

**Modelling the Evolution of Business  
Relationships and Networks as Complex  
Adaptive Systems**

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requirements for the degree of  
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## Statement of Originality

This is to certify that to the best of my knowledge, the content of this thesis is my own work. The thesis has not been submitted for any degree or other purposes.

I certify that the intellectual content of this thesis is the product of my own work and the assistance received in preparing this thesis and sources have been acknowledged.

A handwritten signature in black ink, appearing to read 'Fabian P. Held', with a stylized, sweeping flourish extending from the end of the name.

Fabian P. Held

# Abstract

This thesis seeks to better understand the development and evolution of business relationships and networks from a complex systems perspective, using agent-based modelling. The thesis focusses on the early stages of the development of a business network: the transition from autarky to an interdependent yet decentralised system of production and consumption, that relies on exchange, specialisation and division of labour. The thesis uses existing research on activities and interactions in business relationships in order to identify social mechanisms that constitute a causal explanation of the self-organisation of an interdependent production system. These mechanisms are implemented in a computer model of autonomous agents, and the implementation is validated through the reproduction of stylised facts from prior laboratory experiments. Subsequent model analysis identifies alternative patterns of emergence and investigates the interacting effects of input parameters that define social and economic aspects of the model. The presented model is modularly expandable, facilitating the introduction of new aspects regarding the agents' behaviour, their economic and technological system and their environment, inviting extensions and future research on one unifying platform.

*To my family*

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Sydney, March 2013

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# Chapter 1

## Project Overview

Social and business networks are ubiquitous and an increasingly important area of research attention in many disciplines (Jackson, 2008; Borgatti *et al.*, 2009; Easley & Kleinberg, 2010). But their dynamics and evolution have received limited research attention, with research focusing on comparative static and cross-section surveys and models of stable equilibria. One of the major challenges is to better understand, predict, and control their dynamics, including how they form and evolve and how this shapes their behaviour and performance (Schweitzer *et al.*, 2009; Rauch, 2010).

The increasing attention being given to networks of relationships is apparent in all business disciplines, where the nature, development, and performance of firms, markets, regions, and nations is increasingly being linked to the way economic actors are interconnected, rather than being attributed solely to their individual characteristics. In marketing this focus can be traced to research in channels and B2B markets in the US, Europe, and Australasia (for a review see Wilkinson, 2001) and is of continuing importance (Wilkinson, 2008; Easley & Kleinberg, 2010; Woodside, 2010; Johanson & Vahlne, 2010). In management, strategy, and economics the topic increasingly features in books, articles and special issues in leading management and economic journals (e.g. Schweitzer *et al.*, 2009; Haldane & May, 2011). 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 indus-

tries show a trend towards the formation of collaborative and strategic networks (Achrol & Kotler, 1999).

Several research streams have devoted their efforts to comprehending the dynamics of networks, but our overall understanding is still limited and fragmented. Schweitzer *et al.* (2009) review the current state of our knowledge and argue that, at one extreme, complexity science has developed a macro perspective focusing mainly on network topologies and simple mechanisms that describe network formation and change. At the other extreme are the social sciences. Emphasising realism, they have developed a detailed understanding of the rules which govern actions and interactions of members of a network.

One such stream of research seeks to understand the working of industrial - or business-to-business (B2B) - markets. Out of empirical research about the activities of buyers and seller in business relationships developed a perspective that perceives industrial markets as networks of interrelated relationships. The “markets-as-networks” view developed out of largely descriptive research over more than four decades and therefore provides an ample pool of detailed accounts about the actors’ actions and interactions in these networks and relationships. This thesis seeks to better understand the development and evolution of business networks. To provide a more vivid and comprehensive description of this topic area, a brief review is provided of the main insights from the markets-as-networks perspective.

## **1.1 Markets-as-Networks**

Firms are the primary units of production in an economy. However, they do not do so in isolation, but in cooperation with each other. Their performance and competitiveness and that of the economy as a whole depends, in important ways, on the way firms are directly and indirectly connected to other firms and organisations and on the quality of those relations, including with suppliers, customers, distributors, technology partners, complementors and competitors (Wilkinson, 2008). Firms depend on other organisations for access to key resources, skills and information and co-create these through their interactions and in this way collaborative advantages become a major determinant of competitive advantage and technological progress.

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)

The initial motivation for this research project stems from the insights on business relationships and business networks predominantly developed by the “Industrial and Marketing Purchasing Group” (or “IMP Group”, henceforth IMP). The term business network refers to the interdependent systems of intra- and inter-organisational relations that are involved in markets, including firms, government agencies, and other types of organisations (Wilkinson, 2008). Researchers associated with IMP have developed a rich set of concepts to highlight, describe and understand business relations and networks in marketing, based on a series of case studies and international collaborative surveys of domestic and international relations and networks in business markets.

It is beyond the scope of this thesis to give a comprehensive review of the research associated with IMP. Instead selected aspects of what has become known as the *markets-as-networks* perspective will be highlighted, representing key results from the IMP’s research endeavours. Many others have written about the development of IMP, as well as its precursors, implications, and future agenda and the interested reader will find much more detailed information in the following selection of references: Axelsson & Easton (1992); Easton & Araujo (1992); Ford & Håkansson (2006); Gemünden (1997); Håkansson (1982); Håkansson & Snehota (1995, 2000); Johanson & Mattsson (1994); Mattsson (2004); Mattsson & Johanson (2006); McLoughlin & Horan (2000a,b, 2002); Ritter & Gemünden (2003); Sousa (2010); Turnbull *et al.* (1996); Wilkinson (2001); Young (2002)

The markets-as-networks perspective (MAN) is a theoretical framework that aims to describe and understand the functioning of industrial markets. It perceives industrial markets as a network of interdependent relationships between companies that cooperate, compete, compete to cooperate with each other and cooperate in order to compete more effectively (Wilkinson, 2008). Business relationships are seen as the third type of governance structure that is located somewhere in between organisation through hierarchies and free, anonymous markets

(c.f. Richardson, 1972). It is distinct from other streams of research that understand markets as “exchange facilitating mechanisms” or “price-mechanisms”. The most prominent example of such contrasting views being neo-classical economics, but also the predominantly American view of seller-dominated, mainly consumer market focussed, marketing, which seeks to employ marketing-mix parameters (the *four Ps* Product, Price, Promotion and Placement (i.e. distribution)) to an faceless and atomistic market of buyers (e.g. Bonoma & Zaltman, 1978; Bonoma *et al.*, 1977; Nicosia & Wind, 1977; Webster Jr & Wind, 1972; Sheth, 1977). Based on extensive empirical research, the markets-as-networks perspective emphasises the relational aspects of inter-firm cooperation in business-to-business marketing.

The development of MAN goes back to IMP’s largely descriptive empirical research endeavours in the 1970’s, although theoretical precursors can be found in various other schools of thought. IMP was initiated when a group of European researchers became dissatisfied with the dominant American consumer marketing paradigm of the time. Their findings indicated that in industrial markets longer term supplier-customer relations play a more prominent role than isolated market transactions. Buyers in industrial markets turned out to be just as active as 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 well-acquainted organisations that have been doing business with each other over a significant period of time (Håkansson, 1982; Axelsson & Easton, 1992; Håkansson & Snehota, 1995). Companies take on several roles in these relationships, i.e. customer, supplier, distributor, technology partner, complements or competitor. Some of these relationships last for decades. Through business relations other companies’ resources are accessed, co-created, combined and used, including products and services, information and material resources.

Business relations are built up over time through the economic and social/personal interaction episodes taking place among the organisations and people from each side. Wilkinson & Young (1994) coined the metaphor “business dancing” to describe the intricate interplay between the parties involved in a business relationship. Business relationships go far beyond mere economic exchanges. To a large

extent relationships were found to be informal, relying more on trust, commitment and mutuality (Håkansson & Johanson, 1988). While there may be asymmetries with regard to power between parties, relationships will only continue to exist if those involved perceive them to be beneficial. Based on past experiences, the parties involved form expectations of their partner's future performance and behaviour - which will in turn affect their decisions in the present (Håkansson & Snehota, 1995). Also the establishment and maintenance of such relationships is costly, requiring relationship specific investments and adaptations by both parties (Brennan & Turnbull, 1998, 1999; Brennan & Canning, 2002). The range of costs and benefits or functions that is attributed to business relationships is very wide and varies across relationships (Wiley *et al.*, 2006). Furthermore these costs and benefits can be both direct and indirect. Indirect outcomes could only be realised in the future in the same relation, or, they have spin-off effects on other relations, depending on how the firms in the focal relation are connected with other partners (Håkansson & Johanson, 1993). Those indirect outcomes can be just as important as the direct ones (Anderson *et al.*, 1994).

Any given relationship does not exist in isolation; it is connected to other relations in various ways and, more generally embedded in a wider network of interdependent relationships. These insights lead to a broader focus of IMP research and the notion of markets-as-networks (Blankenburg-Holm & Johanson, 1992; Mattsson, 1997; Ritter, 2000). Connections and interdependencies 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 organisation that we have chosen to qualify as a network.

(Håkansson & Snehota, 1995, p. 19)

The market-as-networks view has three particular features regarding the use and understanding of the term “network”. First, networks are no governance struc-

tures in the sense that this structure is imposed or that it is a technique followed by one dominant organisation to control and organise the other members in the network. Rather, the network concept is a way to visualise and understand the way firms and organisations are interconnected directly and indirectly through relationships. Networks are not under the control of individual firms, though some may exert more influence. Second, networks are not seen as a-priori structures imposed on organisations, instead they are formed in a self-organising way through the actions and interactions of actors involved, as they occur over time. They are continually being made and remade (or not) through ongoing structuring and restructuring processes (McLoughlin & Horan, 2002). The multiple interactions and feedback effects continually taking place in networks lead to a complexity that makes it very difficult to control and predict for any individual actor (e.g. Wilkinson & Young, 2002; Wilkinson *et al.*, 2005). Third, a business network does not have clear boundaries or a dominant centre, like a network captain. The network's scope depends on the adopted perspective and research question in mind; it may vary, depending on the focal actor, the technology, country or product type.

This network perspective on business marketing has wide-ranging implications for understanding the behaviour, the opportunities and strategies available to participants in the network. The structure of the network is both a limiting and enabling factor for individual firms. A firm's relations to others affect the resources to which it has access. Moreover, such "relationships are *substantial*, they are not easy to change quickly and changes are likely to incur significant costs, both in disruption and developing new relationships. This tends to make business markets rather stable." (Ford *et al.*, 1998, p. 43, emphasis in original). However due to the interdependent nature of relationships, change, once it occurs in one relationship, can propagate through the entire network. This can affect the context of other relationships and force them to respond accordingly, propagating change through the system. In general firms co-evolve with their surrounding counterparts, their performance and survival may depend critically on their network partners Ford *et al.* (1998).

In such interdependent surroundings a company is constantly "(...) initiating and responding, acting and reacting, leading and following, influencing and being influenced, planning and (...) improvising, forcing and adapting" Ritter *et al.*

(2004, p. 178). At the same time managers' knowledge about the network they operate in is limited. The full extent of the network that surrounds and affects them, their network context, may be much larger than the network horizon, the part of the network that they are aware of and therefore can effectively take into account (Holmen & Pedersen, 2003). One implication is that firms need to acquire so-called "network competencies" to perform well in the network. They need to be able to manage individual relationships in isolation, as well as the portfolio, or "net", of relationships that they deal with and that they depend on (Möller & Halinen, 1999; Ritter, 1999; Ritter & Gemünden, 2003). Many goals can only be achieved through cooperative action, so a company needs to make sure it has the right partners. Companies compete to cooperate and cooperate to compete; they find themselves in a constant state of *coopetition* (Wilkinson & Young, 1994; Nalebuff & Brandenburger, 1996; Bengtsson & Kock, 2000).

Another important element of the markets-as-networks framework is the understanding that time plays a central role in explaining and understanding exchange. Business relations develop over time and they are path-dependent. Buyers and sellers actively 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). Furthermore, the decisions that firms have made in the past will back their options today.

### **1.1.1 Research on Dynamics and Change**

Researchers associated with the IMP Group and others have undertaken extensive research and theorising regarding the nature and determinants of business relations and networks (for reviews see Wilkinson, 2001; Sousa, 2010). However, a subject that has so far received only limited attention is that of the dynamics of relations and networks, how they emerge and how they develop and evolve over time as well as the mechanisms and processes that drive these dynamics. Fundamentally, IMP thinking is dynamic - it focuses attention on the interactions taking place in relations and how these shape the development of relationship atmosphere and

structure. Nonetheless research on relationship change over time is limited mainly to:

1. Stage models in which a pre-given sequence of stages is assumed to occur with each providing the preconditions for the next, analysis of the processes involved in relation and network development (Ford, 1980; Dwyer *et al.*, 1987);
2. Case studies including descriptive characterisations of relationship histories that highlight some of the processes observed in relationships (e.g. Ariño & Torre, 1998; Huang, 2010; Kinch, 1993; Narayandas & Rangan, 2004; Rond & Bouchikhi, 2004);
3. Partial theories and schematic models describing some of the relevant mechanisms and feedback effects that underlie the dynamics of select aspects of relations, such as trust and power (e.g. Ariño & Torre, 1998; Huang, 2010; Huang & Wilkinson, 2006; Narayandas & Rangan, 2004; Rond & Bouchikhi, 2004; Wilkinson, 1990);
4. Speculative accounts of the patterns of evolution (e.g. Johanson & Håkansson, 1991);
5. Descriptions of some of the mechanisms and processes involved in the dynamics and evolution of business relations and networks (e.g. Haase & Kleinaltenkamp, 2011 in press; Halinen & Törnroos, 1998; Sydow *et al.*, 2009; Wilkinson, 1990; Young & Wilkinson, 2004);
6. General theories of organisational change and development relevant to business relations and networks (e.g. Aldrich, 1999; Van de Ven & Poole, 2005).

In addition, there have been some attempts to use simulation methods. The first attempts were made in the 1960s using Systems Dynamics models with a fixed structure imposed and representative, often aggregate actors Balderston & Hoggatt (1962); Bowersox (1972); Forrester (1961). More recently, some computer simulation models have been developed that capture certain aspects of the

dynamics on the level of the business network. In this way the interaction between exchanges in connected relations have been represented by Boolean rules in NK models that build on the work of Stuart Kauffman (1984); Kauffman & Weinberger (1989) (e.g. Easton *et al.*, 1997, 1999, 2008; Wilkinson *et al.*, 2001). Furthermore, computer simulations were used to examine the effects of market regulations and policies on the evolution of a particular industry (e.g. Følgesvold & Prenekert, 2009). The benefit of these simulations is that they make it possible to monitor the development of the entire system over time and thereby gain an understanding of how the interactions of individuals leads to the emergence of pattern and structure on the aggregate, the network level.

### **1.1.2 Research Questions**

In principle, we may be able to unpack an existing network in terms of the efficiency and effectiveness of its operating and governance structure and the trade-offs involved (Wilkinson, 2001). However, this does not explain how a given network structure came to be, how it will change over time, how it will respond to sudden changes in its environment etc. Many methods that are used in research about the dynamics and change of relationships, such as case studies, cannot easily be applied on the network level as they are too labour and data intensive. Generally, our intuition about feedback effects between micro-interactions at the actor/relationship level and the structure of the network on the aggregate level is still in want of further development.

Research has reached a stage where it is necessary to integrate insights to gain a deeper, more comprehensive understanding of the behaviour and development of economic networks. In order to provide research-based advice to managers and policy-makers, we need to understand the dynamics of business relations and networks, including how they form and evolve. The challenge for managers and policy-makers is not about the management and control of such systems but how to participate and manage in them (Ritter & Gemünden, 2003). We know that these systems are dynamic. We know that actors in these systems are interdependent on each other, and on the system as a whole. But we do not know how these systems develop and we only have a vague intuition about how the system

affects the individual actors' performance, their opportunities and options. It was Adam Smith (1776) who first identified specialisation and the division of labour as the source of our prosperity. In order to specialise, one has to give up some independence and rely on the specialisation of others so in a business network all participants are to some degree interdependent. Also, no one is in overall control, though some may have far more influence on parts of the system than do others. Overall, behaviour and performance in such an interdependent network is not a simple sum of the behaviour of the individuals involved: what happens depends on the way different actors behave and respond and the direct and indirect interactions among these actions and responses taking place over time.

This thesis attempts to provide a basis to better understand the development of business relationships in networks over time. For this, an agent-based computer model is developed that integrates findings from empirical research, describing the actors' behaviour, their actions, interactions and decision making, as they partake in interdependent business relationships. In this model, a network of economic exchange relations will grow from the actors' interactions over time, "from the bottom-up". Hereby, the focus is on implementing the actors' activities realistically, based on well-established and understood social and economic mechanisms, drawing on economic theory as well as empirical research about the development of business relationships. The modelled actors engage in specialisation and division of labour, they negotiate exchange agreements and form relationships over time. The model focusses on the interactions, both social and economic, of the actors and it is built generically and flexibly with regard to production and demand, as well as the physical space. It should easily be possible to plug-in these behavioural modules to simulations that represent the actors' environment in greater detail. It is evident that to explain the development of any real system, much richer information needs to be included in a more comprehensive model. Nonetheless, in keeping this model generic and flexible, it is possible to derive abstract theoretical findings about the evolution of a network of exchange relationships. The insights gained about interactions of behavioural modules however can serve as well-understood foundation for more realistic simulations of real systems.

The research questions I am addressing in this thesis concern the development of a system of exchange relationships. Which are the social mechanisms that

are sufficient for actors to establish a stable network of exchange relationships in which they can reap the benefits of specialisation and division of labour? What is the range of possible network structures that emerge from the micro interactions of these actors? How does an actor's position in such a network affect the actor's performance?

### **1.1.3 Outline of the Thesis**

The thesis is structured as follows:

Chapter 2 provides the theoretical background for this project. Theories of Cultural Evolution and "Economic Change" will provide the motivation for the proposed model. During the development of our civilisation, humans developed the system of division of labour and specialisation, based on a network of exchange relationships. These are the basis for the immensely diversified and interconnected business networks we see today. The model developed here will show how such a transition from autarky to interdependent coordination is possible. Chapter 2 will also introduce the perspective of Analytic Sociology, which is a recent development in sociological thinking concerned with the way we use causal mechanisms as explanations of social phenomena, in this case the development of specialisation and division of labour in an exchange network. This section will introduce the concept of mechanisms and discuss how we can use computer models to explain what causes a social phenomenon. This is followed by an introduction of the methodology used in the modelling process: Agent-based Modelling. This is a reasonably new and very flexible approach to scientific modelling, relying on the enhanced computational capabilities on modern computers to solve massively parallel recursive equations and model the actions and interactions of autonomous actors that are seen as the causes of emergent social phenomena. Lastly, Ch. 2 will discuss Complexity Systems thinking and its insights to the understanding of and conduction research on systems of interdependent entities, providing essential concepts for the analysis of systems in general. Complex systems challenge the applicability of reductionist methods and it has been argued that such an approach is necessary to understand the dynamics of business networks. Chapter 3 presents an overview of the causal mechanisms that drive the development and evolution

of business relationships and networks. These are identified in economic theory and empirical research in marketing and other fields. This overview will serve as the basis for subsequent modelling of actors and their coordination process in the establishment of an exchange network between specialists. Chapter 4 reviews existing computational models that employ some of the mechanisms discussed in Ch. 3. These serve as templates and points of reference for the implementations in the models developed here. Many valuable lessons could be learned from these preceding models, regarding the conceptualisation and the implementation of models. This chapter is followed by a review of my own models that preceded the current implementation. Together with a discussion of the insights and learning process, Ch. 5 will motivate specific insights and decisions that led up to the current version. The final model is strongly influenced by the experimental work of Vernon Smith and others concerning the development of specialisation and discovery of exchange, not only because it serves to validate the model, but also, because they developed another agent-based model about the process themselves. Chapter 6 will discuss their research in detail in order to better contrast the model here and show how the model developed here extends and generalises their work. After this Ch. 7 introduces the concrete model and relates it to the mechanisms discussed before and existing models. This will be followed by validation and a comprehensive analysis of the model's behaviour in Ch. 8. The thesis will conclude in Ch. 9 with a summary and a discussion of future directions of this research. These will include limits of models and additional extensions, potential connections to other lines of research and calibration against known histories.

## Chapter 2

# A Computational Social Science Approach to Marketing Theory

Markets-as-networks and the associated division of labour and specialisation are the result of a self-organising process where individuals act and make decisions on the basis of limited, local information. This is the basic premise of this thesis. As the author (Wilkinson *et al.*, 2010; Held *et al.*, 2010b,a; Wilkinson *et al.*, 2011) and others (Easton *et al.*, 1997; Wilkinson, 2001, 2006, 2008; Easton *et al.*, 2008; Layton, 2009) argued before, business networks can be seen as complex adaptive systems and therefore require a different kind of thinking: More integrated, focussing on the system as a whole, including all the relevant actors and the way they influence each other over time, perceiving dynamics as the norm, and stasis and equilibria as exceptions that require further investigation. The manifold interactions and interdependencies in these networks together with their dynamic nature are posing a challenge to traditional comparative-static and variable-based methods. In response to these challenges this thesis will develop computer simulations of the evolution of business networks that are able to deal with systems like these.

This chapter addresses both the theoretical and the methodological foundations of the project developed in this thesis. The main reason for presenting these two aspects in combination is that complexity is a reasonably new way of thinking, and the distinction between theory and method is not yet fully clear. Researchers

across a multitude of disciplines from the natural as well as the social sciences use complexity thinking, and they all adapt it to their disciplines, dealing with very different kinds of questions and types of data that are peculiar to their field. In fact even the term Complexity Theory should be used with caution, because there is no such thing as *one* theory of complexity and it is debateable - and debated - whether there can ever be a unifying theory of complex systems (see e.g. Mitchell, 2009). Only just recently did researchers try to coin a term for the methodology that deals with complex systems in the social sciences: *Computational Social Science* (Lazer *et al.*, 2009; Cioffi-Revilla, 2010a,b). It refers to scientific methods in the social sciences that use computing and related advanced information processing technologies, independent of the theoretical underpinnings of complex systems. Computational Social Science includes computational modelling, especially agent-based models, social network analysis, geographic information systems, automated information extraction systems and other tools. Despite this recent development, complexity thinking and agent-based modelling are still too strongly interrelated to classify the first only as theory and the latter as the methodology. As a consequence they are discussed together in this chapter, only in separate sections.

The other sections in this chapter serve to highlight various other theoretical and methodological aspects of this thesis. Section 2.1 introduces the concrete theoretical framework that motivates the final model presented here. Together with the insights from existing research (Chapters 3, 4 and 6) it is the basis for the chosen implementation, focussing on the development of specialisation and division of labour from an evolutionary perspective, especially the transition process from autarky to coordinated specialisation. Section 2.2 talks about the theoretical aspects underpinning agent-based modelling as a methodology. It models the social mechanisms that *cause* a social phenomenon as opposed to the approximation of covariation between variables. Similarly, Sec. 2.3 discusses the use of models in general, and the way they can generate insights that are not as easily retrieved from investigations of the original system. Once all these foundations are laid, Sec. 2.4 will introduce agent-based modelling and Sec. 2.5 will discuss the main concepts of complex systems thinking and their implications for research and the ways we can learn about them.

## 2.1 Economic Change

Business networks are abstract constructs that researchers use to describe the collective of interdependent activities of specialised economic actors in the production and marketing process. They describe the structure of interactions between these actors as they jointly create an assortment of goods and services that ultimately will be consumed by the end consumer. This network is in constant flux, being made and re-made, but we speak of a network because there is structure to the actors' interactions that goes beyond random encounters. Through their interactions, their cooperation and their competition, the actors create their own environment of relationships that help them to coordinate their activities as specialists.

In the following it will be illustrated how these relationships can be seen as the foundations that coordinate a system of division of labour, where each actor can focus on the performance of a limited set of tasks, realising the benefits of specialisation. Specialisation means that an actor focuses on the performance of a select few tasks, necessarily leaving other tasks to other actors. Moreover, specialists will develop specialist knowledge about their field of activity so that a division of knowledge goes hand in hand with a division of labour. In turn, specialisation requires subsequent coordination of specialists, so that each of them can also access what they chose to neglect. Compared to a state of autarky, where each actor mainly depends on his own work and the physical environment, specialisation introduces a new kind of uncertainty associated with accessing the required tasks: uncertainty regarding the actions of others. Relationships reduce this uncertainty, and therefore the network serves as an informal institution that helps actors realise economies of specialisation by coordinating their division of labour. In this thesis evolutionary theories of change will motivate how such a system of coordination can come into being. The remainder of the thesis will be devoted to the development of a model of the transition process between autarky and coordinated division of labour, that will allow us to grow and experiment with economic exchange networks on the basis of well researched and established social and economic mechanisms and thereby better understand the workings of our modern highly complex business networks.

Division of labour and economies from specialisation have been identified as the source of human wealth by many great thinkers over the past centuries.<sup>1</sup> There are references dating as early as Plato's *Republic*, but the issue gained in interest especially from the time of the Industrial Revolution in the middle of the 18th century, with the rise of the working class in Great Britain and elsewhere. In his *Treatise* David Hume (1739) refers to "partition of employments" that allows people to jointly increase their productive powers and abilities. Similarly, Adam Smith (1776) in his *Inquiry into the Nature and Causes of the Wealth of Nations* (1776) stated that division of labour leads to a qualitative increase in productivity, using the famous example of pin manufacturing. Later, Karl Marx (1844) identified division of labour as the reason for workers' alienation from production in a capitalist society, but admits that there are technical reasons that make division of labour necessary to achieve a certain standard of living. Economists like Ludwig von Mises (1940) objected to this view, claiming that the benefits gained from specialisation and division of labour far outweigh the negative consequences of alienation. The most prevalent explanation about how the problem of coordination between specialists can be resolved relies on the basic economic principles such as price system and competition in markets that will lead to an efficient allocation of resources (e.g. Hayek, 1945). Just recently Roger Layton (2009, p. 349) argued "Where there is specialization there must also be trade, and, over time, where there is trade there will also emerge the specialized roles and market structures needed to handle trade efficiently".

The economist and Nobel laureate Douglas North (2005) adds to this debate, talking about necessary institutions that facilitate the coordination of division of labour among specialists by a new dimension. He agrees that division of labour is the major source of increases in our productivity. However, he also remarks that advances in specialisation and division of labour go hand in hand with growth of the stock of knowledge and thereby lead to a diversification and division of knowledge amongst the specialists. He concludes that "the coordination of knowledge requires more than a set of prices to be effective in solving human problems" (North, 2005, p. 73), implying that additional institutional arrangements are nec-

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<sup>1</sup>A detailed discussion of the mechanisms that lead to economies of specialisation and division of labour is given in Ch. 3.

essary to efficiently deal with and integrate the diverse knowledge available in a specialised society. Furthermore, economic theories based on the efficiency of the price mechanism do not seem to explain why industrial markets were found to consist of networks of interconnected relationships, instead of random exchanges between buyers and sellers. In fact the common economic assumption of perfect competition in a free market seems strangely at odds with the empirical findings about industrial markets presented in Ch. 1.1. Moreover, the neo-classical economic paradigm was never created to explain processes of change, but static equilibria. North (2005) maintains that closely associated general equilibrium models are ill-fitted to deal with an uncertain and ever changing world that continually evolves in new and novel ways.

North (2005) suggests as a remedy an *evolutionary theory of economic change*. Similar approaches have been used in various disciplines in the social sciences to break out of static mindsets and develop dynamic theories. Examples of these include dynamic theories of cultural evolution (e.g. White, 1959; Sahlins & Service, 1960; Parsons, 1966, 1971; Boyd & Richerson, 1988; Richerson & Boyd, 2004), theories of organisational change (Van de Ven & Poole, 1995; Van de Ven & Grazman, 1999; Poole *et al.*, 2000) and economic change (Nelson & Winter, 1982; North, 2005). Those theories draw on principles already identified by Charles Darwin (1859) in the *Origin of Species*: (Random) variation combined with selective retention through environmental forces lead to an open-ended development of the entities under consideration. The theory suggests that through this process of gradual changes, that are constantly assessed, promoted or demoted with respect to their “fitness” in the current environment, entities (e.g. populations, organisations or societies) can change over time and adapt to the requirements of their surroundings.

There has been much debate about the applicability of biological theories to socio-economic systems. The perspective adopted by North and here follows the framework of dual inheritance theory outlined in Boyd & Richerson (1988). It seeks to explain human behavior as a product of two distinct yet interacting evolutionary processes: genetic evolution as well as cultural evolution. Biological evolution affects to our biological makeup, physical capabilities, etc. and it is driven by selective sexual reproduction. Cultural evolution refers to information

and behaviours that are created by humans and transmitted to new generations through social learning. Whereas selection in the biological sense is associated with the inability to reproduce, the cultural equivalent is the discontinuation of a certain behaviour. Consequently, what may appear like a deliberate act of adaptation over generations may merely be the result of selection - through selective reproduction, imitation or learning (Richerson & Boyd, 2001).

It is the essence of dual inheritance theory that it is the responses to local conditions that guide the evolutionary path over time, both on the biological as well as the cultural level. And explanations of human behaviour can therefore be framed as sequences of adaptations to then current conditions on the biological and on the cultural level. Furthermore, it needs to be emphasised that this theory does not suggest that there is any progression towards a certain goal and no guarantee of survival. In fact, in this framework many alternative evolutionary paths may be possible, as different environmental conditions favour different developments.

Evolutionary theories concerned with the development of socio-economic systems generally assume that human societies, have largely substituted genetic evolution for a self-created social analogue. For example, Boyd & Richerson (1988) propose that cultural evolution, relying on socially learned information, exists on a separate but co-evolutionary track from genetic evolution. While the two are related and interdependent, cultural evolution is more dynamic, rapid, and influential on human society than genetic evolution. By creating an artificial structure of culture and social bonds, human societies have substantially reduced the impact of environmental factors on their lives substituting dependence on each other for their dependence on environmental factors - the “law of nature” has been superseded by the “law of the mind” (Commager, 1950). North himself applies this framework of socio-cultural evolution to the transition from a world where individuals largely depend on environmental forces to a society that supports itself and depends largely on itself.

North’s analysis focuses on the evolution of institutions, including formal incentives such as political structure and property rights, but also norms and conventions and their enforcement characteristics, what he calls “informal incentives” in a society. It is this artificial structure provided by social institutions that allows human societies to reduce their reliance on the physical environment. From an

evolutionary perspective, the development of social institutions may increase the fitness of a society as a whole, making it more resilient and productive and therefore more likely to transmit these institutions to future generations and be imitated by other societies. “The richer the artificial structure, the wider the range of routine decisions that can be made” (North, 2005, p. 36).

The evolutionary advantage of social institutions lies in the reduction of uncertainty and transformation of uncertainty into certainty, or at least calculable risk. North uses a distinction of these terms that goes back to Knight (1921): In a situation under risk, it is possible to derive a probability distribution for the occurrence of events, under uncertainty no such distribution is obtainable and reliable planning as well as theorising under uncertainty is impossible. There are several ways to reduce uncertainty:

- Structuring the existing stock of knowledge - e.g. insurances that turn uncertainty into risk
- Increasing the stock of knowledge - learn more about uncertainty originating from the physical environment
- Altering the institutional framework - reducing the uncertainty of human behaviour by changing payoffs to encourage cooperative activities, inventions and innovations, reduce transaction costs
- Maintaining institutions that are flexible to respond and adapt to novel situations - adaptable institutional systems will avoid a break down and continue to work in novel situations

North argues that the establishment of a suitable institutional framework is the cornerstone to a reduction in the uncertainties of the physical environment. By making the behaviour of humans more predictable, institutions advocate coordination and cooperation amongst people, helping them to learn more about their environment and allowing them to rely more on each other as a society other than on their unpredictable environment. From this perspective the cooperative relations that form a business network can be seen as institutions that help coordinate the productive efforts of individuals. These networks have created their own set of

informal rules and the structure itself is the representation of institutionalised behaviour, forming partnerships and repeating the same or similar interactions with the same partners again and again.

While the underlying source of institutions has been and continues to be the effort by humans to structure their environment in order to make it more predictable, this effort can and frequently does make for increased uncertainty in itself. Social institutions create a new complex environment along with a set of new uncertainties. Institutions like law merchant, patents, institutional integration of distributed knowledge and the judicial system regulate many interactions between humans, reducing the transaction costs associated with economic exchange. But new uncertainties arise through the interdependence of human action and the tools and technology they created through their collaborative efforts. Extreme cases of these new uncertainties include a much wider range of possibilities regarding the society's development in the future, events like the 2008 Global Financial Crisis that are only made possible by the increased interdependence of the system and new threats like a nuclear war and weapons of mass destructions developed from advances in scientific knowledge.

North sees culture as an adaptive process that accumulates partial solutions to frequently encountered problems of the past, in line with arguments of Hayek (1960, 1973) and Hutchins (1995). He sketches the path of development of institutions as they co-evolve with the available knowledge and demographics in a society and as they respond to constantly changing environmental conditions of both the evolving physical and human landscape. The present combinations of beliefs, institutions, demographics and physical environment constitute the foundations for the society's next generation. Thus path dependence becomes a fundamental factor explaining the continuity of society. Institutions can and do change however, sometimes abruptly, sometimes gradually. With regard to their speed of change, North makes a distinction between formal and informal rules. Formal rules are the codified laws, rights and regulations that govern the interactions of people in a society. These can change very rapidly, by a revolution for example, or through change of a democratic government. Informal rules however are more deeply embedded carriers of the artificial structure that reflects the heritage of a society. These include informal constraints embodied in norms of behaviour, con-

ventions, and self-imposed codes of conduct. Informal constraints change much more slowly as they gradually adapt through learning processes. As changes occur in the environment, these are gradually assimilated into the artificial structure of informal institutions.

In conclusion, the merits of specialisation and division of labour are well established facts amongst researchers across many disciplines. However it is less well understood how coordination in such a system is achieved. Common economic models fail to explain empirical findings regarding the networked structure of exchange relationships in industrial markets and they are incapable of explaining the ongoing co-development of division of labour and coordination of specialists. Theories of cultural evolution and economic change argue that social institutions evolved over time, in an open-ended yet path-dependent process, responding only to selective pressures from the environment at any point in time. They also claim that human societies have created artificial structures of social institutions that regulate and coordinate the coexistence of their members, largely superseding their dependence on their physical environment by dependence on each other. Social institutions that promote division of labour and the coordination between specialists are therefore major building blocks in this evolutionary process. Amongst these institutions are property rights and the price mechanism that largely determine the economic incentives of exchange. However, research in industrial markets shows that relationships are maintained between economic actors throughout industries - these relationships come with their own laws, norms and rules. This thesis argues that the *development and maintenance of relationships themselves has evolved as an informal institution*, improving the performance of individual actors as it helps coordination with other specialist.

To understand the dynamics and evolution of business relationships and networks, we need to understand the underlying causal mechanisms that drive their development. In line with the theory above, the investigations conducted in this thesis will focus at the point of transition between societies where the uncertainties were those from the physical environment and to one where the uncertainties arise from the human environment. During this transition humans developed the rules of the new - coordinated and interdependent - game. They specialised in their productive capabilities and became dependent on each other. There is nothing

automatic about such a transition being successful. Therefore we need a better understanding of the social and economic processes that allow for the development of specialisation along with institutions that facilitate the coordination in the resulting system of division of labour.

## 2.2 Analytical Sociology

The evolution and co-evolution of cultures is a very complex phenomenon, involving long time-scales and interactions among many aspects of human life. Therefore the conceptional design of theories that seek to explain what drives the development of a society can easily become convoluted and difficult to communicate. A practice-oriented approach to sociological thinking and modelling has been under development in the last couple of decades, going under the name of *Analytical Sociology*. Developed by Peter Hedström and others at the University of Oxford's Nuffield College, analytical sociology is a novel framework for understanding the complexities of the social world (Hedström & Swedberg, 1998; Hedström, 2005; Hedström & Bearman, 2009; Kron & Grund, 2010; Manzo, 2010). Its main goal is to increase the explanatory power of sociological theory and research, combining an analytic realist perspective with modern computer-based modelling techniques. It draws on the work of James Coleman, Jon Elster, Robert Merton, Talcott Parsons and Thomas Schelling. At the core of this approach is the supposition that all causes of social phenomena lie in individuals' *activities*, because only individuals with their actions have *causal powers*. On this basis, researchers identify social *mechanisms* that drive individually, or in combination with other mechanisms the development and properties of a social phenomenon over time.

The target of analytical sociology is explaining large-scale social phenomena, i.e. collective properties of a social system that are not definable by reference to any single member of the collective. Following Hedström (2005, p. 5) this definition of a collective property includes:

- typical actions, beliefs or desires among members of a collectivity;
- distributions and aggregate patterns such as spatial distributions and inequalities;

- topologies of networks that describe relationships between the members of a collectivity;
- informal rules of social norms that constrain the actions of the members of a collectivity.

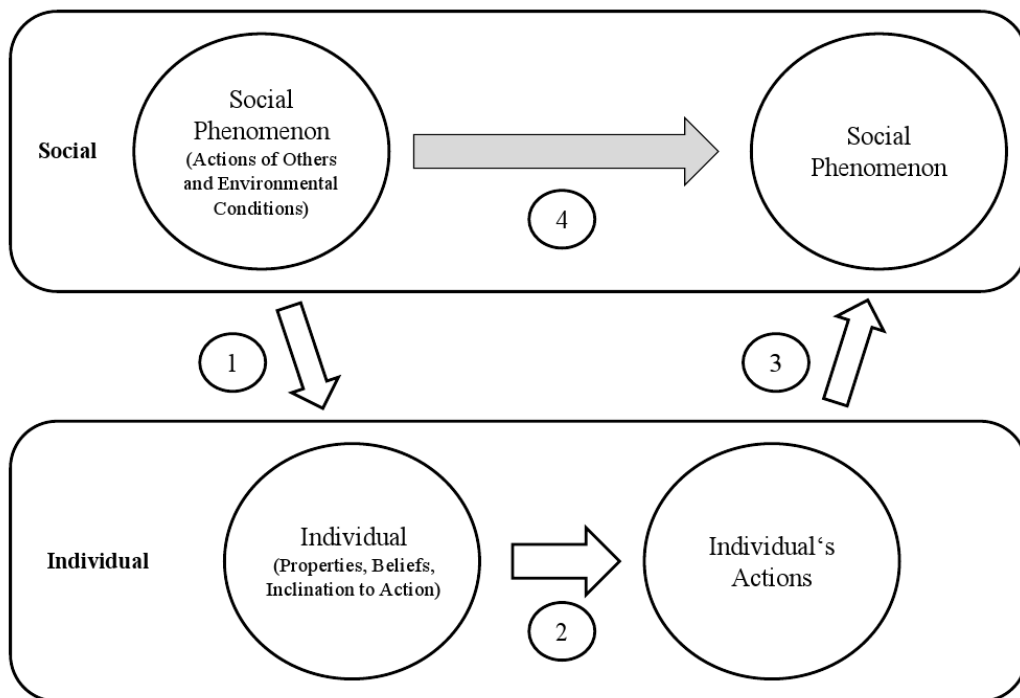


Figure 2.1: Micro-macro graph, after Coleman (1986)

The relation between individual action and social phenomena is illustrated in Fig. 2.1, using the micro-macro graph developed by Coleman (1986). Individuals' actions bring about social phenomena (arrow 3), their orientations to action are influenced by their properties, their beliefs, and opportunities (arrow 2) and these generally depend on the social environments the individuals finds themselves in (arrow 1). However, individuals hardly ever act in isolation from a social context. According to Hedström (2005), this led to much theorising in sociology speculating how one aggregate phenomenon relates to another (indicated by arrow 4), but neglected to show the causal relationships between the two macro phenomena.

Analytical sociology requires proper explanation of the relationship between two social phenomena to follow the causal path (arrows 1, 2 and 3) to show how social phenomena influence individuals' beliefs, properties, opportunities and inclination to action at one point in time, and then how the combination of individuals' actions at a latter point in time bring about the social outcomes under investigation. The properties of social phenomena and changes in them over time must always be explained with reference to individuals' actions, since it is individuals, not social aggregates, which are endowed with causal powers.

Social phenomena in the sense of Analytic Sociology refer only to properties of a group of individuals. The social and the individual mutually influence each other, but ultimately social phenomena are caused by the activities of individuals and need therefore be explained in these terms. This ontological perspective refutes critical realists' notions of the stratification of the social world, that claims entities on a higher level are somehow unique or autonomous from entities on a lower level. The distinction between individual and social is a merely epistemological issue, acknowledging that there are social properties that cannot, in practice, be predicted on the basis of the available knowledge about the individuals in a group.

