

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1Following the descriptions in Leombruni & Richiardi (2005), I will only consider the deterministic case of simulations that do not rely on (pseudo-) random numbers. The authors postulate that their setup can essentially be applied to simulations with stochastic elements too, which would only require changes in the notation.
which is defined over the entire population:

$$Y_t = s(x_{1,t}, \ldots, x_{n,t})$$  \hspace{1cm} (2)

The state the system at any time $t$ can now be deduced by iteratively solving each term $x_{i,t}$ in equation 2 using equation 1, starting conditions at $t = 0$:

$$Y_0 = s(x_{1,0}, \ldots, x_{n,0}),$$

$$Y_1 = s(x_{1,1}, \ldots, x_{n,1})$$

$$= s(f_1(x_{1,0}, x_{-1,0}; \alpha_1), \ldots, f_n(x_{n,0}, x_{-n,0}; \alpha_n))$$

$$\equiv g_1(x_{1,0}, \ldots, x_{n,0}; \alpha_1, \ldots, \alpha_n)$$

$$\vdots$$

$$Y_t = g_t(x_{1,0}, \ldots, x_{n,0}; \alpha_1, \ldots, \alpha_n)$$  \hspace{1cm} (3)

Many models designed for analytical tractability consider only one representative agent. Nevertheless the same recursive representation holds, only that other individuals, and especially the effects of their interactions, are ignored. This setup leads to significant simplifications of equations 1 to 3, as all subscripts $i$ can be dropped:

$$x_{t+1} = f(x_t; \alpha)$$  \hspace{1cm} (1b)

$$Y_t = s(x_t)$$  \hspace{1cm} (2b)

$$Y_t = g_t(x_0; \alpha)$$  \hspace{1cm} (3b)

Here it becomes apparent, that one of the main differences between agent-based models and traditional models is the degree to which we can understand the way the functions inside the model work. The simplifications in traditional models usually allow us to manipulate equation 3b algebraically, in order to state general propositions about the model through derivatives, the comparison of different equilibrium solutions, etc. Agent based-models are not analytically tractable, as $t$ and $n$ get higher equation 3 can easily grow enormous, hindering any attempt at symbolic manipulation, i.e., any attempt to solve it algebraically (Leombruni & Richiardi, 2005, p. 106).

In order to understand the way ABM simulations work, the additional experimental step of analysis is required. The simulation’s various input values (i.e. $x_1, \ldots, x_n; \alpha_1, \ldots, \alpha_n$,
other parameters that define the initial conditions of the world or the functional form of \( f_1(\cdot), \ldots, f_n(\cdot) \) which determine the simulations’ output \( Y_t \). As equation 2 is not known explicitly, it can be attempted to approximate it with a metamodel \( \hat{g}_t(x_{1,0}, \ldots, x_{n,0}; \alpha_1, \ldots, \alpha_n, \beta) \) (Kleijnen, 1998). One simulation run, solves equation 2 numerically and provides a set of input-output data which can then be used for further analysis. The estimation of the structural coefficient vectors \( \hat{\beta} \) in \( \hat{g}_t \) can then be done e.g. by standard statistical techniques such as (multivariate) regression models or analysis of variance (ANOVA).

Simulations can be explored in an experimental way, systematically manipulating the input factors, although peculiarities of simulations need to be considered, in comparison to in-vivo experiments. First, the numbers of input values can be high and the space of possible combinations grows exponentially. Experimental designs can be used to explore the space of input values more efficiently (See e.g. Kleijnen, 2008). Second, in simulations the issue of randomisation is not problematic, as pseudo-random numbers can be used for all elements that do not require systematic analysis (Kleijnen, 1998). Nevertheless, and third, there is always the possibility that the simulation suddenly changes its behaviour for some unexplored input values, so that the metamodel is only a restricted description of the simulation world (Leombruni & Richiardi, 2005).

Theoretically, agent-based simulation models can also be used to estimate the structural parameters \( \alpha_i \) in the real system, which can in turn be used e.g. to derive testable hypotheses about the micro state of the real system. The approach here is only indirect, through model calibration (see section 4.3.3) : If empirical data for \( x_{i,0} \) and \( Y_t \) is available, the metamodel \( \hat{g}_t(\cdot) \) can be applied to this data, in order to derive an estimate of the coefficient vector \( \hat{\beta} \). Initializing the simulation with \( x_{i,0} \) and \( Y_t \) at their empirical values, the derived coefficient estimates \( \hat{\beta} \) depend only on the structural parameters vectors \( a_i \). By calibrating the simulation model, it is now possible to determine the combination of structural parameters that minimizes the difference\(^3\) between \( \hat{\beta} \) and \( \hat{\beta} \). However, this approach is only feasible for simulations that capture the real system in great detail and it requires the availability of data for \( x_{i,0} \) and \( Y_t \)(Leombruni & Richiardi, 2005).

### 4.3.3. Verification and Validation

The methodology of ABM is still in earlier phases of development and the debate about feasible and useful quality standards is still going on. The discussion circles around two central

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\(^2\)The metamodel is an approximation of the simulation programs I/O transformation; it is also called a response surface. (Kleijnen, 1998, p. 174)

\(^3\)Apart from the Euclidean distance, various other distance measures can be used here, e.g. Minkowski distances of order \( p \)
issues: verification and validation. Verification refers to the internal consistency of the simulation software, validation describes the ways in which a simulation represents and relates to the real world. While the former is mostly a technical discussion about correct software development, the latter concerns the interpretation of simulations, their scientific value and possible empirical tests.

Verification has been defined as the process of ensuring that the intelligent system (1) conforms to specifications, and (2) that its knowledge base is consistent and complete within itself (Gonzalez & Barr, 2000, p. 412). It is an important task in the development phase of computer simulations, because even a single deviation, syntactical or logical, in several hundreds, even thousands of lines of code can completely dominate the simulation’s behaviour. Moreover, the translation from theory to computer-readable code usually leaves much room for interpretation and choices in the details. Midgley et al. (2007) discuss their experiences with verification of a modestly complex ABM simulation. The difficulties they experienced lead them to draw two conclusions: (1) to value simplicity more than theoretical sophistication in model specification, and (2) to incorporate assurance methodologies into model development from the outset (Midgley et al., 2007, p. 885).

There are various approaches to verify a simulation. Gilbert (2004) propose unit testing, which tests the smallest independent pieces of code individually and then connect them step-wise to the complete program, using the modular structure of object-oriented programming. A small number of experts jointly ’paraphrase’ each line of code, i.e. verbalize it at a higher level than the source text (Midgley et al., 2007). Also, there are a variety of more formal methods that can be applied: Source code analysis (manual, tool-based or automated), automatic theoretic verification, deriving automata from the program and finite state verification (Holzmann (2000); Hailpern & Santhanam (2002); Cobleigh et al. (2002), cited in Midgley et al. (2007)).

A possible approach to examine the behaviour of AB models across a whole range of parameters lies in Miller’s Automated Non-Linear Testing System. Miller (1998) demonstrates the use of optimization algorithms to ’break’ the target model. This is done by searching for a set of reasonable perturbations to the model’s parameters that produce an extreme deviation from the original prediction of the model.

Once the implementation of an ABM is verified, the next step is to assess its validity. Agent-based simulation models can potentially be validated on two distinct levels, corresponding to the (at least) two levels at which ABM exhibit behaviour. These two levels are 1) the micro-level where validation can be accomplished by assessing the individual agents’ behaviour and 2) the macro-level of the overall system, which can be compared e.g. to aggregate time series from empirical data (Moss & Edmonds, 2005). Axtell & Epstein (1994) embed these two
dimensions in a hierarchy of levels to assess the performance of an ABM:

**Level 0:** The model is a caricature of reality (e.g. established through the use of simple graphical devices). The individual agent’s behaviour resembles real behaviour qualitatively.