Theories developed in the framework of analytical sociology seek to provide explanations of social phenomena. Typically they do not seek to provide descriptions, i.e. answering "what" questions, instead these theories seek to answer "why" questions, detailing the "cogs and wheels" through which social outcomes are brought about. Moreover, it is not accurate prediction that they seek to provide, but a detailed understanding of the causal mechanisms that typically bring about a social phenomenon. In this respect mechanism-based explanations differ from other common types of explanations, namely statistical variance-based approaches, as well as so-called covering-law explanations are often used in the natural sciences (Hedström, 2005). Generally statistical explanations are mathematical models that can, to some degree, recreate the variance and co-variance structure observed in empirical data. Often this reproduction is considered a statistical explanation, however it does not provide an understanding of why the observed variables correlate in the way that was observed. From the mechanisms perspective, correlations and constant conjunctions do not explain but require ex-

planation by reference to the entities and activities that brought them into existence. Covering-law explanations are causal explanations that refer back to an ultimate law, like a law of nature. There are some fields, especially in the physical sciences where such absolute statements are applicable, such as the law of motion, or the law of gravity. However, in the social sciences where the phenomena under investigation are much more complex, only statements about tendencies, regarding which mechanisms *typically* bring about a certain social outcome can be provided.

In the framework of Analytical Sociology the core of an explanation of any empirical phenomenon are social mechanisms. The term “mechanism” is often used loosely and can be confusing. Here it is used to describe causality - attributed only to the activities of actors in a social system. They are the rules that describe how one event leads to another: “a real process in a concrete system, such that it is capable of bringing about, or preventing, some change in the system as a whole” (Bunge, 1997, p. 414). In the terminology of Hedström (2005) social mechanisms are defined in the following way:

Mechanisms can be said to consist of *entities* (with their properties) and the *activities* that these entities engage in, either by themselves or in concert with other entities. These activities bring about change, and the type of change brought about depends upon the properties of the entities and the way in which they are linked to one another. A social mechanism, as here defined, describes the constellation of entities and activities that are organised such that they regularly bring about a particular type of outcome. We explain an observed phenomenon by referring to the social mechanisms by which such a phenomenon is regularly brought about. (Hedström, 2005, p. 25, emphasis in original)

These mechanisms are often left implicit in our theories, models and explanations, especially if we are focusing on the behaviour of variables rather than actors and events (Van de Ven & Engleman, 2004; Buttriss & Wilkinson, 2006). Chapter 3 will review concrete mechanisms that are at work in the development

and evolution of exchange networks, retrieved from existing theories, case studies and other accounts from research in marketing, economics and other disciplines.

The identification of such social mechanisms is guided by the principle of *analytic realism*, in the sense of Talcott Parsons (1937). In order to identify the “cogs and wheels” (Elster, 1989) through which social outcomes are brought about, one must *not* rely on empirically false assumptions, no matter how well they predict the outcome to be explained or how elegant they make a model. Only realistic assumptions about human motivation, cognitive processes, access to information, and social relations can bear the explanatory burden in a mechanistic explanation (Hedström, 2005). For these reasons the realist principle places special importance on the actions and interactions of entities in a social system. This focus on actions and explanations of actions through intentions leads to a precise, intelligible and verifiable understanding of the causal processes, reducing the risk of erroneous causal inferences.

Furthermore, Analytical Sociology suggests that social mechanisms can be identified by dissection and abstraction. Dissection means that a system of inter-related activities is decomposed in order to isolate these activities and the entities that perform them. Abstraction then requires the researcher to move out of focus the elements thought to be of lesser importance, retaining only what is believed to be particularly important for the problem at hand. This is why the term realism needs qualification - Analytic Sociology is realist in the sense that the mechanisms are derived from processes in the real system, however they correspond, not to concrete phenomena, but to elements in them which are analytically separable from other elements (Parsons, 1937). Therefore we speak of analytical realism. Only together dissecting and abstraction make visible and intelligible the mechanisms that drive social processes thus the development of theory requires a delicate balance between realism and abstraction (Hedström, 2005).

A further benefit of the concept of social mechanisms is their modularity and related benefits for theorising in interrelated fields. A theory about the evolution of a social phenomenon may be constructed by reference to a combination of social mechanisms that bring about that phenomenon and these mechanisms may interact with one another in complex ways (Gambetta, 1998). Mechanisms can be seen as “theories-within-theory” or pieces of theory that explain how parts of

an interdependent system work (Stinchcombe, 1991). It is possible that the same set of mechanisms brings about a different outcome if the circumstances change, or when there are other mechanisms at work that partially supersede the former's effects. Through this modularity, theories that consist of related mechanisms can be linked with regard to their inner workings, which can help reduce theoretical fragmentation and may help to bring out structural similarities between similarly disparate processes.

An explanatory theory must specify the set of causal mechanisms that are *likely to bring about* a social phenomenon, and this requires a specification of the causal links in Fig. 2.1, i.e. a theory of how a macro state at one point in time influences individuals' actions, and how these actions bring about a new macro state at a later point in time. Much research has been undertaken with regard to an individual's orientation to action, and how their beliefs, desires and opportunities are influenced by the social contexts in which they are embedded (arrow 1). Similarly there are many insights about the processes by which orientations to action influence their actions (arrow 2). "But when it comes to the link between individual actions and social outcomes (arrow 3) we often resort to hand-waving." (Hedström, 2005, p. 116)

Thomas Schelling (1978) was among the first to demonstrate the difficulties that can arise even in small-scale systems where actors engage in clearly defined, but interdependent activities. The aggregate phenomena in such systems can depend on minute, seemingly unimportant details and cannot easily be inferred from the individual actor's activities. Chaos theory and the theory of complex systems, which will be discussed below, have provided many insights to these problems in social and other systems. In the social sciences, the development of explanatory theory linking individual actions to the social or macro-level outcomes has therefore been among the main hurdles for a long time (Coleman, 1986).

A potential remedy for this problem was seen in the use of mathematical models, such as equilibrium models originating in economics. Hedström and others (e.g. Elster, 1989, 2000; Hedström, 2005) criticise that many of these models force the analyst to introduce intentionally false assumptions to make their models analytically tractable. Such methods are therefore largely incompatible with a realist approach; they are not explanations of what happens, as it happens, but elegant

and parsimonious models of hypothetical worlds much different from our own. Explanations in the analytical realist sense must refer to mechanisms known to be operative in the real-world settings that we are analysing (Elster, 1989).

Computer simulations can be seen as an alternative modelling approach to better understand the dynamics and evolution of social phenomena. During the past two or three decades, a technological revolution has taken place providing ubiquitous access to unprecedented computational power to almost everyone in the industrialised world. With these new machines came new tools and methods, allowing us to grow societies “in-silico” (Epstein & Axtell, 1996) and observe their evolution in fast motion. Computational modelling is not restricted by mathematical requirements to ensure analytic tractability, therefore it gives us a great degree of freedom in choosing the actors, properties and activities that constitute the mechanisms that are supposed to explain the aggregate outcome. Furthermore, computational models do not have to be models of the behaviour of variables, though variables and variable-based statistical models may be measured and estimated based on the characteristics and behaviour of the simulated world - in the same way that it is done in the real world. Through computer simulations - models of the constellations of actors (with their properties) and their activities - we can see if and how social mechanisms bring about social phenomena, as well as monitor their change and evolution.

To better understand how such computer simulations work, and how they can be analysed, the value and use of models in the social sciences will be discussed now, followed by introductions of Agent-Based Modelling (Sec. 2.4) and the concept of Complex Systems (Sec. 2.5). Agent-based modelling is a type of computer simulation that lends itself especially well to the modelling of social phenomena, because by design the software uses individual actors and their activities as its core entity. Complex Systems is a multidisciplinary field of research that deals with phenomena arising from the interactions of many interdependent entities, which includes, among many others, human societies. While there is still an ongoing debate about whether there will ever be a unifying Theory of Complex Systems across all disciplines, this stream of research has developed many concepts and insights that are relevant to the analysis of the evolution and development of a social system. Therefore a review of the most relevant ideas is presented below.

## 2.3 Models - Understanding Through Analogy

Research on the evolution of social systems poses several challenges for researchers that seek to understand them. By definition, the entire system needs to be studied as an integrated whole; therefore, reductionist approaches that disassemble the system and examine its constituents in isolation will fail to grasp the complexities of the system's interactions. Furthermore, the timescales and sheer number of interacting entities go well beyond the limits of our observational capacities.

Models of the real system can be used as an artificial reproduction of the system. Models are simplifications of the real world, which are less detailed and/or less complex than the original (Gilbert & Troitzsch, 2005). Generally they can serve many different purposes, including explanation, prediction, guidance to data collection, discovery of new questions, training, communication, etc. Epstein (see e.g. 2008). As a result of their simplifications, models are more easily accessible than the original; either in the sense that they allow us to do something with them that is not possible with the original or in the sense that they are easier to understand, highlighting only the most essential aspects without distracting details. Models come in many different varieties: Model cars let us enjoy driving without a license - or they allow us to study their aerodynamics in a wind channel; using a hydraulics model A. W. Phillips illustrated the workings of the British economy (Phillips & Leeson, 2000) and Watson and Crick used a theoretical model that accommodated isolated findings related to aspects of the structure of DNA and allowed them to determine that DNA necessarily needs to have the form of a double helix (Watson & Crick, 1953). Even though they are not the real thing, understanding a model can help us better understand the original.

Here we focus on computer models to better understand the evolution of norms and patterns of behaviour in a large-scale social system. Even though this is a comparatively new field of application for computer modelling, there are numerous successful examples available that have used this approach to elucidate the interplay between individual behaviour, social interactions, the emergence of aggregate phenomena and adaptive feedback effects, many of them described in chapter 4.

By translating a verbal theory into a suitable formal language, researchers gain access to a vast toolkit of validated and tested techniques. This step is an essential element of science: Mathematics has helped us understand theories of physics and economics, statistical models are dominant tools in the social sciences and computer models are widely used in the study of our climate, ecosystem and epidemiology, to name only a few. With these tools we can test our models for consistency, explore the range of the model's behaviour and possibly derive predictions from the model in order to assess its validity.

Computer models can be seen as computer assisted-thought experiments that let us assess the implications and consequences of a theory. According to Kuhn (1977, p. 261) "thought experiments give the scientist access to information which is simultaneously at hand and yet somehow inaccessible to him". Computers greatly surpass the logical deductive capabilities of humans and therefore can help us to deduce consequences of the set of assumptions that we call a theory. In situations in which our natural reasoning apparatus reaches its limits, Bedau (1999) therefore refers to computers as a *philosophical crutch*.

Formal models have the advantage that they can be monitored in great detail and they are amenable to a vast variety of manipulations. Concretely computer models enable us to study and experiment with the artificial systems in ways impossible in the real world. Computer models can be run repeatedly, allowing for systematic variations of the conditions and monitoring with various levels of detail. Research with computer models is similar to the way a biologist experiments with Petri dishes. They assemble the necessary ingredients for the starting conditions including the environmental conditions and then they set the experiment going to see what will happen under different conditions. This is tracked using various measures and statistics. The same applies to computer models: Initial conditions are established, including environmental conditions in the form of the rules of behaviour in the code, parameter values, starting values and locations, prior history, and assumptions about the world in which the simulation takes place, and then the simulations begin and are repeated under different conditions and random seeds. Behaviour and outcomes are tracked using various measures and statistics just as you would do in the real world. We can vary parameter values and rules and rules-for-changing-rules to see what happens and learn from this. In

short we can do systematic experiments on our simulation models to learn about the types of behaviour and results that are possible.

Considering the path-dependence of the evolution of social systems, artificial models have another advantage: in the real world we have in effect a sample size  $n$  of 1, our history and what it has produced. Computer models can be run over and over again, to study the effects of chance and probability as well as different starting and environmental conditions, asking “what if?”. This allows us to explore what could have happened, producing alternative histories that could have developed from the same principles, thereby giving us a sense of the robustness of the system, a measure of the range of possible developments and also a chance to learn about critical turning points in the system’s development. As one of the founders of complex systems research, Chris Langton, explains it:

We trust implicitly that there are lawful regularities at work in the determination of this set [of realized entities], but it is unlikely that we will discover many of these regularities by restricting ourselves only to the set of biological entities that nature actually provided us with. Rather, such regularities will be found only by exploring the much larger set of possible biological entities. Langton (1996, p. ix)

Just like statistical and mathematical models, computer models are the formalisation of a verbal theory, but the similarities go further. In essence computer models are recursive, highly non-linear mathematical models. For the computer, any simulation is merely a deterministic, recursive function depending only on a set of exogenous parameters and starting conditions (Leombruni & Richiardi, 2005; Borrill & Tesfatsion, 2010). The model specifies the rules of how the state of the system changes from step to step, and the computer calculates the system’s development over time. Essentially, the computer provides numerical solutions to highly complex, non-linear mathematical problems. However, just looking at these equations would not do us much good because they are usually so complicated and nonlinear that they cannot be solved algebraically. We need to use a computer to solve them, step-by-step, executing each of the many thousand if-then rules at a time.

Another advantage of formalisation is that it makes a theory much more precise than if it is expressed in words alone. 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 model's behaviour, and how the effects of different assumptions affect one another. In the process of sensitivity analysis, one can sweep a huge range of parameters over a vast range of possible scenarios to identify the basins of attraction, thresholds and bifurcation points, even map out the complete phase space of the underlying equations of motion and adaptation.

Computational models have a bad image for some researchers because, they argue, simulations can be made to do anything and are only a result of the assumptions made. In a sense this is true but only in the same sense that mathematics can be used to write down any equation you want and the solution (if one is possible) obviously depends on the assumptions made in formulating the mathematic equation. Still you have to follow the rules of mathematical logic. The same applies to computer simulations, only that they are designed to solve a system of highly non-linear equations representing a complex adaptive system. The only way to "solve" such equations is to count them out with the aid of a computer in order to examine what happens under different conditions, to map out the phase space of possible solutions. The number of potential solutions, patterns of behaviour or attractors resulting from highly nonlinear systems is generally unknown a-priori. We are forced to work it out computationally.

There are however problems that have to be considered when using formal models. Every model is just a *representation of a theory* not the theory itself - which means that we need two steps of abstraction to build a model, instead of just one to develop a theory. This can be an additional source for errors and imprecision and therefore requires an additional step of *model verification*, explicit confirmation that the implementation conforms to the theory (Midgley *et al.*, 2007). Also, there may be several alternative candidate theories, and potentially a variety of possible implementations for each of them, that can explain a real system. So, while a model may well provide us with *an* explanation, in general, the model alone does not provide the means to guarantee that this is the only or true explanation. Epstein (2006) refers to this as *explanatory candidacy*. With formalised

models we can compare these theories and assess their validity. Depending on the availability of data that can be compared with the models' outcomes, it may be possible to use for validation quantitative means such as statistical tests or more qualitative criteria to assess the degree of congruence between the model and real observations (Marks, 2007).

## 2.4 Agent-Based Modelling

Agent-based modelling (ABM) 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 determine their own actions based on inputs from 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 help computers solve problems without human interference.

It was the prospect of modelling the interactions of many autonomous individuals that strongly increased the interest in simulation as a tool for the social sciences (Gilbert & Troitzsch, 2005). In these models complex aggregate behaviour arises not from superposition, but directly, *bottom-up* from actions and interactions of actors at the micro level (Marks, 2007). Technically each agent consists only of a set of logical rules of behaviour and a list of internal states, representing for example its memory, mood or capabilities etc. All the agent does is to collect "sensory" input from its environment and then match its set of rules to the current combination of internal states and external conditions. The behavioural rules will then determine its next action. Moreover, whole populations of such agents can be combined in a computer simulation and it is possible to include input about other agents in any one agent's rules of behaviour. Generally, those agents have limited, mostly local, capacities to perceive their environment, possessing different strengths or objectives; they may have means of interaction and communication, and a limited set of skills regarding the tasks they have to deal with. It is even possible to endow these agents with skills and characteristics heterogeneously. Metaphors such as beliefs, intentions, desires or even emotions are

used frequently to describe the agents' internal states. 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 the basis of these perceptions.

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

In contrast to many mathematical models, computational models need not be so strongly simplified to become analytically tractable. ABM is not restricted to general statistical models of behaviour, central driving equations or representative agents, but can represent in more realistic ways the micro interactions taking place and help us understand how they lead to macro structures and aggregate patterns of behaviour. The outstanding conceptual advantage of agent-based models is that their most basic unit are autonomously acting agents that are represented with "one-to-one correspondence" (Gilbert, 2008): The modelled agents can correspond with the individuals (or organisations) in the real world and their actions and interactions can likewise correspond to the actions and interactions between the real world actors. In such a simulated world the agents have causal powers to bring about change in the model system.

On these grounds ABM as a modelling tool allows researchers to formally model social mechanisms, without the need of abstraction to variables or holistic constructs. We can now focus our investigations on the causal mechanisms that drive a system's development, namely the constellations of entities with their properties as well as their actions and interactions. This allows us to model causality explicitly and in detail, in a way that is new and inaccessible to statistical or mathematical models.

ABM allows us to reproduce and monitor an interactive social system. It has frequently been used to study how macroscopic patterns and regularities observed in society, such as price equilibriums or the evolution of social norms, can be generated from decentralised, local interactions between collections of agents (Ball, 2007). It is worth mentioning that ABM does not attempt to reproduce the complexity of the system directly in the agents, the agents are relatively simple, not overburdened with knowledge and abilities. The focus of ABM is directed on the *interactions* of agents, as they jointly generate social phenomena, analogously to the way these phenomena are brought about in real life. As Epstein & Axtell (1996) already observed: *simple entities, interacting through simple, local rules can produce very complicated behaviour.*

Agent-based models are modular in structure. This means that they can be implemented so that the modules that represent the models' mechanisms are separate from each other, only connected by mutual interfaces. Any module functions independently, irrespective of the other modules' internal workings. Individual modules can be substituted with other variants and the domain of possible combinations can be explored systematically. This is analogous to the systematic administration of experimental treatments in empirical experiments, only at a larger scale. Every combination of modules constitutes one experimental treatment and differences in outcomes between different module combinations can be directly attributed to the differences in modules. This process of model development can also be seen as a gradual evolution and extension of theory about the collection of social mechanisms that drive the evolution of a society. In this way, we can gradually move from abstract and strongly simplified models to more realistic, life-like representations of the system under consideration.

ABM has been under development for more than two decades now, and what has begun as a niche interest of a few scientists has grown to be a recognised method in many fields. A broad selection of textbooks has become available (e.g. Gilbert & Troitzsch, 2005; Tesfatsion & Judd, 2006; Edmonds *et al.*, 2008) and a collection of customised 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 centralised portal for academic discussion, and simulation-based publications appear even in 1<sup>st</sup> tier journals, Midgley

*et al.* (e.g. 1997, 2007); Watts & Dodds (e.g. 2007); LeBaron & Tesfatsion (e.g. 2008); Rand & Rust (e.g. 2011). 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); a model of banking networks developed by Lord Robert May and his colleagues which showed, paradoxically, how the banking network as a whole becomes increasingly unstable as each individual bank diversifies its portfolio to spread its risk in similar ways (Haldane & May, 2011); 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 optimise their production and supply chain strategies (Seibel & Kellam, 2003). Perhaps the most dramatic illustration of the potential value of ABM is perhaps the European Framework challenge research project FuturICT ([www.futurict.eu](http://www.futurict.eu)), which is currently in pilot project stage. This visionary project aims to build a realistic and detailed ABM model of our world - all of it, including the material world (geology and geography), the biological world and the human world. The pilot project that is currently underway is funded by a EU research grant of 2 million Euro. It will be a massive project rivalling the size of the Apollo program, which will involve cooperation among thousands of scientists spanning all disciplines.

The research described in this thesis will use ABM to better understand the development and evolution of business networks. These networks are the result of a process of self-organisation where autonomous actors coordinate their productive efforts in order to realise economies of specialisation at the expense of their independence. As North (2005) argues, at one point in time human societies have evolved to a self-sustaining system where its members' welfare largely depends on each other, as opposed to the uncertainties of nature that determined their lives before. This self-organised production system is an early form of a business network, a collection of exchange relationships that helps coordinate the agents' activities. Using causal mechanisms identified in the literature about busi-

ness relationships and networks, this thesis will construct agent-based models of the actors in an artificial society that learn to self-organise and coordinate their activities. With such models we will be better able to address questions about the dynamics of business networks, as well as the interplay between the structure of the network and the performance of actors within it. These questions are often difficult to address in the real system, therefore a model can be helpful to guide further empirical investigations, develop hypotheses and explore the robustness and resilience of such systems.

## 2.5 Complex Systems

North's evolutionary account of economic change can be seen as a special case of an even wider theoretical framework that concerns itself with self-organisation and emergent phenomena in general: the study of complexity and complex systems. North speculates that the reasons that led to the development of division of labour and eventually to the global business networks we see today lie especially in the selective pressures on the members of the system and the way that cooperation and coordination changed these pressures over time. In the language of complexity, he describes a *complex adaptive social system* that is characterised by continuous feedback between the system and the individual level as well as intelligent and adaptive responses of the individuals to the situations that they find themselves in (see e.g. Miller & Page, 2007). Complex systems (CS) theories seek to explain the dynamics of self-organisation in large systems of interdependent individuals and how they bring about emergent phenomena. Although complex systems thinking does not necessarily rely on evolutionary processes, evolutionary theories like the one brought forward by North (2005) are generally compatible with this more encompassing framework.

At the same time, CS is a very abstract concept and there is no such thing as *the theory* of complexity, which makes it difficult to use it as the sole theoretical basis for a thesis. It has been argued frequently, that business networks should be seen as self-organising complex systems (Easton *et al.*, 2008; Wilkinson, 2008; Wilkinson *et al.*, 2012), but for reasons of accessibility the more concrete theory

of economic change is presented first, followed by the more general perspective of complexity and the relevant findings of this field, presented in this section.

CS thinking is a very diverse school of thought that has found application in a wide range of academic disciplines over the past few decades. A large and diverse body of research has been developed dealing with aggregate phenomena that arise from interactions of numerous interdependent entities and the emergence of business relations; and networks and exchange systems are but one example. An account of the historical development of complex systems thinking especially in the social sciences is proposed by Sawyer (2005), who identifies three waves of development: The first wave of social systems theory (1960-80) centred around Parson's structural functionalism (Parsons, 1961). Following this perspective, society is conceptualised as a system of elements such as norms and institutions that both constitute and perpetuate the system through their functioning. The second wave (1980-2000) manifested itself as general systems theory and was strongly influenced by chaos theory, i.e. the quest to understand turbulent behaviour in low-dimensional systems. Sawyer (2005) highlights that the most distinctive feature between the first and the second wave was a change in focus from structure and stability to dynamics and change (see e.g. Buckley, 1967). The second wave also concerned itself with non-linear effects in dynamic systems and its contributors were the first to question the applicability of traditional, linear mathematic tools to non-linear systems (Anderson *et al.*, 1988; Casti, 1994), and oppose the reductionist approach to science (Gell-Mann, 1994). The third wave began in the mid-1990s. It focusses on the relationship between levels of a system and especially the concept of *emergence*. The wide availability of powerful computers has made it possible to develop new tools and models that can represent aspects that are unique to social systems (as opposed to physical ones), including communication between actors, sense-making and adaptation. This enabled social scientists to adapt the concepts developed in the second wave, largely in the physical sciences, to the requirements in their own fields. A famous example of this is Arthur (1999), who describes the economy as a process dependent, organic, and continuously evolving system that exhibits emerging structures and perpetually novel patterns.

There is not one unanimously accepted Theory of Complex Systems - and there is ongoing debate about whether or not something like that can ever be achieved, especially considering the many different types of systems that have now been associated with the term complexity Mitchell (2009). Nonetheless, CS research has developed a technical vocabulary and a collection of concepts that are helpful to understanding and structuring the analysis of CS. A *system*, as defined by Viscek (2002), is an entity that can be analysed on multiple levels, such as a micro (unit, individual) level and a macro (aggregate, social) level. The main characteristic of a *complex* system is that the laws which describe its behaviour on one level are *qualitatively different* from the behaviour on other levels. A unifying trait of the many current analyses and theories dealing with CS is that they attempt to understand *nontrivial emergent and self-organizing phenomena* (Mitchell, 2009). In the following a selection of concepts relevant to the subsequent analysis will be introduced, including emergence, adaptivity, path dependence, and attractor states and resilience. A comprehensive discussion of all the aspects and variants of complexity theory is beyond the scope of this thesis, but there is a range of introductory and advanced books available that focus on various dimensions of the research available to date (see e.g. Waldrop, 1992; Sawyer, 2005; Miller & Page, 2007; Mitchell, 2009).

“More is different” has often been used to summarise this core characteristic of CS (e.g. Miller & Page, 2007). This expression aptly summarises several theoretical and methodological issues. It challenges the reductionist hypothesis that claims that we can fully understand a system when we disassemble it into fundamental units and then extrapolate from the workings of these parts to the working of the overall system. There may well be systems for which this approach is feasible, but by definition CS are more than just the sum of their parts, in fact the structure of interaction between parts matters greatly and renders simple extrapolation from its entities futile for a better understanding. Knowledge about one level of the system does not directly help us model the higher level of the system (Miller & Page, 2007). “[T]he whole becomes not only more than but very different from the sum of its parts” (Anderson, 1972, p. 393).

In CS the behaviour on the system level is qualitatively different from the behaviour on the entities’ level, although all there is to bring about the system’s

behaviour is the constellation of individual entities (with their properties) and their actions and interactions. It is the *constellation of entities* that brings about this qualitative difference, allowing the system to supervene on its components (Laughlin, 2005). This phenomenon is known as *emergence*: Often not intuitively and sometimes quite surprisingly, complex systems exhibit pronounced changes in behaviour as we shift our perspective from one level of aggregation to another (Miller & Page, 2007; Mitchell, 2009). On the system level, we speak of aggregate patterns, spontaneous order or self-organisation - all these emergent regularities are brought about not by central planning but through local interaction between the system's components. While we are able to grasp the concept of emergence and identify emergent properties of a system, it is not always obvious how these system-level properties arise from the entities' interactions.

Physical-material and chemical CS generally lack a feature that is rather dominant in the development of CS in the living world: *Adaptivity*. This distinction marks the transition from second to third wave studies in CS, according to Sawyer (2005) and the difference is so substantial that Complex Adaptive Systems (CAS) has become a technical term in its own right (see e.g. Miller & Page, 2007). Adaptivity refers to responses of the individuals to their environment including the aggregate state of the system. In CAS emergent properties still develop from the individuals' interactions, but the individuals are able to adapt to what they experience, they learn individually, or over a longer period of time they may evolve<sup>2</sup>. Examples of CS that are not CAS are hurricanes and turbulent rivers (Mitchell, 2009). Especially the importance of feedback effects between their levels is not seen as a core mechanism to induce complexity (Gross & Blasius, 2008). Notwithstanding, all CAS are also CS. Through adaptation on the individual level, CAS can change their behaviour on the aggregate level as well, and therefore change their behaviour over time. When interactions are adaptive and not independent, feedback effects can arise in the system. This can fundamentally affect the system's dynamics. Negative feedback can quickly absorb changes and stabilise the system, positive feedback however has the opposite effect, changes get amplified

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<sup>2</sup>Furthermore Miller & Page (2007) propose to introduce a third distinction - Complex Adaptive Social Systems (CASS) - that describe systems composed of entities that respond to the system's aggregate state as well, able to perceive it, trying to make sense of it, and lastly attempting to influence it.

and increase instability (Miller & Page, 2007). The effects of such multi-level feedback are illustrated in Fig. 2.2 and it is merely a dynamic and ongoing view of the causal mechanisms from social states through individuals to other social states, discussed in Sec. 2.2.

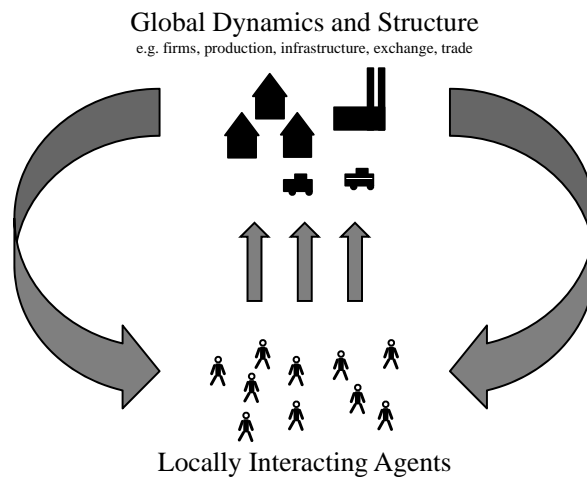


Figure 2.2: Schematic illustration of feedback effects between individual actions and the global structure that emerges from those actions, depicting the emergence of an industrial system of production from the actions and interactions of individuals, that in turn provides the basis for further actions and interactions.

There are many different types of CAS, including business and economic systems, social systems, traffic systems, biological and ecological systems and the World Wide Web. These systems 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 individual level, the behaviour is relatively simple and it is hardly obvious how the complex behaviour on the system level arises. Ants have been found to communicate via pheromones and indirectly through locally changing their environment (stigmergy), but without a central planner, it is hard to imagine how the large collective

can actually build and sustain itself. The CS perspective helps explain why 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). It has been shown that also the price-system can be explained as a CAS. Market prices can emerge from the local interactions of many buyers and sellers making individual mutually acceptable trades. Some pay a higher price than the market equilibrium price of economic theory, some pay less, depending who they run into in the market. Through these individual trades a distribution of prices emerges which is centred on the market-clearing price predicted by economic theory. It emerges naturally from the micro interactions and exchanges taking place over time among buyers and sellers; without the need to assume that a Walrasian Auctioneer sets the price (Axtell, 2005).

CAS are dynamic, developing and evolving over time. Generally their future development is affected by their development in the past, or in short: history matters. Of late, the term *path dependence* has become a popular conveyor of the looser idea that history matters (Crouch & Farrell, 2004; Pierson, 2004; Page, 2006). On the individual level, path dependence describes how states, actions, or decisions faced in any current and future circumstances are limited by the states, actions, or decisions made in the past. This implies that the order of states that a system goes through matters, as well as the type of states on this path. Theoretical, historical, and empirical studies have argued about the effects of path dependence in many fields including the formation of government policies (Hacker, 2002), the choice of technologies (Nelson & Winter, 1982; David, 1985; Arthur, 1994), to the location of cities (Arthur, 1994; Page, 1998) and organisational development (Sydow *et al.*, 2009) and of course the evolution of social institutions (North, 2005), and many others. Page (2006) identifies four general mechanisms that may lead to path dependent development in a system as it affects the context for the entities' activities: increasing returns, self-reinforcement, positive feedbacks, and lock-in. Increasing returns means that the benefits of a choice or action increase with the number of actors that take this choice or action. Self-reinforcement refers to complementary forces or institutions that arise with an activity and encourage

that the activity be sustained. Positive feedbacks are positive externalities that arise when the same activity is performed by other people. Lastly, lock-in occurs when a choice or action becomes superior to any other one because a sufficient number of people have already made that choice.

Through interaction and feedback effects CS can exhibit highly *non-linear* changes in their aggregate behaviour as a result of reactions even to minute changes. First observations of such an effect once gave rise to the development of Chaos Theory - the study of low dimensional yet dynamic systems and their development. In an attempt to forecast the weather with a rather simplistic model of three deterministic but interdependent equations, meteorologist Edward Lorenz observed that even such a simple dynamic system can exhibit unpredictable behaviour. He realised that a small change in the initial condition of the system, such as a difference in rounding precision as in his case, can lead to widely diverging outcomes of the system's development, because these differences are amplified over time, rendering long-term prediction of such systems generally impossible (Kellert, 1993). He referred to this phenomenon as the "butterfly effect", emphasising the system's sensitivity to the minutest initial conditions, brought about by non-linear dynamics (Lorenz, 1963). Non-linear effects also play a dominant role in bringing about emergent system properties in CS and CAS, due to the interdependent nature of the system's entities. Accordingly small changes can be amplified and lead to vastly different system behaviours in the long run.

Although unpredictable, chaotic systems have been found to follow stochastic laws. Their development converges to a so-called *attractor state*, which is a subset of the phase space of all possible states of the system over which a probability measure can be defined. A chaotic system may have numerous attractors, and the initial conditions of the system will determine which of these attractors will be approached. Therefore it is possible to divide the space of initial conditions into *basins of attractions* around each of them, determining which initial conditions lead to which attractor state. For systems like Cellular Automata and Random Boolean Networks, which are rather limited in terms of the individuals' activities, it is in fact possible to run the systems backwards from any attractor state and identify all initial conditions and the paths that lead up to that state (Wuensche,

2011). In terms of North (2005), the study of chaotic systems makes it possible to turn uncertainty about their behaviour into risk - at least in principle.

For low dimensional dynamical systems, such as the logistic map (May, 1976) ( $x_{n+1} = rx_n(1 - x_n)$ ) or the original Lorenz (1963) system of differential equations ( $\frac{dx}{dt} = \sigma(y - x)$   $\frac{dy}{dt} = x(\rho - z) - y$   $\frac{dz}{dt} = xy - \beta z$ ) these attractor states can be plotted to summarise their dynamics visually. The logistic map in Fig.2.3 is characterised by only one parameter  $r \in [2, 4]$  and its single initial value  $x \in [0, 1]$ . The system's dynamics develop depending solely on the value of  $r$ , which determines whether it converges to a single value, alternates periodically between a finite number of values or enters a chaotic attractor where it assumes values in a set range of values, following a probability distribution. The situation is similar for the three dimensional Lorenz equations, however, Fig. 2.4 visualises only one attractor arising from one combination of parameters:  $\sigma = 10$ ,  $\rho = 28$  and  $\beta = \frac{8}{3}$ . Again, the dynamics follow a pattern that is far from uncertain. A distribution that specifies the probability for the system being in any location in the three dimensional space could be approximated if not analytically, then at least through sampling and bootstrapping.

This approach can serve as a template for the analysis of any dynamic system, including complex and complex adaptive systems. Even though CS and CAS focus more on interdependence of activities in a system, their analysis follows essentially the same principles: 1) Identify and describe the states that a system can reach, 2) relate these states to the initial conditions that brought them about and 3) assess the probabilities for each of these states, conditional on initial conditions. CAS however need not necessarily lead to one attractor state, due to the much higher number of dimensions and interdependencies, as well as its capabilities to adapt. In this case the analysis can still describe the emergent patterns and system properties, as well as the robustness of these results. Also, it is of interest how *resilient* a system's behaviour is with regard to the impact of external shocks, i.e. does the systemic behaviour change in response to external forces or is it able to absorb these? In this way, likely *tipping-points* can be identified that, once reached change the aggregate patterns in the system, essentially moving it to another "attractor state". These transitions can happen quite abruptly and lead to fundamental differences (Fisher, 2011).

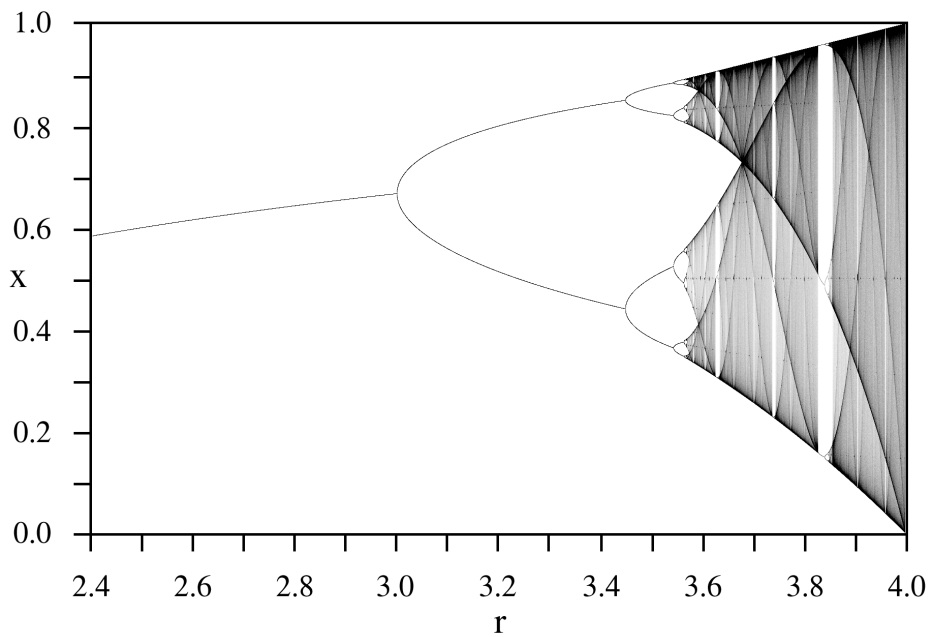
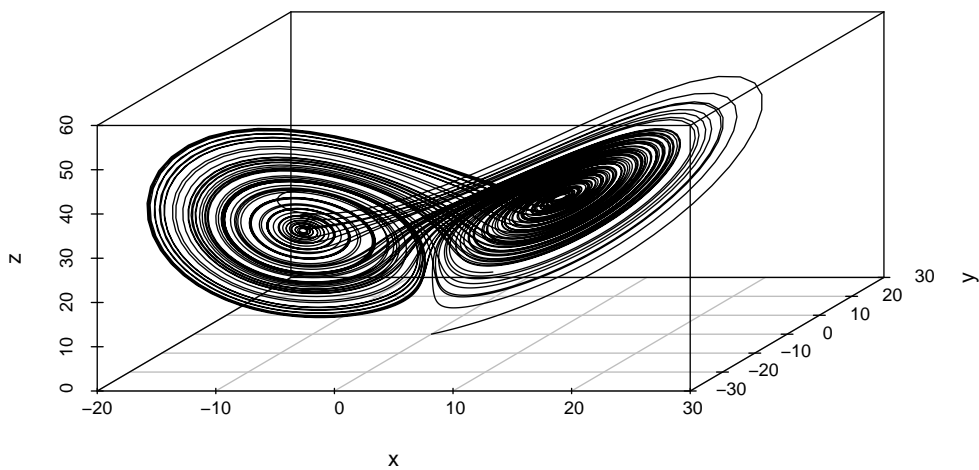


Figure 2.3: Bifurcation diagram for the logistic map for parameters  $r=2.4$  to  $4.0$ , showing the basin of attraction for  $x$ , depending on  $r$

### Lorenz Attractor



Parameters:  $\sigma=10$ ,  $\rho=28$  and  $\beta=8/3$

Figure 2.4: Lorenz attractor for parameters:  $\sigma = 10$ ,  $\rho = 28$  and  $\beta = 8/3$ , initiated at  $x = y = z = 0$

The knowledge we can hope to obtain from the perspective of complex systems is different from the knowledge that is sought for under a reductionist approach. The numerous interdependencies and dynamics of CS render prediction impossible, but we can explore the space of possible developments of a system, map out the likelihood of certain trajectories under given conditions and possibly identify crucial turning points and regions of resilience.

The key to such an understanding however is a sufficiently large number of systematic observations, and systematic experimentations that reveal what kinds of developments are possible within a system. Both of which are limited in a CAS like human society that exhibits emergent properties like norms, laws and culture - as well as the structured interactions in business networks. The empirical database upon which we could build a theory is rather scarce, difficult to access and usually inaccessible for controlled experimentation. However, we can build models of systems that obey the same mechanisms, for example with computer simulations and especially ABM. These models can then be used to explore the space of possible developments and manipulate them to investigate how they respond to influences and interferences that cannot easily be applied to the original system. We cannot go back and rerun history to see how sensitive outcomes are to different factors and interventions, but simulations enable us to observe the range of possible developments of alternative histories, they allow us to ask “what-if?” and explore what *could* happen.

Business networks are CAS. They have evolved over time and they will continue to evolve, driven by their members’ actions and decisions as they respond to new situations in an ever-changing environment. To better understand the development and evolution of business networks, the research presented here will use the abundance of existing findings about the activities of actors in such networks to identify the social mechanisms that drive their development, and then translate these mechanisms into agent-based models of such networks that evolve and develop over time. These models can then help us understand the dynamics of business relations and especially how they interact with and depend on their context, the multitude of other players and relations in the network. Such models can be used to explore alternative development histories and the resilience and robustness of the networks that they bring about. The focus of these models will be on

the realistic representation of the actors' activities and decision making and therefore a toolkit to experiment with social mechanisms and how they bring about the kind of division of labour and coordination of productive efforts that we see in business networks today.

The study of CS is still young, compared to many other disciplines. As Hedström (2005) and Coleman (1986) and many others indicated, the transition between micro activities and aggregate outcomes remains a major conceptual hurdle to theory development. We are only at the onset of developing an intuition about it. Nonetheless, computer simulations allow us to capture important features of the process, identify tipping points, and to conduct experiments of the impact of different factors (Kleijnen, 2008). These models are entirely under our control, allowing us to monitor every aspect of the system and conduct whichever manipulations and experiments we see fit. They are a chance to develop a better intuition about emergent processes and to develop more precise theories that ultimately can be put to the test empirically.

In order to better understand the mechanisms that drive the complex dynamics and interdependencies of business networks that by now connect many industries and countries all over the globe, this thesis will investigate the origins of these networks. Business networks themselves are informal institutions that facilitate and regulate the exchange of goods and services among a large group of specialist producers. They have evolved over time, simultaneously channelling the efforts of their members and providing the basis for future interactions. There is related experimental work (Kimbrough *et al.*, 2008; Crockett *et al.*, 2009, see Ch. 6) that focusses on the same issue, but focusses on the development of property rights and related legal norms that constitute one vital aspect for the development of impersonal exchange and long-distance trade. This thesis complements these efforts, focussing on relational aspects of exchange. Property rights provide the legal framework for barter and exchange, however, the transition from autarky to specialisation in production is also a transition from independence to dependence in consumption. The results are that on the one hand, economies of specialisation can be realised, but on the other new uncertainties and risks arise regarding the sale of produce as well as the reliable acquisition of goods from others. The maintenance of business and exchange relations can help reduce those new uncertainties

and risks and the models presented here will investigate how the development of exchange relations and the realisation of economies of specialisation are interconnected. Through these endeavours it is possible to identify necessary mechanisms that bring about specialisation and division of labour, including mechanisms that are necessary for the establishment and maintenance of relationships. The models developed here will then guide us in theorising about the effects of the structure of interaction in such networks and help formulate empirically testable hypotheses about the evolution of business networks.

# Chapter 3

## Mechanisms - A Review

There are two basic ways of studying socio-economic behaviour: “Collect observational, survey or other forms of data and analyze them, possibly by estimating a model; or begin from a theoretical understanding of certain social behavior, build a model of it, and then simulate its dynamics to gain a better understanding of the complexity of a seemingly simple social system“ (Liao, 2008, p. ix).

Most social and business research follows the former way of scientific inquiry. This field is dominated by linear, comparative-static, variable-based theories and methods and, as illustrated in the previous chapters, dynamics and evolution are mostly absent. Such research is of limited value in showing how real systems behave and evolve over time because they provide no understanding, tests or observations of the underlying *causal mechanisms that drive their development*. Variables are researcher abstractions, they do not exist in the real world and most importantly, they have no causal powers. Associations among variables may be the results of causal mechanisms, but we must be careful not to equate their co-variation with causation. Variables can only guide us in the development and testing of theories that explain how their co-variation and longitudinal patterns come about. In order to develop realistic, comprehensive models that help us better understand the dynamics and evolution business networks, the models developed here will draw on existing research, including descriptions, characterisations, and partial theories about the activities that business actors engage in. These serve

as a basis to identify the underlying social mechanisms and processes that drive change, and thereby bring about the levels and values of variables and their covariances that we can measure and screen more conveniently. The models developed here will reproduce the causal mechanisms in terms of the constellations of entities with their properties and the activities that they engage in. Only, in the model, all these aspects can be subject to experimentation so that we can better understand, how mechanisms interact, or how the constellations of actors affect the progression of activities, to name only a few examples.

There are many types of causal mechanisms at work in business relations and networks including physical, biological, psychological, social and economic. This is because these networks comprise many types of actors acting and interacting, including people and organisations (collective actors), other living things (animals and plants), passive actors like material objects and various kinds of resources and intangibles like ideas, feelings and beliefs. The primary actors are people and organisations and the focus here is on them and the socio-economic mechanisms driving the behaviour, dynamics and evolution of business relations and networks. These socio-economic mechanisms are embodied in the constellations of actors (with their properties) and their activities (Hedström, 2005). Together they bring about the regularities and patterns of behaviour that we observe on the system level, the coordination of production, including specialisation, division of labour and the realisation of economies of specialisation, which are the essence of business networks. Underlying these social mechanisms, are more basic psychological, cultural, legal, but also biological, chemical and physical mechanisms that are beyond the scope of this thesis and are the focus of attention in other disciplines. Layton (2009)

Social mechanisms in business relations and networks, broadly refer to the different types of *actions and interactions* of people and the *direct and indirect effects* these actions have on others and on the actor itself. There are obviously many different types of actions being undertaken by members of these networks and there have been many attempts to identify and classify them. For example, many detailed typologies of marketing functions were proposed as part of the earlier functional approaches to marketing (e.g. Hunt & Goolsby, 1988). Later, more general concepts of collecting sorting and dispersing were proposed (Vaile *et al.*,

1952; Alderson, 1957) and the marketing activities of firms are summarised in terms of the marketing mix (Kotler, 1967). Just recently, Layton (2009) emphasised the importance of exchanges and specialisation in production activities in an account of marketing systems. He showed how these work together with the structures of interactions and organisation in bringing about growth and economic well-being.

These classifications are of limited use to the identification of different types of behavioural mechanisms involved. Instead, based on a review of previous research and theory from economics, marketing and other social science disciplines, five generic types of causal mechanisms can be identified that underlie the dynamics and evolution of business relations and networks (Held *et al.*, 2010b,a; Wilkinson *et al.*, 2010, 2011). The mechanisms are distinguished in terms of the type of processes they seek to explain and consist predominantly of the activities that actors engage in, always contingent on the agent's properties and embedded in their network context and current environment. Each class of activities comprises a number of more specific activities that address various aspects of the more general mechanism:

**Business Acting and Specialising:** Specialising, Learning, Increasing scale, Combining, Limiting, Growing, Intermediating, Outsourcing, Coordinating, Exploration and Exploitation

**Business Mating:** Finding, Being found, Searching, Defining criteria, Informing, Promoting, Targeting, Assortative mating, Evaluating

**Business Dancing:** Getting Acquainted, Learning, Negotiating, Bonding, Sense-making, Socialising, Coordinating, Monitoring, Adapting, Cheating, Terminating

**Interconnecting Relations:** Prioritising, Comparing, Intermediating, Competing, Communicating, Transmitting, Clustering

**Environmental Conditions:** Enabling and constraining effects of interactions with the exogenous environment, including the natural, social and cultural environment.

Production processes have become more and more complicated, requiring a multitude of different skills and the coordination of numerous tasks, all together going far beyond the capabilities of a single individual. Quite demonstratively, Matt Ridley (2010) talks about the computer mouse on his desk which is a “complex confection of many substances with intricate internal design” that, he conjectures, not one person on earth would have all the knowledge to produce on her own from raw materials. The plastic components need to be distilled from oil and formed and assembled in a complicated process, moreover the mouse requires glass for the optics and an array of metals and half-metals for the electronic parts. Furthermore these ingredients need to be combined to form complicated electronic circuits, infrared sensors and radio emitters still small enough to form a device to fit comfortably under one’s hand. Many different tasks need to be performed and coordinated to produce a thing that is nowadays as common and omnipresent as a computer mouse.

Business networks that bring about the production and marketing of computer mice, and many other products and services, include numerous different types of people and firms that perform a wide range of different activities that are required to create and deliver these products and services to their final consumers. All of these actors specialise in the performance of a selection of activities. However these activities are connected to and dependent on each other directly and indirectly through various types of technical, logistical and economic interactions and dependencies. The elements required for the respective sorting step need to be sourced and transported, quantities need to be matched, configurations coordinated, etc. Actors in these networks develop complex patterns of division of labour, each of them specialising in their own activities while simultaneously coordinating their activities with others. It is the central question of this thesis how such complex relationships and networks evolve and change over time.

Each actor in these networks has to deal with two essential questions: First, which activities should it perform itself, and second, how do these activities depend on others and therefore what kind of coordination with activities of other actors do they require? It is this interplay of specialisation and division - coordination - of labour that is the core interest of this thesis. The following sections will illustrate the various activities that actors in such business networks engage

in, in order to perform the tasks that they choose to do and coordinate their activities with others. The decision to perform a certain activity is largely a matter of economic considerations. Section 3.1, which deals with acting and specialising, will focus especially on the economic principles underlying an individual's decisions to perform certain tasks or to leave them to others. Subsequent sections will then discuss the social mechanisms that help business actors coordinate their activities, specifically their mating and dancing, their mutual interdependence and the relation to their environment. Summary tables of the respective mechanisms are provided at the end of each section.

### **3.1 Mechanisms Related to Acting and Specialisation**

The decision to perform a task oneself is largely a matter of one's own cost for performing the task and therefore driven largely by economic considerations. There are many economic principles that affect an actor's efficiency and efficacy in task performance. They can be derived from two broad classes of the actor's properties: These are the actor's *capabilities* and its *control over resources*. The difference between these two is that resources are tradable and non-specific to the actor, while capabilities are actor-specific, non-transferable and often organisationally embedded (Makadok, 2001). Capabilities are skills and knowledge that enable the actor to employ its resources and perform activities with them. Resources can be raw materials or consumables, as well as machinery and infrastructure. In the resource-based view of the firm key resources are considered to be the basis of sustainable competitive advantages between companies and should therefore constitute the cornerstone of a business' strategy (Wernerfelt, 1984; Barney, 1986a,b). Many researchers have highlighted the importance of resources and capabilities and their implications for firm performance (Coase, 1937; Penrose, 1959; Stigler, 1961; Chandler Jr., 1977; Williamson, 1975), and indicate that the heterogeneity between actors is fundamental to the development of an economy (Kirman, 2006). Although the following activities and mechanisms refer to economic principles considerations, this does not imply that there is an optimal behaviour for

any one actor, nor that the actors have all the necessary information and cognitive capabilities to make optimal decisions.

Business actors can affect the level of efficiency with which they perform a task. The selective improvement activity will be referred to as *specialisation*. There are two aspects to specialisation: At any given point in time, the amount of time and effort (and other resources) devoted to the task can help realise *scale effects* and other economies. Changes in efficiency over time can be brought about through *learning and experience effects* that change the actor's capabilities and investments that change its control over resources. The effect of specialisation was first analysed by Adam Smith (1776) in his "An Inquiry into the Nature and Causes of the Wealth of Nations", where he illustrates the benefits of specialised labour in terms of pin making: Dividing the task of creating a pin into four separate smaller tasks increased the worker's output by a factor of almost five. Whereas one worker performing all the operations produced 1000 pins per day, ten workers employed on four specialised tasks could produce 48,000 pins in the same time. Smith saw this as the dynamic engine of economic progress, making each worker an expert in one isolated area of production, thus increasing his efficiency.

Smith's anecdote highlights how important learning and experience effects can be. However, a concrete measurement had to wait for another 160 years until Wright (1936) proposed a mathematical model of the learning curve effect on labour productivity in the aircraft industry. He showed that every time total aircraft production doubled workers learned from repetition and the required labour time decreased by 10 to 15 per cent. Since then, many different mathematical models have been proposed to actually fit the curve (see e.g. Yelle, 1979), but the general mechanism remains undebated: *Repetition* of a task reduces the time it takes to perform it, and the time savings are larger at the beginning of the learning process and they become less pronounced with every new repetition of the task.

In addition to learning and experience effects, there are economic principles underlying *economies of scale* - i.e. outputs of a production process growing faster than its inputs (Basu, 2008). So by devoting more resources to the performance of a certain activity, it is possible to reduce the average costs and therefore increase efficiency. Three general economic principles were outlined by Florence (1933):

- Factor inputs to any production process come in different unit sizes. A specialist machine, a factory, a worker, a vehicle - all operate most efficiently at their individual capacities and these capacities do not necessarily coincide. By operating at a higher scale firms are able to combine such specialist inputs with different operating capacities more efficiently, with less excess capacity in individual machines and sub-processes, due to the *principle of lowest common multiples* (Dixon & Wilkinson, 1986; Wilkinson, 2008)
- Analogously, the *principle of bulk transactions* applies this logic to transactions such as purchases, shipments, communication, and negotiations. Reducing the number of transactions through increasing their size facilitates the use of specialised inputs, and the more efficient use of inputs with fixed costs. Economies arise in terms of savings in personal contact and negotiation time, financial settlements and also in transportation costs and the infrastructure and machinery involved. (Dixon & Wilkinson, 1986; Wilkinson, 2008) In short: it is more efficient to send one full truck than two only half-full ones.
- The *principle of massed reserves*, that is closely related to the concept of *pooled risk* (Stigler, 1946) states that widening the customer base can lower the ratio of inventory costs, bad debts and other costs to total costs. It relies on the law of large numbers from probability theory, stating the sample average converges to the expected value with increasing sample size (Poisson, 1837). Accordingly, random fluctuations in demand and other uncertain events across customers become more likely to cancel each other out when the customer base is large, which reduces risk and the costs associated, while at the same time increasing planning reliability.

There are various other economic principles that may guide an actor's decision to perform a task - or a collection of tasks together. The principles above apply not only to the more efficient use of inputs in the performance of a single activity; they can also come into effect when an actor performs certain combinations of activities that share common inputs, which is reflected in the concept of *economies of scope* (Dixon & Wilkinson, 1986; Wilkinson, 2008). Richardson (1972) refers to

such interrelated activities as *similar*. The performance of similar activities by the same economic actor holds the potential for *economies of scope*, as they require the same resources and capabilities for their undertaking and therefore increases the scale of usage for each of them. Richardson (1972) states that the range of activities of any actor are necessarily limited by its resources and capabilities - and consequently the actors tend to specialise in activities that match these capabilities and resources to exploit *comparative advantages* (Ricardo, 1817) - doing what they do better relative to others.

Also there are limits to the extent that a firm can gain from the operation of these economic principles or mechanisms and economics of scale and scope. These show the operation of other types of social and economic mechanisms. As first remarked by Adam Smith (1776) “the division of labour is limited by the extent of the market”, and later explained by Stigler (1951) in an article by the same name, the size of the firm will depend on the size of the markets it serves and this puts an upper boundary at the scale on which it can operate. In other words, the potential for specialisation of one actor depends on the level of specialisation of others in the market. What others decide to source out determines the size of the market for any one actors’ outputs. Stigler (1951) argues that there are activities with increasing costs to scale that constrain the ability of a firm to achieve savings in other activities. Examples of this are marketing (and management) activities, including increasing transport and communication costs necessary to reach more physically and psychological distant customers. Even though the costs per unit transported or communicated are falling, the costs per unit sold increase (Shove, 1930). This economic mechanism may have a limiting effect on the scale at which other activities can be performed as well.

More generally, the interdependencies among activities affect what an actor can do and how efficient its activities are, as they develop over time. This is reflected in the *principle of non-proportional change* (Boulding, 1953), which states that a uniform increase in a linear dimension of a structure will increase the structure’s area by the square and its volume by the cube. Accordingly, when an actor changes the scale of one activity or the use of a certain resource, this may lead to tensions with the efficiency of other activities and their underlying inputs. Edith Penrose (1959) was the first to identify such an effect empirically, studying man-

agerial and administrative restraints on the speed of a firm's growth. Managers rarely perform at full capacity right when they enter a new company. They need to learn about the company, absorb tacit knowledge and familiarise themselves with their colleagues and other contact persons. This makes managers a scarce resource internally. As a result, any expansion that requires the recruitment of more new human resources is dynamically constrained regarding its speed and magnitude.

To resolve the conflict between efficient scales of operation for different activities, an actor can choose to outsource some activities to external specialists. These specialists can perform similar activities for a number of firms and therefore gain efficiencies internally through the economic principles and mechanisms discussed above. The first to provide a systematic account of this process of division of labour was Robinson (1931), showing how economies can be realised through specialists which would otherwise not be available to the firms using their services. As a result of that we see firms that specialise in particular assortments of activities that match their capabilities, resources and capacity and offer value to other firms in exchange for value they receive in return.

Outsourcing of activities brings benefits, but not for free. The activities and interactions of the different actors involved have to be coordinated and controlled and this leads to various types of transaction costs. They were first introduced by Commons (1931) and form the basis of the New Institutional Economics School of thinking. In their widest definition "transactions are, not the "exchange of commodities," but the alienation and acquisition, between individuals, of the rights of property and liberty created by society, which must therefore be negotiated between the parties concerned before labour can produce, or consumers can consume, or commodities be physically exchanged" (Commons, 1931). Coase (1937) describes transaction costs as "costs of using the price mechanism", arguing that there is a trade-off between the economies that can be gained through specialisation and the various types of costs that arise because coordination between firms requires more resources than coordination within a firm. These costs include search, negotiation, writing and enforcing contracts, transportation and costs associated with risk and uncertainty. It was Williamson (1975, 1981, 1985, 1991) who extended this analysis to focus on transaction costs that arise from oppor-

	Similar	Dissimilar
Complementary	Intra-firm coordination	Interfirm coordination
Non-complementary	Aggregation	No coordination

Table 3.1: Richardson's (1972) classification of activities and their coordination

tunistic behaviour and identifies asset specificity, information-asymmetry, limited cognitive capabilities and uncertainty as factors leading to costly, opportunistic exploitation. These may be seen as the operation of other types of social and economic mechanisms in markets. Transaction costs lead to the develop of other types of mechanisms to deal with them including different types of market organisation and various types of social and economic processes, as described below.

The existence of transaction costs and the way they are managed affects patterns of specialisation and how they develop over time. This in part depends on how closely coordinated different types of activities have to be. Richardson (1972) classified activities not only on basis of their similarity, but also based on their *complementarity*. Complementary activities in some way depend on each other, for example they may represent different stages in a productive process and therefore need to be coordinated. He claims that firms tend to specialise mostly in similar activities and attempt to keep similar and complementary activities within. In contrast, dissimilar activities offer the potential for outsourcing. However, if dissimilar activities are complementary as well, they will also offer problems in terms of opportunistic behaviour and transaction costs. His classification is shown in Table 3.1.

Helping actors coordinate their activities can itself become the activity of a specialist. There are economies of *reduced contacts* that can be attained through the activity of intermediaries, another type of specialist actor, who mediate between a number of sellers and buyers, such as wholesalers, reducing the number of transactions in the system and making each one individually bulkier (Hall, 1949).

Recent research has extended the classical ideas of transaction cost analysis by a much more detailed and comprehensive analysis of the interdependencies of activities in a production process, revealing in more detail the mechanisms involved. *Modularity theory* (Baldwin & Clark, 2000) represents these interde-

dependencies as a network of activities and actors. The production process is a sequence of activities that are assigned to the actors. The analysis then focuses on the degree of coordination that is required between the actors as they perform their activities. Activities explicitly include transactions, such as flows of material and information exchange, feedback as well as iterative and uncertain flows between actors. A module is a group of activities that are highly interdependent on one another, but only minimally dependent on what happens in other modules (Baldwin & Clark, 2000, p. 63). High transaction costs arise when the production process requires close coordination between actors, while low costs arise when modules of activities can be confined to only one actor who then passes on the results to the next actor as a self-contained unit. Associated research shows that organisational processes change with the introduction of new product and process architectures and also that those new process architectures then give rise to new markets and new industries (Baldwin, 2008). Standardisation and the definition of design rules are common strategies to reduce the interdependence between activities and modularise a production process. They reduce 'mundane' transaction costs, for example for quality control, counting and payment, and potentially, they also reduce the opportunities for opportunistic behaviour and costs associated.

All the activities described above are dynamic in nature, enabling actors to respond to an ever-changing environment and new information, changes in technology and many other developments. However, the necessary adaptations do not come without effort. Whether it is new activities, or different cooperation partners - the search for new opportunities is costly itself and its outcomes are often uncertain. Generally these investments occur prior to classical transaction costs and in some situations their size and uncertain outcome may prohibit specialisation, cooperation and the realisation of associated economies. The basic dilemma that business actors face is that of *exploitation versus exploration*. March (1991) analyses the complications that can arise in allocating resources between the two, particularly considering that the distribution of costs and benefits across time and space, may be different for the two strategies. He argues that exploration strategies tend to require more time to realise their benefits. Furthermore his findings suggest that an exclusive focus on exploration, just like an exclusive focus on exploitation, is problematic for the continuing success of a business in a compet-

itive industry. Without exploration new opportunities will not be identified and eventually competitive pressures will be too strong, while without exploitation a business cannot realise the potential of opportunities and will therefore succumb to competitors. In such circumstances business actors have to find a trade-off between investing their resources in exploiting what they have and exploring what they could have.

Mechanism	Description	References
Specialising	Actors decide to undertake some activities and not others.	Smith (1776)
Learning	Repetition leads to learning curve effects.	Wright (1936); Yelle (1979)
Increasing scale	Realise economies of specialisation through better matching of factor inputs, bulk transactions and massed reserves.	Florence (1933); Dixon & Wilkinson (1986)
Combining	Performing suitable combinations of activities can lead to economies.	Richardson (1972); Baldwin & Clark (2000); Baldwin (2008)
Limiting	Division of labour is limited by the extent of the market. At certain scales some activities may also exhibit increasing costs to scale, therefore limiting the potential of task performance.	Stigler (1951); Shove (1930)
Growing	The change in scale may affect different activities in a non-proportional way, so what may lead to efficiencies for one task may create additional costs from another.	Boulding (1953); Penrose (1959)
Intermediating	Intermediaries can realise economies of reduced contacts, helping other actors coordinate their activities.	Hall (1949)
Outsourcing	Activities can be actively outsourced to other actors so they may realise efficiencies.	Robinson (1931)
Coordinating	Coordination between actors is costly, the associated transaction costs arise from negotiation, controlling and uncertainty about the partner's behaviour.	Commons (1931); Coase (1937); Williamson (1975, 1981, 1985, 1991)
Coordinating	Coordination costs may depend on the activities to be coordinated and the properties of the products produced.	Richardson (1972); Baldwin & Clark (2000)
Coordinating	Coordination between actors can facilitate the realisation of comparative advantages.	Ricardo (1817)
Exploration	The search for new opportunities is costly but necessary in the long-term.	March (1991)

Table 3.2: Overview of mechanisms that drive the individual's specialisation decisions and the conditions for coordination and division of labour in a business network.

## 3.2 Business Mating Mechanisms

To realise the benefits of specialisation business actors need to coordinate their productive activities. While the considerations above may guide them in deciding what the actors do themselves, they do not generally bring about a suitable division of tasks between them. The first essential step in coordinating their efforts therefore is to find each other. Only then can they attempt to bring about and coordinate division of labour.

Research on business relations and networks suggests that the relevant mechanisms here are of economic, but also to a large extent of social nature. For an exchange to take place partners have to be aware of each other, consider each other as potential partners and jointly they have to agree to cooperate. Although this topic is essential for the development of relationships, there exists little research describing the actual processes and underlying mechanisms of the initiation of business relationships. The majority of existing theories treat the existence of some kind of initial connection between economic actors as a given (e.g. Ford, 1980; Ring & Ven, 1994; Wilson, 1995; Leonidou, 2003; Narayandas & Rangan, 2004). However, from an evolutionary perspective this seems hardly feasible. In the following the initiation process will be discussed based on two main activities that also constitute the main mechanisms: first, finding and being found, and second evaluating prospective partners.

The first step of relationship initiation concerns the awareness of prospective exchange partners and there are two basic ways to create awareness: search and promotion. Relationships can be initiated by actors that systematically *search* for partners through their existing personal and professional networks (Frazier, 1983), or through advertising and communication efforts that actively seek to “position” and “posture” for a specific or general audience (Dwyer *et al.*, 1987). Searching for a new exchange partner is a goal-oriented activity, initiated by an actor to improve its access to certain resources or capabilities. When an economic actor realises shortcomings regarding resources or capabilities that it currently does not possess or control, it will initiate a deliberate search process for potential suppliers. The dominant search criterion will be complementarity in resources and capabilities, or combinations thereof (Anderson & Narus, 1991; Collis & Mont-

gomery, 1995). This search may rely on various sources of information, including salespeople and other boundary personnel, as well as directories, websites and trade media (Wilkinson, 2008). An alternative approach is to invite tenders from other actors, asking them to offer solutions that provide access to the required resources or capabilities. Moreover, personal and professional relationships are an important *source of information* when it comes to the establishment of new exchange relations. New partners are often identified as a result of past or present interactions (Havila & Wilkinson, 2002). These relations provide information and thereby reduce search and evaluation costs as well as lower uncertainty (Li & Rowley, 2002). Referrals and recommendations from trusted third parties are another source, including personal and professional networks of relations. Businesses learn about the characteristics of potential partners through their existing relations, including their reputation, capabilities and resources, or lack thereof, the potential fit with requirements and contact points.

Complementary to the search process, actors may engage in *promoting* activities to make themselves more visible in the marketplace and easier to find for searching actors. Actors may engage in unilateral “positioning” and “posturing” to display their attractiveness either to a specific target or to a general audience (Dwyer *et al.*, 1987). Among these promotional activities are advertisements in trade media and publications in technical journals, distribution of catalogues and newsletters and the maintenance of websites and listings in specialist directories. These promotional activities may be supported by comprehensive market analysis to identify market segments and competitors and to develop suitable products and product assortments to fit the segments. Moreover, many businesses actively promote their potential through a designated sales force that goes around nourishing existing relationships but also scouting for new ones - “farming” and “hunting” customers (Hedaa, 1996). Salespeople aim to establish personal relationships and learn about potential business partners. An important aspect of their job is to help prospective partners to identify needs for which they themselves can provide solutions.

Once awareness is created and suitable cooperation partners are identified, the establishment of a cooperative relation is an active decision by both parties involved. Consequently decision processes on both sides have to be taken into ac-

count (Wilkinson *et al.*, 2005). The establishment of a relation is a joint decision, requiring mutual consent of both parties, although sometimes there may be little choice in the market and relations may be forced in some cases. Both partners will evaluate the prospective value of a cooperation for themselves and only cooperate if in the short or long run they expect to benefit from the relation. The matching of new business partners is not a random process, but a well structured one, leading to assortative mating that depends on many aspects of the pairing under consideration, such as the current connections of the actors, their economic needs, resources and capabilities, but also their history, knowledge and experience.

The decision to cooperate is a joint decision by both parties, and various mechanisms are at work that will simultaneously affect the actors' decisions. There is extensive research about assortative mating both in the human and in the animal world (e.g. Walster *et al.*, 1966; Spuhler, 1968; Vandenberg, 1972; Murstein, 1976; Buss, 1985; Diamond, 2002). Among human couples, many physical characteristics were found to be correlated, but even stronger similarity was found regarding socio-economic characteristics such as religion, ethnic background, race, status, age and political orientation (Diamond, 2002). Various mechanisms have been proposed to explain this phenomenon; among them are attraction, propinquity, and similarity. Wilkinson *et al.* (2005) explain how their analogues may apply to the decision making in business relationships:

**Attraction:** Attraction for economic actors is predominantly derived as net value that can be gained through a relationship, i.e. the costs and benefits for each party in the relationship in the short and long term. A necessary condition for the establishment of a business relationship is, that at the onset each of the two actors expects to receive a positive net gain through the cooperation. Furthermore, in light of scarcity of time, work and resources, they will also consider the prospective gains from alternatives, should they be available. The main determinant of attractiveness for each party is the partner's complementarity in terms of capabilities and resources. The exchange relation is a means for both partners to gain access to the other's resources. The economic value of the relationship will then lie in the net benefits gained through the relation, i.e. the access to resources and capabilities that an

actor does not possess or cannot efficiently provide for itself (Anderson & Narus, 1991; Day, 1994).

**Propinquity:** Actors that move in similar spheres - geographic or social - increase their chances and frequency of encounters. If they frequent the same places, groups and events they will meet more often and they will find it easier to obtain information about each other indirectly. Furthermore, each party will have a better understanding of the other's circumstances if they experience them directly for themselves. These encounters can be initiators for relationships or opportunities for their further development. Examples of these effects can be observed especially in dense industrial clusters such as the Silicon Valley and Northern Italy (Porter, 1990; McKendrick *et al.*, 2000; Wilkinson *et al.*, 2000). At the same time large distances - geographical as well as psychological - can be problematic for the establishment and maintenance of relationships. Circumstantial information is less easily available and encounters between the two parties may be less frequent. Furthermore, physical and time separations between countries may complicate and delay communication and coordination tasks and increase behavioural and environmental uncertainty (Johanson & Vahlne, 1977). Monitoring and controlling over distances can become difficult and costly (Rosson, 1984).

**Similarity:** The decision to exchange and cooperate economically is a joint decision between both parties, and this includes a negotiation and courting process. Similarity between partners can have positive effects on the negotiation process as similar actors may find it easier to relate to and understand each other, to reach agreements and to coordinate behaviour. If they find themselves in similar situations, for example regarding relative size, market share, reputation and financial strength (Lambert *et al.*, 1996), they may share goals and face the same problems and their partner's future behaviour may be easier to anticipate (Hoetker, 2005; Håkansson & Snehota, 1995). In contrast cultural differences increase the problems of communication and misunderstandings. Differences here include language, psychological and socio-economic characteristics as well as business customs and practices. (Hall, 1959; Hofstede, 1980; Tronpenaas, 1994)

Mechanism	Description	References
Searching	Search for partners through existing personal and professional networks.	Frazier (1983); Wilkinson (2008)
Defining criteria	Define which resources and capabilities are sought from a new partner	Anderson & Narus (1991); Collis & Montgomery (1995)
Informing	Use information from existing partners to reduce search and evaluation costs and lower uncertainty	Havila & Wilkinson (2002); Li & Rowley (2002)
Promoting	Actively position and posture for a specific or a general audience.	Dwyer <i>et al.</i> (1987)
Targeting	Identifying partners through market analysis, and maintain relations through sales personnel	Hedaa (1996)
Evaluating	The economic value of the relationship will be assessed in the expected net benefits gained through the relation.	Anderson & Narus (1991); Day (1994)
Assortative mating	Attraction, propinquity, and similarity may be reasons for many matches between similar partners.	Wilkinson <i>et al.</i> (2005)

Table 3.3: Mating mechanisms characterised by the activities that precede a relationship, the activities of finding and being found and initial evaluation.

### 3.3 Business Dancing Mechanisms

In the most general sense, a business relationship is a “mutual orientation of two firms towards each other. This implies that the firms are prepared to interact with each other and expect each other to do so” (Johanson & Mattsson, 1991, p. 258). Economic actors establish and maintain a relationship through their interactions with each other over time. The activities they engage in include economic exchanges, but also social interaction, coordination, bargaining and cooperation, information exchange and learning and many others. The relationship is constantly under development, being made and re-made, established, maintained, altered and broken. On both sides, the partners maintain and constantly update a *mental model* of their counterpart that combines economic and social aspects, memories of past interactions and expectations about the future. With every new interaction this model is updated; it can be confirmed with consistent new experiences or it can

be altered and shaken by new experiences that are inconsistent with the actor's previous expectations.

As a theoretical framework the IMP interaction model (Håkansson, 1982; Håkansson & Turnbull, 1982, , see Figure 3.1) summarises numerous dimensions that can affect the development of a business relationship. It is dynamic in nature, focussing on the development of the relationship over time and it also takes into account that every relationship develops in a certain context, or environment, that includes the other players in the industry. The possible range of actors' activities goes from short-term interactions such as the exchange of goods, services and information, financial transactions and personal communication to long-term developments such as adaptations of one's technology and work processes to better match the partner's requirements. The social aspects of the relationship are referred to as *relationship atmosphere* that characterises their relation in terms of power/dependence, trust/opportunism, closeness/distance, cooperation/conflict and expectations. This atmosphere can be the basis for the development of relationship-specific norms that strongly affect the development of the relationship between firms and shape the characteristics of that relationship over time (Hallén & Sandstorm, 1991; Håkansson & Snehota, 1995).

The first steps in a relation are considered to be crucial for the future development and they are most vulnerable to termination (Rosson, 1986). At the onset of a new exchange relation, the partners make efforts to learn about each other, they form their mental models, expectations and rules of interaction. Dwyer *et al.* (1987) refer to this as the *exploration phase*. Newly joint partners explore the possibilities of cooperation and evaluate potential benefits and obligations. They may try out *test* purchases or samples of the new partners' offerings that allow them to assess product and service quality, without committing too many of their own resources (Narayandas & Rangan, 2004). Through their communication and interaction, the partners learn about each other's needs and capabilities, which allows them to mutually develop suitable offerings for another. Also they establish the social dimensions of their relation; the power-dependence relation is likely to surface in the *negotiation* process (Bergen *et al.*, 1992). The relative power of partners affects prices as well as the division of cooperative surpluses, efficiencies and cost reductions (Mallen, 1967).

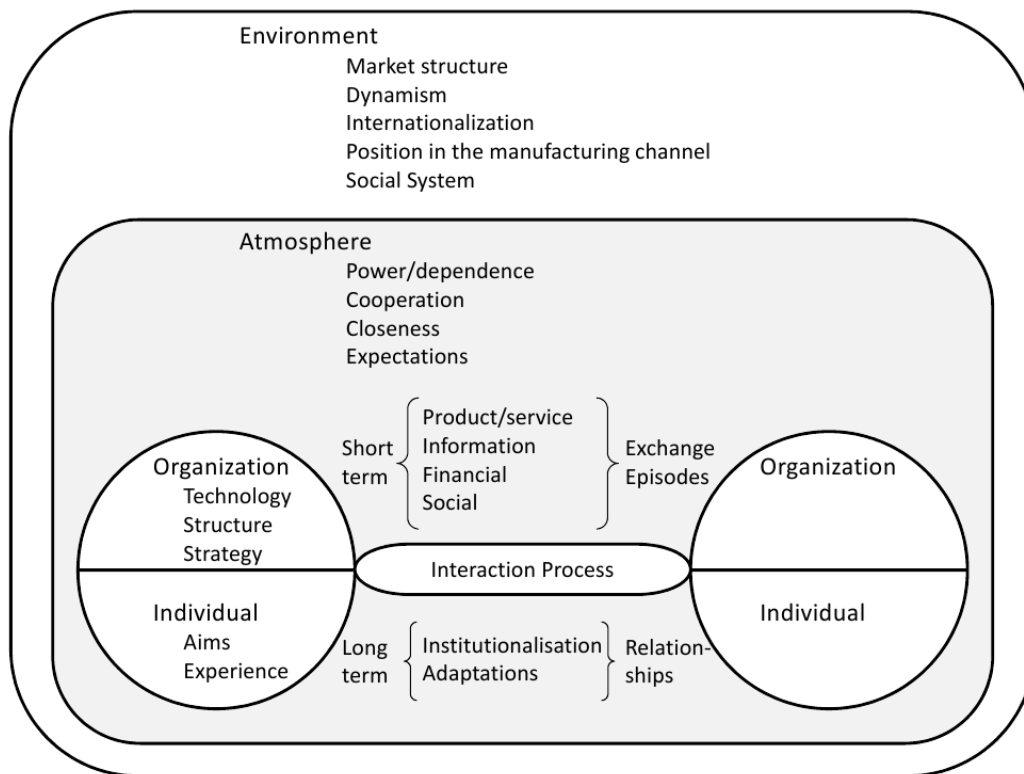


Figure 3.1: The IMP Interaction Model, after Håkansson (1982, p. 24)

Simultaneously, the parties will develop initial perceptions of fairness, commitment, trust and closeness. Both actors will not restrict their evaluation of the other's performance to the economic aspects of the exchange, but *assess* the actions outside of the negotiated agreement as well, in order to establish a comprehensive mental model of this new relation (Bitner, 1995; Grönroos, 1994; Narayandas & Rangan, 2004). Dwyer *et al.* (1987) suggest that both parties already develop norms and expectations at this stage of the relation, affecting its future development. The exploration phase may be very brief, or it may include an extended period of testing and evaluation.

The maintenance of business relationships helps reduce uncertainty about the partner's future actions. There are two ways to reduce the uncertainty here: improving knowledge about the partner and reducing the set of possible behaviours for the partner. The first way is about the actors' learning through the ongoing in-

teractions, both economic and social: Partners learn about each other through every new encounter and their accumulated knowledge about each other helps them to form better expectations about the other's future behaviour. Through interactions actors can learn about the quality of their partner's products and services, their reliability, trustworthiness, commitment and cooperativeness. Regarding the reduction of possible behaviours, the available mechanisms are more diverse, including legal agreements, economic influence, communication and the invocation of social norms. Each of these mechanisms is described in more detail below.

Knowledge and understanding of the partner serves as a social lubricant that may help the partners work together more smoothly. The more the partners know about each other, the better they can anticipate the other's needs and actions which also reduces the likelihood of communication errors and misunderstandings. Through repeated interactions, relationship partners grow accustomed to each other, they adjust their expectations, sense-making and mental models of each other (their *schema*, see Welch & Wilkinson (2002)). They may develop personal bonds which improve their mutual understanding and coordination over time (Håkansson, 1982) which may be enhanced by dedicated socialisation efforts (Heide & John, 1990). The degree of information sharing and coordination is often part in the concept of *closeness* of a relationship (Wilkinson & Young, 1994; Iacobucci & Hibbard, 1999). Tight social bonds facilitate an improved exchange of information, which makes it easier to anticipate changes and other problems that may affect the cooperation of economic actors.

Division of labour requires ways for partners to reliably coordinate each other's activities, in turn reducing the uncertainty associated with each partner's behaviour for the other. There are two direct and explicit ways in which uncertainty regarding an actor's behaviour can be reduced through restrictions of the set of possible actions: legal contracts and influence, i.e. the use of power. *Legally binding contracts* are one way to formalise commitments regarding the future actions of partners in a relationship (Grossman & Hart, 1980; Hart & Moore, 1990). Problems with this approach can arise because the environment of a business relationship is not static, but can be highly volatile and uncertain. Changes in technology or the environment might render an existing contract suboptimal and partners have to adjust. Adaption processes may be hindered by the agents' limited knowledge and

information processing capacities (Grossman & Hart, 1986; Hart & Moore, 1988). Apart from contractual provisions, equity arrangements (Osborn & Baughn, 1990; Rindfleisch & Heide, 1997) or less formal mechanisms, such as information sharing and joint planning provide further ways to coordinate two partners' actions (Palay, 1984; Noordewier *et al.*, 1990).

*Direct influence* is an alternative mechanism to reduce the potential actions of another economic actor. Influence is the use of power in a relationship that is facilitated by one party's dependence on the other, which is generally attributed to the former's demand for the resources and capabilities that the other controls and the alternative supply conditions for these resources and capabilities. The potency of a resource to become a source of power can be summarised in terms of its value, inimitability, rarity and non-substitutability (Wilkinson, 2008).

More covert mechanisms that may help coordinate and reduce the partners' range of activity rely on social norms and personal bonds between the actors. The actors rely on various social rules and conventions that determine what is deemed appropriate or decent in a certain situation and thereby reduce their set of acceptable behaviours. This is not to say that actors instrumentalise these rules to manipulate their partners and coerce them to perform certain actions. Rather these conventions evolve as part of the relationship in conjunction with the social bonds that the actors develop over time. If actors establish a sense of *cooperativeness*, they implicitly commit to jointly addressing issues that may arise, solving problems in a way that does not excessively disadvantage only one party. This is often accompanied by a sense of *commitment* to the relationship, motivated by the prospect of a fruitful long term relationship (Wilkinson & Young, 1994; Iacobucci & Hibbard, 1999). The establishment of *trust* is a similar mechanism; it discourages opportunistic behaviour that would negatively affect the social bonds, especially the trust between actors. Focussing on this dimension of the relationship, Huang & Wilkinson (forthcoming) propose a comprehensive process model of the development of trust in a relationship, in which the partners constantly learn about each other as they interact in a dynamic environment. Each partner evaluates the experience and outcomes of interactions and compares them to currently held expectations. They will either find their trust confirmed or refuted and, considering their prior beliefs regarding their partner, the environment, their shared history

and their own situation, each actor will then update their assessment of the relationship and adjust their trust accordingly. Both partners will then enter the next episode of interaction with an updated set of beliefs and trust. This model shows how perpetual feedback effects between these different aspects of a relationship drive its development over time, nurtured and repressed by the actors' actions and their interpretations of them. Through the establishment of social bonds between the actors, various social norms begin to apply to the business relationship and they dictate what kind of behaviour is socially appropriate, in addition to other contractual and legal requirements.

In conjunction with measures to coordinate a partner's activities beforehand, division of labour may also require that partners evaluate and control the other's performance during or after the execution of a task. These monitoring activities are costly and they are often characterised as another type of transaction costs. The efforts of monitoring and performance control that partners can perform cost-efficiently are limited. The resulting information asymmetries provide the potential for moral hazard and conflict of interests, generally considered as principal-agent problems (Eisenhardt, 1989).

There is no unique path of development for business relations regarding the (combination of) mechanisms they use to coordinate their activities. Researchers have developed several different categorisations of business relations which differ with regard to the mechanisms used for coordination (e.g. Wilkinson & Young, 1994; Cannon & Perreault Jr., 1999; Bensaou, 1999). These typologies characterise relationships along the social dimensions of interactions. All relationships include those dimensions, but they may differ with regard to their specific characteristics.