**Level 1:** The model is in qualitative agreement with empirical macro-structures (e.g. established by plotting distributional properties of the agent population)

**Level 2:** The model is in quantitative agreement with empirical macro-structures (e.g. established through statistical estimations and tests)

**Level 3:** The model is quantitative agreement with empirical micro-structures (e.g. determined from cross-sectional and longitudinal analysis of the agent population)

Axtell & Epstein (1994) emphasize that these levels are *progressive*, in the sense that if a model is satisfactory on any given level it implies that it also satisfactory on all levels below that level. This reasoning highlights the primacy of a simulation’s micro foundations, the individual agents’ behaviour and the rules that govern it. If a model is not able to reproduce agent behaviour that qualitatively resembles the behaviour of real individuals to a sufficient degree, the entire model is useless. Only after this minimum requirement is met, is it possible - or sensible - to examine emergent macro structures, and compare them qualitatively or quantitatively to empirical counterparts. The rules that govern the agents’ behaviour are the formalizations of real world processes in a simulation model. And the first and most important level to assess the validity of our formalization is to assess whether the chosen implementations lead to satisfactory individual behaviour.

The ranking above provides a general orientation that tells us where to look and in which order to do it. However more detail can be added to this approach. Carley (1996) discusses various other types of validation that blend into the hierarchy above, and she also presents various concrete methods to assess an ABM simulation’s validity.

Axtell and Epstein’s level 0 is equivalent to what Carley calls *face validity*: The computational model has an appearance such the model, taken at face value, “seems to jive with reality” Carley (1996, p. 10), the agents’ behaviour looks right. However, two independent aspects contribute to the apparent fit of the model: First, *process validity* is given when the processes implemented in the simulation model agree with the real processes. Taking the example of a model about the diffusion of innovation in a network (e.g. Watts & Dodds, 2007), agents should learn about the innovation from their neighbours. Second, *parameter validity* is
attained when input parameters of the model match parameter observed reality. In the same example, the parameters for the adaptation processes, such as the probability of adaptation at each encounter, should be realistic, maybe even derived from experimental evidence. Taken together both aspects are usually sufficient to provide face validity. However, it is possible that the individual agents’ behaviour looks right, but is based an unrealistic combination of parameters and processes, so it is important to consider parameters and processes independently, because they provide a deeper insight into how face validity is attained.

A suitable approach to establish face validity of a simulation is *grounding*, which can also be used to argue for parameter or process validity. Grounding aims to establish that the simplified mechanisms in the computer model do “not seriously detract from its credibility and the likelihood that it will provide important insights” (Carley, 1996, p.12). Researchers argue for the reasonableness of their model, and they can enhance that claim by carefully articulation of applicability, limitations and scope conditions for their model, or by reference to other, related models. “Grounding is largely a matter of story telling” Carley (1996, p.12). It is also possible to ground a model through its input, or through its output: Grounding through initialisation means that the starting parameters or procedures for the model are set to match a real world scenario. In order to ground a model based on its outputs, these have to agree with stereotypical facts or stylized behaviours (“stylized facts”) observed in reality. It is not the sole purpose of ABMs to replicate only known stylized results but the replication of non-surprising results first is a form of model validation.

Axtell and Epstein’s level 1 is essentially equivalent to what Carley calls pattern validity. Their level 2 however, can be divided into at least two more precise levels of validity. First, *point validity* requires the simulation’s output statistically agrees with observed data in the mean. Second, *distributional validity* requires that the simulation’s results have the same distributional characteristics as the real data, such as means, standard deviations, and generally belongs to same type of distribution, e.g. a normal distribution. Lastly, level 3 equates to value validity where the simulation is required to match real data on a point by point basis. For all three levels, to methods can be used to assess the simulation’s validity: Calibrating and empirical verification. The level of validation achievable does then depend on the performance of the simulation, research goals, as well as the quality of the data available.

Calibrating a model means that it is tuned to fit detailed set of real data. The goal of this approach is to establish the feasibility of the computational model by showing that the model can generate results that match the real data. If we can reproduce aspects of what has happened with a simulation model, we are inclined to be more confident to use the same model to explore what could happen. Calibration can cover all four levels in the above hierarchy. In one step,
the processes and parameters within the model are compared with data about the processes and parameters that produced the behaviour of concern (level 0). In another step the model’s results are compared to real life data (levels 1-3). Calibration is conducted on the basis of at least one detailed data set, that represents typical behaviour of the subject matter. Carley (1996) recommends participant observation or other ethnographic data for calibrating as other sources cannot usually provide the necessary richness of detail about processes as well as outcomes.

Figure 5 shows that calibrating is a multi-step, usually iterative process. It may require the researcher to both set and reset parameters, and also to alter the fundamental procedures, algorithms, or rules in the implementation. If agreement of results with data (within reasonable tolerance) is not reached, first the model’s parameters, then the underlying processes are tuned. If these alterations do repeatedly not lead to a satisfactory fit, it is possible to add lower level or auxiliary processes that were originally thought to be less important.

Carley uses the term verification to describe a set of techniques for determining the validity of a computational model’s predictions relative to a set of real data. To avoid confusion, this type of verification will be referred to as external verification. In contrast to calibrating, the model is not changed during external verification, the focus is on validating the model’s results not its internal workings. As a result, the level of detail in the data required to conduct
Figure 6: External verification on the basis of two data sets, from Carley (1996)

external verification is less than for calibration. External verification can be applied for levels 1-3 in the framework by Axtell & Epstein (1994). For level 1 above mentioned graphical and qualitative means can be used, and for levels 2 and 3 rigorous statistical tests are required, to assess point, distribution, or value validity on the aggregated and on the individual level, respectively. External verification can be conducted on the basis of one or more different data sets, or even independent parts of one large data set. A schematic illustration of this approach is shown in Figure 6).

There are some caveats to ABM simulations that need to be borne in mind when it comes to the assessment of validity. First, the simulation model will likely contain random elements. These elements are necessary if some parts of the model are not to be determined from the beginning, for example, agent decisions may involve random processes or heterogeneity among the agents’ is initiated through random allocation of certain traits. Second, simulations are path dependent and may be very sensitive to initial values that determine the simulation’s entire development - and may partially be random, too. For both of these reasons it is common practice to aggregate results of numerous simulation runs in order average out the impact of random elements in the model, exact correspondence cannot be expected in every run of the model. At the same time, processes in the real world may be path dependent, too, which means that the observed development of events does not necessarily coincide with the average
of various simulation runs. For these reasons validation on higher levels of the above hierarchy are very difficult to achieve.
5. Modelling Mechanisms

The computer simulations described here are formalized models of one or more of the mechanisms identified above as relevant to building dynamic, evolutionary models of business relations and networks. The mechanisms are captured in the rules that drive the behaviour and responses of each agent in the system. We will not be able to adequately represent all of the mechanisms outlined in section 3 in one model, as it would be too complex to make sense of. However, some representation of each of the five types of mechanisms has to be part of any complete model of business relations and networks. In building our own models we will draw on particular realizations of mechanisms represented in other models and experiment with alternative realizations to see their effects of the model.

Many simulation models use mechanisms that are similar in structure to the ones outlined in section 3. In some cases these were built specifically to capture economic processes (e.g. Tesfatsion, 1997), while in other cases, their motivation came from domains such as biology (e.g. Seufert & Schweitzer, 2007) or sociology (e.g. Pujol et al., 2005). Nonetheless, based on the similarity of the implemented mechanisms, it is possible to utilize them in the process of model development and to draw on their results.

In the following we use representative examples of models in which one or more of the mechanisms of interest have been modelled. Some form part of more comprehensive models designed to represent actual systems and others are more abstract formulations, focusing on specific mechanisms. A summary overview of all the models reviewed so far is presented in Tables 6 to 11 in Appendix A.

5.1. Simulations Related to Specialization and Division of Labour

Not many simulations address specialization. Usually heterogeneity among agents in a model (people or firms) are built in at the outset, rather than emerge endogenously. For example the Sugarscape model includes more than one commodity and agents share the labour of harvesting them, sharing the fruits of their labour through welfare-improving (i.e. mutually agreeable) bilateral barter (Epstein & Axtell, 1996).