As relationships develop over time, another dynamic mechanism gains importance: *Adaptation*. As actors engage in continuous interaction they learn how to coordinate their activities more effectively, they learn about each other, they establish routines, reduce monitoring costs and they adapt their resources, processes and technologies. All of this can reduce the costs of cooperation. These adaptations can however have other effects: the associated investments can be highly specific, useful only within the relationship. Economists speak of *asset specificity*. Through investments in relationship specific assets an actor will increase its

switching costs and this leads to lock-in effects with greater potential damage from opportunistic behaviour. In turn these investments affect the power-dependence relation between the two parties Williamson (1975, 1983, 1985, 1996). At the same time, investments into a relationship can be a signal of commitment, trust and willingness to cooperate and may alter these social bonds between actors accordingly.

Relations terminate when one party stops interacting, temporarily or permanently. Potential reasons for this are manifold: Diminishing economies from cooperation can be caused by technological or environmental changes, as well as dynamics of market conditions. Changed conditions may undermine the complementarity and attractiveness of the partners to each other and better alternatives may arise. Business actors continuously monitor and re-evaluate their relations and compare them with other potential alternatives. Predisposing factors that may accelerate relationship termination can be cultural and communicative differences between partners or inherent complexities in the exchange (Halinen & Tähtinen, 2002). These affect especially the development of social bonds in a negative way.

There are however mechanisms that counteract the termination of a relationship. So-called attenuating factors include resource ties and personal bonds that increase the “stickiness” of a relationship as they develop over time (Halinen & Tähtinen, 2002). Investments and adaptations in a relationship result in sunk-costs for the relationship and they may counteract the ending of the relationship. Other attenuating factors can be process costs, disadvantages for future business and potential network limitations. The personal bonds between actors can have intrinsic value that may also function as a safeguard. Working and cooperating with supportive partners has value in its own right, as people like to do business with each other. Such relationships can be seen as a source of power, motivation and creativity (Anderson *et al.*, 1994). Also, it was found that social bonds can outweigh economic failures: in highly committed relations even gross incompetence did not result in termination (Young & Denize, 1995).

Experiences and knowledge from interactions with an exchange partner stay with the people that were involved in the exchange relationship. These people may take on new positions, or jobs at other companies, and they will remember the partners they dealt with in the past. These experiences may have favourable or

unfavourable consequences should a new encounter with a prior exchange partner occur. Havila & Wilkinson (2002) refer to this as the *principle of conservation of relationship energy* and they discuss several cases which highlight, that the termination of an exchange relation between organisations need not necessarily sever all the social ties that have developed between the actors involved. Individuals will maintain their personal bonds and take them with them to their new positions where they can be useful or disadvantageous to the establishment of a new exchange relationship.

Mechanism	Description	References
Getting Acquainted	Partners get to know each other and develop expectations and their rules of interaction	Dwyer <i>et al.</i> (1987)
Learning	Partners seek to learn about each others' capabilities and needs through cautious interactions at reduced commitment.	Narayandas & Rangan (2004)
Negotiating	Partners negotiate their prospective cooperation influenced by the power and dependence relation between them.	Bergen <i>et al.</i> (1992); Mallen (1967)
Bonding	Partners develop perceptions of fairness, commitment, trust and closeness, based on economic and social aspects.	Bitner (1995); Grönroos (1994); Narayandas & Rangan (2004)
Sensemaking	Over repeated interactions, partners adjust expectations, and mental models of each other.	Welch & Wilkinson (2002)
Socialising	The development of personal bonds introduce social dimensions to a business relation	Håkansson (1982); Heide & John (1990)
Coordinating through contracts	Reducing uncertainty about a partner's behaviour through contracts.	Grossman & Hart (1980); Hart & Moore (1990); Grossman & Hart (1986); Hart & Moore (1988)
Coordinating through other arrangements	Less formal arrangements like equity arrangements, information sharing and joint planning may help coordinate partners' actions	Osborn & Baughn (1990); Rindfleisch & Heide (1997); Palay (1984); Noordewier <i>et al.</i> (1990)
Coordinating through power	Social and economic power can be used to enforce a partner's compliancy	Wilkinson (2008)
Coordinating socially	A sense of cooperativity, commitment and trust can motivate partners to help each other	Wilkinson & Young (1994); Iacobucci & Hibbard (1999); Huang & Wilkinson (forthcoming)
Monitoring	Partners monitor and evaluate each others' cooperation.	Eisenhardt (1989)
Adapting	Adaptations and associated investments are undertaken to meet requirements of a relationship.	Williamson (1975, 1983, 1985, 1996)
Cheating	Through opportunistic behaviour actors may seek their on benefit at the expense of a cooperation partner.	Williamson (1975, 1983, 1985, 1996)
Termination	Each party in a relation can terminate the cooperation, based on considerations of an economic and social nature.	Anderson <i>et al.</i> (1994); Young & Denize (1995); Halinen & Tähtinen (2002)

Table 3.4: Dancing mechanisms characterised by the interactions in relations, concerning their initiation, coordination and termination.

### 3.4 Mechanisms Interconnecting Relations

Individual business relations are connected to other relations in many ways forming highly complex networks of interdependent relations. Firms are simultaneously involved in many relations with suppliers, customers, competitors and complementers (Brandenburger & Nalebuff, 1997) which are interconnected and interact in various ways. Individual relations are also connected to other relations forming business networks of various kinds by which products and services are created and delivered to customers. The networks of interdependent relationships that firms are involved in both enable them to specialise but also constrain them in their options and activities (Blankenburg-Holm & Johanson, 1992; Ritter, 2000; Ritter *et al.*, 2004). In these networks of relationships, no one actor is “in charge”, dominating the entire network, although there are differences between the actors regarding their power and dependence on each other. All the actors, in a network are “initiating and responding, acting and reacting, leading and following, influencing and being influenced, planning and coping, strategizing and improvising, forcing and adapting”(Ritter *et al.*, 2004, p. 178).

There are several mechanisms that indicate how relationships interconnect and interfere with each other. From an economic perspective, scarcity of resources and labour is one of the main restricting factors regarding the cooperation between actors. A firm’s resources are limited and the demands of different partners might be diverging, so that a firm will have to *prioritise* and decide how to serve incompatible requests (Turnbull *et al.*, 1996). Evaluations and comparisons of economic and social outcomes of relationships are conducted (Anderson & Narus, 1984; Anderson *et al.*, 1994). Perfect substitutability of one partner for the other is generally unobtainable because of minor economic or social differences. Relationship changes will always require adaptation on one level or another, even though they may be rather minor (Hallén *et al.*, 1991).

Other interdependencies arise through the structure of interactions between them. From an aggregate perspective, each actor occupies a unique position in the overall network of relations that they are involved in. Some positions bring benefits such as access to resources, attractiveness to others, power, connections to

new actors and information. In this way emergent macro properties of the network exert a feedback effect on individual actors' behaviour (Anderson *et al.*, 1994).

Some networks may exhibit *structural holes* (Burt, 1992, 2004) - i.e. missing links between actors that provide potential for the reduction of transaction costs by connecting distant parts in the network and substantially changing the patterns of knowledge development and diffusion (Wilkinson & Young, 2002). Bridging positions in a network can also have significant effects on costs and efficiencies. They can be a source for economies of specialisation and therefore be attractive for *intermediaries*. The establishment of intermediaries 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 transactions to link a seller and buyer not one when they deal direct. Intermediaries can take an active role by bringing a partner together with other existing partners (Håkansson, 1982). Examples of this include access to new markets or industries, where an already established intermediary can use its existing relations to introduce a new actor.

Many marketing textbooks explain the potential value of intermediaries using examples such as that shown in Figures 3.2 and 3.3 in terms of reduced contacts/transactions and bulk transactions. While both economic efficiencies can be calculated for both states, little is known about the transition process and the coordination efforts between actors that bring about this new network configuration.

Some attempts have been made to explain the conditions under which intermediaries can arise. Balderston (1958) focussed the interaction between economies of specialisation and competition. A single specialist 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 is referred to as the *principle of minimised total transactions* by Hall (1949).

The social bonds in a business network serve as a means for the *diffusion of information*. Actors engage in conversations as part of their business interactions

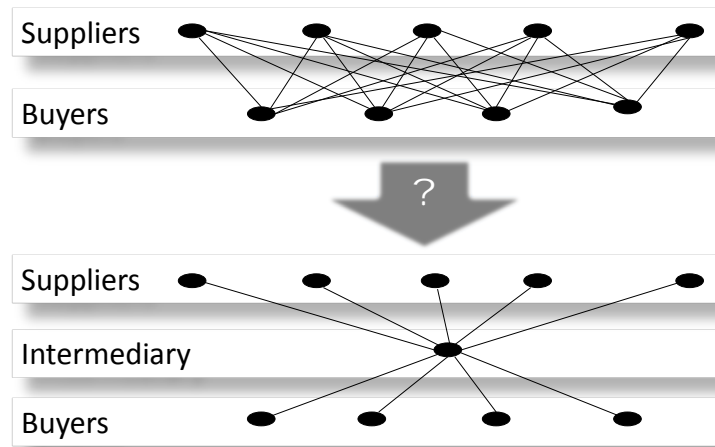


Figure 3.2: Schematic presentation of economies of reduced transactions, after Wilkinson (2008, p.49).

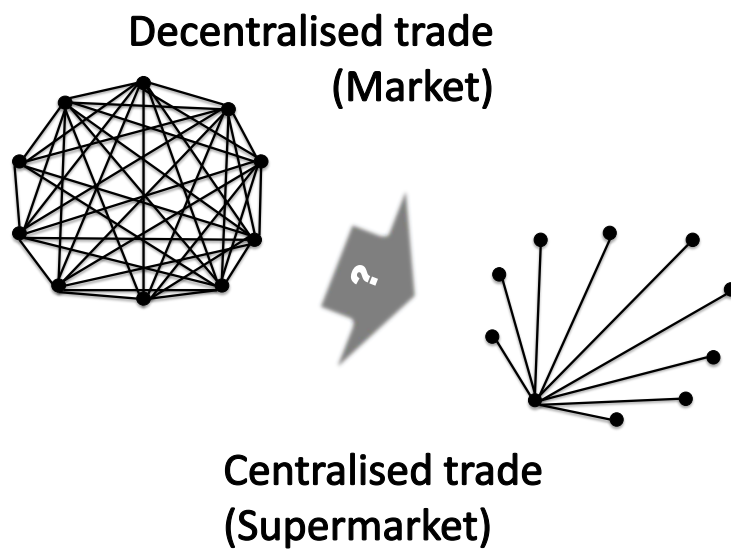


Figure 3.3: Schematic presentation of the economies of reduced transactions through the establishment of one central point of contact.

and information is passed on from one member of the network to the other. Analogously, reputation and trust can be transferred through relations.

Reputation about an actor's behaviour is communicated and diffused through the network of relationships and may affect mating and other decisions of actors that -for example- have no direct experience with a new potential exchange partner. Håkansson & Johanson (1988) coined the term "network identity" to describe the views, both internal and external, about a firm's role and position in relation to the other participants in the network. This is another example of the potential feedback effects of an actor's position in a network on its own behaviour, as well as the others' behaviour towards it.

Structural change can *propagate* through the network as a change in one relationship alters the environment for others and triggers reactions to that change, thereby affecting further relationships, triggering more change and so forth. As relationships develop over time, their economic or social bases change, firms may become aware of better alternatives and experience changes regarding their attractiveness to other firms. Relationships generate change by themselves, but they also function as recipients and as transmitters of change, affecting other relationships in the network (Halinen *et al.*, 1999). Like "domino effects" sequential, consecutive changes in relationships are transmitted through the network, irrespective of whether they are set in motion at the actor or at the relationship level (Hertz, 1999). The interactions and the atmosphere in any of these relations can affect, positively or negatively, interactions in others that are connected to it (e.g. Anderson *et al.*, 1994; Blankenburg-Holm *et al.*, 1996; Wiley *et al.*, 2009).

Another type of economies of scale can be realised when actors combine their demand, for example through spatially clustering and jointly benefitting from public goods, like infrastructure in industrial parks. Such spatial clustering of industries was first observed by Alfred (Marshall, 1898, 1919) - discussing the "industrial districts" of England in the late twentieth century. He observed that firms that concentrate on the manufacture of similar products were geographically clustered. Like today's Silicon Valley, or the cluster of textile manufacturers in northern Italy, these clusters benefited from *joint demand* effects and consequently easy recruitment of skilled labour and rapid exchanges of commercial and technical information through informal channels. Also, as a cluster it is possible to share the

benefits of improved infrastructure such as a dedicated transportation network. Lobbying and other industry initiatives can be seen in the same way. Joint efforts coordinated through the network of interactions can help realise many benefits that individuals cannot realise on their own. These are external economies of scale and will benefit all firms within the industry.

Mechanism	Description	References
Prioritising	An actor's resources are limited therefore it has to prioritise when meeting incompatible requests from others.	Turnbull <i>et al.</i> (1996)
Comparing	Facing a new alternative partner, an actor will evaluate the value of their cooperation based on economic and social criteria.	Anderson & Narus (1984); Anderson <i>et al.</i> (1994); Hallén <i>et al.</i> (1991)
Intermediating	Specialists make the structure of interactions more efficient bridging structural holes through intermediation.	Håkansson (1982); Burt (1992, 2004)
Competing	Actors seek to fill the same or similar positions in a network and have to compete for connections.	Balderston (1958)
Communicating	Information about other actors' reputations and other details are communicated and diffused through the network of relationships.	Håkansson & Johanson (1988); Havila & Wilkin-son (2002)
Transmitting	Changes in relationships affect other actors indirectly, leading them to adjust their relations as well.	Hertz (1999); Easton & Lundgren (1992); Anderson <i>et al.</i> (1994); Blankenburg-Holm <i>et al.</i> (1996); Wiley <i>et al.</i> (2009)
Clustering	Several actors with similar interests can organise and coordinate their strengths and demand in a network, realising economies through joint action and aggregation effects.	Marshall (1898, 1919)

Table 3.5: Mechanisms of interaction between relationships. These characterise indirect effects that arise through the interconnectedness of relations in a network.

### **3.5 Environmental Conditions and their Impact**

Business relations and networks operate and develop in the context and conditions of their particular environments that may both enable and constrain the actors' activities in various ways. It also affects the way the types of mechanisms described above actually operate and the specific effects they have. The environment includes other types of non-business organisations and actors that act and interact with business firms including government, legal, educational and cultural organisations. It also includes the broader or "macro" environment in which business operates. Sometimes these external organisations, such as government and customer organisations, may be included as actors in business networks because of the extent to which their actions and interactions play a role in the dynamics and evolution of the network

The macro environment includes the actual physical material and biological environment in which business operates including: its geography and topology, which affect the abundance and location of resources such as raw materials, food and water, and its ecology structure, which affects the nature and location of habitats conducive to different types of economic activities. These conditions affect the specific nature of the costs, opportunities and problems economic actors have to deal with and the way different mechanisms actually operate. The state as well as the variability of the environment matters as they affect the nature and extents of the risks and problems of adaptation that actors encounter. Natural disasters or wars will not leave a business network unaffected.

Furthermore, the macro environment includes the social-cultural space in which businesses operate. Businesses depend on the level of knowledge and the institutional framework, the legal institutions and moral norms. Social-cultural norms and laws set boundaries to the activities that can be performed legally and morally. Business law includes various rules for behaviour that affect interactions between firms and the kinds of relations that can be formed and not formed. These include contractual, property rights and trade practices acts. Also, the development of specialisation and division of labour will have important externalities through its impacts on people's lives, the environment, social institutions, politics and power, religious and other values, as well as social life in general (e.g. Layton, 2009).

The technological and knowledge environment represents the knowledge available in the society in which firms operate. This is reflected in the techniques available to carry out different tasks, including how firms communicate and interact, and affects the specific extent, nature and impact of scale, scope and learning curve effects. Technology and knowledge also change and evolve, in part as a result of the activities and interactions taking place in business relations and networks. People and firms learn by doing and develop and improve ideas through the interactions taking place among economic actors (Ridley, 2010; Romer, 1986, 1990; Rivera-Batiz & Romer, 1991; Roy *et al.*, 2004; Roy & Wilkinson, 2004).

Changes in technology and ideas lead to changes in behaviour that can impact on business relations and networks via the operation of different mechanisms. For example, changes in cost and revenue functions affect patterns of specialisation, transaction costs and the impact of scale and scope efficiencies. It is beyond the scope of this thesis to consider and model the mechanisms underlying the dynamics and evolution of technology and knowledge. For the purposes of this thesis they will be treated as environmental conditions affecting the specific nature and impact of various behavioural mechanisms.

The models developed here focus on the dynamics and evolutions of business relations and networks. Therefore detailed mechanisms underlying the *changes* of the environment will not be included. This would go far beyond the scope of a thesis in marketing and business. Instead the various types of environmental conditions and impacts are treated as exogenous conditions, values or impacts on specific aspects of the model.

Concrete examples of the importance of environmental conditions can be found in another stream of research that touches on the development of exchange networks and division of labour: archaeological studies. In recent years, several research projects sought to understand the rise and demise of societies with computational tools like the ones applied in this thesis. These studies include the Kayenta Anasazi in Long House Valley (Axtell *et al.*, 2002), the larger Pueblo culture in the U.S. Southwest (Kohler *et al.*, 2005) and the Maya civilisation (Heckbert *et al.*, 2012). Among others, the relevant mechanisms in these studies included the concrete representation landscapes, spatial distribution of settlements and household activities, traditional forms of leadership and coordination, agricultural productiv-

ity and plant growth cycles as well as climatic variation (e.g. Varien *et al.*, 2007; Johnson *et al.*, 2008; Kohler *et al.*, 2012). Many of these mechanisms are undoubtedly relevant to the concrete system, but cannot easily be incorporated in a generic model of the emergence of an exchange network.

Archaeological studies also highlight the dependence of relevant activities on their social-cultural environment. Smith (2010) explains the development of various ancient cities from the bottom-up, through the activities of ordinary inhabitants, including their ways of maintaining interdependent social networks to satisfy their everyday needs. Similarly, Renfrew & Cherry (1986) collect information about socio-political processes in early societies, such as imitation, competition and the exchange of material goods and information. All these systems were subject to idiosyncratic ritual, legal, moral and social conditions that strongly influenced the actors' behaviours. This constitutes a challenge for the identification of relevant mechanisms in this thesis. There are activities, such as gift giving (Mauss, 1970), that are highly relevant to the historical development of exchange, but have undergone a change in meaning. Consequently they are not encountered in current business networks any more, at least not in the same form. Considering that the models developed here ultimately seek to provide a better understanding of the development of current business networks, the assessment of relevance of any mechanism is necessarily undertaken from the perspective of economic agents in a current social-cultural environment. As a result of this focus, there are mechanisms of historical relevance that must be left aside here.

## Chapter 4

# Existing Models and their Implementation of Mechanisms

Many of the mechanisms described above have previously been implemented in computational models and their workings have been explored by others. This provides a rich basis for further development of the model envisioned here. Existing implementations can be divided into two broad types: generic models and specific simulations. Generic models generally investigate the workings and interactions of a select few mechanisms in an abstract setting, in order to improve our understanding and explain if and how these mechanisms bring about emergent phenomena. The term simulation will be used for comparatively rich models that seek to replicate a realistic scenario, typically including detailed descriptions of the actors' properties and the environment that surrounds them. Simulations also include a wider range of mechanisms. Their purpose is not so much to gain an abstract understanding of how those mechanisms work together, but to replicate entire system in-silico, affording experimentation and analysis of counterfactual developments. In Hedström's terms, models are more abstract than simulations.

The goal of this project is to build an abstract model guided by the principles of analytic realism, i.e. including mechanisms based on their realism, and not solely because of their mathematical elegance. In this way, the analysis will provide a well-grounded understanding of real mechanisms that are sufficient to drive the development of exchange relationships. At a later stage these modules of mech-

anisms could be included in richer and more realistic simulations, modelling the concrete environment including natural resources, realistic interdependencies and compatibilities in the product space, as well as learning effects that reflect realistically the combinations of activities that allow producers to realise economies of specialisation. In this way, it should be possible to combine the improved knowledge about the system's dynamics gained in the first stage with the ability to derive testable hypotheses about the concrete system.

This chapter will review a selection of models that implemented relevant mechanisms and discuss the insights gained from their analysis. Some form part of more comprehensive simulations designed to represent actual systems and others are more abstract formulations, focusing on understanding specific mechanisms in isolation. The models are divided into two broad types. The first type are models that capture the *dynamics of the network structure* itself and concern mechanisms more relevant to the modelling of business mating, connecting relations and environmental impacts. The second type of models investigates the dynamics *within a given network structure*, which deals with business dancing mechanisms or the way interactions take place between and among actors and how they learn and adapt. These two types are not independent of each other, as the ongoing processes of interaction in and between relations are both shaping and shaped by the network structure around them (Wilkinson, 1990). A network is in the constant state of being and becoming.

The selection of models presented here are the essence of a cross-disciplinary review of relevant models of the dynamics of activities on networks, the dynamics of changes of network structure and the intersection of these two general classes: the dynamics of activities on changing networks. The review included models from biology, chemistry, physics, ecology, economics, sociology, marketing, finance, psychology, and others and was presented as part of Held *et al.* (2010b) and Held *et al.* (2010a).

## 4.1 Models Related to Specialisation and Division of Labour

Despite the importance of the issue, there are only a few existing models that address the self-organisation specialisation and division of labour in a group of autonomous actors. These models face numerous challenges in terms of agent capabilities and performance. Agents here need rules that specify their own behavior directly related to the tasks at hand, but they also require means to coordinate their actions with other agents. Moreover, all these rules need to be flexible so that the agents can adapt to a changing environment as the simulation develops. The models presented in this Section illustrate different approaches to dealing with these issues, yet each of them captures only select aspects of a much larger and complex process.

### **BankNet**

Specialising, Increasing scale, Intermediating, Searching, Attracting, Prioritising, Evaluating

The effects of specialisation in the presence of risk and transaction costs are explored in the BankNet model (Sapienza, 2000). All agents are supplied with random amounts of income, and their goal is to deposit it profitably. Complementing these depositing activities, in every given round, a randomly selected few agents are assigned an “opportunity”, i.e. a potential value creating project. However, any such project requires investments that are greater than the amount of funds currently available to the agent. Investments can be provided by any other agent, by passing on the deposits it received from others in the current round. Agents maintain two different relationships throughout the model run: one deposit link to the agent that will receive deposits after they have been allocated in every round, and a borrow link that will be used to seek investments from one other agent whenever the original agent is assigned an opportunity. Every agent maintains these two relationships; however each of them will encounter other agents randomly and may decide to redirect these relationships if the newly encountered agent is superior to the current one in terms of its past performance as an investor

or as a source of loans. One agent can however be the target of multiple deposit and borrow links at the same time, associated payouts and loans will be split evenly.

In BankNet specialisation is implemented as a learning effect, depending on accumulation of experience over time. The success of opportunities depends on the experience (i.e. prior successes) of the agent that supplies the funds for the project; the more experience, the better the chances of success. The interpretation of this mechanism is that investors provide more than just funds, but also consultation and guidance in the course of the project's execution. Therefore increased experience in launching successful projects leads to more success. The model also includes a mechanism related directly to cost savings through economies of scale: all investors have costs for the transactions they make, but their marginal costs decrease with the number of transactions performed. Therefore investors operating at a larger scale become even more attractive to potential depositors.

The positive feedback effect of specialisation is tied in with two mechanisms related to the attraction of depositors: Depositors will receive payouts only when an opportunity is successful. Put simply, an agent will become more attractive to depositors by being successful. At the onset, this is a random process, but will diversify the agent population as they accumulate experience over time, some more, some less successfully. An indirect way to increase attractiveness is hedging. Investors can be the recipient of more than one borrow link, therefore they can potentially hedge the risk of failure between various projects, reducing the probability of a complete loss across all investments.

With regard to the attraction of borrowers, the mechanisms in place have mixed effects. On one hand positive feedback of success has positive effects regarding attraction and retention of borrowers. As the investor receives more money, it will be able to provide higher levels of financial support to projects and they could in turn realise higher net profits (because successful projects will always return a fixed percentage on their investments). On the other hand however, hedging has negative effects, as it increases the number of borrowers that have to share available funds between them. Therefore, the more borrowers are connected to any one agent, the less attractive that agent becomes for each of these, as well as new borrowers.

The model is initiated with randomly connected agents that will then adjust their relations when they meet an agent that better suits their requirements. The development of the system is then as follows: After only a few hundred rounds the numbers of banks, i.e. agents that receive investments and requests to borrow money from them, declines drastically. A stationary state with a few specialised banks emerges. These banks are those with the lowest transaction cost and greatest experience, which generates the highest absolute returns. The process of selection is apparent in the early stages already. The successful banks are singled out through chance events and trial and error and, through being the first to gain economies of scale and experience.

BankNet is the only model that endogenises both specialisation of capabilities through a learning process, as well as the development and maintenance of a network or relationships. With this, it captures essential mechanisms underlying the emergence of banking intermediaries, including heterogeneity in capabilities, feedback and lock-in effects as well as path-dependence. Following the initial strategy of extending a well understood simulation through new modules of mechanisms, BankNet was replicated to explore the feasibility of extending it to a more comprehensive model of diverse business relationships. The results were mixed. While it was possible to replicate the model, some of its main findings could not be reproduced. Furthermore with the improved understanding of the model's implementation it turned out to be a rather problematic foundation for further extensions (further details are provided in Sec. 5).

- BankNet does not include a pricing mechanism, or any other way to endogenise the negotiations between agents. Instead, volumes, returns, costs and prices are set exogenously, which severely restricts the expandability of the system.
- The model is limited to the exchange of one “good”, i.e. money. Any extension to more goods would have to account for exchange rates or rates of substitution between different goods. But considering that the BankNet does include neither mechanisms of production nor mechanisms of consumption that could serve as a basis to calculate these, suitable adaptations

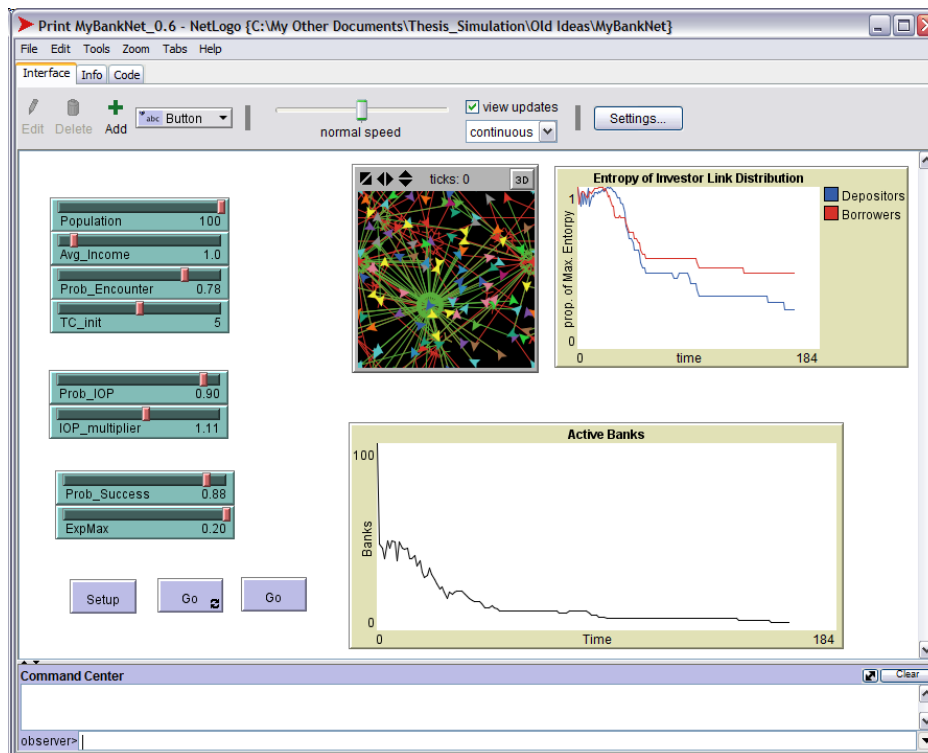


Figure 4.1: Screenshot of the replication of the BankNet model by Sapienza (2000). The small window in the centre shows the agents with their deposit and borrow relations. One bank has emerged as dominant recipient of deposits, but several other agents also still serve as investors.

would change the character of the model profoundly and the insights gained from the original model would become nearly irrelevant to the new model.

- In BankNet the focus is on the relationships between lenders and borrowers, therefore it is assumed that money just appears in the agents' hands at the beginning of each round so that the processes of lending and borrowing can take their course. More comprehensive models of the exchange of goods however would have to account for ways in which money is earned and if/how that process is related to the production of goods.
- The mechanisms regarding the formation and maintenance of relationships in BankNet are limited; agents randomly encounter each other and initiate a relation if they compare favourably to current partners. The number of

relationships is limited to two and they are static, either existing or not. This setup hardly reflects the complex social and economic mechanisms at work in relationships in the real world.

### **Self-Organizing Innovation Networks (SEIN)**

Specialising, Learning, Combining, Searching, Assortative mating, Negotiating, Adapting, Clustering

Another collection of models concerned with the development of specialisation in conjunction with collaborative networks is the SEIN model (Gilbert *et al.*, 2001) and its successor SKIN (Ahrweiler *et al.*, 2004; Gilbert *et al.*, 2007, <http://cress.soc.surrey.ac.uk/skin/home>). This model focuses especially on the knowledge base and capabilities of actors that enable them to produce certain goods as well as develop innovations. Every actor's capabilities are represented as a set of "kenes", a structured collection of technological, political, social and economic capabilities. Kenes classify the expertise regarding a certain ability in various technological fields, and they change over time, as actors acquire knowledge through research and development. SEIN also models learning through the accumulation of experience and it includes a mechanism of "unlearning", leading to the forgetting of unused skills.

Agents produce "artefacts", such as a new design or a new drug through a combination of a subset of their kenens. An underlying fitness landscape, which is unknown to the agents, identifies those artefacts that are successful and become innovations, i.e. successful new products and processes, and it rewards the successful agent. However, successful innovations deform the landscape so that the reward for a second similar artefact is reduced.

Each agent pursues a specific "research strategy": focussing independently on its own area of expertise, imitating others' successful behaviour, joining forces collaboratively with a partner or engaging in collective research efforts. The latter strategy allows agents to combine their skills in clusters of partnerships. These clusters can only be joined after a successful cooperation with one of its members outside of the cluster. The simulation proves to be sensitive to initial conditions in an industry; such as the distribution of capital, the number of firms and their ten-

dencies to develop and cooperate. It successfully reproduces stylised facts found in industries as diverse as communications and biotechnology.

Extensions of this model of innovation development have been developed, most notable the SKIN model, which requires the agents to buy and sell their products to each other. Production requires raw materials as well as more refined inputs that can be purchased from other agents. In this model agents do not need to form cooperative clusters to access each other's capabilities, they can simply purchase goods on the market. Production is prohibited if the agent cannot combine the necessary capabilities, raw materials and refined goods required. Prices are determined adaptively, increasing them while sales take place, and reducing them as long as this is no more the case. The simulation starts out in a situation where all agents produce a product that they can sell, and prices are initiated randomly. Also the agents are initiated with a certain amount of starting capital. From there on, agents adjust their prices, learn and improve their abilities. Unsuccessful agents can go bankrupt, and new start-ups will enter in successful sectors.

SKIN and SEIN are conceptually related to a model of an evolutionary theory of economic change developed by Nelson & Winter (1982) that analyses the process of competition between innovators and imitators. They combine 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, because initially minor comparative advantages are able to reinforce themselves.

- The succession of research projects and publications using the concept of *kenes* makes them a well-documented implementation to represent the capabilities of actors.

- The original SEIN model focuses exclusively on the agents' technical capabilities, their knowledge and expertise and how these can evolve through cooperation and competition under selective pressure. While certainly relevant to the development of products, the model does not include social dimensions of cooperation.
- The exogenous fitness landscape is likely to affect the model development strongly. However, there seems to be no equivalent in the real world that could be used to validate the shape and structure of this landscape.
- Only the later SKIN model extended this approach by the introduction of a market where actors can exchange their goods and acquire resources required for production. This market introduces mechanisms related to supply and demand, that affect the agents' production decisions, however the market remains atomistic and anonymous, still lacking any elements of social relationships.
- The overall development of these models is noteworthy, as it demonstrates the modularity of agent-based models, and how it can be used to understand the workings of subsets of mechanisms first (SEIN) and then extend them to investigate their interactions with other mechanisms (SKIN)

Specialisation is closely associated with learning. People learn about their own capabilities and improve their skills through their own experience and through social learning and imitation. There is an abundant selection of possible implementations, reflecting different philosophies about the nature of learning. Suitable choices will of course depend on the simulation's purpose, as well. Brenner (2006) reviews the development of learning mechanisms and their various sources, such as psychology, statistics, biology or artificial intelligence. His categorisation of learning mechanisms may serve as a guideline to select an appropriate implementation. At the most abstract level, there are two generic types of learning: Non-conscious and conscious learning. When conscious actions in the learning process are not important, simple reinforcement learning is recommended, such as the Bush-Mosteller model. It can only be applied to situations where individuals have to choose repeatedly from a finite set of options. Those options that have

been chosen more often in the past will become more likely to be chosen in the future. Conscious learning becomes important in situations where for example an agent needs to assign meaning to observations, form beliefs about future events, or generally when understanding is necessary. In these more complicated situations, the options are simplified routine-based learning mechanisms or the explicit representation of beliefs in the learning mechanisms. 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, even affording creative actions. Among others, genetic algorithms are examples of this class of mechanisms, their use in the model developed here will be discussed later. An overview is given in Tab. 4.1 on page 94. For further details and references, see Brenner (2006).

	Non-conscious Learning	Routine-based Learning	Belief Learning
Psychology-based Models	Bush-Mosteller model, Parameterised learning automaton	Satisficing, Melioration, Roth-Erev model, VID Model	Stochastic belief learning, Rule learning
Rationality-based Models			Bayesian learning, Least-square learning
Adaptive Models		Learning direction theory	
Belief Learning Models		EWA model	Fictitious play
Models from AI and Biology		Evolutionary algorithms, Replicator dynamics, Selection-mutation equation	Genetic programming, Classifier systems, Neural networks

Table 4.1: Classification of learning models, from Brenner (2006)

## 4.2 Models Related to Mating

Finding and being found are essential activities that stand at the onset of every relationship. Models of networks cannot do without, because at some point, the network has to be created in order to study it, or the activities that happen on it. Therefore the literature available on examples of this is abundant. At the same time, only few publications make this aspect of networks their focus - often some generic algorithms are used to create networks with desired properties. This led to a situation where there are only about a handful of generic mating algorithms available that are used frequently just because they are “well established” or convenient to compute. These algorithms may not adequately represent the mechanisms at work in the system to be modelled, or even lead to network structures that are equivalent to those of the real system. Nonetheless, there are publications that seek to provide alternatives that are better grounded in theory and empirical research. In the following an overview of the range of models that are currently available is presented.

## Generic Models of Network Formation

Searching, Defining Criteria, Assortative mating, Promoting

The range of models on partner search mechanisms is abundant, as it is one of the core mechanisms necessary to design a model of network formation. 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 ( $N$ ), Erdős & Renyi (1959) show that different structures emerge in the network when the probability for the formation of links crosses certain thresholds. Their analysis includes various types of subgraphs such as triangles, circles, and fully connected pentagons. Another algorithm that reproduces features that are frequently observed in real social networks is Watts and Strogatz' small-world procedure (Watts & Strogatz, 1998). It produces networks that exhibit a high clustering coefficient and short average path lengths at the same time. The algorithm starts out with agents arranged in a ring, i.e. each of them connected to a certain number of neighbours to its left and to its right. Then, with a certain low probability, each of these connections can be dissolved and replaced by a new one, connecting one of the old partners to another agent randomly selected from the other agents in the network, that this agent is not yet connected to.

Preferential attachment is another mating mechanism that has received substantial attention in the literature (Barabási & Albert, 1999). A network is "grown" through the addition of new members to the network consecutively. These new members connect to the existing network by establishing exactly one new connection to an existing member, choosing their new partner with probabilities relative to the number of links already connected to that member - 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 (e.g. Watts, 2004). Scale-free networks are characterised by a degree distribution that can be represented as

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

This distribution describes the frequency of network members in terms of their number of links, their so-called "degree". In scale-free networks, a very small number of members have a very high degree and are therefore referred to as *hubs*.

At the same time many network members have only a very small number of connections. On a log-log plot the scale-free degree distribution follows a straight line.

Preferential attachment has been extended and imitated in various ways, in order to include a richer variety of mechanisms. 1) 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. 2) Older agents in the original model tend to have more links, simply because they had more opportunities to be the target of new incoming connections. This effect has been counterbalanced by an additional parameter that decreases their attractiveness proportional to their age. This changes the resulting degree-distribution to an exponential function, if the impact of ageing is strong enough (Dorogovtsev & Mendes, 2000). 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 a variation of snowball sampling. 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 a 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).

An alternative mechanism for the formation of a social network has been proposed by Hamill & Gilbert (2009). The model introduces the concepts of a two-dimensional "social space" in which the agents hold positions relative to each

other and have a “social reach” of varying length. This social space can be interpreted in terms of geographic space, but also in terms of similarity regarding certain properties, attitudes or opinions. The smaller the distance between agents, the more they have in common. Relationships will be formed only between agents that are sufficiently similar so they can both reach each other. For a sufficiently large population of agents the structure of the resulting network depends predominantly on the ratio of social reaches, and only to a limited degree on the agents’ relative locations upon initiation. Controlling the mixture of reaches and system sizes, this model reproduces a range of statistical measures observed in real networks, including low density, short path lengths, high clustering, fat tails and assortativity of degree of connectivity.

- Both the random as well as the small-world network have received a lot of attention because of their mathematical simplicity. The random network often serves as a null model to contrast other, more sophisticated models against it. Both are not meant to be mechanistic models of the development of a network, but methods to create a network structure that can then serve as a basis for other processes.
- Preferential attachment is probably the most extensively studied mechanism of network formation. This is not because it models a mechanism that is at work in a lot of social networks, but because it is sufficient to bring about scale-free networks. In many situations however, preferential attachment may play only a minor role in explaining the emergence of scale-free structures, as many extensions and variations have shown. In mechanistic explanations, the case for preferential attachment has to be made for every system anew, either on a theoretical or empirical basis.
- The model by Hamill & Gilbert (2009) provides a flexible framework to create networks with varying aggregate characteristics. These can be tuned and adapted to model very specific situations. At the same time it is based on generic and sensible sociological principles, namely similarity (social distance) and reach, both of which could be interpreted in a mechanistic way. However, this model conflates the measure of similarity that determines the

agents' position with the measure for reach that determines who can link to whom. Given that the ratio of different reaches assigned to the agents determines the resulting network structure, the applicability of this model seems to be limited.

### 4.3 Models Related to Cooperation

Early on, simulation studies explored the development of games on network structures. Classical game theory focusses on the strategic interactions between two agents, defining equilibria and dominant strategies that result for various combinations of payoffs in the matrix that defines the game played. One extension of this approach is evolutionary game theory (Maynard-Smith & Price, 1973), that evaluates the stability and fitness of strategies within a population of players. Selection and mutation can lead to various equilibria, each with their own characteristics and propensity to invasion by other strategies. Networks provided the opportunity to extend game theoretic findings straight forwardly, allowing researchers to impose structures of dyadic relations and repeat the same interactions studied before (e.g. Nowak, 2006). It has been found that many network structures affect the evolution of a game and favour cooperation in comparison with non-structured games. Santos & Pacheco (2005) find an explanation of this surprising result. One cause is the interconnection of hubs in many network topologies, especially those following a power-law degree distribution. Random networks do not necessarily connect 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.

#### **Trade Network Game**

Searching, Terminating, Negotiating, Getting Acquainted, Learning, Cheating

Above mentioned models and many others have shown that the structure of interactions can have a substantial impact on the development of a system. Many dynamic models allowed for evolution of strategies over time, however the structure of interactions was generally held fixed. Stanley *et al.* (1995); Ashlock *et al.*

(1996) and Tesfatsion (1997) were among the first to endogenise the development of the interaction structure over time. They studied the development of populations of agents playing the Prisoner's Dilemma (PD) under various constraints, but most prominently they included a mechanism of partner choice and refusal in their models. While they did not explicitly model the network of interaction, they allowed their agents to form expectations about the other agents' strategies and the associated payoffs for themselves. Choice and refusal decisions were then made on basis of these expectations: outgoing requests for interactions were sent to the highest ranking agents and incoming requests from agents with expected payoffs falling below a certain threshold being rejected right away. With this mechanism, agents essentially maintain directed relations to one another, on the basis of which a network could have been constructed. However, the focus of this project was on the evolution of strategies when choice and refusal is possible, and on the effects of several market conditions.

The PD is probably the most extensively studied game theoretic scenario used to represent social dilemma situations in economics and other social sciences. It is a strategic game between two agents where both of them can choose to defect or cooperate. The payoffs then depend on the joint actions of both players. The rules of the game are set so that cooperation for both would lead to the highest joint outcome, but defection is attractive for each of the agents as it would increase its personal payoff, at the expense of the other agent. However, if both of them defect at the same time, both of them will receive a payoff far below the joint cooperative solution. Table 4.2 shows an exemplary payoff matrix. Tesfatsion (1997) uses the PD to model "trade", especially the fulfilment of an agreement by two exchange partners that both have an incentive not to adhere to it. With her collaborators she developed a modelling suite that provides the means to change various parameters of this generic model and represent a range of different market settings.

At the core of the model are the PD and the agents' expectations about their payoffs from interactions with others. These are initiated for all agents at the same value. The agents then learn and adjust their expectations through interactions as a weighted sum over all their outcomes from past interactions. The agents can take the roles of sellers, buyers or generic traders that can buy as well as sell. The numbers of these agent types are further exogenous model parameters. Buyers

		Player 1	
Player 2		cooperation	defection
cooperation		3,3	0,5
defection		5,0	1,1

Table 4.2: Prisoner’s dilemma payoff matrix

approach sellers with high expected payoffs and leave them with a request for interaction; sellers receive these requests and maintain a waiting list, or refuse the buyer right away, should it meet its minimum standards regarding expected payoffs. The numbers of requests that buyers as well as sellers can issue or receive are exogenous parameters also. Lastly, the user gets to set penalties for refusals received, as well payoffs for those agents that take on the role of “wallflowers” neither sending out nor receiving any requests for interactions.

Tesfatsion (1997) introduces a generic simulation platform that allows researchers to explore the development of the PD with endogenous partner selection for markets with varying numbers of trader types. Suggested scenarios include: 1) A two-sided labour market where one set of agents (workers) offers their services to another, separate set of agents (employers). Every worker can make offers to a number of employers, or it can choose to be unemployed. Each employer can hire up to several workers, but employers can also refuse work offers. 2) A self-organising labour market where agents are flexible, able to function as both buyer and seller, or worker and employer. 3) A mixed market that represents intermediated markets (e.g. financial markets). In this scenario, the group of buyers and the group of sellers overlap but do not coincide. Pure buyers could be thought of as depositors, the buyer-sellers are the intermediaries (banks), and the pure sellers are seen as capital investors (borrowers).

The analysis then systematically assesses the effects of model settings, namely comparing random matching with choice and refusal, the quota of requests acceptable for sellers, and the effects of the penalty associated with refusal. In the self-organising markets, where agent roles are not determined from the start, random matching led to poor average outcomes close to the payoff for uniform defection. The size of the refusal penalty is irrelevant for this scenario, since refusals never occur under random matching and non-unlimited acceptance quotas. When

matching with choice and refusal was enabled, the average fitness score achieved was much higher, approaching the possible maximum of global cooperation as long as seller acceptance quotas are unlimited, in accordance with previous findings (Stanley *et al.*, 1995; Ashlock *et al.*, 1996). In these circumstances, agents are refused by others only if the latter find them to be intolerable because of past defections. If however, a sellers' quotas are reduced, allowing them to only accept one offer per round, the number of rejections issued throughout the simulation suddenly increases substantially. These rejections however function no longer as a signal about the acceptability of offers, but mainly reflect the sellers' limited capacities. If the rejection penalties are sufficiently high they have a profoundly negative effect on the average payoff. Reducing these rejection penalties immediately increases the system's performance but with the consequence that too low penalty levels can slow down the learning and search process, as agents do not immediately have an incentive to move away from a partner that refused them and therefore waste several rounds approaching the same seller again and again. Under conditions with low penalties the agents exhibit increasingly volatile maximum and minimum average fitness scores with no discernible improvement in average fitness scores.

The results for two-sided markets are similar, but not identical. Experiments with 24 agents, grouped as 12 buyers and 12 sellers showed that random matching leads to average fitness scores above the level for global defection and below the wallflower payoff. At the same time average fitness scores under choice and refusal did not evolve to the global cooperation level. The explanation for both deviations from the findings above lies in the relatively high number of sellers compared to buyers. Buyers are generally achieving high fitness scores while sellers tend to achieve lower scores. The selectiveness of buyers combined with the general acceptance of sellers that tolerate all offers above their expectation threshold appears to allow buyers to form long lasting parasitic relations with sellers, i.e., relations characterized by successful defections within the limits permitted by the sellers' minimum tolerance levels. When the sellers' quotas are reduced, random matching again leads to average attained fitness scores close to the mutual defection payoff. With choice and refusal the average scores approached the level for mutual cooperation with penalties set to zero. As in the scenario above, penalties

will have a detrimental effect on the average score as soon as they are raised above zero. Further analysis of quotas for both buyers and sellers ranging from 3 to 12, showed that the average fitness score attained tended to evolve to the mutual cooperation payoff level and to be just slightly below the maximally attainable fitness score when refusal payoffs were included in the calculations.

- The studies by Tesfatsion and her collaborators are among the earlier examples of simulation methods used to understand social phenomena. It is a simple model, combining mechanisms of strategic behaviour in an iterated PD with mechanisms pertaining to the formation of expectations from memorised experiences. The simplicity of the model affords a comprehensive exploration of the parameter space. Through their systematic analysis the differences between the null model that matches agents randomly and the model with choice and refusal become very distinct and through further investigations the sources of these differences can be explained.
- Interestingly, the generic modelling suit presented in Tesfatsion (1997) is named “evolutionary trade network game” and accordingly the interpretations of all these examples use the language of trade and exchange. As mentioned above, the network itself is modelled only implicitly through the recurring interactions of agents. But more concerning is the notion that trade interactions are appropriately captured by PD games. Although results show that choice and refusal of partners in this game is a sufficient explanation for the emergence of cooperative behaviour, this does not mean that a) cooperation in real business networks is dominated by the players’ strategic considerations about short term gains in exchange episodes as represented in the PD and b) the social mechanisms that bring about cooperation in the real system rely strongly on choice and refusal.
- One aspect of the model needs to be highlighted critically: The evolutionary process in the model is driven by a genetic algorithm (Holland, 1975), that selects strategies on the basis of their performance and creates innovations through recombination of existing strategies and random mutation. The unconventional modelling choice in the implementation here is that the

agents coincide with their strategies and the evolutionary process acts directly on the actors in the system. Essentially, the worst performing agents are removed from the population every round, only to be replaced by new agents that inherit variations of the remaining, well performing agents. This clearly is not a truthful representation of any trade system and an unusual implementation of the genetic algorithm. More recent implementations (e.g. Holland, 1992; Midgley *et al.*, 1997) represent the agents' strategies individually, as properties of the agents. The evolutionary processes that drive the development of strategies do not affect the agent directly, but the population of strategies it maintains. It is unclear how this implementation of the evolutionary process affects the cooperative outcome in the trade network game.

### **Coevolution of Structure and Strategy**

Searching, Terminating, Negotiating, Getting Acquainted, Learning, Adapting,  
Cheating

In contrast to Tesfatsion (1997), there are models of cooperation in dilemma situations that make explicit use of relationships and networks. Zimmermann *et al.* (2004); Zimmermann & Eguíluz (2005); Eguíluz *et al.* (2005) let agents interact in iterated PD, played on an endogenously evolving network. The network ties represent the agents' interaction structure explicitly. The agents follow most basic strategies and they are bounded rational with regard to their cognitive capacities: They either cooperate or defect, without memory and therefore independent of results in previous rounds. Each agent can only play one strategy per round, giving the same response to all its neighbours simultaneously. Agents are assumed not to have the computational power to anticipate strategic moves of opponents. They change their strategies through imitation, copying the strategy of the best performing agent that they are directly connected to.

The interaction structure co-evolves with the agents' interactions: Through a random process the agents are given the option to terminate a relationship and establish a connection to another, randomly selected partner. Breaking of ties in this model is however only possible with mutual consent. An agent is dissatisfied

with a relationship if it receives less than the maximum outcome possible considering its current strategy. Due to the mutuality condition, only ties between two unsatisfied agents can be broken. Consequently, only two defectors can terminate their relationship. Two cooperators have no reason to terminate and a cooperator will be held captive by a connected defector, although this is not in its interest. The allocation of termination opportunities is then modelled as a random process controlled by an exogenous probability parameter. If an agent terminates a connection it will immediately establish a connection to a new partner. As agents are assumed to be ignorant towards future outcomes from interactions with any of the other agents, the search is modelled as a random choice from the population of other agents. Also the new partner will always accept the new connection for the same reason.

The model analysis shows two distinct paths of development for the model: either the system reaches a state of global defection or it develops to almost total cooperation. In the latter situation a network structure develops that resembles chains of cooperative agents, with a minor population of defectors around the edges, exploiting the cooperators. The main determinant of the system's development is the bonus for defection determined in the payoff matrix, i.e. the difference in payoff for defecting compared to cooperating. Under a certain threshold the fraction of cooperators will slowly, but steadily, increase until the vast majority adopts this strategy. However, if the difference in payoffs rises above a certain threshold, the fractions of cooperators oscillate for many rounds and the system will enter a path-dependent, unpredictable trajectory, eventually reaching one of the two states: full defection or predominant cooperation with occasional defection. The authors note that in the resulting steady states defectors are found to be on average wealthier than cooperators, the spread of this strategy is however prevented by the limited imitation mechanism. Also, the network structure becomes more hierarchical as the bonus for defection increases. At the top of these hierarchies are cooperation leaders that are surrounded only by other cooperators. With their high payoffs they function as role models for others to imitate a cooperative strategy.

- The dynamically evolving interaction structure of this model adds a new dimension to the understanding of the PD. The general definition of the game's payoff matrix is: Temptation > Cooperation > Mutual Defection > Sucker's Payoff, and for iterated games  $2 * \text{Cooperation} > \text{Temptation} + \text{Sucker's Payoff}$  to ensure that alternating strategies are not better than the socially desirable outcome. In this dynamic and networked version of the game, it becomes apparent that there are two regimes of the game development. With low levels of Temptation, the exclusion mechanism facilitates the spread of cooperation, while with higher Temptation the stable outcome of the system turns into a path dependent process that is highly influenced by random processes leading either to full defection or nearly full cooperation. This surprising finding is only reported for particular parameter constellations, but suggests an avenue for further research.
- While explicitly modelling the dynamic structure of interactions, this model represents agents' decisions in a very myopic way. They either follow static and predetermined rules or their behaviour is driven by entirely random processes. The authors do not suggest any particular situation that they might be modelling, but explore the dynamics of an abstract model.

### **Cooperation in Evolving Social Networks**

Searching, Terminating, Negotiating, Getting Acquainted, Learning, Adapting,  
Cheating

Extending the works of Tesfatsion (1997) and Zimmermann & Eguíluz (2005), Hanaki *et al.* (2007) explore the dynamics of a similar system that also endogenises the development of relationships in a population of interconnected agents playing an iterative PD. Again the agents are bounded rational, playing the same simple strategy with all their neighbours. Also adaptation of strategies is modelled through imitation of the best performing neighbour, but decelerated by making update events random over time and including a small error term.

Every round, each agent gets the option to make one change to its connections, either creating a new link to another agent, or removing a link to one of their neighbours. A random process determines which connection the agent will

review and whether to start with a potential termination or with the creation of a tie. In this model, the decision to terminate a relationship can be made unilaterally, whereas the creation of a new relationship requires mutual consent. Hanaki *et al.* (2007) add a variety of mechanisms that affect the agents' decision making at this point: ties are costly, new partners are selected through a mixed process, partially at random, and partially as friends-of-friends, in style of "triadic closure bias" identified by (Rapoport, 1963). Furthermore, like in the previous models decisions are made on the basis of expectations, however, there are three variants of predicting the new agent's behaviour: 1) if it is a friend-of-a-friend, it is assumed that the shared friends will pass on information about its last move and it will be expected that the agent will play this move again. If the agent is a stranger, the other two variants come into play 2) expectations about a stranger's behaviour are formed as a function of all prior experiences with other agents, or alternatively 3) these expectations are formed as a function of prior experiences with strangers only.

The model analysis shows that unilateral termination of unsatisfying relations is a scalable mechanism to enforce high levels of cooperation under many system configurations. The cognitive demand of this mechanism is only dependent on the number of neighbours for each agent, and therefore independent on the overall system size. Also, more frequent review of existing connections increases this effect and tends to generate higher levels of cooperation. At the same time, the cost of relationship maintenance also has a positive effect on cooperation. This somewhat counterintuitive finding can be explained through its effects on the overall number of connections - the network's density. Expensive ties lead to sparser networks and these are more resilient when it comes to the invasion of defecting strategies. The more partners a defector has, the greater the payoff of this strategy and its appeal to other agents. Also it becomes less likely that all of the defector's cooperating partners will successfully break their ties before they themselves adapt the superior strategy and initiate a cascade of defection throughout the network. In densely connected networks, the intrusion of defection is hard to contain. Triadic closure has a negative effect on cooperation, as it favours local clustering that, again, make it easy for defection to establish itself and spread in a densely connected neighbourhood. The unilateral termination of relationships leads to -

on average - better connected cooperators, while the defectors are isolated, at the fringes of the network.

The mechanisms for information transmission also have significant effects on the prevailing level of cooperation. While full information about a new partner's actions is good for the individual's decision to connect or not, it has a negative effect on the population's level of cooperation. The authors suggest that the successful spread of cooperation requires both exclusion and recruitment of defectors. With too much or too precise information about a defector's behaviour, it will be ostracised from the network permanently, despite the possibility that it could be integrated again, if it were connected to a self-sustaining constellation of cooperators. With only one connection to such a cooperation cluster, the defector is likely to change its strategy without causing harm to the cluster. As a result the fraction of cooperators would increase. Similarly, forming expectations about future encounters only through encounters with strangers leads to a high level of suspicion in the population and isolated agents are rarely integrated into the network, leading to a reduced overall level of cooperation as well.

- This model highlights the importance of social aspects in the co-evolution of cooperation and interaction structure. In extension to the previous models it investigates the effects of the triadic closure bias as a mating mechanism that affects the development of the structure. It also explores the differences between variations of information transmission and communication between the agents as a decision making mechanism. This substantially extends previous models that maintained a rather limited representation of social interaction, focussing on the strategies of the game.
- The issue of unintended consequences of intentional actions that is often at the centre of complexity research becomes very apparent in this model. Triadic closure, as well as provision of complete information through mutual friends, has a negative influence on the overall level of cooperation in the population. The exclusive nature of these mechanisms only becomes apparent when they can be switched on and off in systematic experimentation. In this case, the simplicity of the underlying strategic activities and the

comprehensive understanding about its dynamics established in previous research facilitates greater focus on these new features in the model.

There are many more models that deal with the co-evolution of interaction structure and strategies, a complete review of which would not be feasible nor productive for the purpose of the thesis. Instead a selection of the most relevant results will be highlighted here.

Many simulation studies examine the impact of network structure on cooperative behaviour in game theoretic settings and there are many network structures that have been found to directly favour cooperation. For scale-free networks Santos & Pacheco (2005) find that certain players act as hubs maintaining a high number of connections to many other agents. These hubs tend to be connected to one another as well and they can form self-sustaining clusters of cooperation that allow them to promote cooperation amongst the other agents and ward off attacks of isolated defectors. Santos *et al.* (2006) and Pacheco *et al.* (2006) investigate the effects of time scales associated with the evolution of strategy and of structure. They find that for any given average connectivity of the population, there is a critical threshold for the ratio between these processes, above which the systems generally favour the spread of cooperation. A high rewiring speed of connections essentially changes 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 global cooperation can emerge. Lugo & Jiménez (2006) explore the effects of taxes and subsidies on the development of co-evolving networks of PD players. They show that taxes can increase the fraction of cooperative behaviour in the population for all possible fractions of initial cooperation. The mechanism under investigation taxes defectors and distributes the taxes among cooperators. Through this, cooperation becomes relatively more attractive compared to defection. Smaller numbers of initial cooperators are needed to reach higher levels of cooperation, faster. Interestingly this effect proved to be persistent, so that they could gradually phase out the tax-based transfer mechanism and the system retained a high level of cooperation.

The Prisoner's Dilemma is a very abstract representation of a coordination problem under incentives that detract from socially preferable outcomes. It is debateable whether this represents the interactions in an exchange relationship satisfactorily - as is suggested by Tesfatsion (1997) and others. The position taken in this thesis is that exchange is mutually beneficial as it allows for the realisation of economies of scale and scope. While issues of contract fulfilment might still arise in relationships, it is assumed that existing legal and social mechanisms are sufficient to enforce the agents' honesty and their faithful commitment to the terms of exchange. After all, above studies show that reputation and the threat of exclusion from the network are sufficient to enforce high levels of cooperation. Therefore, dishonesty and defection will not be assumed to be the core point of investigation.

## **4.4 Models Related to Exchange**

Models of exchange assume that cooperation between people is possible without continuously having to solve dilemma situations. While standard economic thought suggests that the price mechanism is sufficient to coordinate the interests of buyers and sellers in a market, several studies emphasise that this result hinges on assumptions such as the absence of transaction costs and the unrestricted availability of information. Computational models allow for a relaxation of those assumptions and an exploration of the effects of such deviations from the perfectly competitive market. The models presented here focus on restrictions that arise through structured interactions among buyers and sellers and their effects on the overall system performance.

### **Distributed Exchange**

Searching, Negotiating

The "market" in the economic sense is an institution that finds the equilibrium between supply and demand in an economy, using the price mechanism. Although the market clearing price can be derived from principles about the rationality of actors, this is hardly a mechanistic account of how prices in an economy are actually arrived at. An often used procedure of how such an ideal market could be

organised is the Walrasian auction: agents calculate their demand for any good at every possible price. The auctioneer then announces a price and agents state how much of each good they would like to supply and how much they would demand at that price. If supply and demand do not match, the auctioneer adjusts the price, lowering it in case of excess supply, raising it in case of excess demand, until balance is reached. A Walrasian auction provides for perfect competition: information is complete and there are no transaction costs.

The Walrasian auction is often used to illustrate how a perfectly competitive market could be organised, even though it is behaviourally unrealistic. Axtell (2005) proposes an alternative to a Walrasian auction that arrives at a market clearing price without assuming an central auctioneer, namely decentralised exchange. In fact, he argues that the non-polynomial complexities of the computations required by the Walrasian auction make this approach computationally infeasible. In decentralised exchange traders communicate and trade with each other through private, pairwise interactions. They are randomly paired to trade amongst each other so that all traders may hypothetically interact with all others. Multiple pairs of agents can trade multiple goods at a particular time, but no agent can trade with more than one other agent at a particular time. The agents' valuation of goods is represented through strictly convex preference functions, and to determine which and how many goods are exchanged the agents communicate these preferences directly, realising a new allocation on their joint contract curve.

The results show, that the number of interactions necessary to arrive at a nearly stable allocation throughout the population scales linearly with the number of agents, and squarely with the number of goods available. The Walrasian auction, however, scales to the power of four. Interestingly, the results of the distributed exchange mechanism differ from the auction results in other regards as well: the exchange process exhibits price dispersion, yields allocations that are not in the core, i.e. leaves room for improvement by coalitions of agents, it modifies the initial distribution of wealth, leading to more homogeneous allocation that are always stable, but path-dependent.

- This model shows how agent-based models can provide explanations for certain emergent phenomena, such as the functioning of a market, that are

behaviourally more realistic and therefore serve as a better explanation in terms of generative mechanisms.

- At the same time, the improved model still makes strong assumptions about the behaviour of agents, namely their perfect awareness of their valuations in the form of preference functions, and their immediate success at negotiating exchanges that improve the endowments of both negotiation partners. On one hand, these assumptions help to keep the deviations from the original model at a minimum, as they are in line with classical economic thinking, on the other hand, they remain idealisations of real humans' behaviour, that facilitate computations, but do not represent how people make decisions or how they interact with each other.

### **Exchange on Networks**

Exchanging, Structure of Interactions, Intermediating, Negotiating

The network structure of interactions has been shown to affect the outcomes of simple exchange systems. Wilhite (2006) systematically compares a range of network structures on which agents engage in a simple barter economy, exchanging two goods with exogenously predetermined neighbours. Upon initiation, the agents are allocated a certain endowment of one of two goods, but they all share a utility function that would allow them to increase their utility through exchange. They will then engage in barter with their direct network neighbours until they cannot improve their utility level any more. Results show that the underlying structure of interaction strongly affects the resulting distribution of goods ranging from almost equal distributions to strong inequalities, with wealth and poverty depending exclusively on the agent's position in the network. The different types of networks used in this study are reproduced in Figure 4.2.

The results show that generally hubs are able to acquire more wealth, and this effect can be strongly enhanced by the underlying structure. Completely connected networks 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, while leading a balanced distribution of wealth. However, the number of exchanges required is comparatively

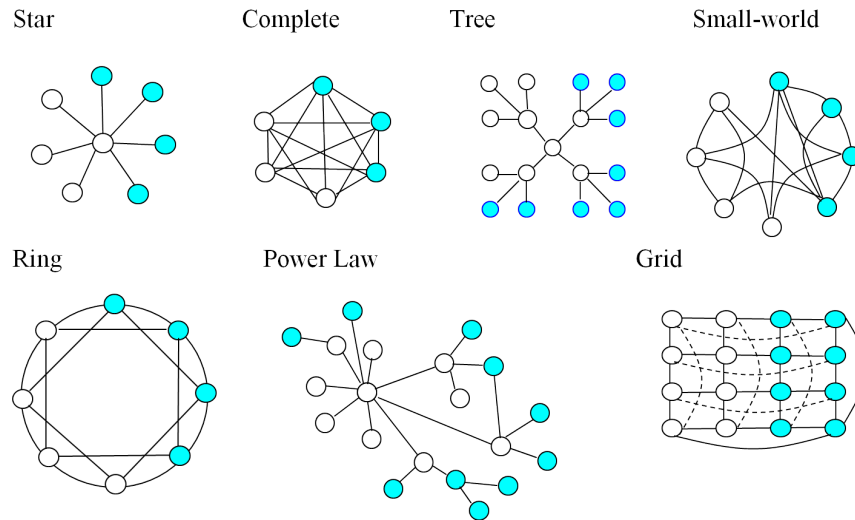


Figure 4.2: Seven network types used in Wilhite (2006, p. 1018)

high. A ring-shaped network topology connects each agent to only a small number of 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. They exhibit a short average distance between any pair of network members and simultaneously many local 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: smaller numbers of exchanges, total rounds, as well as total searches. However, these networks are more heterogeneous regarding the final distribution of wealth. Agents that occupy an interconnecting position between two groups are clearly outperforming others, accumulating about ten times the average wealth. Small-world networks seem to 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”.

- Wilhite's model clearly shows that structure matters. The agents' activities are reduced to a minimum so that the differences in results can be attributed directly to the only factor that is varied systematically: The networks structure.
- The analysis covers a range of networks, although many are motivated more theoretically rather than empirically. Star, ring, grid and tree networks are abstractions that represent an extreme type of network which is unlikely to have many empirical counterparts. On the other hand, there is more than one type of scale-free network, and the analysis does not address the issue of varying exponents in the power-law function. An interesting extension of this model would be to relate the effects of network properties such as clustering coefficients, path-lengths or the coefficient of the power-law distribution to the performance of the network.
- Lastly, the networks in this model are static. Therefore nothing can be said about adaptive systems that could potentially self-regulate and adapt to avoid problematic results caused by the network structure.

### **Networks of Exchange and Communication**

#### Structure of Interactions, Exchanging, Communicating

Economic exchange networks need not necessarily have the same structure as networks for other processes, such as information exchange. The interrelation of the structure of these two processes is explored by Ladley & Bullock (2008). In this model bounded rational agents trade with and at the same time gather information from their neighbours within a trade network. Agents are connected by two types of networks, one that determines which agent is able to trade with whom, and the other determining which agents receive information about the terms of an exchange. The networks investigated within this model are exogenously determined and fixed throughout a model run. The traders assume the roles of buyers and sellers of one homogeneous indivisible good. At the beginning of the simulation sellers are allocated one unit of the good, and both buyers and sellers are also assigned a reservation price randomly drawn from the same uniform distribution of prices. In addition to these set reservation prices, the traders seek to realise a

margin. This margin is agent specific and adaptive: agents try to learn about the market clearing price and set their margins accordingly. Through their communication network they gather the terms of their neighbours' trades as well as their success or failure in order to optimise their own price and margin. If an exchange was successfully executed above a seller's asking price, that seller will increase its margin, and analogously, a buyer will decrease its margin, if it receives information about an exchange that was successfully executed above the price it is currently willing to pay.

The focus of analysis is however not the resulting price dispersion, but the evolution of updating rules with which the agents respond to new information. The magnitude of changes to every agent's margin is modelled as the "ZIP" learning rule (Cliff & Bruten, 1997). This is a simple learning algorithm that attempts to maximise the amount of profit made by the trader based on information it hears from other market participants. The algorithm has parameters that regulate how much weight is given to new information in contrast to medium and long term averages. The model endogenises the tuning of these parameters and allows the agents to adapt them over time, in order to respond to their position in the networks.

The model analysis compares four different settings: 1) fully-connected trade network with fully-connected information network; 2) scale-free trade network with fully-connected information network; 3) fully-connected trade network with scale-free information network; and 4) trade and information flow connected by the same scale-free network. Results show that the network's structure affects the learning of strategies and the profits of traders. A trader's ability to profit and to identify the equilibrium price is positively correlated with its degree of connectivity within the market. Less densely connected networks lead to more heterogeneous payoffs and well-connected traders are found to benefit from aggressive trading behaviour, as they have a wider range of potential trading partners. In all cases the traders' valuations approach the equilibrium price regardless of their connectivity in the information; however, those traders with more connections converge faster than those with fewer connections. Also the agents develop different learning strategies depending on their connectivity in the network: Traders that receive much information through their communication network tend to de-

velop rules that make them respond promptly to new information, while agents that receive information more sparsely become more cautious and tend to focus on long term trends, as new information could be an outlier and therefore misleading. In terms of trading opportunities a central location has a clear advantage over more peripheral position because of the many trading opportunities.

- The model of Ladley & Bullock (2008) stands out among many other models in that it explicitly represents and analyses the effects of differences between two types of interaction: exchange and communication about the exchange. And not only do the results show that these differences matter from an aggregate perspective, changing the overall performance of the system, but they affect the agents themselves on the individual level. Depending on the agent's position in the networks, the number of links it holds for exchange as well as communication, it develops different strategies that are adapted specifically to the environment it faces.
- A problem with this model so far is that it is limited to only a couple of network structure, namely a fully connected model and a scale-free network with unspecified scaling coefficient. The authors themselves mention that this will require further exploration and potential calibration with empirical data.
- Nonetheless the main insight gained here is that the structure of interaction matters - and structure can differ, depending on the types of interaction.

## **4.5 Models Related to Social Relations**

Lastly, there are models that focus on social dimensions associated with economic interactions. In various settings these have been shown to be the causes of behaviour that is different from standard economic models. Sometimes they can be helpful in overcoming problems and sometimes they are problematic in that they foreclose certain preferable outcomes.

## **The Beer Game and Extensions**

Getting Acquainted, Learning, Bonding, Coordinating through other arrangements, Prioritising, Comparing, Competing

Supply chains are systems of business actors that in essence organise the transport of goods from the producer to the consumer. They may engage in various sorting activities, building up and breaking down assortments of goods, but their core function is to bring the goods from where they are produced to where they are consumed. In supply chains the activities of actors have a spatial as well as temporal dependence and therefore require efforts of coordination. To illustrate the difficulties that arise with these interdependent activities Jay Forrester at MIT's Sloan School developed the "Beer Game", a board game in which players take on the roles of actors in a supply chain for cases of beer. Their task is to coordinate their stocking and ordering activities while there are time delayed deliveries and only limited information regarding the other players in the system. The most frequent outcome is the "whiplash effect", where the combination of small deviations from optimum orders and misjudgements of consumer demand together propagate quickly through the system. Players tend to overcompensate in their responses and the entire system builds up backlogs and/or large excess inventories (see e.g. Sterman, 1989; Mosekilde *et al.*, 1991; Sterman, 1992).

Forrester's beer game serves as the basis to model the effects of trust on the performance of a self-organizing five level supply network Kim (2009). Five agents are located on each level of the game, and initially they are connected with every other player in the levels above and under them. Each of them is equipped with rules to forecast their demand, and manage their ordering and supplying decisions. The simulation explicitly includes a parameter called "trust" in these decision rules. Trust evolves throughout the simulation rounds, relative to the traded volume with the respective agent. It reflects how well the expectations towards orders from an agent in the adjacent levels have been met in previous interactions. If orders or shipments exceed the amounts requested, trust increases, while negative results reduce trust. Eventually the model reaches a stable state, including strong and weak relationships between select agents in the individual layers and some agents are almost excluded from the distribution process. These outcasts are

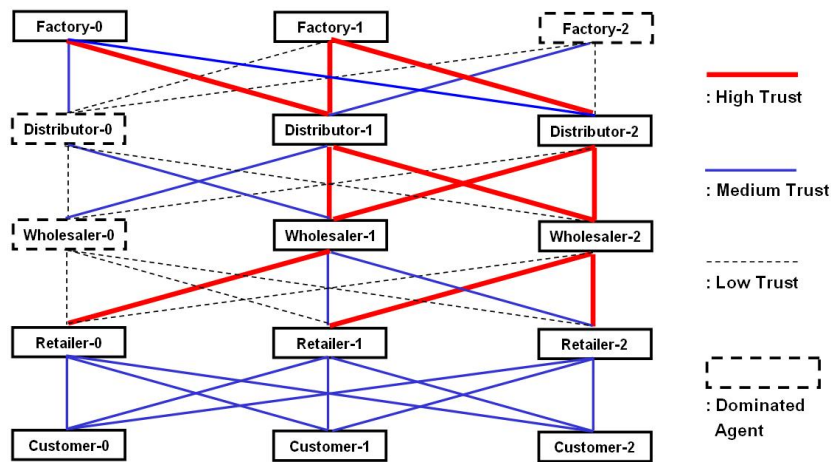


Figure 4.3: Network of trust in the supply network

characterised by a low level of “trust” by the other agents. In Fig. 4.3 the agents in dashed rectangles could not establish a strong collaborative relationship based on high trust level with at least one of their upstream or downstream agents. While they are still able to trade, their trading amounts are relatively small.

- This 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 simultaneously affects the agents’ decisions with regard to how they allocate orders and which orders they give preference to. This mechanism is self-reinforcing, cementing the structure of interaction in early rounds and thereby enhancing the path-dependent development of the system.
- The model shows how a non-economic mechanism helps to reduce uncertainty by reducing transaction costs from demand volatility and storage costs. “Trust” is a measure of confidence regarding the estimates of future shipments.
- It is debateable whether the term “trust” is the best concept to describe the mechanism that is actually implemented in this model. It seems to be much less about trust into the other agent, but trust, or confidence, in one’s own prediction or expectation of the other’s behaviour.

### **Marseille's Fish Market**

Searching, Getting Acquainted, Learning, Bonding, Socialising, Coordinating through other arrangements, Adapting, Prioritising, Comparing, Competing

Social dimensions of business relations can reduce transaction costs. In a model of the Marseille Fish Market (Kirman & Vriend, 2001) agents learn to realise positive effects of loyal behaviour regarding the costs of stock keeping and risk associated with fluctuations of demand. In this model the agents represent buyers and sellers that come to the market every day, selling the catch of the day, and bargaining for good prices in a morning and an afternoon session. It should be noted that the goods traded are perishable, losing their value after every trading day. All sellers receive the fish from the same external source at the same constant cost and they have to set the amount of fish they intend to sell on any given day. Buyers choose which seller's stall they want to queue at and which price they would deem acceptable. The sellers have to decide which price to ask for, and also they get to determine in which order they want to serve their customers. They can differentiate between buyers with regard to their familiarity, remembering those that have queued at their stall before. Sellers can choose to serve more familiar agents earlier, in the same way, or later than other agents.

The decision making processes are modelled as classifier systems which are a form of reinforcement learning (see, e.g. Bush & Mosteller, 1955; Sutton, 1992; Roth & Erev, 1995). The agents maintain lists of rules that cover the entire range of possible actions in any given situation: where to queue, what price to accept etc. Associated with these rules are probabilities of activation, that determine the likelihood of any one rule being activated in an applicable situation. In the course of the model's progress, the agents learn through experience - whenever a rule is executed, the agent learns about its performance, i.e. the outcomes it receives in the current round. Both buyers and sellers seek to maximise the profit they are making and evaluate rules on this basis. High outcomes increase the probability of choosing the same rule again in a similar situation, while low outcomes decrease this probability.

In the course of the model run the agents learn to engage in and reward loyal behaviour. For sellers, this reduces risk and costs through fluctuation in demand

as they can now plan to serve a steady customer basis. They learn to treat loyal buyers favourably which in turn is an incentive for buyers to continue and expand their loyal behaviour. Buyers reduce their risk of missing out on the day's catch and generally they do so at a low price, which is another result of the coordination process. The model reproduces stylised facts of price dispersion and high loyalty in the market, both of which agree with empirical observations at the original Fish Market.

In a co-evolutionary process, buyers learn to become loyal as sellers learn to offer higher utility to loyal buyers. In turn the sellers learn to offer higher utility to loyal buyers as they happen to realise higher gross revenues due to reduced fluctuation in demand. Since the same population of sellers and buyers is present every day in the same market hall, and since there are no real search costs, switching costs, or product differentiation (see below), at first glance, these stylized facts may seem somewhat puzzling.

- This model uses simple learning algorithms to control the agents' behaviour. Without having a concept of "loyalty" themselves, the agents develop patterns of repeated interactions that can be interpreted as loyal behaviour.
- Buyers and sellers in this model co-evolve, each of them affecting the other's performance directly through their actions and decisions. Nonetheless, the agents succeed in self-organising and teaching each other through incentives to coordinate their actions in a way that is beneficial for both of them. The authors note that there is an order effect in the learning processes for both buyers and sellers: first sellers learn to ask for prices in the lower spectrum, just because the probability of success for high prices is too low. Second some buyers explore loyal behaviour and sellers discover the benefits of encouraging these buyers to continue their loyalty. Sellers begin to reward loyalty and thereby set incentives for all buyers. Third, more and more buyers discover that loyal behaviour is rewarded and therefore they tend to queue in front of one seller.
- Remarkably, this model leads to coordination and loyal behaviour although it omits several mechanisms that might be considered relevant for this kind

of behaviour in reality: sellers do not remember their customers personally, but classify them as more or less familiar. Also, there are no switching or search costs and the model does not include any assumptions about social relations. In its simplicity, this model provides a sufficient explanation for loyal behaviour, following the paradigm of explanations through a minimal set of generative mechanisms. However, this does not mean that it provides a realistic account of the mechanisms that drive loyal behaviour in the real system. Many other combinations of mechanisms may lead to similar aggregate behaviour, especially since feelings of loyalty and trust exist and have been shown to affect people's decision making and behaviour.

### **Formation of Coalitions and Alliances**

Searching, Defining criteria, Assortative mating, Coordinating socially,  
Comparing, Intermediating, Competing, Communicating, Transmitting,  
Clustering

In the presence of limited resources or other sources of conflict, coalitions of agents may form, in order to provide mutual support for each other and help overcome obstacles that their members could not overcome individually. Gavrilets *et al.* (2008) model the mutual support of agents as a probabilistic evolutionary process in a competitive society. In this society conflicts arise randomly between individual members and they are resolved through a random process, with success depending on the involved individuals' competitive strength, which is an exogenous and fixed parameter for every agent. In this model it is also possible that agents involved in a conflict can receive support from several agents, forming a coalition that can oppose the other party. The strength of the coalition depends on the individuals' strength, but also - and even more so - on the size of the group. This mechanism guarantees that even the strongest individual can be overcome by a large enough coalition.

Coalitions are also formed through a stochastic process. There are two parameters that drive the decision making process of each individual agent: one fixed, global parameter determines the probability that an agent becomes aware of a conflict between any pair of agents. The second parameter describes an agent's affinity to every other agent, and it influences if and with whom that agent sides

with in a conflict, provided the agent is aware of the conflict. The agents' affinities change over time, affected by the experiences the agents make when they work together in a coalition. Taking the same side in a conflict increases the affinity between two agents, independent of the conflict's outcome. However, a positive outcome is more beneficial than a negative outcome. Again, this models a simple type of reinforcement learning. In the same way, taking opposite sides in a conflict is detrimental for an agents' affinity. Note that through differences in affinities, it is possible that two agents that found themselves on the same side in a conflict between one pair of agents can choose different sides in the next conflict between another pair. Coalitions are not stable groups, and conflicts can arise within them - decisions about coalition choice are made on the basis of individual relations, not group membership.

The primary result of model analysis is that from these individual relationships groups emerge. Individuals that belong to the same group obtain similar levels of success and this is only weakly correlated with their individual strength and the probability of success is no longer defined by the individual's fighting ability but by the size and strength of the alliance it belongs to. The size, strength, and temporal stability of coalitions are dependent on the model's parameters but are also strongly influenced by stochastic elements in the model, so that they vary dramatically from one run to another even with the same parameters. Nevertheless, once one or more coalitions with a high degree of internal clustering are formed, they are typically stable. The transition from a state with no coalitions to a state with one or more alliances occurs suddenly, upon crossing a certain parameter threshold. Surprisingly, there are conditions where a single alliance comprising all members of the group can emerge which then divides available resource evenly. The competition among unequal individuals can paradoxically result in their eventual equality and within-group conflicts promote the development of cooperation on the group level.

- This model implements a very simple way of how agents may cooperate to compete with others, focussing on the idea that there is strength in numbers.
- The authors emphasise that the model relies on very basic behavioural and cognitive assumptions. The agents only follow their affinities, explicitly

avoiding to evaluate the costs and benefits of certain actions and decisions. They act on limited local information, unable to optimise the outcomes of their activities. On one hand this shows that coalitions can be an emergent result of such simple interactions. On the other hand the authors admit that this may better reflect the decision making processes in social animals - such as primates - than the decision making in human societies, because strategic considerations may be much more relevant to the decisions of agents with higher cognitive capabilities.

### **Networks of Mutual Support**

Searching, Defining criteria, Assortative mating, Evaluating, Comparing, Termination, Clustering

In a similar model Hegselmann & Flache (1998) analyse how networks of mutual support can evolve in a world that is inhabited exclusively by rational egoists, who are heterogeneous regarding their need of support through others and who choose their partners in opportunistic ways. The agents' risk classes, that determine their probability of needing support, are common knowledge for all agents. The agents interact in a support game, where not helping at all is a dominant strategy in a single game. However, there is a cooperative equilibrium resulting from "supergame strategies" if the probability of being involved in a further iteration of the game is sufficiently high. If probabilities and risk classes match between neighbours, they establish a support relation, guaranteeing support in case of emergency. Otherwise they sit next to each other without interaction.

The agents interact on a grid-like network; however, they may change their position on the grid through randomly allocated migration opportunities. The probability of migrations is the parameter of interest in the model's analysis. Based on the agents' complete information about each other's risk classes and their assumed perfect rationality, they can calculate the expected value they would receive from any given neighbourhood. Migration is restricted to empty spaces on the grid within a certain window around an agent's current position. In the course of the model's development, the agents self-organise into supportive neighbourhoods with structures that differ substantially depending on the probability of migration: if this probability is low, the least susceptible agents form the core of supporting

neighbourhoods with other agents gathering around them annularly in ascending order of risk. The most susceptible agents are excluded and live as “outcasts” at the outer borders of the network. Under medium risk, members of the extreme risk classes establish support relations only amongst themselves, isolated from all others on the grid. The second best risk class now forms the core of the support networks which is surrounded by a layer of other agents in descending order of susceptibility. If the change of migration is high, both of the most extreme risk classes are unable to form any support relations with others, even within their own class. The individuals remain isolated across the grid. The second most extreme risk classes now form segregated clusters amongst themselves, while the more intermediate risk classes establish a support network with a similar annular structure as seen before.

- This model makes very strong assumptions about the agents’ rationality and their cognitive capabilities. They do not need to learn about the behaviour of their current and potential new neighbours through interaction or experience, but they know in advance how they will behave. Everyone is aware of everyone’s risk class, and expectations about the support behaviour of agents are always correct, because every agent is perfectly rational and will act accordingly, maximising its utility.
- The authors claim that under these circumstances support networks can evolve among rational egoists with unequal endowments. These networks exhibit class segregation as they self-organise, with agents in intermediate risk classes, benefiting most from the rules of the game. Through the establishment of support relations, the agents manage to decrease the inequality of the payoff distribution across risk classes.
- Many of these effects are however not to be seen as emergent properties of the system, but as assumptions included in the agents’ decision making processes. The agents are omniscient and perfectly rational. Whenever they get the opportunity to migrate to another position, they will pick the best position they can reach. Their behaviour is not adaptive, because they will always support whoever is “worth” supporting and refuse support to

those that are beneath them, from a strictly rational point of view. The only activity the agents engage in is migration. With considering these comparatively simple dynamics, the model bears a resemblance to optimisation algorithms such as simulated annealing (Kirkpatrick *et al.*, 1983; Cerný, 1985). There, a solution to an optimisation problem is sought by randomly relocating elements of the solution in a high-dimensional search space in an iterative process. In this model, the agents' movement is not random and the search space is co-evolving with the positions of the agents. Nonetheless, the ensemble of agents explores spatial arrangements in order to maximise their individual outcome, essentially solving the optimisation problem that is defined through the rules of the game they are playing: finding the best matches for their risk classes conditional on the payoff matrix.