The BankNet model (Sapienza, 2000) is an example of a model where specialization emerges endogenously, in the form of specialized banking intermediaries. All agents are identical at the beginning of the simulation. Each round, they receive money which they hand to another agent in order to invest it for them. Initially the choice of investors is basically random as all agents have the same chance of investing the entrusted money successfully. But agents gain experience points with every successful investment, and more experienced agents automati-
cally have better chances of success in future investments. In addition to the positive effects of accumulated experience, the model also includes a mechanism of scale efficiencies, which makes investment activities more cost effective the more money a single agent is entrusted with in a given round. Gradually some agents set themselves apart from the rest of the population through success, experience and size, and at the same time, they become more attractive as investors for others. As the simulation continues, more and more agents decide to select one of these lucky few as the one they want to entrust their money in. Banking intermediaries emerge.

This model captures essential mechanisms underlying the emergence of intermediaries including random fluctuations, heterogeneity, positive feedback and lock-in effects, restricted choice, imperfect knowledge and learning effects, which can be adapted to show how intermediaries emerge in marketing and business networks. This model has been replicated in a more general way using NetLogo and will be demonstrated during the presentation, an illustrative, yet more detailed slide show is provided in Appendix B.

Nelson & Winter (1982) model the process of competition and between innovators and imitators. They merge the Schumpeterian concept of competition with an evolutionary framework of variation and selection. In this model, firms have two ways to improve their productivity. They can invest in research towards innovation or towards imitation of best industry practices. Random processes are used to determine the success of either endeavour. The model comes in two variations. First, innovations can be independent of each other, changing a firm’s productivity only gradually. Second, when cumulative technology effects are enabled, an innovative success gives a firm not only better techniques, but also a higher platform for the next period’s search. This mechanism leads to path-dependence in the model development and ‘lock-ins’ into certain technological pathways as minor comparative advantages are able to reinforce themselves.

The mechanisms proposed by Nelson & Winter (1982) have been extended in many ways. For example, learning and specialization in the context of research and innovation networks is observed in by Gilbert et al. (2001). Agents are equipped heterogeneously with a set of technological capabilities, specialized abilities and a associated levels of expertise, abstractly represented by a triple of numbers, a “kene” (Gilbert, 1997). They use their skills to produce “innovation hypotheses” that are then offered in a marketplace which randomly determines their success of failure. Agents can follow different research strategies: work independently, imitate others, or coordinate research in collaborations or networks. Agents can learn and specialize, led by the success of earlier innovations, so that they concentrate their expertise in selected areas, and forget about others.
5.2. Simulations of Business Mating Mechanisms

The literature on partner search mechanisms in simulations is abundant, as it is one of the core mechanisms necessary to design a network simulation. The simplest models of network generation use random pairing. Exploring the impact of different pairing probabilities $p$, as a function of the number of members in the network ($N$), Erdös & Renyi (1959) show that different structures emerge in the network after crossing certain thresholds, which are shown in Figure 7.

![Figure 7: Subgraphs in a random network](image)

Preferential attachment is another mating mechanism that has received substantial attention in the literature (Barabási & Albert, 1999). A network is grown by adding new members to the network consecutively. They form connections to existing members with probabilities relative to the number of links that they have already - in a way, the rich get richer. Preferential attachment was the first mechanism to generate scale-free networks, a pattern found in many social and economic networks and the internet.

In terms of network analysis, the absolute number of connections held by each network member, or node, $i$ is called its degree $k_i$. The overall distribution of degrees is often used to describe the nature of the network. The characteristic of scale-free networks is that their degree distribution can best be described by a power-law function: The fraction $P(k)$ of network members with degree $k$, can be represented as

$$P(k) \propto k^{-\gamma}$$

Power-law functions are scale-free, in the sense that they keep the same shape independent of the scale of inspection. The network can have 100 or 100,000 members, on a log-log plot the degree distribution always follows a straight line. In scale-free networks, a small number of members have a degree far above average (hubs), while many have only a very small number of connections.

Preferential attachment has been extended and imitated in various ways. 1) Agents might lose attractiveness with age which changes the resulting degree-distribution to an exponential
function, if the impact of ageing is strong enough (Dorogovtsev & Mendes, 2000). 2) Bianconi & Barabási (2001) add a fixed, exogenous parameter of attractiveness to the attributes of each network member which adds linearly to the probability of preferential attachment. The resulting degree distribution is a weighted sum of different power-laws, depending on the distribution of the new parameter. 3) New relationships can be established relative the members’ activity level. Fan & Chen (2004) found that if activity is represented using chaotic functions, scale-free degree distributions emerge. However, if activity follows a periodic pattern, this is not the case. 4) Performance has been used as another criterion to attract new links. New network members form connections to existing members with probability relative to received pay-offs in the strategic “Snowdrift Game”. This mechanism, too, leads to the emergence of scale-free networks (Ren et al., 2006). 5) Vázquez (2000) uses a mechanism that mimics literature research, or maybe a form of inheritance. A new member is randomly connected to an existing member in the network and then “walks along” this member’s existing connections to connect to them with a given probability \( p \). Depending on the size of \( p \) the emerging networks either have a finite average degree or a power law degree distribution without no finite average. Another interpretation of the last mechanism is that it represents a kind of referral system, corresponding to empirical research results that many new firm relations come from previous relations (e.g. Li & Rowley, 2002).

Another approach to explore a emergence of relations and network structure resulting from simple, local rules is presented in Hamill & Gilbert (2009). Agents are distributed in a “social space” and have a “social reach” of varying length. Relationships can only be formed between agents that are sufficiently close so they can reach each other. An illustration is given in Figure 8 Controlling the mixture of reaches and system sizes, many statistical parameters of real networks can be reproduced. This approach can be seen as a prototype of in-silico networks which grow on the basis of similarity. Beyond physical distance, this mechanism is compatible with many different concepts of distance, be it technical standards, corporate culture or simply awareness of an agent’s existence.

Early on, simulation studies explored the development of strategic games on network structures. Stanley et al. (1995) and Ashlock et al. (1996) ran iterated Prisoner’s Dilemmas (iPD), giving their agents the options to choose and refuse interaction with other agents on the basis of expected payoffs. Table 4 shows the particular values of payoffs used by Ashlock et al. (1996). In these simulations, the agents’ strategies, which decide how they choose to cooperate and defect, evolve over time, based on their performance. The agents’ expectations develop in parallel, as the agents experience the behaviour of more and more interaction partners. The decisions to interact must be made in mutual agreement of both partners, and is dependent
on a global acceptability threshold regarding the agents’ expectations. As a result, almost full cooperation emerges in most cases. Only high levels of intolerance regarding defections, or low costs refusal and social isolation, can lead to the emergence of “wallflower ecologies”, in which all agents are socially isolated.

The structure of simulations that lie between these two extremes exhibit many peculiar interaction patterns. A particular pattern has been termed Raquel-and-the-Bobs Smucker et al. (1995), which is an intertwining of two interaction patterns that repeatedly arise from one another. Bobs follow a strategy that defects once, at or near the beginning of an interaction. Raquels cooperate consistently. The pattern begins, when a Raquel appears in homogeneous population of Bobs. Raquel cooperates from the beginning, and soon receives cooperative returns from the Bobs she encounters. Instead of constantly interacting with new partners, Bobs establish a cooperative relationship to the Raquel. Her strategy becomes more successful and replicates, so that more Raquels evolve in the system. However, when a certain number of Raquels have appeared in the system, the fitness of Bobs surpasses that of Raquels and tips over the evolutionary process. Due to the strict evolutionary mechanism, usually all Raquels are then eliminated from the system. Figure 9 schematically shows the development of one such cycle, until the number of cooperative Raquels becomes so high that in the next step, evolution would favour the reproduction of Bobs only, as in the initial situation.
Figure 9: Development of the network of interactions in a population with Bobs (blue) and Raquels (red), adapted from Ashlock et al. (1996)
Tesarfsion (1997) further developed this model in what she calls her “evolutionary trade network game”. Using a more intricate matching mechanism, she examines the development of an iPD for two sided markets and one for one-sided intermediation. The simulation includes evolving strategies, memory, transaction costs and partner choice based on expectation. It supports earlier findings, as high levels of cooperation can be maintained in this more complex setting, too.