# Chapter 5

## Model Development Process

The model presented in Ch. 7 is the current result of an iterative process, in which the scope and goal of the project co-evolved along with the understanding of the meaning and functioning of models that were developed on the way. This means that many different avenues were pursued, some of which turned out to be dead ends, others may be revisited at a later point in time. Nonetheless, all of them are part of the development process and provided new insights on how agent-based models can be used to better understand the development and evolution of business relationships and networks from a complex systems perspective. This section discusses a selection of previous models and emphasises the insights gained at the respective stages of model development. The presentation will be using the terminology of mechanism of business interactions; however the framework itself developed during the course of the project<sup>1</sup>.

### 5.1 A Model on Specialisation

#### **My BankNet**

Specialising, Increasing scale, Intermediating, Searching, Attracting, Prioritising,  
Evaluating

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<sup>1</sup>All models presented here are implemented in NetLogo (Wilensky, 1999) and are available for download under <http://snipurl.com/fhthesis>.

The first model developed was an adaptation of the BankNet model (Sapienza, 2000) introduced above. It is among the few published models that explicitly model the process of agents' task specialisation as an endogenous process, and therefore seemed to be an appropriate starting point. The BankNet is a model of intermediation where agents can engage in three tasks (depositing money, investing and producing). Instead of performing all these tasks themselves, the agents specialise and work out a system of division of labour. The intermediaries realise economies of reduced contacts as they aggregate deposits and reliably provide investments for producing agents, thereby reducing search and transaction costs. In the original model, a select few banking intermediaries emerge as the simulation progresses, they have the most investment experience and are therefore very attractive for investors and investment seekers alike. As there is a condition in the model that limits every intermediary's attractiveness to investment seekers, there is typically more than one intermediary in the system.

The replication of the original model was not fully successful: although a small number of agents achieved a permanent expositional position as recipients of deposits, the requests for investments kept fluctuating between them and a small group of other agents (see Fig 5.1). So while the model exhibited some degree of specialisation, it cannot be said that intermediaries emerged, that concentrated on a certain sensible combination of tasks. However, other deficits of the model led to the decision not to pursue its extension and therefore a detailed examination of the reasons that lead to the differences in behaviour was omitted. Nonetheless, the lessons learned from this modelling exercise were manifold:

**Model Presentation:** Although the original article presents the model design in great detail, there were a few aspects, concerning for example the initial experience and accumulation of capital, that were not described at all, or only ambiguously. Some of these issues could be resolved by contacting the author via email, however, he did not have all details, as the article was published more than a decade ago. Most of these missing details were not central to the understanding of the model mechanics, but their lack became apparent, when it came to reproducing the model and attempting to replicate its results. This shows how important it is to document a computational

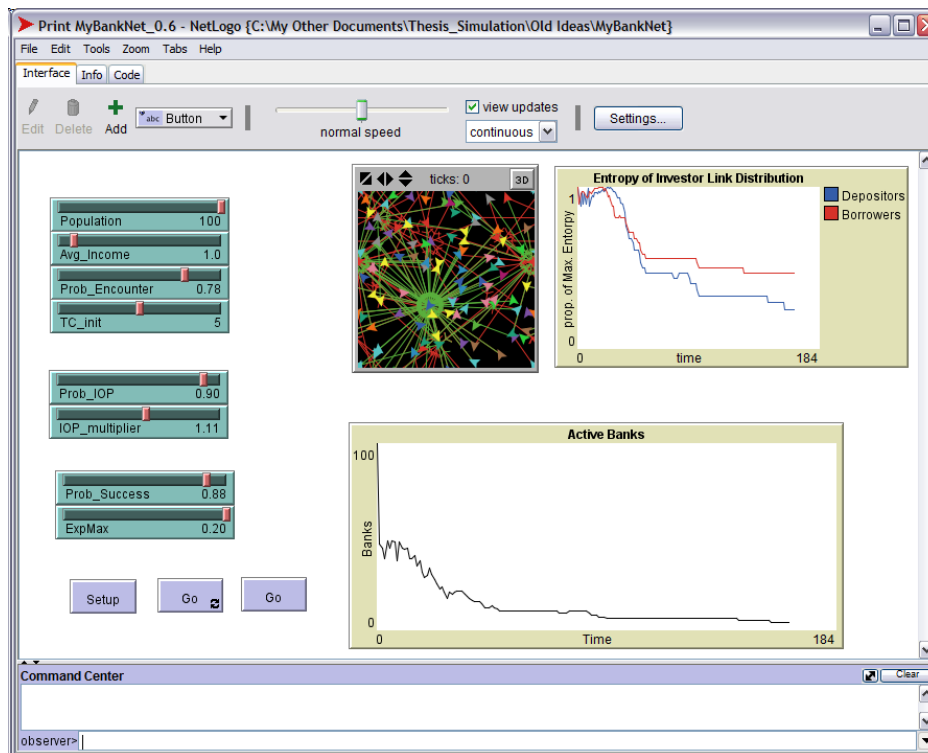


Figure 5.1: Screenshot of the replication of the BankNet model by Sapienza (2000). The small window in the centre shows the agents with their deposit and borrow relations. One bank has emerged as dominant recipient of deposits, but several other agents also still serve as investors.

model comprehensively, along with initial conditions and auxiliary assumptions that are not core to the modelled phenomenon, but integral elements of the implementation. As chaos theory demonstrated, emergent results in dynamic systems can depend on the most minute elements in a system. Publicly available repositories such as OpenABM.org, that allow researchers to upload, share and maintain their models online offer an alternative way to disseminate models without loss of detail.

**Extensions:** The decision to replicate the BankNet was made in order to provide a starting point for further extensions through other modules of relevant mechanisms. As a functioning model of endogenous intermediation, it seemed ideal as a basis to model the self-organisation of a distribution channel, including at least producers, wholesalers and retailers of goods.

The rationale was that modular extensions of mechanisms would slowly increase the richness and level of realism of the model and help reveal how the emergent structure of interactions is affected by a new mechanism. This would facilitate a structured analysis of the mechanisms effects as they are added “one-by-one”, revealing the causal interdependence between activities and structure. While elegant in theory this approach was not feasible, at least not with BankNet. After the successful introduction of an alternative link through which orders could be placed and goods received, an attempt was made to introduce a second commodity for exchange. This proved to be incompatible with the way the existing mechanisms were implemented. BankNet is designed as a model of money transfers - as opposed to goods and services, money tends to be easily priced using its nominal value. BankNet does not include any mechanisms of price assessment, or comparison, or even payment; the links represent money flows and credit lines that are either fully activated or not. But the technicalities of exchange were not the only problem: in the original implementation money just appeared in every round, allocated through a random process. For a re-interpretation of this model as production and distribution process, this randomness would have to be replaced by deliberate action, possibly including demand forecasting and actual production efforts. And not only would intermediation be an activity affording specialisation, but production as well. Therefore, the new model would have to include production functions as well. But to keep the emergence of specialists endogenous, these functions must be adaptive and also somehow connected to the specialisation of intermediation activities. Ultimately, the knowledge advance coming from the original model analysis did not seem to warrant the numerous and complicated adaptations necessary, especially because they would lead to an extended model that bears only the smallest resemblance with the original. Therefore, efforts to expand the BankNet were suspended in order to build a new model from scratch.

**Perspective:** Because of the limited expandability of the BankNet, it became apparent that future uses and expansions of a model need to be at least *anticipated during its implementation*. This realisation affected the coding style used in subsequent models. Most code is now explicitly modular, separating every agent activity, decision making process and interaction. In technical terms, every activity is represented as a reporter-procedure that does not alter the state of the simulation directly but returns a proposal of an updated state that can then either be introduced into the model, or not. This helps to keep the software modules independent of each other and facilitates the introduction and substitution of modules in future updates and extensions.

## 5.2 Parsimonious Models of Select Mechanisms

The literature review of what drives business networks quickly revealed that division of labour, facilitated by specialisation and exchange are the fundamental drivers of business networks, supplemented by various technical and legal aspects and of course social mechanisms. At the same time, the only model that included these fundamental mechanisms, the BankNet, turned out to be infeasible for extension and among the other models reviewed there were no obvious alternatives that could have served as a flexible basis for further model extensions. Consequently it was decided to build new models from scratch, using inspiration from existing models and the activities of business actors identified in the reviews. The strategy at this point was to model select mechanisms in isolation (to the degree that isolation is possible), and then combine them to see how they interact. The simple models would be implemented following the example of many existing models, trying to make as few assumptions about the model as possible, so that the analysis can explore the entire parameter space and understand their workings completely. Through the subsequent combination of these models, it would be possible to better understand the interaction of mechanisms by comparing their performance in isolation and in combination with each other. The first models developed along these lines were “Sticky Relations”, “Spread of Reputation” and “Networks of Specialists”.

## Sticky Relations

Searching, Getting Acquainted, Bonding, Socialising, Coordinating socially,  
Terminating

Once it was decided to build a new model from scratch, the new question was how to build it. Reviewing mechanisms of business interactions showed what *could* be in there, but that does not mean that all of these mechanisms need to be in the model. As discussed above, a model is an abstraction from the real system, smaller, simpler and therefore supposedly easier to understand. The first response was to build several very abstract models that each focus on one or two mechanisms and the way they interact with each other. Following this design philosophy three models were developed, each of which will be briefly presented here: Sticky Relations, Spread of Reputation, and Networks of Specialists.

The Sticky Relations model is a very basic model of network dynamics that combines three mechanisms: First, the structure of interactions is represented by the network of relations. Second, the nature of relations changes with age. As agents adapt to and learn from each other, their relationship is assumed to become more valuable and robust and is therefore less likely to terminate, and third relations are terminated and replaced by new ones, which requires a search and mating mechanism. A screenshot is shown in Fig. 5.2.

The structure of interactions is initialised through well-known algorithms, namely preferential attachment (Barabási & Albert, 1999), random matching (Erdős & Renyi, 1959) and small-world rewiring (Watts & Strogatz, 1998). It is assumed that these networks exist from the start, so that the other processes can develop on these structures. Likewise, search and mating draw on related and equally well understood algorithms: preferential attachment (Barabási & Albert, 1999), random matching (Erdős & Renyi, 1959) and friends-of-friends matching, implementing Rapoport's "triadic closure bias" (Rapoport, 1963). Each of these network structures can be combined with each of these additional search mechanisms. The humble innovation in this model is that it introduces the termination and replacement of relations together with an ageing component, that makes them

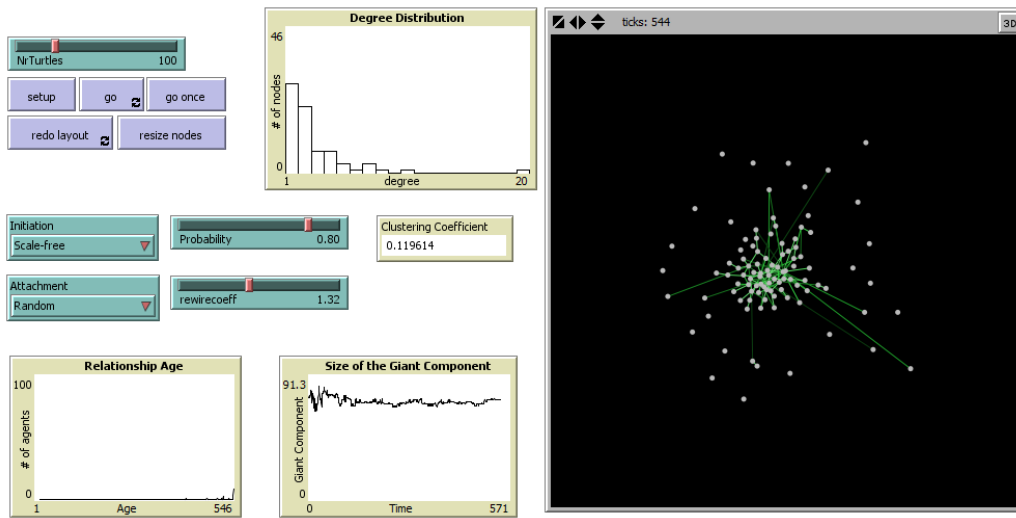


Figure 5.2: A representative run of the Sticky Relation model. The network was initiated as a scale-free network and dynamic rewiring is made randomly. The model shows isolates that drift away from the core of the network. Although over time the individuals that are isolated may differ, the average number of isolates has stabilised already.

more likely to persist the older they get. Relationship termination is modelled as a random process with adaptive probability of termination:

$$p_t(ij) = \frac{1}{(1 + \text{age}(ij))^\gamma}, \quad (5.2.1)$$

where the age of all relations  $ij$  is measured in rounds and  $\gamma \in [0, \text{inf}]$  is an exogenous parameter that controls the effect of ageing.

Exploratory results of this model show that most combinations of initial network and rewiring produce dynamic networks with scale-free degree distributions: few agents with many links and many agents with only a few links. Preferential attachment and friend-of-friend rewiring produce agents that are isolated from the main component of the network, while random rewiring does not introduce new isolates, but hardly affects the number of isolates if they are present upon initiation. The ageing parameter seems to introduce a two-phase regime into the model: for  $\gamma > 1.3$  the rewiring ceases quickly and the network assumes a nearly steady state, because the remaining relations become well-established and therefore the

probabilities for relationship termination are very low. For lower values of  $\gamma$  the rewiring dynamics continue and no steady state can be reached.

## **Spread of Reputation**

### Learning, Communicating

The Reputation Spread model is based on an idea that is very similar to that in Ladley & Bullock (2008). Interaction and communication do not necessarily have to have the same structure, especially when considering interaction in a business context and communication as a social activity. However, the model development did not go very far. To foreclose the lessons learned: it soon became apparent, that a) the interactions represented were not so central to the development of business networks that they should be the fundament of our model here, and b) the model did not - and could not, by design - lead to surprising emergent outcomes.

The model's mechanisms are fairly simple: Two types of agents (buyers and sellers) form two separate networks. Every round one buyer gets to interact with one seller across networks and they exchange one unit of a good. However, there is a certain, exogenous and fixed probability that a seller cheats on the buyer by providing inferior quality. The buyer will evaluate its experience and update its opinion about the seller. Also, it will share its updated opinion with its direct neighbours in the buyer network. A buyer's opinions are formed as the average of all observations relating to any other agent, over the entire duration of the simulation, essentially calculating the expectation, in light of the present information. A first extension of this model is to make the buyers more cautious, refusing interactions with sellers that they consider frauds. With this extension the decision to buy from a certain seller is conditional on its standing with the seller, as it can veto the random allocation of exchange partners. A screenshot of a typical simulation run is represented in Fig. 5.3.

The results of this model were not surprising. With hindsight, the whole model could be described as a complicated aggregation algorithm, where one side of the model (the buyers) has to learn about the hidden parameters that determine - and are revealed through - the other agents' (sellers) observable behaviour. Through the communication network, that connects all buyers, this process is sped up to some extent, as information is shared amongst them, but in the end, every buyer

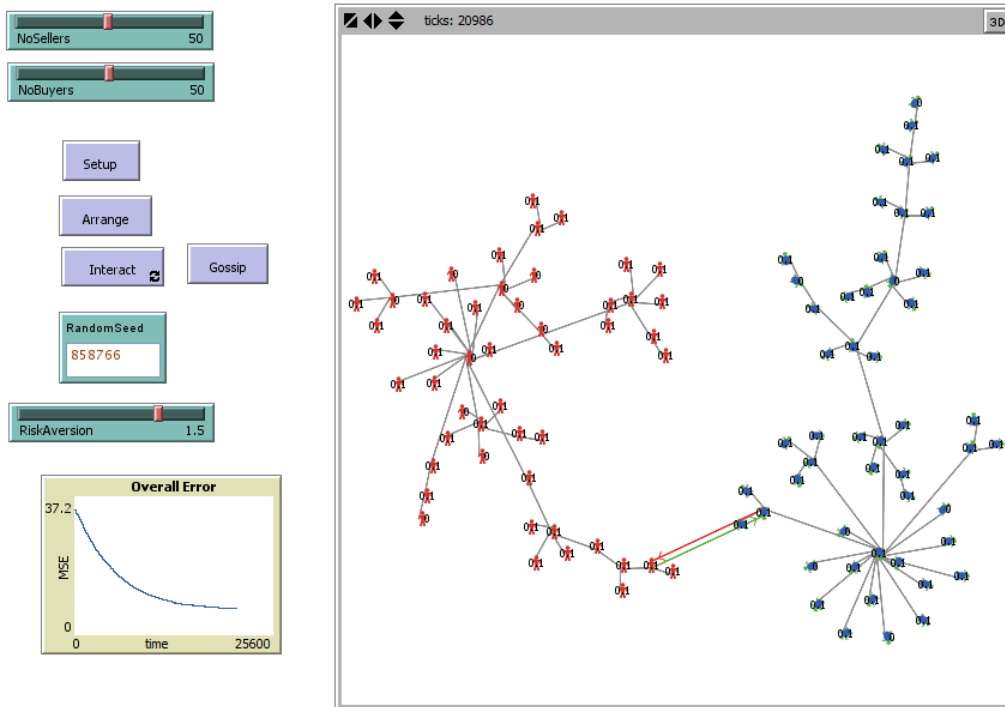


Figure 5.3: The Reputation Spread model. Buyers in red estimate the sellers' (blue) probability of cooperation. The labels indicate the standard error of the agents' estimates.

will have gathered enough information about each seller so that its estimate about any seller's behaviour is unbiased and correct in the limit. The risk aversion parameter only introduces an artificial threshold that precludes interactions between buyers and sellers once the buyers' opinion is below the threshold, essentially terminating the process of information gathering at some point. As a result the best estimate of the seller's parameters may come with a strictly positive degree of uncertainty.

### **Networks of Specialists**

Specialising, Learning, Increasing scale, Exchanging, Coordinating through other arrangements, Negotiating, Prioritising

The model Networks of Specialists tries to capture the essence of specialisation and the coordination efforts that come with division of labour. Here, specialisation is seen from the point of view of an agent that advances in performing a certain (assortment of) tasks, gaining more and more experience over time and thereby improving the capabilities associated with the tasks. Agents become better at what they are doing by doing it repeatedly. The model does not, however include the creation and identification of new opportunities that could become attainable through the accumulation of (technical) skills and knowledge. The range of possible tasks is fixed throughout the model run and determined exogenously. It is assumed that each task is a production task that leads to the creation of a commodity that can be exchanged between agents. Exchanges occur in a social space where agents have access to a group of other agents within a certain social reach. Apart from the learning processes that help agents to improve their skills, they also have a certain amount of energy that they can allocate to production tasks. Energy is created through consumption of goods, and is infinitesimally divisible between tasks. The allocation decisions are the only other adaptive element in the model: Agents learn to allocate their resources to the production of goods that are costly to obtain from other agents within their reach. On the basis of these three main activities, specialising, exchanging and coordination in production, the model leads to a self-organised production system that realises economies of specialisation through the division of labour.

The learning effect of specialisation is implemented as a variation of a logistic function that takes as its input the vector of experience  $V_i = (v_{i1}, \dots, v_{im})$ ,  $v_{ij} \in \mathbb{R}$  which consists of the sum of each of the  $m$  goods units ever produced by agent  $i$  and maps it to a vector  $R_i = (r_{i1}, \dots, r_{im})$ ,  $r_{ij} \in [0.5; 1.5]$ , that represents the productive capabilities of that agent. The specialisation function is

$$r_{ij} = \frac{1}{2} + \frac{1}{1 + \exp^{-\frac{v_{ij} - \mu(V_i)}{\sigma(V_i)}}}, \quad (5.2.2)$$

where  $\mu(V_i)$  is agent  $i$ 's mean production experience across all products so far, and  $\sigma(V_i)$  is the standard deviation. This means that first, the production experience is standardised across all goods, so that the distribution has mean 0 and a standard deviation of 1. In the second step, these normalised values that now range approximately from -3 to 3, are mapped onto a sigmoid-shaped function between 0 and 1 with the logistic function and finally they are shifted up by 0.5 in the last step. The algorithm is illustrated in Fig. 5.4. The idea behind this algorithm is twofold: on one hand it models that agents improve in what they are doing by doing it - in the most basic form of behavioural learning. On the other hand, the algorithm takes into account that the theoretical limit for all production experience is positive infinity. Given enough time, every agent's experience in the production of any good will surpass any threshold. Therefore, the algorithm normalises experience values, so that productive capabilities for one type of good are relative to the agent's experience across all goods.

The vector of productive capabilities  $R_i$  that is the result of the specialisation algorithm is the main component of the agent's production function. It determines how many units of a good an agent can produce per unit of energy:

$$y_{ij} = r_{ij} * x_{ij} \text{ or, } Y_i = R_i * X_i, \quad (5.2.3)$$

where  $X_i = (x_{i1}, \dots, x_{im})$ ,  $x_{ij} \in \mathbb{R}$  is the vector of inputs, in terms of energy, that agent  $i$  allocates to the production of each good. This allocation is determined through a simple heuristic, based on the agent's own costs of production  $\frac{1}{r_{ij}}$ , the average of prices that the agent had to pay for each good when it bought it from others, its own demand and expectations about the sales in the next round.

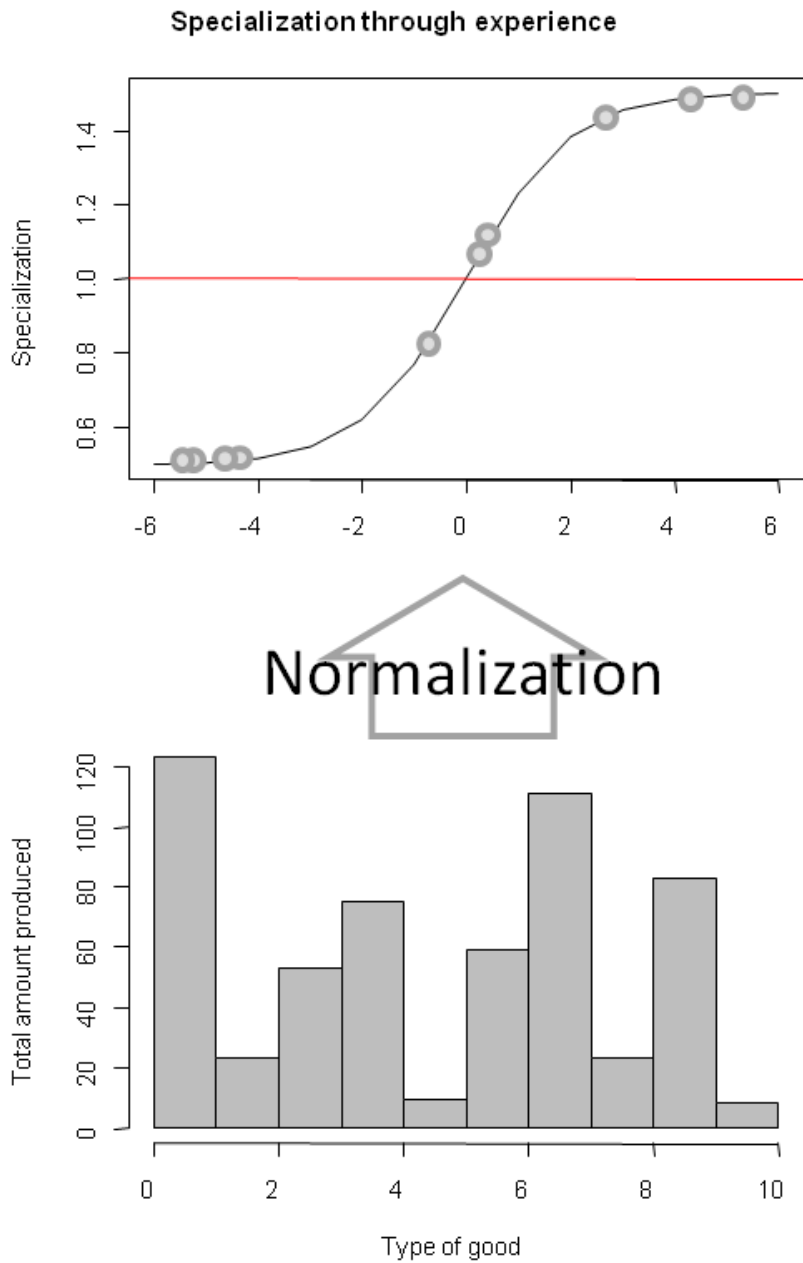


Figure 5.4: Schematic illustration of the specialisation algorithm that maps the agent's production experience to its production capabilities, coefficients for the production function in the range of 0.5 to 1.5.

“Prices” are calculated from exchanges, but as there is no unified measure of prices, such as money, an agent has to use a proxy. The price for the good received in an exchange is taken to be the amount of energy that the agent had to invest in the production of the good that was given away in the exchange. Parallel to the prices they pay, the agents keep track of the units and types of goods that they sell to others. Combining all this information, the algorithm for energy allocation works in two stages:

1. Determine which goods are cheaper to buy than to produce directly. For those that are preferably produced directly, enough energy will be allocated to satisfy the agent’s own needs. Should not enough energy be available, energy is allocated proportional to demand.
2. Allocate all excess energy proportionally according to sales forecasts. These forecasts are derived from retrospective sales, calculating the share of sales for each good relative to the agent’s total sales across all goods.

Exchange is negotiated between two randomly paired agents that are within their respective social reach. The algorithm that settles exchange is based on the agents’ current stock of goods and also draws on their consumption function. The latter is kept very simple in this model. It is an adaptation of a Leontief production function Allen (see e.g. 1968) and it was chosen because of its simplicity, but also because it emphasises the importance of assortments: agents in the Network of Specialists can only consume a set combinations of goods, concretely they need to have equal amounts of each of the  $m$  goods to consume and to transform the goods back into allocable energy. The energy retrieved from consumption is to equal the total number of units consumed and the agent consumes as much as possible. Consequently consumption is limited by the good with the minimum stock (e.g. with  $m = 5$  goods, and agent  $i$ ’s stock is  $S_i = (2, 3, 2, 4, 5)$ .  $i$  will consume two units each, retrieving  $5 * 2 = 10$  units of energy and the stock vector after consumption would then be  $S_i^* = (0, 1, 0, 2, 3)$ ). The exchange algorithm makes use of the fact that consumption will be determined by the good with the lowest level of stock. An agent approaches one of its neighbours at random and they compare their current stock. They select one pair of goods that shows the biggest difference in stock levels - one good that agent  $i$  stocks in excess while

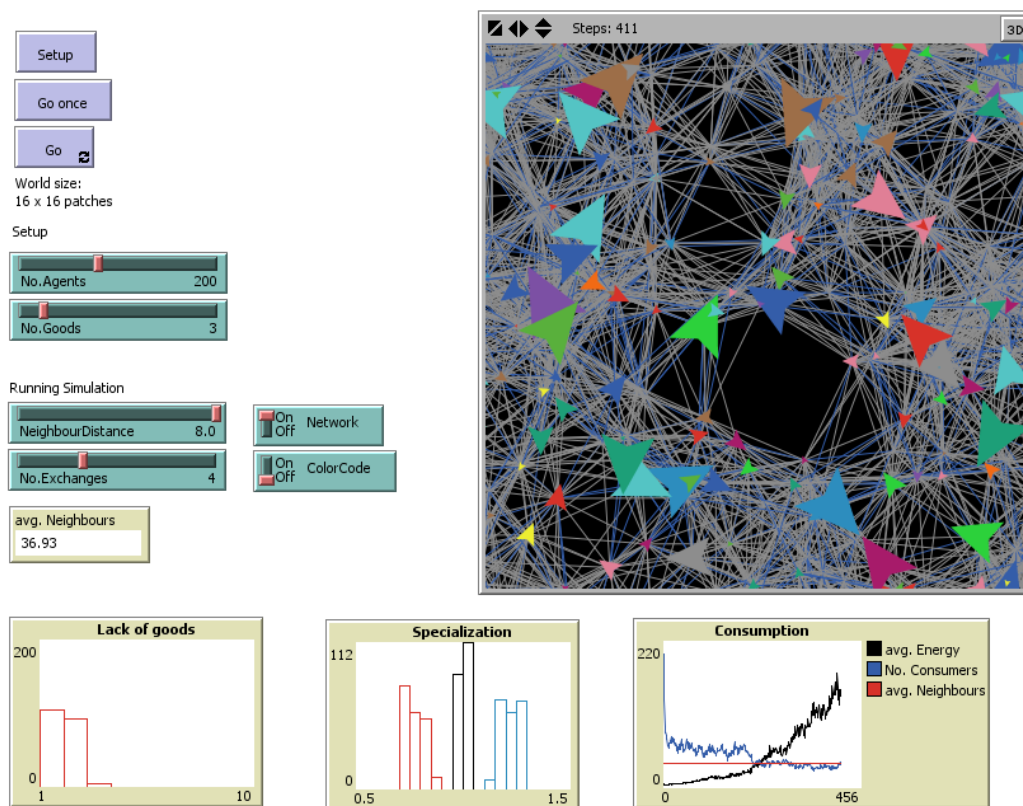


Figure 5.5: Screenshot of the Network of Specialists. After more than 400 rounds the population of agents shows a heterogeneous distribution of energy available to the individual agent, represented by their size.

agent  $j$  needs it, and another good that agent  $i$  needs while  $j$  has plenty of it. Of these, they will exchange equal amounts of units, up to an amount where both could still benefit. The number of units is determined by another simple heuristic: both agents calculate how much of the good they would need to get it to the average stock level of all goods combined. The agents will then exchange the smaller amount of units required by either of them - or as much as they have available, should this number be too high.

The Network of Specialists is still a rather abstract model of the process of self-organised specialisation and division of labour. Agents' actions and decision making is driven by simple heuristics instead of complicated optimisation routines that would presuppose highly-developed cognitive capabilities. Neither

production nor consumption are at the core of this model, therefore very simplistic representations of these mechanisms were chosen. At the same time, the agents are equipped with capabilities that allow them to monitor their surroundings, remember their past experiences and anticipate the future. Their advanced adaptive capabilities include learning and specialisation, demand forecast and price estimation.

For small numbers of goods ( $m \leq 4$ ) and an initial energy level of 5, the model successfully endogenises the division of labour amongst agents, and moreover, in the process of specialisation the agents increase the amount of energy in the model. Division of labour allows each of them to focus on the production tasks that they are good at (i.e. where  $r_{ij} > 1$ ), so with every production step they produce more units of goods than they have to invest units of energy. Another noteworthy outcome of these processes is that they lead to a heterogeneous distribution of energy amongst agents, as path-dependence and the structure of interactions favour the activities of some agents, while they hamper others. This is accompanied with a heterogeneous degree of specialisation amongst agents.

For higher number of goods ( $m > 4$ ) the model development seems to depend on the initial energy level. It has been observed that the population reaches a state of stasis, where all energy is bound in stocked goods, but cannot be transformed back into energy because the agents do not possess complete assortments for consumption, and no exchange between neighbours can resolve this predicament.

### **5.3 Models of Realistic Agent Behaviour**

For reasons that will be discussed in detail below, the envisioned strategy of modularly combining individual models turned out to be infeasible in the case of business networks and relationships. In short, there is little data available to validate the individual, or the combined model. And seeing that only the combined model would describe the essential mechanisms that drive the development of a business network, it became apparent that the isolated models are theoretically rather questionable. With this improved understanding of the task at hand and the associated challenges, it was decided to pursue a different modelling strategy. Using the extensive knowledge about business actors' actions and interactions, the new

goal was to develop a model that represents actor behaviour as realistically as possible, grounding their behaviour in existing research and minimising the amount and strength of assumptions that are not backed by research. Of course, it is difficult to assess where abstractions and simplifications affect the model's essence and where they are permissible; therefore the model design is to some degree a matter of subjective judgement. Through successive amendments and variations, the models below were developed as a result of presentations and discussions with domain experts and experts in modelling alike.

### **BusiNET**

Specialising, Learning, Increasing scale, Exchanging, Negotiating, Getting Acquainted, Learning, Coordinating through contracts, Adapting, Terminating, Intermediating, Comparing

The BusiNET is an advancement of the Network of Specialists model, lifting some of its restrictions in order include relevant aspects all five classes of causal mechanisms. Especially, it allows the agents to search for exchange partners themselves, establish relationships with them and improve their relationships' performance over time. A detailed technical description is presented in Appendix A. The presentation in this section focusses on the theoretical improvements and the model's bearing in the overall development process. A screenshot of an exemple run is given in Fig. 5.6.

In BusiNET agents continue to be consumers and producers of goods and they can learn over time how to perform a production task more efficiently. In fact, the model relies on the same experience/production function as its predecessor, the Network of Specialists. The main advancement is the agents' capability of indirect exchange and their ability to establish exchange relationships themselves. The original consumption function also remains unchanged. However, indirect exchange that goes beyond pairs of agents requires a universal means of exchange. Therefore instead of energy, the agents' input into their production process as well as the basis for all their calculation and decision making processes is now money. Technically, this only changes the name of a variable; however the interpretation of the model is now very different.

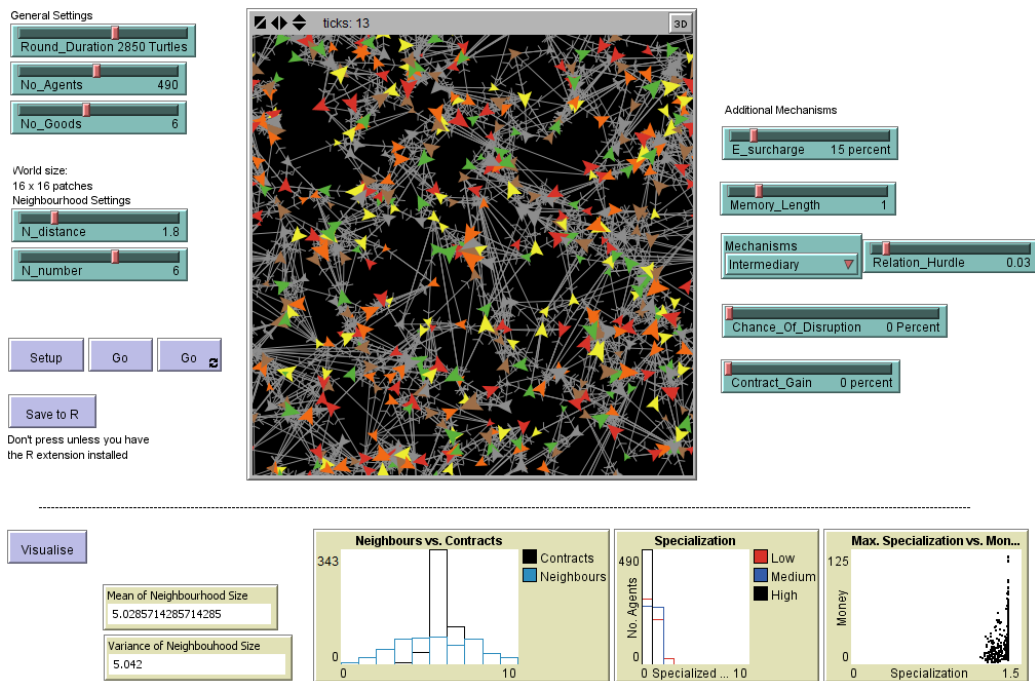


Figure 5.6: Exemplary screenshot of the BusiNET model. 490 agents have formed a network of exchange relations that allow them to engage in intermediated exchange and specialisation in the production of six different goods. The monitors at the bottom capture the development of relations and clusters of interacting agents, as well as their individual specialisation and wealth.

The agent's ability to establish exchange relationships themselves endogenises the development of an interaction structure. In comparison to the Network of Specialists model, the BusiNET does not require a predefined network, instead the agents decide for themselves who is an important exchange partner that warrants their ongoing commitment. These decisions are based on the agents' own interaction experiences, as they gradually learn about each other and simultaneously develop their capabilities. The mechanisms introduced for mating and relationship formation work as follows: an agent is randomly selected from the population to be the current round's *buyer*. This means the agent will initiate a search for sources that can provide the good that it requires most. This means, that the agent will ask other agents in its vicinity to provide a quote for the unit price of that good. Their quotes will be determined primarily by the agents' production function. The buyer will compare the received quotes as well as its own production costs and then order the good from the cheapest source. Contracts come into play when the cheapest offer undercuts all the other offers by a substantial margin (an exogenous parameter). This signals to the buyer that the source should be retained for future purchases, in order to safeguard the cheap access to that particular good. In this model, these binding contracts can be established unilaterally. They have the primary effect that, whenever the buyer requires the same good again, the purchase order will be sent directly to the contracted source, without evaluation of others. To include a mechanism of relationship termination, the model includes a parameter that randomly triggers relationship re-evaluation, where the buyer invites other quotes despite the established contract. Should another quote be of better value, then the contracted relation would be terminated and substituted with the new one. A further extension of the model allows change in relationship performance over time (similar to the model of Sticky Relations), making them more efficient as they are used more often, reducing the costs of exchange between the two parties.

The second advancement of this model is that it now allows for intermediated exchange, i.e. the agents that are contacted by the buyer need not necessarily be the producers of the good in question. If they have a contracted relationship with another agent for the procurement of the good, they will forward the request for a quote to their own source and assuming the role of an intermediary. Moreover,

their source does not have to be the producer either - as long as there are contracts for the procurement of the good requested, agents will pass on the request until the producer is found, and then they will return the quote to the buyer. The only limiting factor to these chains is that agents require payment for their services. Producers as well as intermediaries will use *cost-plus* pricing to determine the quote they pass on towards the buyer, adding a certain margin for themselves to the price. While this mechanism should have a limiting effect on the overall length of such intermediated supply chains, the improved performance of well-established relations can counteract this effect.

This model is built so that some mechanisms of interaction can be added modularly, allowing researchers to examine their effects in systematic experiments. The BusiNET null-model therefore consists only of agents that are scattered randomly in the social space. They produce and consume several goods and they are capable of learning during the production process. Starting from this most basic setting, the following additional mechanisms can be added modularly:

- Direct exchange of goods with other agents within the social-reach,
- Ability to relocate if exchange possibilities are not satisfactory at current location,
- Cost-plus pricing for production and intermediation services,
- Remembering the last  $n$  sources for each good,
- Establishing an agreement to purchase a certain good from only one source,
- Intermediation: The ability to pass on an order for a certain good to other agents,
- Re-evaluating of contracts,
- Increasing efficiency of exchanges in mature relationships,

Exploratory analysis of the model shows that in the null-model, agents quickly form clusters of neighbours. Depending on the number of goods in the simulation

and the number of agents considered for quotes, these clusters are stable or undergo bursts of reorganisation between phases of stability. Specialisation occurs within these groups and the agents engage in exchange that increases the overall money available in the system. This is caused by a conjunction of loss-less consumption and value creating production through specialists. The only way that money could be removed from the system is through non-specialised production and this is quickly foreclosed through the agents' self-organisation. The inclusion of memory interferes with the clustering of agents in the social space, because agents still remember their previous sources for a good and are able to request a quote from them, too. Allowing for contracts without intermediation accelerates the value creation process and increases the degree of specialisation that agents achieve. The effects of intermediation depend on the parameter for cost-plus pricing and the gains for well-established relationships. Detailed experimental analysis would be required to identify the patterns of interactions and their dependence on the model parameters.

The BusiNET is the first model in this project designed under the primacy of *micro validation*. This was a response to the realisation that validation through emergent patterns on the macro level is problematic at best, as longitudinal data on the network level is scarcely available. Consequently the series of models that have been derived from the BusiNET have all been built to represent agent behaviour realistically - not as abstract Prisoner Dilemmas, or other games, using realistic assumptions about their cognitive capabilities and including the adaptive learning processes that govern the interplay between an actor and its environment. There is an abundance of research about the behaviour, decision making and interaction of businesses in relationships in marketing, economics and other fields, and this provides the basis to identify the causal mechanisms - in terms of entities with their properties and the constellations of their activities - that bring about social phenomena. These mechanisms are the modules to build a theory about how economic actors specialise and self-organise their division of labour. However, this new perspective led to another problem: finding the right level of abstraction in terms of a sensible combinations of mechanisms to build a model and the associated theory that would convincingly explain the self-organisation of specialised production processes we see in business networks.