Zimmermann et al. (2004) let agents interact in another iPD, but they give them the option to terminate a relationship if they are both defecting and are not satisfied with this outcome. A new partner can then be selected randomly or by choosing a “friend of a friend”. These mechanisms lead to a hierarchical interaction network that sustains a highly cooperative stationary state. Connecting to friends of friends leads to the development of high clustering in the network. Interestingly enough, Hanaki et al. (2007) find that the latter mechanism does not favour cooperation in a setting where the termination of a relationship is based on myopic cost/benefit considerations.

Pujol et al. (2005) use mechanisms grounded in social exchange theory to examine the structure of a network emerging from local information, bounded rational optimization, and randomly arising conflicts. Agents play the support exchange game and have different levels of attractiveness and memory. Their behaviour leads to small-world and power-law network structures, i.e. the number of connections which would connect any given pair of agents is relatively low, and many agents have only a few connections while a few central players become hubs with many relationships. The resulting network structure depends heavily upon the exchange game’s payoff structure and on the accuracy of information the agents receive about their neighbours’ reliability. It demonstrates that market intelligence, regarding both customers and competitors can provide a competitive advantage and how incentive structures affect network development.

Both models mentioned in the previous section also include elements of business mating. In the innovation model by Gilbert et al. (2001), agents can agree to combine their expertise in cooperative clusters. However, as an entry barrier, agents must have cooperated successfully with one of the cluster’s members before. In the BankNet model, agents maintain two qualitatively different connections to other agents. One connects to the agent that they will entrust with their cash in the next round, the other becomes relevant when an agent is randomly assigned an “opportunity”. These opportunities always need additional financing from other agents, and it’s the second type of links that is used to send out loan requests to other agents. Every round, each agent compares the potential of one other randomly selected agent to what he received from the two agents he is currently connected to. If the new agent appears to have
more potential in one or both respects, the respective connection is redirected towards him. Through this mechanism of direct comparison, all agents gradually move their links to the few extraordinarily well performing individuals.

5.3. Simulations of Business Dancing Mechanisms

The development of economic relations has been examined extensively in the social sciences, but so far simulations deal with only a few aspects of this. Iterated game theory models have been used to a large extent to model interaction and coordination situations. Axelrod and Hamilton’s early simulations focused on the iterated prisoner’s dilemma game and the conditions under which cooperative strategies emerge (Axelrod & Hamilton, 1981). Later work has also considered other types of games and the evolution of strategies as a result of the experience of and performance in interactions over time. Tesfatsion’s trade network game uses IPD to model interactions and also uses the outcomes to affect choice and refusal of partners (Tesfatsion, 1997).

The positive effects of loyal behaviour regarding the costs and risks of stock keeping demand fluctuations are examined in a simulation of the Marseilles Wholesale Fish Market by Kirman & Vriend (2001). The same actors meet on a daily basis. Sellers have to set the amount of fish they intend to sell at the beginning of any given day and buyers choose where to queue for supplies and which price they are willing to accept. The sellers then have to decide the price they want to ask and in which order to serve their customers. Sellers are only aware of “faces they have seen before”, and can follow a strategy to reward them, or not. Buyers update their queuing strategy continuously, increasing the probability of giving orders to previously successful buyers. In the course of the simulation, the agents learn to engage in and reward loyalty which proves to be advantageous for individual players and the efficiency of the entire system.

Kim (2009) built a model of a self-organizing supply network on the basis of the “Beer Game” model (Sterman, 1989; Mosekilde et al., 1991; Sterman, 1992). The purpose of the original model was to show the complexities in the order process of a linear supply chain. Kim’s extension models a more complicated network with three layers on each of the five levels in the chain. Each agent equipped with rules to forecast their demand, and manage their ordering and supplying decisions. Moreover, this model adds a parameter called “trust” to the decision making process. This parameter reflects how the expectations towards “trust” to the decision making process. This parameter reflects how the expectations towards an agent in the adjacent levels have been met in previous interactions. If orders or shipments exceed the amounts requested, trust increases and negative results decrease trust. Similar to the simulation of the Marseille’s Fish Market, a non-economic mechanism helps to reduce uncertainty and
risk by reducing demand volatility and storage costs.

Learning mechanisms are a very important to the interaction processes in business relationships. The selection of possible implementations is abundant. They reflect different philosophies about the nature of learning and suitable choices always depends on the simulation’s purpose, too. Brenner (2006) reviews the development of learning mechanisms and their various sources, such as psychology, statistics, biology or artificial intelligence. He derives the list of recommendations presented in Figure 10, which may serve as a guideline to select appropriate learning mechanisms for the right purpose. He distinguishes two situations that require different choices of learning mechanisms. First, there are situations where conscious actions in the learning process are not important. In cases like this, the Bush-Mosteller model, which is a simple formalization of reinforcement learning is recommended. It can only be applied to situations where individuals have to choose repeatedly from a finite set of alternatives. Second, situations where conscious efforts become important, e.g. when they require to assign meaning to observations, to build beliefs about future events, or generally when understanding is necessary. In these more complicated situations, the researcher has to decide whether simplified routine-based learning mechanisms are sufficient for his purposes, or whether it is important to include belief learning mechanisms that mimic real learning processes more closely. Routine-based learning mechanisms are based on simple fundamental principles of learning. Their key characteristic is that there is a direct connection between the agents’ experiences and observations and their behaviour. While they may not be appropriate to model conscious learning efforts, they may be sufficient to describe behaviour. Belief learning mechanisms are motivated by cognitive learning theory. They represent the beliefs an agent holds about the world explicitly. These beliefs are formed on the basis of observation and experience and they affect the decisions and actions an agent makes. The advantages of belief learning mechanisms are that they represent cognitive processes more realistically than routine-based mechanisms and that they may provide the agents with a greater degree of autonomy, allowing even for creative actions. Among others genetic algorithms, briefly discussed in section 4.3.1 are examples of this class of mechanisms. For further details and references, see Brenner (2006).

5.4. Simulations of Mechanisms Connecting Relations

Many existing simulations fit best into this category, as they look at the effects of network structure on its members. A great number among them examine the impact of network structure on cooperative behaviour in game theoretic settings. Many network structures favour cooperation. Santos & Pacheco (2005) find an explanation of this surprising quality in the
Figure 10: Steps to choose an accurate learning model for representing economic behaviour, from Brenner (2006)
interconnection of hubs in many network topologies. Artificial, random networks do not necessarily connect such hubs with each other and as a consequence, cooperation is fostered much less strongly. Ohtsuki et al. (2006) find that sparsely connected networks favour cooperation in strategic games, seemingly independent of their global structure.

The position in a network can strongly affects an individual performance. Wilhite (2006) analyses the effects of structure in a simple barter economy with two goods on fixed networks. The members of these economies start with an inhomogeneous endowment of two goods and exchange with all the other agents they are directly connected to, as long as they can improve their utility level with this exchange. Figure 11 summarizes the different types of networks used in this study.

The results show that strong inequalities in the distribution of wealth can arise based on the network’s structure and on the agent’s position in the network. Agents with many connections, so-called hubs, are generally found to acquire more wealth. This effect is more pronounced in centralized networks, such as the star and the tree.

The results reproduced in table 5 show the performance of the overall network’s structure with regard to selected critical measures. Completely connected a lead to rather homogeneous wealth distributions but require high costs for searches, the maintenance of relations and negotiation. The power-law network minimizes the number of searches required, providing while
Table 5: Reproduction of Table 3 from Wilhite (2006, p. 1038): Results of a trade simulation on various fixed network structures, it shows averaged values over multiple simulation runs and the respective standard deviation in brackets.

<table>
<thead>
<tr>
<th>Network Type</th>
<th>Number of Edges</th>
<th>Rounds of Trading</th>
<th>Total Trades</th>
<th>Total searches</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complete</td>
<td>500500</td>
<td>157</td>
<td>468748</td>
<td>1568430000</td>
</tr>
<tr>
<td></td>
<td>(8.75)</td>
<td>(3314)</td>
<td>(8741250)</td>
<td></td>
</tr>
<tr>
<td>Star</td>
<td>999</td>
<td>452</td>
<td>481443</td>
<td>2257740</td>
</tr>
<tr>
<td></td>
<td>(2.81)</td>
<td>(2396)</td>
<td>(14035)</td>
<td></td>
</tr>
<tr>
<td>Ring</td>
<td>2000</td>
<td>35681</td>
<td>45102011</td>
<td>142724800</td>
</tr>
<tr>
<td></td>
<td>(239.93)</td>
<td>(55205)</td>
<td>(959720)</td>
<td></td>
</tr>
<tr>
<td>Grid</td>
<td>2000</td>
<td>2515</td>
<td>3250932</td>
<td>10062000</td>
</tr>
<tr>
<td></td>
<td>(50.45)</td>
<td>(3983)</td>
<td>(201800)</td>
<td></td>
</tr>
<tr>
<td>Tree</td>
<td>999</td>
<td>34742</td>
<td>2039978</td>
<td>138968000</td>
</tr>
<tr>
<td></td>
<td>(1548.56)</td>
<td>(155332)</td>
<td>(6194240)</td>
<td></td>
</tr>
<tr>
<td>Small-world</td>
<td>2000</td>
<td>3719</td>
<td>3766458</td>
<td>14872000</td>
</tr>
<tr>
<td></td>
<td>(592.11)</td>
<td>(466836)</td>
<td>(2368440)</td>
<td></td>
</tr>
<tr>
<td>Power</td>
<td>2000</td>
<td>422</td>
<td>7446698</td>
<td>1689600</td>
</tr>
<tr>
<td></td>
<td>(24.35)</td>
<td>(13736)</td>
<td>(97400)</td>
<td></td>
</tr>
</tbody>
</table>

providing a well balanced distribution of wealth. However, the number of trades required is comparatively high. A ring-shaped network topology connects each agent to only a small number of close neighbours. This highly redundant structure necessitates a very high number of exchanges to come to a stable distribution of goods. Small-world networks are derived from rings, by substituting a relatively small number of cross-group connections for connections to direct neighbours (Watts, 1999). They have properties of that are found frequently in real social networks, namely a short average distance between each pair of network members and still many clusters of members who are mainly connected to members of their own group. In this model, the small-world network outperforms the initial ring structure in all respects. There is an incentive for traders to occupy an interconnecting position between two groups: The distribution of goods is not too inhomogeneous, but cross-group traders are clearly in advantage, accumulating about ten times the wealth of others. In small-world networks provide a trade-off between the numbers of links, searches and rounds to market clearance and the homogeneity of the wealth distribution. 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”.

In the presence of limited resources or other sources the success of one relation might
depend on the success of another. The aforementioned adaptation of the Beer Game supply network includes an interesting coupling of mechanisms. Trust is built up on the basis of positive experiences, but it also affects the agents’ decisions with regard to how they allocate orders and which orders they give preference to. In Figure 12 the agents in dashed rectangle could not establish a strong collaborative relationship based on high trust level with at least one of its upstream or downstream agents. While they are still able to trade their trading amounts are relatively small.

Facing conflicting interests, we may encounter the emergence of competing groups. Gavrilets et al. (2008) assume that such groups are based on an underlying affinity network. Conflicts arise randomly between pairs, other agents can join in and support one side, based on their affinity towards the parties involved. The outcomes of these conflicts affect the agents’ affinities over time, making the winning side more attractive. The simulations exhibit a sudden phase transition after which distinct alliances emerge, although their size varies strongly. Once this process has begun, there is no other reasonable strategy but to join one of these alliances.

Models of opinion dynamics examine how opinions adapt in a population on the basis of social contacts. Holme & Ghoshal (2006) builds a model where the change of opinion and the change of connections goes hand in hand. Links and opinions are initially placed uniformly at random. An agent adopts a neighbour’s opinion with probability $p$ or he grows a new link to node with an opinion similar to his own with probability $1 - p$. Depending on the size of $p$, the model shows a separation into several small or one big unanimous cluster. Also there exists a value $p_c$ which leads to a continuous phase transition and a very long time to reach
consensus. Apart from opinions such a mechanism could also reflect the adaptation of certain industry standards, technology or innovation.

5.5. Simulations about the Impact of the Environment

The environment in simulations can be seen from an applied or a technical perspective. In the applied sense, the environment reflects the empirical environment and it is the purpose of the model to investigate how changes in the environment affect the development of the simulation. In a technical sense, the environment reflects modelling assumptions that are necessary to implement the model as software, but which are not motivated by empirical evidence. Through systematic exploration of alternative implementations, the robustness of the model’s results is tested with regard to these particular assumptions. There are, of course, mechanisms that do not clearly fit into only one of both categories.

An example for an applied example is the analysis of the impact of taxes and subsidy mechanisms in a game theoretic setting. Lugo & Jiménez (2006) introduce taxes and subsidies to influence agents’ behaviour in early stages of a network based iPD game. Cooperation becomes relatively more attractive compared to defection. Smaller numbers of initial cooperators are needed to reach higher levels of cooperation, faster. Essentially, they changed the payoff structure of the Prisoner’s Dilemma to to favour cooperative strategies. Interestingly enough, they could switch off their tax-based transfer mechanism in stages and the system retained a high level of cooperation.

More technical results find the relation between the time scales of actions on the network and the speed of the rewiring process of the network to be a key determinant. A high rewiring speed of connections can essentially change the payoff structure of strategic games so that they favour cooperation. Pacheco et al. (2006) show that if the network rewiring process is fast enough relative to the interactions that occur on the network, it can change the payoff structure of the PD and Snowdrift games so that they favour cooperation.

Environmental influences can also be introduced directly through the payoff structure of strategic games. Pujol et al. (2005) build a model of cooperative exchange behaviour based on sociologically grounded mechanisms. The agents use simple decision heuristics, based on imperfect, local information. Their results show that the emerging network structures depend heavily on the harshness of the exchange game, in particular the ratio of costs to benefits in a social exchange. Furthermore, the accuracy of information the agents receive about attractive potential exchange partners from their network relations affects the development of the network structure.

Networks of interaction and for the transmission of information do not necessarily coincide.
This assumption is investigated by Ladley & Bullock (2008) who connect agent with one network for trade, and a different network for the gathering of price information. They look at all four possible combinations of scale-free and fully connected networks, one used to gather price information and the other used to find actual trade partners. Agents have the capability to adapt their trading and pricing strategies over several generations, relative to their fixed network position. It is found that the network’s structure affects the learning of strategies and the profits of traders. Less densely connected networks lead to more heterogeneous payoffs. Well connected players have more choices and can make more profits, but the abundance of available (and possibly inaccurate) information may also lead to inferior results.

The effects of spacial arrangements, location and infrastructure have been investigated in the literature on self-organizing urban dynamics. An urban area is represented by a grid of cells, or zones, each of which is characterized by a vector of socioeconomic indicators. These indicators include e.g. the numbers of blue and of white collar residents, volumes of the export and of the local industry, levels of elementary tertiary and rare functions and financial activities. Furthermore the area’s infrastructure is included in the model, e.g. in the form of major transport ways (Allen, 1983). Much like system dynamics models, these indicators are coupled through equations of motion, so that positive and negative feedback effects drive the development of the system. However, the underlying spacial structure, the arrangement of neighbouring zones and the immobile infrastructure have an effect on these models, too (Crosby, 1983; Allen, 1997). The same concept of an underlying heterogeneous spacial structure has more recently been used in agent-based models of urban organization (e.g. Portugali et al., 1997; Benenson, 1998).

5.6. Discussion

I have reviewed literature in economics and marketing to identify key mechanisms of marketing and business networks. These were grouped logically as mechanisms of specialization and division of labour, business mating, business dancing, connection between relationships and environmental impacts. Contrasting these mechanisms with implementations in network simulations yields many potential ways of representing these mechanisms in simulation models interesting insights. While examples for every category are available, there are still gaps requiring additional modelling effort.