As it turned out, another feature of agent-based modelling became apparent at this stage of model development: they are a *visual, intuitive and interactive way to communicate theories*. Stakeholder and domain experts alike can be engaged in the model development process and provide their positions and insights regarding the implementation of mechanisms and overall construction of the model. This approach has been used to inform projects as diverse as ground-water management in pacific atolls (Dray *et al.*, 2006) or the management of a marine park in Canada (Parrott *et al.*, 2011). During conferences, workshops, seminars and in one-on-one conversations, the BusiNET and its successors were presented and discussed and the insights gained informed the incremental development of the model. The main issues raised with regard to the implementation presented here were as follows: 1) The underlying social space is problematic, in that it strongly affects the networks that agents can form while at the same time it is hard to manipulate the space and distribution of agents experimentally, as there is no straight forward interpretation or real-life equivalent. 2) The implementation of the specialisation algorithm implies a process of “unlearning” of tasks that are performed less frequently. The present implementation was criticised as an extreme and unrealistic case, because the strength of the effect of unlearning is symmetric to the effect of learning. 3) It was suggested that the maintenance of relations should incur costs so as to make less frequently used contracts even less attractive. 4) The current implementation implies constant marginal production costs, which might hamper specialisation and exclude economies of scale from the model. 5) Unlimited production capacity is a problematic assumption because it misrepresents the competition that can arise between specialists.

### **SpecialNet**

Specialising, Learning, Increasing scale, Exchanging, Negotiating, Coordinating through contracts, Adapting, Intermediating, Comparing

The SpecialNet is a major extension of the BusiNET model, responding to some of the comments and criticisms received during the discussions of the model. It uses an upgraded specialisation function that reduces the effect of “unlearning” substantially, and it is initialised with an exogenously determined network structure, so that the effects of this initial structure can be analysed systematically. This

substitutes the blurry notion of a social space with a well defined social network structure, while still allowing for dynamic rewiring in the course of the model run. Smaller extensions were included in the updated model, introducing heterogeneity of agents regarding their margin in cost-plus pricing, and allowing for variations in the algorithms that select the current good to be purchased and the quantity of that good that will be ordered.

The new specialisation function introduces a term that increases the range of possible levels of specialisation relative to the total production experience. This satisfies three requirements at the same time: the more often a task is performed, the better an agent becomes at it, the learning curves are steep at the beginning of the process and flatten out towards the end, and improving on the capabilities to perform one task may reduce the capabilities of performing another, but the magnitude of the negative effect is below the magnitude of the positive effect. The resulting function is as follows:

$$r_{ij} = \frac{1}{2} + \frac{1}{1 + \exp^{-\frac{v_{ij} - \mu(V_i)}{\sigma(V_i)} * \log_{100} \sum V_i}}. \quad (5.3.1)$$

A graphical representation of this updated specialisation function is provided in Fig. 5.7. It illustrates the shift of the potential for specialisation as the agent gains more production experience. The resulting production coefficients that are calculated from the agent's experience through the specialisation function would lie on one of the S-shaped curves. Depending on  $\log_{100} \sum V_i$ , the function is either a short, nearly straight line ranging from 0.98 to 1.02 (highlighted near the y-axis of Fig. 5.7) or, with increasing experience, extending to the s-shape used in previous models highlighted to the right of the image.

The second improvement of this model is the explicit representation of the network of interactions in the initiation step of the model. This allows the researcher to analyse the effects that different initial structures of interaction networks have on the development of the system. While the initial implementation assumed a random scattering of agents in an undefined social space, the updated version offers various types of well-known social networks to model which of the agents engages with whom. These new communication structures include random, scale-free, small-world, star and circle networks. With this change, the interpretation of

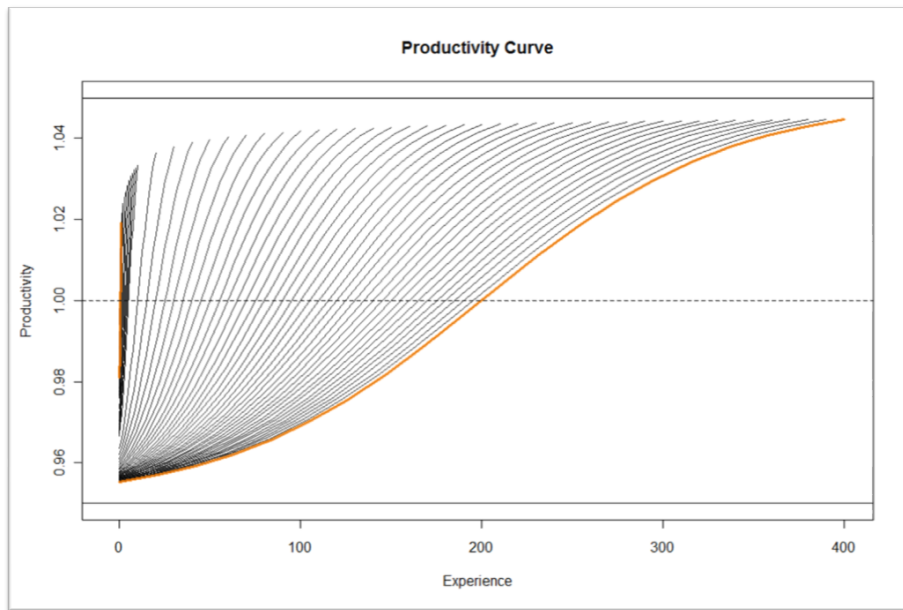


Figure 5.7: Graphical representation of the updated specialisation function in SpecialNet. The potential for specialisation shifts as the agent gains more production experience.

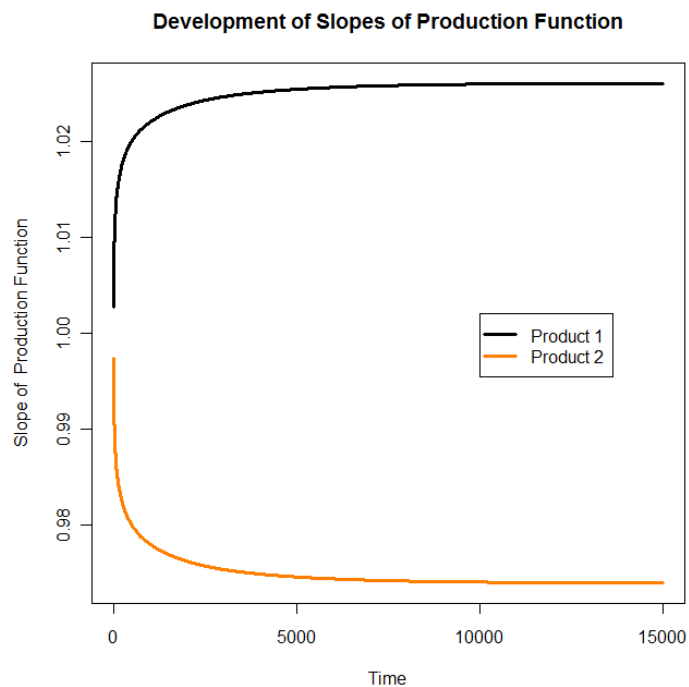


Figure 5.8: SpecialNet, exploration of the specialisation function: For one agent and two goods the graph shows the development of production coefficients over a large number of rounds.

links in the model changes slightly. They no longer represent contracts, but communication channels that allow the agents to interact with each other. Nonetheless the agents are able to establish binding contracts with each other. Only these will be represented as an attribute of the agent, not an explicit entity. The new representation of contracts does however not interfere with the analysis of the network of contracts. As in the previous model they could be analysed with tools of social network analysis, only the extraction from the model is different. Moreover, the update allows researchers to monitor the network of existing communication channels in addition to the network of contracts. This was not possible before.

In order to get an impression of the effects of the new specialisation mechanism, a number of small-scale experiments were conducted. In a system with only one agent and two goods, the agent will alternate between the production of either good. Initial small differences in production experience will eventually lead to specialisation, but on a comparatively low level (production coefficients around 0.98 and 1.02, see Fig. 5.8). Nonetheless, the agent will lose money over time. This can be explained as follows: upon initiation the previous production experience is assigned at random. In the presence of other agents, this creates a population of heterogeneous producers, but with only one agent, this will determine at which task the agent can realise economies of specialisation, and at which production task it will effectively lose money. These differences, although small in scale will persist throughout the model run, as the number of units produced over time will be identical for each good. However, the losses made on the one good will never be fully compensated by the gains made on the other and so eventually the agent will go bankrupt.

With three goods, the potential paths of specialisation for one isolated agent look different again. In this case it is possible for the agent to retain money throughout the model run. Figure 5.9 relates the average gains from production upon initialisation to the average gains across all goods after 100 rounds of specialisation. The size and colour of the dots indicates wealth remaining to the agent upon completion. It shows that about a third of the model runs lead to positive developments and increases in wealth, while the other two-thirds lead to stagnation and depletion of funds. The exact mechanics for these outcomes are revealed in Fig. 5.10. It shows the same simulation runs with the same colour coding, but this

time comparing the production slopes upon initialisation to those upon completion of the model runs. It becomes apparent that the initial conditions determine the course of the agent's specialisation and performance in the rest of the model. An agent will perform well and on average create gains through production only if two out of the three production slopes are relatively steep from the beginning on, while one is very flat by comparison. The production of two goods with steeper slopes will then over compensate the losses incurred in the production of the third. Like in the case with two goods, these differences will be maintained throughout the run because the individual's consumption function requires equal amounts of each good.

Further experiments were conducted to better understand the interaction of a small number of agents. Additional service margins were set to zero and intermediated exchange was prohibited. Two agents and two goods, will always and quickly solve their production problem and specialise in the production of one good each, quickly gaining experience and economies through specialisation. With three goods two agents also develop a form of division of labour, one becoming a specialist in the production of one good, while the other focusses on the other two. Lastly, two different outcomes have been observed for four goods and two agents: in 87% of 200 observations, the agents both specialise in the production of two goods, whereas in the remaining runs, one agent becomes a specialist in producing only one good while the other produces three. In the latter case the duo will prosper, but not as much and as quickly as in the other case.

Small fully connected networks of four agents lead to three different outcomes: In 38% of cases four specialists emerge, complementing each other. In 60% of cases one agent becomes a consumer, two turn into specialists of one good and one agent specialised in producing two goods. In the remaining 2% of cases two consumers and two specialists of two goods each emerge.

The structure of interaction has a substantial effect on the development of the model. Arranging the four agents in a star network, with one agent in the centre as the only connection to the others, leads to qualitatively different results. All agents take part in the production process and the centre agent accumulates wealth disproportionately. If the centre becomes a specialist regarding only one good, other agents will continuously lose money because they cannot compensate

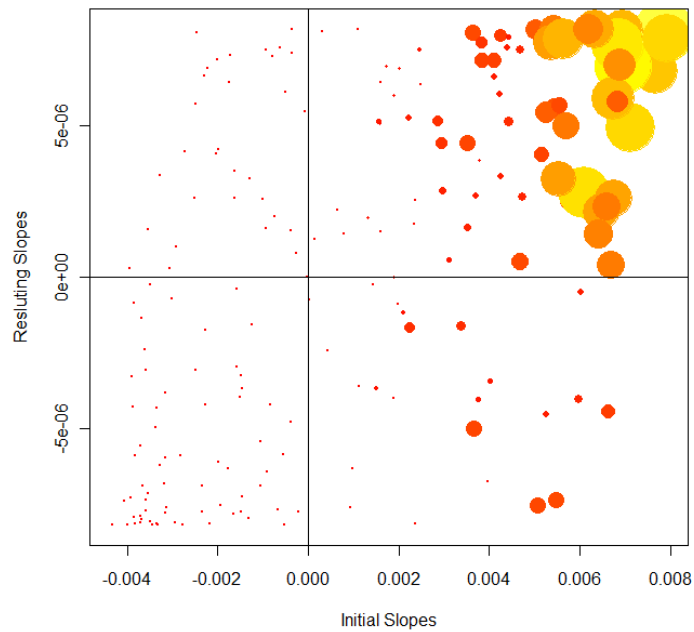


Figure 5.9: Agent specialisation and performance with one agent and three goods. The graph relates the average gains from production upon initialisation to the average gains across all goods after 100 rounds of specialisation. The size and colour of the dots indicates wealth remaining to the agent upon completion.

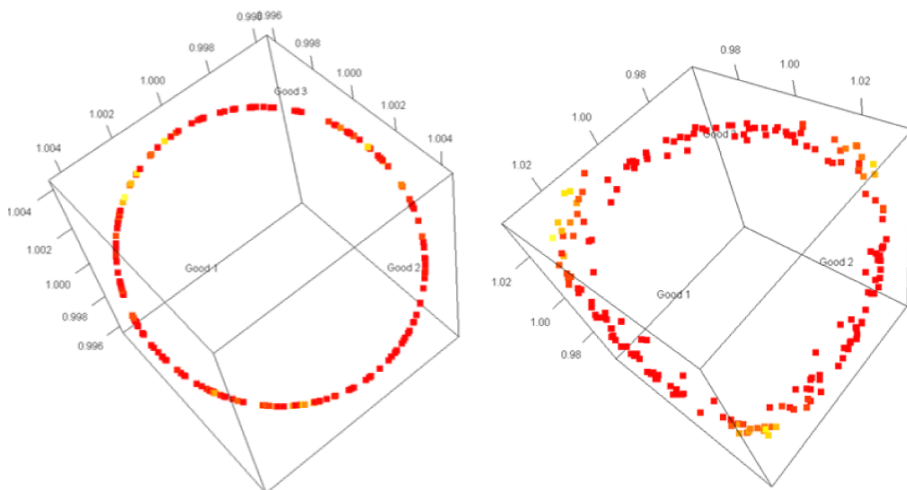


Figure 5.10: Agent specialisation and performance with one agent and three goods. Slopes of the agent's production functions individually for each good, upon initialisation (left) and after 100 rounds (right).

three non-specialised goods by themselves (49% of observed model runs). However, if the centre becomes a specialist producing two goods, other agents stand to benefit from the division of labour (51%). The centre player may prosper together with only one other fully complementary agent or work together with two of them. Partially complementary agents lag behind regarding the accumulation of wealth and in few cases it has been observed that peripheral agents can be trapped with little money and an unfit specialisation. Lastly, the effects of a ring network were investigated. In this network every agent has connections to two others and is isolated from the third. This setting shows very interesting dynamics, either leading to a system of four specialists that each have to produce one good that they are not specialised in for themselves, or two of the agents without direct connection to each other develop an indirect interdependence through the other two agents. In this case they often change their main specialisation as orders from the other agents shift between them, until eventually the system settles in a static state.

Again, SpecialNet was presented and discussed on various occasions, including seminars at the Queensland University of Technology, the University of Technology Sydney and the University of Sydney. The discussions pointed to two main aspects of the model that could be improved: first, individual learning as the main source of specialisation gains and second, the seemingly limitless resources that allow for boundless value creation under the right conditions. In earlier presentations of the SpecialNet model, the implemented specialisation mechanism was often interpreted as a representation of *economies of scale*: the more an agent performs a task, the better that agent becomes in performing it. It was pointed out that this should be referred to as a type of *individual learning* as opposed to economies of scale, because agents execute a task repeatedly, not at a larger scale. Production functions that allow for economies of scale need to be non-linear to allow for decreasing marginal cost to scale. However, this requirement conflicts with the implementation of the SpecialNet exchange algorithm. Orders are executed one at a time and cover only one unit each, therefore the model does not afford the accumulation of orders of any scale greater than one so that economies of scale by this definition cannot be obtained. The second issue - limitless resources - addressed another fundamental assumption in the model. It did not model the production process itself, but focussed on the exchange and the specialisation pro-

cess. As a side effect, nothing constrained the efforts that agents commit to the production of a good, as long as the agent is paid for its efforts. Not only is this unrealistic, but it also precludes from the model many other mechanisms that have been shown to drive the development of business networks, including cooptation, prioritising and risks associated with the scarcity of supply.

## **5.4 Résumé of the Model Development Process**

This sequence of models shows the progression of the project as it evolved over the duration of three and a half years. Starting out with the objective to better understand the development and evolution of business relationships and networks as complex adaptive systems using agent-based modelling, various models were developed, adapted and discarded again. In this process each step led to new insights and a better understanding of the task at hand, the tools available and the obstacles on the way. This learning process included aspects of model design and content, more methodological considerations about epistemology, validation and quality criteria of the model and last, but not least an improved understanding of the capabilities and limitations of agent-based modelling. The results - or better, the current state - of these deliberations and insights is presented in Ch. 2, but a brief review of the process may better motivate why certain paths were taken and others avoided on the way to the model presented in Ch. 7.

The main question that drove this exploration and development process was “how to make a good model” of a business network, however, without having a clear conception of what “good” might mean in this context. Two separate reviews were conducted, the first mapping out the existing knowledge of the behaviour of business actors in a networked environment, the second identifying existing models that address related issues. Summaries of these are given in Chapters 3 and 4. From these reviews we gather existing insights about the mechanisms that drive business relation, and how this knowledge has already been applied in other models. Many of these models seem to use Ockham’s razor as a guideline for their model design. Following this law of parsimony, they try to make as few assumptions as possible to construct their model. Among these models are Tesfatsion (1997); Zimmermann & Eguíluz (2005); Hanaki *et al.* (2007); Axtell

(2005); Wilhite (2006) and many others. The initial models here followed the same kind of thinking, building models like the BankNet and the other models of select mechanisms based on the principle of parsimonious model design. As it turned out, in the case of business networks, this approach is rather problematic, mainly for two reasons: validation and explanatory value.

Accounts about what constitutes *appropriate validation methods* diverge, ranging from theoretical argumentation to comparison with empirical data by statistical means (see e.g. Carley, 1996; Moss & Edmonds, 2005; Küppers & Lenhard, 2005; Marks, 2007; Midgley *et al.*, 2007; Ormerod & Rosewell, 2009; Railsback & Grimm, 2011). Irrespective of the many diverging views about it, validation is in essence concerned with questions about the degree to which the insights gained from a model are applicable to the real phenomenon. Answers to this have to take into account the phenomenon investigated, the existing knowledge about it and of course the method used. Agent-based models can be validated on three levels: input data, output data and the model content itself, and the diverging validation philosophies put different emphasis on each of them. Data as input can be used to calibrate the model to a particular scenario, for instance re-creating a concrete real-world situation. The output data of the model can be compared to data about the original phenomenon, and the qualitative or quantitative agreement between these two then assesses model validity on this level. Input validation is only feasible when data is available for comparison with the model output. Lastly, the model content is the implementation of a theory in computer code; therefore validation requires a theoretical argument about how this model and the theory fit in with the existing body of research and existing theories.

Surveying the available body of research regarding business relationships and networks, it became apparent that *plenty of knowledge and theory is available* concerning the individual actors' behaviours and decision making, and also that many of these call for a dynamic and networked perspective. At the same time not much data is available about the development of such network structures over time. The quality of information available is totally different from other disciplines that also apply ABM and CS thinking, e.g. ecology or social biology. The only available longitudinal data set of the same network at different points in time is transaction data from the Japanese car manufacturing industry (Luo *et al.*, 2011, Forthcom-

ing), which contains snapshots from 1983, 1993 and 2001. Despite gaining access to this data set, it was decided that it is ill-fitting for validation purposes of the existing models, as it is too specific. The Japanese car industry is renowned for an idiosyncratic cooperation/management practice called *Keiretsu*, characterised by very close cooperation and knowledge transfer between companies and blurred boundaries of ownership between them (Ellram & Cooper, 1993; Ahmadjian & Lincoln, 2001).

Looking at the models developed in the first phase of this project, the lack of data for output validation was concerning. The data available restricts potential validation strategies to the reproduction of very generic aggregate patterns, such as the mere existence of an exchange network, or the successful specialisation and division of labour among agents or the realisation of economies of scale. While a case could be made for the models on this basis alone, it would not be strong. Moreover, parsimonious models deliberately make strong simplifications, including only selected mechanisms and limiting the agent behaviour to a minimum of activities necessary to model only the mechanism(s) in focus. Examples of this are adaptation in relations in the Sticky Relations model, communication in Spread of Reputation and specialisation and exchange in the Networks of Specialists. Isolating mechanisms is common practice, as the model review in Ch. 4 shows, and choosing the right level of abstraction and simplification is one of the main challenges in the design of ABMs.

Abstractions are made to work out the essential drivers in a system, in order to make models easier to understand and analyse than the original. Nonetheless there is always a trade-off between abstraction and realism. Each step of abstraction to some degree disconnects the model from the real system, leaving it to the researcher and his peers to decide where abstractions can be made so that the model maintains its relevance to the original system, and which are suitable assumptions to make if gaps in our existing knowledge need to be filled to implement the model. Parsimonious models are very abstract, claiming to make only a few assumptions about actors' actions that are then sufficient to reproduce - and explain - emergent phenomena. Nevertheless their minimal assumptions impede the model validation on the level of theoretical content, exactly because they represent agent behaviour in a very abstract, reduced way. In light of the knowledge

base available on business networks, parsimony as a guiding principle started to appear less and less ideal.

In parallel to the implementation of the first parsimonious models, and during a phase of learning about the plethora of existing models, the author developed a better understanding of how agent-based models differ from other modelling techniques, which eventually led to the perspective illustrated in sections 2.2 and 2.3. However, this improved understanding only led to question the *explanatory value* of the models developed to that stage. From a perspective of Analytical Sociology, ABM has the potential to model the social mechanisms that cause the emergence of a social phenomenon. It models the constellation of actions and interactions of actors in a population and computes how these develop over time, thereby *explaining causally* how a social phenomenon is brought about. This is a fundamentally different kind of thinking from statistical models, for example.

On one hand the explanatory value of ABM lies in the way they reproduce the original system on the level of causal relations, modelling how one thing leads to another as agents act and interact with each other over time. On the other hand, through abstraction of details of the original system, ABM help simplify the system under consideration and focus the explanation only on the essential parts. To construct such a causal model the system is decomposed into its constituent entities and activities and then, using analytic abstraction, the crucial entities and activities that bring about the phenomenon in question are isolated. From this epistemological perspective, there is a danger that models become *too simple*, as they abstract away essential parts of the system and end up modelling - and explaining - a different system altogether. At the same time there is a danger that models include too many mechanisms, which can make them difficult or impossible to understand. After all, it appears that a good model is a model that finds a good balance between these two diverging constraints.

Reviewing the state of the project's development process at that stage, it appeared that all the parsimonious models that had been implemented fell subject to the first problem. These models were unrealistic despite better knowledge. They abstracted too much so that they impeded their explanatory power. Aggravating this problem was the lack of data to validate both their outputs and inputs, so that the only viable way of validation was the solid theoretical foundation of

their content. But, following the law of parsimony this content was very abstract, describing aspects of business networks in an artificial isolation that just do not occur in isolation in the real world. It seemed hard to make a case for the scientific value of these models after all.

Struggling with these issues it became apparent that parsimony is a rather ambiguous concept in the context of ABM. There is a difference between what could be referred to as *technical parsimony* and *theoretical parsimony*. Technical parsimony refers to the complicatedness of the model in terms of algorithms employed and the number of parameters included etc. It seems likely that this kind of thinking comes from mathematics and mathematical modelling where generality of a proof or statement is high, the fewer assumptions are required in order to derive it. And the quality of a proof is higher the more general it is. Another reason is given by Midgley *et al.* (2007) in their plea for *minimalist models*. They refer to technical reasons of verification and model assurance that dictate to build models with as few parameters as possible. Contrastingly, theoretical parsimony refers to the quantity and strength of assumptions required to construct the theory underneath a model. This interpretation of the term parsimony is much closer to the original meaning of the heuristic referred to as Ockham's razor, that demands to select from among competing theories the one which makes the fewest assumptions. Applied to model design this would mean that theoretical parsimony addresses how far the simplifications and abstractions in the implementation remove the model from what is known about the original system. Thus, parsimony may mean something very different depending on whether it refers to models or theory. These two interpretations may not be irreconcilable, but at least there appears to be a certain tension between them.

To the largest extent the models reviewed in Ch. 4 are very parsimonious regarding their technical assumptions, but rather intense when it comes to the strength and number of theoretical assumptions they make regarding human capabilities, actions and interactions. They often make strong theoretical assumptions about the agent behaviour for technical reasons, in order to simplify the underlying mathematics and minimise the number of parameters that govern the model's behaviour. Likewise, the models that were developed at the beginning of this project were parsimonious mainly in the technical sense, following the examples of those

models dominating the existent literature. Considering the available knowledge base in the case of business networks, which includes detailed accounts of the actors' activities and interactions and the scarcity of data to validate the aggregate network output, this strategy to model design does not appear to make the best use of the information available.

With this new perspective the task at hand appeared in a new light. ABM are useful to improve our understanding of how the interactions of many agents lead to the emergence of social phenomena. The social phenomenon investigated here is the emergence of a business network where actors specialise and coordinate their production and marketing activities in a self-organised way, without central coordination, and only with limited local knowledge and influence. However, the lack of longitudinal data about business networks impedes the possibility to validate the model outcomes quantitatively. Nonetheless much is known already about the actors' individual actions and interactions in the system. Abstract, technically parsimonious models require validation on the basis of their outcomes, because for a better understanding of the model and to keep the elements that determine the model behaviour at a manageable level, they simplify and abstract wherever possible. At the same time, the simplification made for technical parsimony are often very strong theoretical assumptions reducing the explanatory value of the theory associated with the model. With hindsight, the solution to this problem may seem obvious: in order to have a model that is understandable, yet affording validation based on its content as well as qualitative outcomes, technical parsimony must be sacrificed for implementations of mechanisms that are well-grounded in the existing literature. These would not be technically parsimonious, but they would be as close to the real system as possible. The danger of creating a model with too many parameters could be countered by choosing the underlying mechanisms so that the majority of variable elements in the model can be sensibly informed through theory, so that the variable parameter space that needs to be explored for a satisfactory understanding of the model remains small. The aim was now to build a model that makes as much use of the available knowledge as possible, creating a tool to extrapolate what kind of emergent behaviour can arise from well understood micro-interactions. This strategy would simultaneously benefit the validity of the model content.

Following this realisation, the task at hand was to build richer models of the actions and interactions in business networks, based on the mechanisms discussed in Ch. 3. Still, it was clear that not all these mechanisms could be included in the first model. The development and analysis of such a comprehensive model would be beyond the scope of a single thesis. Therefore, it was necessary to select for implementation a suitable combination of mechanisms that capture the essential activities of actors in a business network. The BusiNET and the SpecialNet models were major development stages in an ongoing process of refinement and readjustment of the model, which eventually led to the model that will be presented in Ch 7. Both models focussed on the aspects of specialisation and exchange that could lead to division of labour and the formation of a business network, trying to represent these as realistically as possible. They did however still make strong simplifications, especially regarding the production process and the certainty with which they could identify prices and superior exchange solutions.

Serendipitously the discussions of existing models brought attention to a series of experiments (Crockett *et al.*, 2009; Kimbrough *et al.*, 2007, 2008, 2010) and a related agent-based model (Kimbrough, 2011) about the development of specialisation and exchange as a discovery process. These works by Vernon Smith and others use an artificial production setting and investigate the behaviour of human subjects as they discover their productive capabilities and ways to coordinate their production in order to realise economies of specialisation. These works are very specific with regard to the situation they model: economies with a small number of actors producing maximally two or in a special case three different goods. The details will be presented in the following chapter. Relevant for the project here is that their work provides an abstract production setting that can be implemented in an agent-based model and at the same time, they documented how actual people act and interact in a setting like this. Their settings and insights can be used as a benchmark case to calibrate a model against.

Fortunately, Smith and his collaborators have not yet exhaustively explained how specialisation and division of labour is brought about. The model by Kimbrough (2011) is very specific to the settings in the proceeding experiments. In its current implementation it is only able to model an economy of two goods, an therefore unable to represent a situation where a group of diverse specialists has

to coordinate their activities. To some part this is already due to the settings in the experiment but also several crucial procedures in the model are implemented so that there appears to be no straight-forward way to generalise them, without creating a completely different model. Consequently, the model developed here draws on both the existing experiments and the existing model, but it will remain independent, focussing on explaining the coordination in a diverse business network. For validation purposes, the previously reviewed mechanisms will inform the agents' behaviour and the situation in the experiments will serve as a benchmark. The model will include the experimental setting as a special case, but it will be able to go far beyond that.

## **Chapter 6**

# **Research about the Evolution of Specialisation**

Business networks as they are described in Sec. 1.1 are informal institutions that coordinate the participants' actions and interactions in the process of production and marketing. Each of the participants has its own role that is a result of its capabilities and resources, its history, its partners and its position in the overall network. From this perspective the concept "business network" refers to the structure of interactions of its members, including their social and economic dimensions: flow of goods, resources and information, personal relationships, trust, reputations and many more. Existing research (as summarised in Sec. 1.1) emphasises the importance of social aspects in these networks that often make them distinctly different from anonymous mass markets. It is the core position of this thesis that a business network is the manifestation of a self-organising evolutionary process that allows participants to specialise and reap efficiency gains from the division of labour, because it creates relations between actors that reduce the costs, risks and uncertainties associated with the coordination of specialists. The reasons for this improved coordination are manifold and work on different levels: repeated exchanges can become routine, contracts better define terms of exchanges, continuous flow of information leads to improved understanding, emotional bonds between actors encourage cooperative behaviour etc. The central mechanisms associated with relationship development in business networks were presented in

Sec 3.3. So far, research is scarce regarding the effects of these social mechanisms on the aggregate, the network level but evidence suggests that their impact on economic activity is much stronger than common models of atomistic markets and anonymous exchange give them credit for.

Section 2.1 introduced an evolutionary theory of economic change put forward most prominently by Douglas North (2005). The essence of this theory is that economic change is an open-ended, yet path-dependent adaptive process during which formal and informal institutions are developed as partial responses to selective pressures and constraints. Apart from technological progress, it is these formal and informal rules of economic interaction that determine the performance and progress of an economy and society as a whole. As these institutions evolve continuously over time, they each lay the foundations to their successors, directing and restricting the range of possible next steps. The present combinations of beliefs, institutions, demographics and physical environment constitute the foundations for the society's next generation. From an evolutionary perspective, the advantages of such a system of social institutions lie in the reduction of uncertainty and risk affecting human production and lives. By creating an artificial structure of culture and social bonds, human societies have reduced the impact of uncertain environmental factors on their lives substantially, substituting dependence on each other for their dependence on uncontrollable environmental events. A wide range of formal and informal institutions allow people to rely more on each other, coordinate their actions and lay the ground for specialisation and a fruitful division of labour. These institutions include laws and contracts and their manifold enforcement mechanisms, but also means to social control like reputation, as well as trust and the dependability of promises, handshake agreements and many others like these. Relying on these institutions people regulate and structure their economic interactions, as detailed in Sec. 1.1, this can reach the of complexity exhibited in modern business networks.

This evolutionary perspective on economic change and the path-dependent development of economic systems including business networks is a comparatively novel way of looking at phenomena in economics and marketing alike. We are only in the early stages of developing the concrete theoretical underpinnings to formulate scientifically relevant questions and empirically falsifiable hypotheses

about the matter. Conceptualising the development of a business network as a self-organising emergent result of the decisions of individuals raises many new questions about the processes involved, the relevant time scales, the system's potential of growth, the interdependence of stages of development and the system's health and resilience towards external shocks. Agent-based models play an important part in this process of theory development as they help us develop a better intuition about the complex interactions that bring about emergent phenomena in complex systems over time (Bedau, 1998). Thereby ABM complements and extends existing methods of scientific inquiry and is likely to attract more attention in the foreseeable future.

Specifically regarding the evolution of specialisation and division of labour, an exemplary attempt to model the discovery process of specialisation and exchange was undertaken by Erik O. Kimbrough (2011). This article was published in a very timely fashion, and in fact it was pointed out to me as a potential remedy for the problems identified in the SpecialNet model. Recall that the models presented in Ch. 5 developed consecutively through the learning process that reflects the development of this thesis: from rather abstract models of few isolated mechanisms to more realistic models that were richer and more realistic in terms of the mechanisms they included. After various adjustments and reconfigurations, the last model - the SpecialNet - already exhibited interesting behaviour in terms of the competitive and cooperative behaviour of agents, depending on the structure of their interaction. However, there were still unresolved issues regarding the suitability of abstraction regarding the agents' way of production, especially the implementation of economies of scale and overly simplifying assumptions about resource restrictions and production capacities. Kimbrough's model had exactly that - and more. It combined insights from a series of laboratory experiments (Crockett *et al.*, 2009; Kimbrough *et al.*, 2007, 2008, 2010) in which subjects had to "discover" specialisation and division of labour under various institutional settings. Kimbrough derives the implemented mechanisms from models of rational choice, machine learning and chat protocols that were part of the experiments in an attempt to represent the agents' decision making realistically. Through this effort Kimbrough's model provides a tested and well understood economic framework for the production aspects of similar models, and at the same time it can serve as

a benchmark case for comparison and calibration of models that are more generic and expandable, like the one developed here.

The remainder of this chapter will be used to motivate and introduce the final model of the development and evolution of business relationships and network. As it is in many aspects an extension of the model developed by Kimbrough, the first step will be to introduce the experiments that are the basis for Kimbrough's efforts. These were conducted by Nobel laureate Vernon Smith, Kimbrough himself and their colleagues at the George Mason University in Fairfax, Virginia. The basic economic parameters are the same for the experiments and Kimbrough's model, and they will be a special case of the model developed here. Also, a brief review of the experimental treatments and their results will be given. These are of interest here, because they describe the economists' perspective on the evolution of specialisation and division of labour. It is remarkable that, despite their focus on formal institutions such as definition and enforcement of property rights, the experiments' results show that it is the personal relationships, individuals' sense-making and communication that determine the experiments' outcomes. These findings are consistent throughout the experiments and reconfirm the position taken in this thesis, namely that it is the social aspects and informal institutions that affect the success or failure of business networks. After the description of the experiments, Kimbrough's model will be introduced in detail, providing the basis of comparison with the final model developed here, in the next chapter.

## **6.1 Vernon Smith's Experiments**

The evolutionary perspective of economic change implies that economic systems develop in a path-dependent manner, where the formal and informal institutions at any given point in time are among the key determinants of the trajectories that the system can take from there. So far, our knowledge about the developments and transitions that lead from one system of institutions to another is limited at best. Crockett *et al.* (2009) identify one critical juncture in the development of an economic system as the transition from self-sustained autarkic production to a system of specialisation and division of labour. At this crucial point of transition, members of a society learn how to rely on each other and through their coordinated

efforts achieve unprecedented economies of specialisation: In North's theory of economic change this is an important step towards the establishment of a framework of social institutions that fundamentally changes the relationship between individuals and their environment. However, there is nothing automatic about such a transition being successful and it must be assumed, that at that point in time, future implications and consequences are not clear to all the members in the system. The Nobel laureate Vernon Smith and his colleagues identified the gap of knowledge in the economic literature about this critical transition point and set out to investigate how a society can learn to specialise in a series of laboratory experiments (Crockett *et al.*, 2009; Kimbrough *et al.*, 2007, 2008, 2010). These experiments were deliberately set up to minimise the influence and restrictions on their participants, so that their actions and interactions give insight into the *process* that leads to specialisation, or not.

The underlying question of all these experiments is "How might any exchange institution emerge in an environment in which specialisation pays but there are no exogenous institutional guidelines or third party enforcement of agreements?" (Crockett *et al.*, 2009). Detailed records of the exchange activities and communication among participants allow them to examine the process of discovery of exchange and specialisation opportunities, as those involved discovered the comparative advantages each had in producing different products and the potential gains from trade. The experiments are interrelated and some are extensions of or precursors to others - which is however not reflected in their publication dates. The central piece is Crockett *et al.* (2009), henceforth CSW, which investigate the discovery process of exchange and specialisation in a simple economy where two goods are produced and consumed by a group of people that are heterogeneous with regard to their productive capabilities and their consumption preferences. The treatments here address the search process for suitable exchange partners and the effects of information available to participants regarding their productive capabilities. Kimbrough *et al.* (2010) uses the same economic setting, but removes institutional property rights from the system, so that members can access goods of other members without their consent. Kimbrough *et al.* (2007) has more exploratory character, analysing the results of one experimental session that simulates an economy with three goods, where participants are grouped by

their productive capabilities: each group is able to produce two of the three goods and with some of the members capable of travelling to a market place to barter for the third, missing good. The emphasis of this experiment was on the discovery and development of interpersonal trade in addition to personal exchange. Lastly Kimbrough *et al.* (2008) investigate the effect of institutional histories on the emergence of interpersonal trade. In a two-day setup, the experiment first introduces participants to the simulated environment of a two-goods economy, in one treatment with, in the other without property rights. On the following day, these two treatment groups resume their interactions in a new economy like the one in Kimbrough *et al.* (2007), with three goods and property rights in place for everyone. After the detailed description of the base-line setting of CSW, a brief review of their findings will be given.

The economy in CSW consists of two, four or eight participants that each are assigned a certain “type” which defines their production capabilities and the utility function that drives their consumption with regard to the two goods (red and blue) available in the economy. These types are called *odd* and *even* and in each experiment there is an equal number of each type. Both agent types have Leontief preferences over  $r$  units of red and  $b$  units of blue:

$$U_{\text{odd}} = \min(r, 3b) \quad U_{\text{even}} = \min(2r, b)$$

This means that an even participant who obtains  $5r$  and  $10b$  for consumption will gain utility of 10, just as a participant with  $5r$  and  $20b$  and a participant with  $20r$  and  $10b$ . The lower number will decide which level of utility can be realised, and excess units go to waste.

Leontief preferences are chosen to reduce the cognitive processing load for participants, because they have no external means like reference tables, or calculators to derive expectations of their utility. The preferences are set so that they favour the safety of home production relative to complete specialisation at the risk of failing to find trading partners.

In each round participants have to allocate ten units of time  $t$  to the production of  $R$  units of red and  $B$  units of blue. The production functions are

$$\begin{aligned}
 R_{\text{odd}} &= [13/(10\sqrt{10})]t^{5/2} && \approx 0.41t^{5/2} \\
 B_{\text{odd}} &= \frac{1}{10 - (300\sqrt{10}/13)^{2/5}}(10 - t) && \approx 2.25(10 - t) \\
 R_{\text{even}} &= [13/(10 - \sqrt{260/11})]t && \approx 2.53t \\
 B_{\text{even}} &= (11/10)(10 - t)^2
 \end{aligned}$$

Apart from the size of the group, the experimental treatments address the knowledge of participants regarding their production functions. They vary between *unknown* where they only get to observe the production outcome of their time allocation and have to work out for themselves what they are capable of, *known* where a complete production table is provided displaying all possible combinations of outcomes and lastly, *recall* where a blank production table is provided and filled gradually with the production results realised. This parameterisation was chosen to make specialisation risky but potentially quite profitable. Based on the Leontief preferences complete specialisation in the absence of exchange will result in a payoff of 0, compared to a maximum of 26 and 30 that they could realise in autarky. The competitive equilibrium would require complete specialisation of odds and evens in combination with exchange after production, leading to realised utilities of 80 and 90 units.

The simulated environment contains a field and a house symbol for each group member and a central chat room where they can exchange messages throughout the experiment. Production happens on the field symbol; where at the beginning of each round symbols for the produced goods appear. Consumption occurs in the house. Participants are informed that they can move goods in their field using their mouse, but they are not informed that they may drag and drop icons into the houses of others as well. The formulation that is chosen is that their payoff is based on “items that have been moved into your house”. Goods that are not consumed at the end of a round will expire and disappear. The experiment lasts for six periods, each consisting of six rounds of 100 seconds for production and exchange, followed by a 100 second break where participants can focus exclusively

on communication in the chat room. They are left to discover their production potential, their ability to exchange as well as the most efficient allocation of resources and the “prices” of exchanges.

CSW’s findings indicate that exchange is generally characterised by a growing number of bilateral relationships that persist over time. A small majority of participants either settle in autarky or specialise to their comparative advantage immediately. The remaining participants typically do so over the course of time, and most substantial and sustained exchange occurs between appropriately specialised participants of the opposite type. The exchange relations are highly personal and social. Even when alternative sources are available, the participants are hardly tempted to explore other options and they remain loyal once they find a suitable partner. From the economists’ perspective it is remarkable that the economies did not develop a multilateral double auction to organise exchange, which is usually associated with markets organised by institutional setting in the experiments. Over the duration of the experiment, participants discover efficient product allocations where few gains from exchange remain unexploited and few participants could earn higher profits by unilaterally deviating from their level of production. However, this does not mean that all economies reach the competitive equilibrium which requires both full specialisation in producing the comparatively advantaged good and then exchanging with a suitable partner. There are economies that do not - or only slowly - discover and exploit their ability to exchange and therefore cannot realise their specialisation potential. This effect is particularly pronounced in sessions with only two participants, but eight participants are also less likely to discover exchange compared to four participants. In the eight-person economy, this effect can be attributed to the increased difficulty of finding a matching partner for exchange. This was tested in a scenario where a group of eight was consecutively assembled from four groups of two, over two groups of four, to one group of eight. This treatment called *Build8* reduced search costs and led to an increased utilisation of exchange and higher degrees of specialisation. In the two-person economies it is a matter of discovery, either participants become aware of the possibility of exchange and exploit it early on, or they remain unaware of it throughout the experiment. Treatments regarding the participants’ knowledge

about their production functions did not show substantial effects on the experiments' outcomes.