- Only few examples could be found for the development of specialization in simulations. However, either these were not built to analyse the network structure (Nelson & Winter, 1982; Gilbert et al., 2001), or the mechanisms employed were only crude approxima-
• Many simulations deal with search mechanisms and their impact on network topologies. Some already mimic empirical processes. Nevertheless, there seem to be no simulations allowing agents to negotiate the terms of a relationship at the outset along the lines of discussions in transaction cost theory in terms of types of governance structures.

• Many simulations rely on satisfaction to decide about the continuation of a relationship. However, simulations do not yet capture the evolution of relationships, ongoing investments or the development of a relationship atmosphere. In most simulations a connection either exists, or not. Kirman & Vriend (2001) and Kim (2009) can be seen as an exception here.

The simulations discussed stand representative for a large range of simulations. They strive for generality and minimalism at the expense of being grounded in real contexts. However we must avoid the trap of making our models too complex and detailed, what would make them as difficult to fathom as real world systems. The aim of modelling is to capture and analyse the effects of key mechanisms, irrespective of whether the model is a simulation, mathematical, in words or figures. Thus models avoid large number of parameters, distributional assumptions, and complex interactions to reduce model complexity to such a degree, that the developments in the simulation are still comprehensible. Midgley et al. (2007, p. 892) recommend to “look for the one or two key aspects” that drive 80% of the overall system’s variance as the basis for a minimalist model. In line with this reasoning I will focus on key mechanisms in the empirical literature that appear most important.

I plan to combine basic mechanisms modularly to develop more complex simulations. These initial models are sometimes described as toy models as they are the first stage of the model building process. I plan to demonstrate some of these as part of the presentation of this proposal.

I am proceeding to reproduce the essential features of relevant models of relations and networks using NetLogo as the platform in a business network context. NetLogo is freeware and is a more user friendly programming environment than other agent based systems that have been developed, such Swarm, Anylogic, Repast and Mason, which require high level expert programming skills. Also, the latest version includes links or relations between agents as actors in their own right, as well as dimensions of the environment. NetLogo models can be scaled up at a later stage to run on more powerful platforms using high level languages.

The first level toy models of different mechanisms can be examined and compared to real word mechanisms before moving on to combine them in more comprehensive simulations in
a modular fashion. This will enable us to better understand interaction effects among mechanisms as well the effects of individual mechanisms. They can also be calibrated and evaluated as far as possible.
6. Conclusion

Business relationships are dynamic, they are embedded in a larger network of interconnected relationships and change over time. Current research and theory in marketing give very limited attention the issue of dynamics and change in marketing systems. The dominant variance-based and cross-sectional approaches cannot capture the development of relationships over time, narrative and longitudinal research are usually so data intensive that they have to focus on the development of one relationship, or the interactions between a very small number of them.

In order to advance our understanding of the dynamics of business relationships and networks, we intend to build computer models of the key mechanisms that drive their development. These mechanisms are the causal drivers implicit in many existing theories, so it was possible to identify them on the basis of existing literature. However, even though we may be able to identify these mechanisms individually, there are many unsolved questions: How can these mechanisms be formalized? Can they be parametrised? How do they affect the development of a relationship over time? How do different mechanisms interact with each other. In how far affect the mechanisms in one firm the developments in others, if they are directly, or indirectly connected to it? How do they affect the development of a network? How does the network affect them? The Ph.D. thesis that is envisioned as a result of this project address some of these issues, but in light of the novelty and scope of this endeavour, it will not be able to answer all these questions exhaustively. But it can make the first steps in this direction and provide a basis for further research.

The approach proposed here will look at business relationships and networks from the perspective of complexity theory. Business networks are self-organizing systems, where heterogeneous businesses act and interact with each other, on the basis of local and limited information. Together they form and reform the network, a complex adaptive system, where feedback effects from its members to the overall structure and from the structure to its members affect the development over time. Members’ actions affect each other directly or indirectly and the multiplicity of interactions make it hard to anticipate the consequences of any one deliberate action.

Agent-based modelling and simulations can be used to model and study such complex adaptive systems, exploring their behaviour in an experimental fashion. Businesses can be represented as autonomous software agents that have inbuilt characteristics and also interact on the basis of defined rules. These rules are formalizations of mechanisms that are identified to drive developments in real business relationships and networks what includes mechanisms of a psy-
ological, social, technical or economical nature. Computer simulations make it possible to monitor the system’s development in great detail on the level of individual agents as well as on the aggregated network level.

The structure of ABM programs is modular, which means that a basic model of core mechanisms can be extended systematically with new mechanisms, or variations of old ones, to examine their impact on the system’s development. The review in section 5 showed that there are many mechanisms that can inform the development of new models. Systematic examination of main and interactive effects among mechanisms can be done on the basis of experimental designs. The main focus of analysis here will be the development of network structures. We will examine the types of structures that emerge under different conditions, and analyse the robustness and sensitivity of these results with statistical means.

The main method of model validation will be grounding, in order to argue for the models’ validity. Section 3 identified five different categories of mechanisms thought to drive the development of business relationships and networks. These will serve as templates for the rules implemented in the simulations, establishing its process validity. Furthermore, configurations of existent business networks can be used to ground initial parameters of a sufficiently advanced model. Such a model must include enough mechanisms that it has the potential to reproduce a real-world system to useful detail. Calibration techniques can then be used to “fit” the model and the initial conditions to approximate observed micro and macro behaviour, at least to the degree of stylized facts of reality. The aim of this approach is to establish the model’s face validity. Showing that it is possible to replicate non-surprising stylized results, increases our confidence when we use the same model to investigate what could happen. Furthermore, the previous modular analysis of the mechanisms’ main and interactive effects will provide a basis to explain the developments of a simulation in a causal way.

Figure 13 summarizes a tentative schedule for the completion of the thesis within a time horizon of 18 months. During the entire model development process, it will be necessary to monitor new developments in the simulation and modelling literature, in order to keep the contribution up-to-date. The schedule can roughly be partitioned into 3 phases: First, exploration of mechanisms in toy models, second, combination of mechanisms in a large model, and finally experimental analysis and write-up of results.

In the first phase, a build basic models will be built using the programming environment of NetLogo (Wilensky, 1999). This tool has been developed specifically to provide easy and intuitive introduction to ABM simulations. I will formalize mechanisms of each of the five types identified and explore their working and simple interactions. At first, a very basic exchange model will be implemented which can then be gradually extended through other
Continuing review of existing simulation models
Formalization of mechanisms
Programming
- Basic exchange model
- Extension through mechanisms
Quasi-experimental analysis of mechanisms’ effects
Exploration of emergent behaviour
Java implementation by professional programmer
Quality testing, assurance
Tentative calibration
Analysis of emergent behaviour
Writeup

Figure 13: Tentative schedule for the completion of the Ph.D. thesis
mechanisms, independently or in combination. As far as the capacity of NetLogo allows, first experiments can be run, to explore the emergent behaviour of a model that includes a combination of more mechanisms at the same time.

However, the comfort and ease of NetLogo come at a cost, and it is likely that the program will be too slow to compute thousands of simulation runs of an advanced model within reasonable time. Therefore, in the second stage an external programmer will be included to develop the advanced model, implementing it in Repast or SWARM, both are Java-based languages customized for ABM. They might be able to reduce computational costs significantly. Sufficient time is scheduled to conduct quality assurance and model verification.

In the final phase this model can be calibrated to realistic scenario(s), to see if it is possible to reproduce realistic developments and also the overall model behaviour can be analysed in an experimental way. Allowing four month to write the final thesis, this schedule should suffice to submit the thesis by March 2012.
### A. Appendix: Overview of Reviewed Models

<table>
<thead>
<tr>
<th>Reference</th>
<th>Mechanism</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nelson &amp; Winter (1982)</td>
<td>Focus on innovation or imitation, random successes, path dependence</td>
</tr>
<tr>
<td>Gilbert et al. (2001)</td>
<td>Specialization in technical fields, capacities are numeric values</td>
</tr>
<tr>
<td>Sapienza (2000)</td>
<td>Specialization through experience and efficiencies of scale</td>
</tr>
</tbody>
</table>

Table 6: Models of mechanisms related to specialization

<table>
<thead>
<tr>
<th>Reference</th>
<th>Mechanism</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pacheco et al. (2006)</td>
<td>Active linking: Nodes can control the number, nature, and duration of their interactions</td>
</tr>
<tr>
<td>Slanina &amp; Kotrla (2000)</td>
<td>Attachment by similarity</td>
</tr>
<tr>
<td>Holme &amp; Ghoshal (2006)</td>
<td>Combination of opinion dynamics and rewiring</td>
</tr>
<tr>
<td>Helbing et al. (2009)</td>
<td>Imitation of strategies and migration to more favourable positions</td>
</tr>
<tr>
<td>Vázquez (2000)</td>
<td>Inheritance of old connections</td>
</tr>
<tr>
<td>Ravasz et al. (2002)</td>
<td>Iterative duplication and reintegration of links, following the idea of hierarchical modularity</td>
</tr>
<tr>
<td>Dorogovtsev et al. (2001)</td>
<td>Link inheritance</td>
</tr>
<tr>
<td>Simoni et al. (2006)</td>
<td>Linking based on preference for innovations or imitation</td>
</tr>
<tr>
<td>Hanaki et al. (2007)</td>
<td>Links have maintenance costs, search for new partners through friends-of-friends</td>
</tr>
<tr>
<td>Dorogovtsev et al. (2000)</td>
<td>Loss of attractiveness with age</td>
</tr>
<tr>
<td>Hamill &amp; Gilbert (2009)</td>
<td>Nodes are distributed in social space and have a social reach of various lengths</td>
</tr>
<tr>
<td>Jain &amp; Krishna (2001)</td>
<td>Nodes sustain or damage each other through links</td>
</tr>
</tbody>
</table>

Table 7: Models of mechanisms related to business mating
<table>
<thead>
<tr>
<th>Reference</th>
<th>Mechanism</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zimmermann et al. (2004)</td>
<td>Partner selection random or through friends-of-friends</td>
</tr>
<tr>
<td>Bianconi &amp; Barabási (2001)</td>
<td>Preferential attachment, additional fitness parameter</td>
</tr>
<tr>
<td>Ren et al. (2006)</td>
<td>Preferential attachment relative to performance</td>
</tr>
<tr>
<td>Amaral et al. (2000)</td>
<td>Preferential attachment, link decay and upper bound for degree</td>
</tr>
<tr>
<td>Dorogóvtsev &amp; Mendes (2000)</td>
<td>Preferential attachment, nodes loose attractiveness with age</td>
</tr>
<tr>
<td>Fan &amp; Chen (2004)</td>
<td>Preferential attachment, relative to activity</td>
</tr>
<tr>
<td>Albert &amp; Barabási (2000)</td>
<td>Preferential attachment, relative to degree</td>
</tr>
<tr>
<td>Barabási &amp; Albert (1999)</td>
<td>Preferential attachment, relative to degree</td>
</tr>
<tr>
<td>Gilbert et al. (2001)</td>
<td>Access to collaborative clusters only after successful cooperation</td>
</tr>
<tr>
<td>Bollobás (1985)</td>
<td>Random attachment</td>
</tr>
<tr>
<td>Erdös &amp; Renyi (1959)</td>
<td>Random attachment</td>
</tr>
<tr>
<td>Watts &amp; Strogatz (1998)</td>
<td>Randomly rewiring to receive a small-world network</td>
</tr>
<tr>
<td>Hales &amp; Arteconi (2006)</td>
<td>Rewiring and strategy adaptation to foster cooperation</td>
</tr>
<tr>
<td>Gong &amp; Leeuwen (2004)</td>
<td>Rewiring relative to similarity</td>
</tr>
<tr>
<td>Hornquist (2001)</td>
<td>Rewiring through weighted links mechanism (neutral evolution)</td>
</tr>
<tr>
<td>Rosvall &amp; Sneppen (2007)</td>
<td>Rewiring to improve network position</td>
</tr>
<tr>
<td>Sapienza (2000)</td>
<td>Specialization through experience and efficiencies of scale</td>
</tr>
<tr>
<td>Gross &amp; Kevrekidis (2007)</td>
<td>Spread of disease, potential to break ties to infected</td>
</tr>
<tr>
<td>Hales &amp; Edmonds (2005)</td>
<td>Tagging to &quot;recognize&quot; cooperative players in PD</td>
</tr>
<tr>
<td>Zimmermann et al. (2004)</td>
<td>Termination of unsatisfactory relations, new links randomly or through friends-of-friends</td>
</tr>
<tr>
<td>Eguíluz et al. (2005)</td>
<td>Possibility of refusal in PD</td>
</tr>
</tbody>
</table>

Table 8: Models of mechanisms related to business mating (continued)
<table>
<thead>
<tr>
<th>Reference</th>
<th>Mechanism</th>
</tr>
</thead>
<tbody>
<tr>
<td>Axelrod &amp; Hamilton (1981)</td>
<td>Interaction as iterated Prisoner’s Dilemma, evolution of cooperative strategies</td>
</tr>
<tr>
<td>Stanley et al. (1995)</td>
<td>Interaction as Prisoner’s Dilemma, evolution of strategies, partner choice and refusal based on expectation</td>
</tr>
<tr>
<td>Tesfatsion (1997)</td>
<td>Interaction as Prisoner’s Dilemma, evolution of strategies, partner selection based expectations, different market settings</td>
</tr>
<tr>
<td>Kirman &amp; Vriend (2001)</td>
<td>Able to learn that loyal behaviour can be mutually beneficial</td>
</tr>
<tr>
<td>Pujol et al. (2005)</td>
<td>Attractiveness and memory affect strategy and partner choice in a game setting</td>
</tr>
<tr>
<td>Kim (2009)</td>
<td>Trust built in the course of interactions and used to reduce uncertainty</td>
</tr>
<tr>
<td>Tomassini et al. (2010)</td>
<td>Dissatisfaction increases the risk of relationship termination</td>
</tr>
</tbody>
</table>

Table 9: Models of mechanisms related to business dancing
<table>
<thead>
<tr>
<th>Reference</th>
<th>Mechanism</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gavrilets et al. (2008)</td>
<td>Affinity - Formation of coalitions as response to the occurrence of conflicts</td>
</tr>
<tr>
<td>Miller &amp; Page (2007)</td>
<td>Binary state, changed through majority rule with respect to connected neighbours</td>
</tr>
<tr>
<td>Stocker et al. (2002)</td>
<td>Communication on networks, comparing hierarchies and scale-free structures</td>
</tr>
<tr>
<td>Santos &amp; Pacheco (2005)</td>
<td>Existence of hubs promotes the spread of cooperation</td>
</tr>
<tr>
<td>Fronczak et al. (2006)</td>
<td>External pressure on the network leads to rewiring of old links</td>
</tr>
<tr>
<td>Paczuski et al. (2000)</td>
<td>Interaction effects between neighbours, synchronization</td>
</tr>
<tr>
<td>Eguíluz et al. (2005)</td>
<td>Path dependence leads to the emergence of social roles</td>
</tr>
<tr>
<td>Ebel &amp; Bornholdt (2002)</td>
<td>PD on a random network, effect of avalanches caused by strategy change</td>
</tr>
<tr>
<td>Miller &amp; Page (2007)</td>
<td>Schelling’s Segregation model: If unsatisfied, relocation to unoccupied location</td>
</tr>
<tr>
<td>Keeling (1999)</td>
<td>Spread of disease and immunisation through a network, different structures</td>
</tr>
<tr>
<td>May &amp; Lloyd (2001)</td>
<td>Spread of disease and immunisation through a network, different structures</td>
</tr>
<tr>
<td>Pastor-Satorras et al. (2001)</td>
<td>Spread of disease and immunisation through a network, different structures</td>
</tr>
<tr>
<td>Karsai et al. (2010)</td>
<td>Spread of disease through a network, different structures</td>
</tr>
<tr>
<td>Nowak (2006)</td>
<td>Strategy evolution in games on simple networks</td>
</tr>
<tr>
<td>Bartolozzi et al. (2005)</td>
<td>Synchronisation through thresholds</td>
</tr>
<tr>
<td>Wilhite (2006)</td>
<td>Trade on different network structures</td>
</tr>
<tr>
<td>Watts &amp; Dodds (2007)</td>
<td>Varying network structures and methods of contagion: absolute thresholds and probabilistic</td>
</tr>
</tbody>
</table>

Table 10: Models of mechanisms related to connections between relations
<table>
<thead>
<tr>
<th>Reference</th>
<th>Mechanism</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adamic et al. (2001)</td>
<td>Different strategies for information search in networks</td>
</tr>
<tr>
<td>Portugali et al. (1997)</td>
<td>Environment represents urban structure</td>
</tr>
<tr>
<td>Benenson (1998)</td>
<td>Environment represents urban structure</td>
</tr>
<tr>
<td>Jain &amp; Krishna (2001)</td>
<td>Evolutionary pressure leads to the emergence of self-sustaining clusters</td>
</tr>
<tr>
<td>Seufert &amp; Schweitzer (2007)</td>
<td>Evolutionary pressure leads to the emergence of self-sustaining clusters</td>
</tr>
<tr>
<td>Ehrhardt et al. (2006)</td>
<td>Link decay on the basis of various distance measures</td>
</tr>
<tr>
<td>Goh et al. (2003)</td>
<td>Network distributes the impact of local distortions (avalanches)</td>
</tr>
<tr>
<td>Ohtsuki et al. (2006)</td>
<td>PD on networks, sparse structures favour cooperation</td>
</tr>
<tr>
<td>Tsukamoto &amp; Shirayama (2010)</td>
<td>PD with three mechanisms for evolution/imitation: fittest neighbour, replicator dynamics and proportional to fitness</td>
</tr>
<tr>
<td>Ladley &amp; Bullock (2008)</td>
<td>Separate networks for information transfer and interaction</td>
</tr>
<tr>
<td>Rosvall &amp; Sneppen (2006)</td>
<td>Speed of communication depending on network structure</td>
</tr>
<tr>
<td>Lugo &amp; Jiménez (2006)</td>
<td>Taxes and subsidies in PD, can be used to encourage the development of cooperation</td>
</tr>
<tr>
<td>Watts (2000)</td>
<td>Thresholds for adaption affect percolation effects</td>
</tr>
</tbody>
</table>

Table 11: Models of mechanisms related to environmental factors
B. Appendix: Illustration of the BankNet Model

Among the many simulations reviewed, the BankNet model by Sapienza (2000) was one of the few that included mechanisms that led to the emergence of specialized intermediaries. For this reason I replicated the model in NetLogo, on one hand to gain an exact understanding of how the mechanism is implemented and on the other hand to use it as a potential basis for future extensions.

Two mechanisms that are of importance for the emergence of intermediaries here. First, agents improve their chances of successful investments through experience, gained through successful investments. Second, investments are associated with costs which depend on the total capital stock of the investor. Thus agents that are able to attract more deposits can realize economies of scale. Both mechanisms have a positive feedback on each other and towards themselves and lead to a path dependent development. If an agent performs above average in early stages due to change effects, it will increase its experience, attractiveness and most importantly, its chances to perform above average in the following rounds.

Every agent maintains two independent, directed connections to other agents in the system throughout the simulation. At the beginning of each round, every agent is endowed with a random amount of cash and they directly hand it over to one other agent through the “deposit link”. The second link becomes important when an agent is randomly allocated an opportunity, which can only be realized with financial support from other agents. Through the “borrow link” an agent can sent out one request for a loan. At the beginning of each round, some agents are chosen to compare the previous performance of their links to the performance they would have had, if they had been connected to another, randomly selected agent. If the links would have performed better, the agent is allowed to switch one or both links to the new, more promising target. This mechanism uses past performance to form expectations about future performance, and tends to make all agents link to those few agents who perform extraordinarily well, in the long run. The progression of a few simulation runs is depicted in the slides on the following pages.

Currently I am working on a concept to adapt this model to a situation where goods and services are exchanged. The basic mechanisms needed are supply and demand; something must be created, and consumed - in the BankNet these were random events. Next, a form of exchange must be introduced; diversity of goods and needs would be a basis to motivate exchange. Exchange would become necessary if the agents were unable to produce all the goods they require, themselves, so that they have to trade with others. The simplest variant of this would be a barter economy with two goods, similar to the setup used in Wilhite (2006).
The pricing could be dependent on the agents’ utility or simply fixed exogenously.

At this stage the key problem is to choose a mechanism that introduces specialization in the system. One alternative is to introduce transaction costs, associated with the size or number of transactions. However, this requires another mechanism that makes agents buy more than they require in the first place, so that they can eventually learn about the benefits of bulk transactions. Should this be a random process? Should there be speculative behaviour?

The next step would be to include a mechanism that allows for the establishment of buyer-seller relations over time, such as the trust-mechanism in Kim (2009) or loyalty in Kirman & Vriend (2001). Or it could be as simple as in the BankNet model, relationships are established, and may be changed when a more promising connection is encountered. Alternatively, reinforcement learning could be used to make buyers come back more likely to sellers that they had positive experiences with. All these are elements that will be explored in the early stages of the modelling process.
At the beginning of each round, every agent receives a random amount of money $[0, 2]$. The agent deposits the money by giving it to another agent, who supposedly knows better what to do with it.
Some agents are chosen (A) at random to have an encounter with one other agent (B).  

A asks B about its performance in the previous round.

A’s deposit link is redirected to B if B’s ROI (sum of returns) was higher than C’s (to whom A is currently connected to)

A’s borrow link is redirected at B if B’s capital/(number of borrowers +1) is higher than C’s.

Let’s assume B had a higher ROI than C

The agent deposits the money by giving it to another agent, who supposedly knows better what to do with it.

This is automatically done through each deposit link.
Randomly, agents are chosen to find an investment opportunity (IOP)

They cannot finance the IOP on their own, so they ask for money through their borrow links.

Say C has an IOP, it will ask B for money.

And A has an IOP, it will ask C for money.

All agents count their incoming loan requests and then divide their capital evenly.

Deposit links keep their value „in mind“
Each agent with an IOP draws a random number \([0,1]\) to determine the IOP’s outcome.

In this example, let’s say A and C both get 0.5

An IOP is successful if IOP outcome < exogenous success hurdle (say 0.4) + investor experience

A’s investment fails:
IOP: \(0.5 > 0.4\)

C’s investment succeeds:
IOP: \(0.5 < 0.4\)
Payback

A’s IOP leads to a loss for investor C. It will not receive its’ investment back.

C’s IOP is successful and it returns the loan + interest – transaction costs to B.

Interest is fixed for all agents

Transaction Costs depend on the total capital available to the investor in that round

Experience

Through its’ successful investment B gains in experience.

B’s ROI is high, which makes it more attractive for investment links.
At the beginning of each round, every agent receives a random amount of money $[0,2]$. The agent deposits the money by giving it to another agent, who supposedly knows better what to do with it.
Say C meets B

C redirects its deposit link to B, because B had (more) returns in the previous round than A.
Deposit **World 1**

All agents deposit their cash

---

**IOP World 1**

All agents receive an IOP with 0.5

C receives a lot of money, because it asked B for funds

B receives nothing, because A has no capital

A receives a little.

Depending on C’s success B either *improves its position* as an intermediary or it the system looses a lot of money.
In another world B meets A

B redirects its deposit link to A, because A (0) had (more) returns in the previous round than C (−x)

[N.B. The deposit link takes its previous value with it – in the current implementation this does not affect C, in any way, the money magically reappears]
References


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Persitz, Dotan. 2010. *Power and Core-Periphery Networks*. Tech. rept. SSRN.