CSW summarise the discovery process that leads to the competitive equilibrium in these exchange and production economies in three steps:

1. Arriving at the idea to trade, which may require 'mind reading' (inferring thoughts from words and actions) and imitation (limited to 4- and 8-person economies),
2. Finding a suitably endowed trading partner with whom one can benefit from the power of exchanging through specialisation, and
3. Building the relationship by increased specialisation over time.

The next experiment presented in Kimbrough *et al.* (2010) adds another component to the discovery process of specialisation and exchange: the lack of formally defined and enforced property rights, referred to as the *Steal* treatment. The authors reason that from an evolutionary perspective, property as an institution is a necessary requirement for the development of exchange and therefore investigate what happens in a simple economy if property is not enforced. The experimental setup here is exactly as in the *Build8* treatment of CSW, only that it is possible for each of the participants to move goods from any field or house. However, they still need to discover that they can take goods from others, just as they must discover that they can give, exchange and specialise. Theft is not a given, but once discovered, no exogenous constraints prevent it.

These experiments provide many insights, again pointing to the importance of social aspects in the understanding of economic exchange. Most prominently, each of the six experimental sessions develops in its unique way, shaped by the participants' sense making, communication and interaction. The variance of outcomes across sessions increases substantially. Under the *Steal* treatment the average rate of specialisation is significantly higher in the first weeks compared to the results in CSW. However, this advantage is eliminated by the end of the experiments. This may be explained by the fact that many participants interpreted their ability to *take from* others as another method of settling barter, analogous

to the act of *giving to* someone. Consequently, participants have two ways of discovering exchange and are therefore more likely to realise its benefits, including economies of specialisation. This finding is further supported by the fact that the volume of exchanged goods under the *Steal* treatment is substantially below the levels observed in CSW when looking only at goods that are given from one participant to another. However, the differences disappear when the taking of goods under mutual consent is accounted for.

Turning to the efficient allocation of produced goods, the average shows no significant difference in the first three rounds between CSW and the *Steal* treatment. However while CSW find that waste is minimised towards the end of the experiment; it increases substantially under the steal treatment. Primarily, this effect is caused by a few sessions in which stealing becomes the dominant method to acquire goods. One session, which is distinguished by its lack of sociality and communication in the chat room, starts with stealing, continues with stealing and ends with stealing, as a war of everyone against everyone else. Two other sessions discover stealing in the course of the experiment and do not manage to contain it. At first, individual members try to argue for a cooperative solution, but they themselves cannot resist the temptation of theft. Once they lose their moral high ground, and their arguments appear to others merely as “cheap talk” the groups lose trust in one another and their economies go to ruin. Scattered pleas for cooperation are drowned out by uncontrolled theft. These sessions stagnate regarding their degree of specialisation and exhibit substantial waste of goods at the end of each round. In the fourth session, theft is spreading in one group of four, while the other explores the possibilities of cooperation and exchange. After the merger of both groups, the participants argue in the chat room, even using social pressure to get unwilling parties in line. Eventually they manage to convince each other that cooperation would benefit them more and that they should therefore cease to steal. The fifth session starts out cooperatively, although one group of four struggles to coordinate their production efficiently. Once the participants are joined to one group of eight, the four successful cooperators share their knowledge about specialisation and together all participants thrive and realise near optimal outcomes. The last session also achieves extremely high levels of specialisation; however, it does so with one participant outlawed from the rest of the group. The outlaw

cannot be convinced to cooperate but keeps on stealing from others, despite their attempts to reason with him and ultimately his exclusion from cooperative exchange. The group settles in a state where the outlaw steals from everyone else and all the others steal predominantly from the outlaw while generally engaging in barter amongst each other. 70% of all theft involves the outlaw in one way or another.

Kimbrough *et al.* (2010) also report the results of additional sessions, introducing three mechanisms of protection against theft to the institutional setting: the first mechanism allows participants to hide from the actions of select individuals at a cost, second, one of the participants is selected to become a sheriff, able to protect himself and/or others at his own expense, and last, the possibility to make a publicly displayed and binding pledge not to steal. The experiments show that these private protection mechanisms tend to worsen outcomes on average. Private protection or commitment mechanisms seem to encourage opportunistic theft, which in turn begets spiteful retaliation, followed by more theft and more retaliation. At best, they were made redundant as the group develops other solutions to solve their coordination problem.

Across all these treatments, it becomes apparent that in order to establish an efficient production system, informal institutions are paramount. At the onset a group must view itself as a community, so that the informal institutions that they establish to coordinate their actions become binding in character. In a second step they must understand how exchange brings about mutual gains and that therefore respecting property is in their own interest. This process of convincing requires that those who make these claims lead by example, respecting the property of others and improving their station through exchange. At the same time others must be receptive to arguments about cooperation and then must be willing to conform to the group's convention. The mechanisms that can be observed to contribute to the development of a successful economy include communication, establishment of trusting interpersonal relationships, authority and the organisation of credible social pressure. On this basis, it is possible to evolve property rights endogenously and in turn establish successful exchange relations and realise economies from specialisation.

The next article, Kimbrough *et al.* (2007), extends the scenario in CSW towards a more comprehensive exchange system. The new experiment simulates an economy with three goods for consumption in a spatial environment where three groups of four participants form “villages” and can engage in exchange and mediated trade with each other. The villages are identical to medium sized groups in CSW. However, that means that each of these villages is capable of producing only two of the three goods. Participants have to discover that two of each village’s members, so-called “merchants”, can travel to a designated area between the villages to meet other merchants, chat with them and ultimately exchange goods there. The production functions are analogous to CSW, allowing participants to produce either blue-red, blue-pink or red-pink, depending on the participant’s home village. The consumption functions are extensions of those in CSW, adding the third good, that can only be acquired from other villages, as a multiplier  $\pi(x) \in [1, 2.88]$ . This means that the results of the previous (two good) Leontief utility functions are multiplied with  $\pi(x)$  which is a monotonically increasing function of the number of units of the third good that the participant obtains. As a result, participants can nearly triple their utility if they obtain enough of the third good.

The productive capacity of merchants is reduced by half, compared to the members of their group that are unable to travel. The authors assume that these new utility functions give a strong incentive to acquire the third good. The experiment then focusses on the process through which specialisation, personal exchange within the village and impersonal exchange between merchants is discovered and developed.

Kimbrough *et al.* (2007) present the results of only one experimental session with twelve participants. Two of these three villages discover and largely exploit their capabilities to specialise, exchange and trade with each other. However, the third village, despite discovering these capabilities, cannot agree to cooperate and exchange amongst themselves, and their merchants leave to trade only their own goods in the common meeting place. The experimenters observe, that the participants’ development and learning process is not driven by their ambition to maximise outcomes, but rather they occasionally hit on a constellation that “seems to work”, and then behavioural inertia sets in. They satisfice, rather than optimise

and they are creatures of habit. Regarding their communication and the social aspects of the economic system, it is remarkable that the exogenous grouping into villages seems to have a substantial effect on the participants' interactions. Within their village, the communication is personal and casual in nature. Especially the two more successful villages develop a sense of community, cooperation and implicit trust. Towards the end, goods are exchanged without further communication on a routine basis, as participants have learned which tasks they have to perform to be successful as a team. Returning merchants take a small cut for their services, but otherwise distribute the third good amongst their peers voluntarily. The personal nature of their interactions seems to mitigate excessively selfish behaviour in the villages. Contrastingly, the interactions between merchants from separate villages do not reflect any personable behaviour. In the merchants' chat room no sense of community arises, and the conversation consists mostly of price quotes and negotiations. For example, the term "we" that occurs frequently in the village chat rooms is not used at all. Lastly, it is remarkable that within successful villages, participants share advice and recommendations to improve their production and they also discuss that the third village seems to be struggling in this regard. However, there is no single attempt to help the merchants from the third village in the merchant chat room, even though that would have improved the supply of goods for everyone. In this experiment decisive in-group out-group thinking dominated the participants' interactions.

The last set of experiments in Kimbrough *et al.* (2008) investigate another aspect of North's evolutionary theory of economic change, namely how past institutional and social histories may affect the developmental possibilities of future social arrangements. The experiment takes participants through two stages, on two consecutive days. In the first stage, they get to go through any of the treatments reported in CSW or through the Steal treatment of Kimbrough *et al.* (2010). These two treatments are referred to as "Property Rights History" (PRH) and "No Property Rights History" (NPRH). The main experiment is then conducted on the second day: Maintaining a division by treatment, the first day's groups are merged to groups of twelve and then allotted to villages in the style of Kimbrough *et al.* (2007), which means that property rights are enforced for all groups on the second day. The experimental setup remains unchanged except for a small variation of the

consumption functions. The effect of the third good that must be obtained from another village is again included through multiplication, but this time they use a step-wise multiplication function. For example, the participants in the village that can only produce red and blue will generate the following levels of utility from their goods, depending on their number of units  $p$  of the pink good:

$$U_{\text{odd}}^{r,b,p} = \begin{cases} 1 \cdot \min\{r, 3b\}, & p < 2 \\ \frac{7}{8} \ln(p+2) \cdot \min\{r, 3b\}, & \text{if } 2 \geq p < 26 \\ 2.91 \cdot \min\{r, 3b\}, & p \geq 26 \end{cases}$$

$$U_{\text{even}}^{r,b,p} = \begin{cases} 1 \cdot \min\{2r, b\}, & p < 2 \\ \frac{7}{8} \ln(p+2) \cdot \min\{2r, b\}, & \text{if } 2 \geq p < 26 \\ 2.91 \cdot \min\{2r, b\}, & p \geq 26 \end{cases}$$

The overall question then asked in this experiment is how the two distinct institutional histories regarding property rights affect the evolution of specialization and exchange.

The results show that the treatments have an effect on specialization and exchange, but indirectly, through their promoting or inhibiting effect on the development of interpersonal relationships and informal, social institutions. Although specialization and the creation of both personal and impersonal exchange networks are observed under both treatments, the history of unenforced property rights hinders the participants' ability to develop personal social arrangements and effectively exploit impersonal long-distance trade. Exchange networks develop to highly varying degrees and appear to depend strongly on the members' interpretation of their situation and their sense-making. The economies under the NPRH treatment show deficits regarding their wealth as well as the equitability of their distribution of earnings and they are much less specialised than their PRH counterparts. In the chat room transcripts it becomes obvious that the cause of this is the lack of sociality in the NPRH sessions. Communication in NPRH villages is less personal and community-minded than PRH villages and the members' interactions imply a lack of trust between them. Consequently NPRH groups do not approach their consumption and production issues cooperatively. Analogously to

Kimbrough *et al.* (2007), Kimbrough *et al.* (2008) find that across treatments there is a divide between personal exchange in the villages and impersonal exchange in the merchant area. Merchants hardly learn from each other or imitate successful behaviour and get together “only to do business”.

## **6.2 Kimbrough’s ABM of the Discovery of Specialization and Exchange**

Specialization and exchange are the bedrock of economics. As Adam Smith (1776) first noted, wealth is created through the division of labor, and the extent of that division (thus wealth) is limited by the extent of the market. [...] While economics was built on these insights, scant attention has been given to the process by which economic agents discover opportunities for welfare-improving exchange and specialization. [...] The crucial fact is that profitable opportunities for specialization are not known a priori but must be discovered as part of a grouping trial and error process, a “discovery process”. Kimbrough (2011, p. 491)

Building on the findings in CSW and the other experiments above, Kimbrough (2011) constructs a formal model of the process of discovery of specialisation and exchange in small-scale societies like those in the experiments. As indicated by the introductory quote, scant attention in economics has been given to the process of discovery and coordination of specialisation, the development of division of labour and the resulting cooperative networks. The challenges in formalising the process, not just its outcomes are manifold: The experiments showed clearly that the participants’ behaviour is far from optimal: they satisfice rather than optimise; they learn through trial and error as well as socially through communication and imitation, their trajectories of development display much variation, both regarding the speed of development and also regarding the efficiency of the final outcome. Kimbrough decides that classical economic modelling tools are unsuitable to formalise the development process of a system that exhibits features like that, and instead chooses to implement an agent-based model.

Kimbrough’s model (KM) focusses strongly on the individual’s decision making and learning process and the reproduction of patterns found in CSW’s original experiment. The main contribution in Kimbrough (2011) is to calibrate the model by exploration of the parameter space, so that its outcomes match the observed patterns of specialisation and efficiency, both regarding their variability and regarding development over time. KM reproduces the settings in CSW’s baseline experiments with eight participants as well as the *Build8* treatment that gradually merged smaller groups until they reach the size of eight. Recall that in this setting there are two types of agents, odds and evens, that differ regarding their productive capabilities and their preferences for consumption and they get to produce, exchange and consume two goods: red and blue. The production functions yield increasing returns to time allocated in one of the two goods:

$$\begin{aligned}
 R_{\text{odd}} &= [13/(10\sqrt{10})]t^{5/2} && \approx 0.41t^{5/2} \\
 B_{\text{odd}} &= \frac{1}{10 - (300\sqrt{10}/13)^{2/5}}(10 - t) && \approx 2.25(10 - t) \\
 R_{\text{even}} &= [13/(10 - \sqrt{260/11})]t && \approx 2.53t \\
 B_{\text{even}} &= (11/10)(10 - t)^2
 \end{aligned}$$

And consumption is modelled through Leontief preferences requiring a relatively higher proportion of one or the other good:

$$U_{\text{odd}} = \min(r, 3b) \quad U_{\text{even}} = \min(2r, b)$$

KM is designed to replicate the process of discovery which includes the temporal development of the system. Accordingly, it is set up to also match the time scales, repeating the process of production, negotiation, exchange and learning for 35 periods (i.e. CSW’s 40 periods minus the chat sessions every seventh day). The agents’ design focusses on the learning processes, employing a number of learning heuristics that are “meant to capture the incremental process by which humans explore and master their environment” (Kimbrough, 2011, p. 494). Their setup is best described as two-layered: one layer for activities and one for learning. Their activities are controlled by internal parameters that determine how they specialise

and whether and with whom they seek to exchange. These first-layer parameters are in turn adjusted internally, through learning processes in the second layer of the agents' decision making processes. The calibration and model analysis focusses on the impact of selected parameters in the second-layer.

For 35 rounds, the model repeats the following procedures, stepwise across all agents:

1. Production
2. Exchange Partner Selection
3. Autarkic Consumption
4. Exchange
5. Update Exchange Probability
6. Update Learning Strategy and Level of Specialization
7. Update Willingness to Exchange

**Production:** Analogous to the use of the production dial in the CSW experiment, every round begins with agents producing the number of goods according to their current degree of specialisation. Each of them gets to allocate  $t = 10$  units of time and produces according to its assigned production function. The degree of specialisation is initiated neutrally between goods and is updated at the end of every round. Agents then store their red and blue goods for subsequent consumption and exchange.

**Exchange Partner Selection:** The next step simulates the partner selection process. It is implemented as a stochastic process in which each agent picks one of the other agents as a prospective partner. For this every agent maintains a list of values that specifies with which probability it will choose each of the other agents. Again, these probabilities are updated at the end of each round. Only if two agents select each other in the same step, will they get to initiate negotiations and exchange in the fourth step. The list of probabilities is initiated uniformly, so that at the beginning of the simulation no agent

has any preference to select any one agent over the others. Over the course of the simulation, the agents will increase the probabilities, increasing the probability to return to partners with which they had favourable exchange experiences, at the expense of those with which they have no experience, and those with whom they could not settle for an exchange. Also, it is possible that an agent gives up on trade entirely and adopts an autarkic stance, should too many exchange attempts prove fruitless.

**Autarkic Consumption:** In the third step, the agents go through a first phase of consumption, using up as many of their self-produced goods as possible and maximize autarkic earnings according to their utility function. This will typically leave them with one good in excess and not more than a couple of leftover units of the other good. These will be the subject of prospective negotiations and exchanges in the next step. Goods do not carry over to the next round. Everything that is not consumed by the end of a round will be wasted.

**Exchange:** If a pair of agents was matched successfully in step two, they will negotiate an exchange in the fourth step. In order to derive a suitable redistribution of their remaining goods, an algorithm determines how to minimize total waste based on their pooled goods and the agents' utility functions. The calculations are performed as an integer-programming problem that is able to identify optimal solutions in finite time. The agents' exchanges conclude the series of interactions and activities and the agents will turn to their learning processes, updating their internal parameters for activities in the next round.

Once the agents conclude their exchanges, each agent  $i$  calculates the overall utility realised in this round ( $t$ ):  $u_i(t)$ . They will then update their selection probabilities for future partner selection  $\delta = (\delta_{i1}, \dots, \delta_{in})$ , their strategic orientation  $l \in \{\text{"short-sighted"}, \text{"far-sighted"}\}$ , their level of specialization  $s \in [0, 10]$ , their current direction of specialisation  $d \in \{-1, 1\}$ , and lastly their general attitude towards exchange  $w \in \{\text{"true"}, \text{"false"}\}$ . KM models these learning processes through a selection of adaptive algorithms which are controlled by the following exogenous parameters.

1.  $e^A \in \{10, 15, 20\}$ : The point of reference to assess utility outcomes in autarky.
2.  $e^T \in \{15, 20\}$ : The point of reference to assess utility outcomes after exchange.
3.  $\sigma = 0.6$ : The specialisation increment.
4.  $\nu = 0.3$ : The trade probability increment. Results reported for KM derived with  $\nu = 0.3$  and are supposedly robust for values of  $\nu \in \{0.3, 0.4, 0.5\}$ .
5.  $\omega_i \in [0, 1]$ : The agents' initial level of conservatism.
6.  $\mu = \nu/2$ : The “conservatism increment”, increases the probability for unsuccessful autarkists to become willing to exchange again.
7.  $\eta_i \in [0, 1]$ : The agents' probability of mimicking successful others.

The status and origin of the concrete values used for these parameters is somewhat debateable.  $e^A$  and  $e^T$  are subject to the experiments in Kimbrough (2011) and are calibrated so that the model reproduces observed behaviour.  $\nu$  is validated through grid search, also. However, the other agent-specific parameters are set randomly ( $\omega_i, \eta_i$ ), and global values ( $\sigma, \mu$ ) are set exogenously, but no reason is given for their specific values.

**Update Exchange Probability:** The first learning step updates the agents' lists of selection probabilities for future partner selection, if they took part in an exchange in this round. This procedure is implemented as an adaptation of *interactive reinforcement* (Skyrms, 2004). The probability  $\delta_{ij}$  of agent  $i$  selecting its current exchange partner  $j$  for future exchanges will be adjusted depending on the realised outcome  $u_i$ :

$$\begin{aligned} \text{if } u_i(t) \geq e^T : \delta_{ij}(t+1) &= \delta_{ij}(t) + \nu \\ \text{if } u_i(t) < e^T : \delta_{ij}(t+1) &= \delta_{ij}(t) - \nu \end{aligned}$$

At the same time the selection probability for all other agents  $k \neq j$  with  $\delta_{ik} > 0$  is adjusted proportionally:

$$\begin{aligned} \text{if } u_i(t) \geq e^T : \delta_{ik}(t+1) &= \delta_{ik}(t) - \frac{\nu}{|\delta_{>0} \setminus \delta_{ij}|} \\ \text{if } u_i(t) < e^T : \delta_{ij}(t+1) &= \delta_{ij}(t) + \frac{\nu}{|\delta_{>0} \setminus \delta_{ij}|} \end{aligned}$$

The decrementing process allows some  $\delta_{ik}$  to fall to zero, and once those probabilities reach zero, they remain so indefinitely.

**Update Learning Strategy and Level of Specialization:** The second learning step adjusts the agents' resource allocation and thereby their prospective level of specialisation. At first, the agent reassesses its strategic orientation  $l_i$  which will determine the reference point to assess the current round's performance. The agent can be  $l$  = "short-sighted" which means that it compares its current performance  $u_i(t)$  to  $u_i(t-1)$ , its performance in the previous round, or "far-sighted", where the point of comparison becomes the minimum requirement for satisfactory performance in autarky  $e^A$ . The strategic orientation is then derived as follows:

$$\begin{aligned} \text{if } u_i(t) \geq e^T : l_i &= \text{"far-sighted"} \\ \text{if } u_i(t) < e^T : l_i &= \text{"short-sighted"} \end{aligned}$$

Kimbrough suggests interpreting these two learning rules as describing an agent's discount rate or their level of risk-aversion in the exploration of their own capabilities.

Once the strategic orientations are set, a modified hill-climbing algorithm determines the next round's level of specialisation. The agents explore their own capabilities by gradually increasing or decreasing  $s_i$ , which indicates the amount of time invested into the production of one of the two goods, while  $10 - s_i$  will be invested in producing the other one. The agents are initiated with a direction of specialisation  $d$  that they will follow until their strategic orientation indicates that their performance falls below a certain threshold. This threshold is either  $e^A$ , their required minimum earnings in

a state of autarky, or  $u_i(t - 1)$ , their profits in the previous round. Kimbrough reports that an exclusively short-sighted focus on the last round's performance has detrimental impacts on the development of specialization and exchange, because agents get trapped too easily in local maxima of their utility function. Therefore he introduces the two levels of strategic orientation where agents are prepared to endure short-term underperformance. The adjustment of an agent's level of specialisation is then conducted as follows:

$$\begin{aligned} \text{if } l_i = \text{“far-sighted” and if } u_i(t) < e^A : & \quad d_i(t) = -d_i(t - 1) \\ \text{if } l_i = \text{“short-sighted” and if } u_i(t) < u_i(t - 1) : & \quad d_i(t) = -d_i(t - 1) \\ s_i(t) = s_i(t - 1) + d_i(t) \cdot \sigma & \end{aligned}$$

**Update Willingness to Exchange:** In the last learning step, the agents evaluate their overall attitude towards exchange, essentially deciding whether they will be available for exchange with others and continue to search themselves or alternatively whether they settle down in autarky and try to optimise their production in isolation. Agents become unwilling to exchange if they attempt to exchange, but perform below their point of reference  $e^T$  in two consecutive rounds. Unwilling agents can however revert back to willing through social learning and imitation. If there is any exchange at all in this round, it is assumed that all unwilling agents are aware of it, and decide through a random process whether or not to try and exchange again. This process is determined through the agents' initial level of conservatism  $\omega$  and a count of the number of times that the agent was disappointed by its performance, relative to its points of reference to assess utility outcomes in autarky ( $e^A$ ) as well as exchange ( $e^T$ ). Let  $x_i$  be the number of times that agent  $i$  performed below its point of reference, then  $p_i = 1 - (\omega - x_i \cdot \mu)$  is the probability that it will turn from unwilling to willing. In addition, whenever such a change of willingness occurs, the agent will initiate a separate second random process and decide with probability  $\eta$  to imitate the specialisation level of one of the exchanging agents or maintain its prior specialisation. Should the random process choose to imitate, the agent will

copy the specialisation level of a randomly selected non-autarkist which can be of the same production type, or the opposite.

For validation purposes Kimbrough (2011) then calibrates the model to match stylised facts from CSW's experiments, using a grid search for all combinations of  $e^A \in \{10, 15, 20\}$  and  $e^T \in \{15, 20\}$ . His own interpretation of these treatment parameters is vague. At one point he motivates them as "proxies for the agent's risk aversion and/or discount rate [...] representing an agent's maximum acceptable risk at any given level of production and conditional on whether that agent acts in autarky or trades." (p. 500) and also mentions that "the origin of these parameters is not accounted for in the model, but they could be described in the literature variously as resulting from concerns for reciprocity, fairness, or social preferences" (p. 494). Higher values of either of these parameters imply that agents will more readily abandon incremental production-space searches once they lead to decreases in earnings, lower values make agents less sensitive to losses and allow them to go further in their explorations.

For validation, KM focusses on reproducing the levels of specialisation and efficiency achieved by human participants in the CSW experiments. Kimbrough looks at overall averages, but also at the stratification of performance and its development over time. For this he repeats the simulation 1800 times for each parameter combination. CSW found average efficiency to be 4.24%, at a mean level of specialisation of 44.49%. The results for several KM parameterisations are represented in Table 6.1.

CSW report strong variation among the groups' with regard to development and levels of performance. In order to assess the variation of performance and its development over time in KM, the output data for each of the parameter combinations is organised into six groups of 300 sessions, ordered by the realised efficiency in their final period. This leads to one group with the 300 most efficient sessions, the next group includes the experiments that perform in places 301 – 600 and so on. These groups are then matched to the six experiments in CSW and compared to the experimental data on the basis of their weekly averages of efficiency and specialisation. Two-sided Mann-Whitney tests find few significant differences in means across parameters and mostly in the first week (i.e. the

Treatment		Efficiency (%)	Specialization (%)
$e^A$	$e^T$		
10	15	2.83	44.23
15	15	4.38	42.93
20	15	4.28	41.66
10	20	3.21	43.72
15	20	3.53	43.76
20	20	4.58	41.99
CSW		4.24	44.49

Table 6.1: Average efficiency and specialization by treatment, adapted from Kimbrough (2011).

first six simulation rounds). Similarly 95% bootstrapped confidence intervals for the efficiency of simulations include the CSW means in all but the first weeks.

In a second validation step the model is adjusted to replicate the CSW *Build8* treatment, where groups of eight agents are gradually assembled from groups of two via groups of four. The simulated agents respond to this treatment in a similar way to the participants in the experiment: The average levels of specialisation and efficiency increase and the discovery of specialisation progresses faster, compared to the standard treatment. However, the quantitative comparison between simulation and experiment shows less congruence. The 95% bootstrapped confidence intervals for  $e^A = 10$ ,  $e^T = 15$  contain all the experimentally achieved means, and  $e^A = 20$ ,  $e^T = 20$  takes two weeks to yield results that include the experimental means. However, all other treatments fail to replicate results in the first week, and then again in the last week, indicating that their trajectory of development moves away from human behaviour.

Kimbrough (2011) concludes that his model successfully replicates the complex process of discovery regarding specialization and exchange that participants experienced in the CSW experiments. He claims that relatively complex human behaviour can be captured by a combination of bounded hill-climbing to model their specialization processes and reinforcement learning to model their exchange decisions. KM focusses on the individual behaviour and learning processes that occur internally within each agent, motivated by the conversation protocols from

CSW experiments. In the validation step, he uses a grid search to calibrate the mode in order to reproduce human behaviour as closely as possible. While adjusting and exploring the effects of parameters  $e^A$  and  $e^T$ , other aspects in his implementation remain less well motivated and understood, including the strategic orientations that control the hill-climbing algorithm, and the algorithm for social learning with its parameters for conservatism ( $\omega_i$ ), the conservatism increment ( $\mu = \nu/2$ ), and the probability of mimicking ( $\eta_i$ ). More exploration would be necessary to gain a comprehensive understanding of how these aspects of the model work.

Beyond these minor deficits regarding its validation, the major drawbacks about this model are its limited expandability and the lack of social dimensions in the agents' decision making. It is built to model the behaviour of participants in the CSW experiments with eight participants and two goods, and it does so with considerable success. However, just like the BankNet by Sapienza (2000), it does not easily afford expansions or adaptations to other related systems, especially not to systems that comprise more than two goods. The algorithms that drive specialisation (hill-climbing) and exchange (division with minimal waste) as they are currently implemented, can only be used in a setup with two goods. There does not even seem to be a straightforward way to adapt the model so that it could capture the behaviour observed by Kimbrough *et al.* (2007) with their three-good economies. Waste minimisation is especially unlikely to be a good exchange strategy when exchanges with two agents are necessary to achieve superior outcomes. Social aspects of exchange relations are implemented very rudimentarily in KM, despite clear contrary evidence from protocols across all the preceding human subject experiments. Both issues will be addressed in the model developed here.

Regarding the better understanding of business relations and networks and the development of specialisation and exchange, these limitations are rather unfortunate. KM captures many essential mechanisms especially regarding the agents' individual decision making and learning processes, and as discussed above the model is also well validated; but due to its implementation it is not a feasible starting point for further analysis. Consequently, an alternative model will be developed here that is able to treat the settings in CSW and KM as a special case,

but beyond that, will also be able to model more complicated systems that include more (or less) agents, more goods, a spatial structure, more flexible production and consumption functions, and last but not least social elements that allow the agents to coordinate their activities. The next chapter will introduce this model and explain how it is related to the mechanisms of interaction discussed in Ch. 3. In Ch. 8 insights from exploration, validation and analysis of this improved model will be presented. The concluding chapter will discuss the new model's limitations and the further potential for exploration of more realistic scenarios including spatially distributed agents and a more complicated product space.

## Chapter 7

# EGS - A Model of the Development of Specialisation and Exchange

This thesis attempts to develop a better understanding of business relationships and networks as complex adaptive social systems, using agent-based modelling and drawing on an evolutionary perspective of economic change. Working under the assumption that networks of exchange are the result of an evolutionary process that enables people to reap the benefits of specialisation and division of labour, a computer model was developed to simulate the processes through which agents learn to specialise, coordinate their efforts and increase their wealth while at the same time they develop a dependence on each other and have to some degree give up their autonomy.

Kimbrough (2011) presents a similar model (KM) that simulates a learning process through which agents coordinate their productive efforts. However, the implementation of this model is restricted to the special case of a society with two goods only. Several algorithms in Kimbrough's model are not generalisable in a straightforward manner, which means that the model cannot be easily applied to more comprehensive and realistic systems. However, it seems reasonable to assume that the processes in a more complex system with more than two goods will differ substantially. This chapter will present an alternative model referred to as *Expandably Growing Specialists* (EGS) model that is able to simulate the

same processes of learning, discovery, specialisation and coordination in a much broader and more flexible range of settings<sup>1</sup>.

The representation of such a system as computational model allows us to monitor its development in great detail over time, on the level of the agents as well as the social aggregate level. Furthermore it allows us to conduct experiments that would not be possible in the real world, due to ethical, financial or capacity constraints.

## 7.1 Model Description

EGS is the implementation of a theory of the development and evolution of specialisation and exchange relationships and business networks. It emphasises that the coordination of economic activities is an important aspect of the development of specialisation and division of labour and also, that the social aspects of relationship formation and maintenance between economic actors are important aspects of this process. One of the main goals of this model is to implement it flexibly, allowing for extensions and variations especially regarding the product space. A researcher using EGS can adjust a range of settings, controlling both the individual agent's properties as well as the constitution of the agent population most flexibly. Future extensions are anticipated by building the model modularly, so that individual procedures that drive the agents' behaviour can be altered and extended, while the other model aspects remain untouched.

In essence, the agents in EGS are heterogenous producers and consumers of various goods, that are capable of realising economies of scale and coordinating their productive efforts in order to minimise their individual workload. They engage in search and mating, trying to find suitable partners, and through open ended negotiations they can identify comparative advantages in production and realise mutually beneficial exchanges. The agents are heterogenous regarding their consumption preferences and their productive capabilities, yet they are not omniscient so that they have to discover their own production capabilities, identify suitable exchange partners and they may settle for suboptimal negotiation results.

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<sup>1</sup>EGS is implemented in NetLogo (Wilensky, 1999) and is available for download under <http://snipurl.com/fhthesis>.

The model schedule goes through three consecutive phases every round: 1) mating and dancing, 2) producing and 3) learning. The short pseudo-code in Fig. 7.1 illustrates the main processes and their scheduling, and serves as an outline for the subsequent discussion of EGS modules.

```
---- Phase 1)
  Exploitation or Exploration
    (decide how many negotiation attempts to make this round)

  Searching
    (approach partners actively and passively receive others)

  Negotiating
    (coordinate activities and commit to produce goods)

*repeat until no agents are searching for partners anymore

---- Phase 2)
  Producing
    (consumption is not modelled explicitly)
    (calculate working hours and leisure)

---- Phase 3)
  Learn about Production Capabilities
    (remember costs for produced units)

  Learn about Partners
    (remember time savings from exchange with each partner)

  Learn about the Number of Negotiation Attempts
    (remember total time saving from the chosen number
    of negotiations)
```

Figure 7.1: Pseudo-code of the schedule for agent procedures performed by every agent in every round in EGS

The model consists of agents that find themselves in a *social space*. Based on the distances in the social space, some pairs of agents are more likely to encounter and interact with each other than other pairs. Each agent has a selection of in-

dividual properties that controls its economic behaviour, including its productive capabilities and consumption preferences. Also, there are agent specific parameters that control each individual's search and mating behaviour, however in the analyses presented here, these parameters are set homogeneously across the entire agent population. Furthermore the agents have a memory of past interactions over a certain number of rounds, allowing them to relocate good exchange partners and evaluate current experiences on the basis of past ones.

Like KM, EGS models a world populated with a number of heterogeneous agents. The agents' primary activities are to consume and to produce in order to satisfy their demand for consumable goods. The only factor input for production available to the agents is their time and calculations are made based on a 10 hours' work day. Although overtime is possible, agents pursue the goals to satisfy their demand while simultaneously spending as little time as possible working. Moreover, the agents are able to interact with each other, to approach each other (searching, targeting), compare their productive capabilities (getting acquainted, learning) and negotiate to coordinate their production efforts in order to share economies of specialisation and reduce their working hours mutually (specialising, increasing scale, outsourcing, coordinating).

The model does not presuppose that agents already know their ideal course of action and therefore it includes two procedures of individual learning. The first relates to the agents' productive capabilities. These are fixed but unknown to the agent when the model is initiated and can only be discovered through actual experience. The agents discover what they are capable of. The second learning procedure relates to the discovery of exchange. Agents have to experience the benefits of cooperation and decide for themselves how much time they want to spend searching for cooperation partners and negotiating exchanges (exploring and exploiting). Their partner choices can take into account past exchange experiences and agent-specific parameters control to what degree they prefer negotiation partners that they had good experiences with in the past. Both learning processes are motivated by KM and CSW, modelling the discovery process that goes along with specialisation and division of labour. Extending beyond the experimental setup, costs for partner search are introduced in EGS as an exogenous parameter, so that their effects can be systematically explored and analysed.

In EGS, consumption is the limiting factor of the economic system. Agents seek to satisfy their demand - through their own production or through exchange with others. However, an agent will only be available to negotiate exchanges as long as it searches for alternative sources for items that it demands itself. Once an agent has settled for sources for each of the goods it demands, it will cease to search for partners and also refuse any additional orders from others (prioritising, competing). This means that an agent uses exchange as a means to satisfy its own demand and to make efficient use of its time and efforts. Once an agent sees its demand satisfied, it will remove itself from the pool of potential partners that are available for negotiations.

In their decision making the agents consider only their own demand - their productive capabilities are only relevant to devise the details of an exchange. Agents seek to minimise the time they need to invest in production, and devote their surplus time to unspecified - but presumably more pleasant - leisure activities. In the settings investigated in this thesis, agents are always able to sustain themselves individually - in autarky. But in order to increase their leisure time, they need to find suitable partners, commit to exchange agreements and cooperate with each other.

The development of relationships as a means of coordination is another core feature in EGS. As agents learn more about their partners and their potential for cooperation, they begin to approach well matching partners more often than others, slowly developing persistent relations with a group of select partners. These relations are not binding like a contract, but more like social bonding and the formation of habits that CSW observed in their experiments (learning, bonding, sense-making, socialising, coordinating socially). These relationships emerge as the simulation progresses; they are not hard wired or represented as entities, but reoccurring interactions like relations in real business networks. The current implementation allows for exogenous adjustments of the strength of the agents' loyal behaviour, and tests of the effects of various options for search and targeting mechanisms.

As an agent-based model, EGS seeks to explain emergent social phenomena. In this case these are the self-organisation of specialisation and division of labour and the development of a network of relations between independent agents that

learn to use inter-personal mechanisms to coordinate their activities and realise economies of specialisation. These are emergent phenomena in the sense that the agents themselves find the (near) efficient solution of cooperation, only motivated by their individual advantages and equipped with the capabilities to conduct negotiations and exchange production tasks amongst each other.

Stochasticity plays a minor role in this particular model, relevant only for scheduling and some of the agents' decision making procedures. A random number generator controls the scheduling of agents' actions, deciding in which order they get to search for new partners. Furthermore, when agents face the decision of determining the number of search attempts at the beginning of a new round in the model, a conditional adaptive random distribution is used to make this choice. Lastly, stochasticity plays a role in the negotiation process, helping pairs of potential exchange partners find creative solutions to redistribute their production tasks amongst each other.

The agents are initiated with identical properties, except for consumption function and production capabilities which can be set exogenously to model different situations and degrees of heterogeneity in the population. At the beginning of the model the agents have no memory of past interactions, they are largely unaware of their production capabilities and have an inclination to spend little time searching for possible exchange partners. They are, however, fully aware of their own demand, and they could start immediately searching for potential exchange partners.

In the following, the implementation of the main procedures from Fig. 7.1 will be presented. The notational conventions are as follows: Greek letters refer to exogenous parameters, lower-case roman letters refer to values, bold lower-case letters to vectors or lists and upper-case romans refer to matrices or collections of lists. Should a parameter be a function of another, this will be indicated by round brackets (e.g.  $f(x)$ ). Agents are generally indexed as  $i$  (ego) and  $j$  (alter), goods are denoted as  $k$ . Tables 7.1 on p. 192 and 7.2 on p. 193 give an overview of all the parameters in the model.

The most important parameters in the model will be subject to experimentation, in order to assess their effects and interactions. Their effect on the model will be assessed through systematic exploration of the model's parameter space

and matching sensitivity analysis in Ch. 8. These parameters include the number of agents,  $\nu$ , which theoretically is limitless but will be restricted to smaller agent populations to facilitate comparability with experimental settings in CSW. The same holds for the number of goods,  $\mu$ , which will be restricted to the range between 2 and 4, because they are logically tied to the parameters for each agent's production capabilities  $(\mathbf{a}_i, \mathbf{b}_i)$  and demand  $(\mathbf{y}_i)$ . The introduction of each new type of good increases the model's parameter space substantially. Furthermore, each agent's search and mating decisions will be influenced by what will be referred to its "preference for loyal behaviour". Controlled by the parameter  $\lambda$  an agent will tend to choose its partners for negotiations based more on previous encounters or more on their proximity in space. Various procedures use the agents' past experiences to predict or evaluate future developments. For this reason, each agent maintains a limited memory of relevant events. The length of this memory is controlled by the parameter  $\rho$ . Lastly there are three parameters that affect an agent's decision making process about how often it will attempt to initiate negotiations.  $\iota$  represents the weight that is given to new information when it is combined with the existing knowledge base,  $\kappa$  is the time cost associated with each negotiation attempt and  $\varepsilon$  specifies the amount of random variation introduced to this decision making process. Lastly, the parameter  $\psi$  determines the level of effort that agents put into each negotiation process. It controls the resources for the algorithm that models the negotiation process and with high levels of  $\psi$ , this algorithm is more likely to identify superior negotiation results.

<b>Experimental parameters</b>		Value/Range
$\nu$	Number of agents	4, 16
$\mu$	Number of goods	2, 4
$\iota$	Increment to adjust the probability distribution for the number of search attempts	0, 2
$\kappa$	Cost (time) per search attempt	0, 1
$\varepsilon$	Probability of deviation from the chosen number of search attempts	0, 100%
$\lambda$	Agents' preference for loyalty	0, 100%
$\rho$	Agents' memory length	0, 20
$\psi$	Generations of the Genetic Algorithm	$2\mu$
<b>Other global parameters</b>		
$\tau$	Workhours per round	10
$d^*$	Maximum distance	22.62
$\phi$	Parameter to determine the initial probability distribution for the number of negotiation attempts	0, 1
$\gamma$	Arbitrary scaling factor for partner scores	50
<b>GA related parameters</b>		
$\theta$	Number of candidate solutions of the genetic algorithm	30
$\chi$	Crossover rate of the genetic algorithm	70%
$\xi$	Mutation rate of the genetic algorithm	1%

Table 7.1: Overview of parameters and variables in the Expandably Growing Specialists (EGS) model - Global parameters

<b>Agent attributes and variables</b>		
$x_i$	Agent leisure	$0, \tau$
$x_i^* = \tau - t_i(\mathbf{y}_i^a)$	Leisure in autarky	$0, \tau$
$\mathbf{y}_i = (y_{i1}, \dots, y_{i\mu})$	Set of goods demanded each round	$\mathbb{N}_0^+$
$t_i(\mathbf{y}_i^a)$	Costs to satisfy demand in autarky	
$\mathbf{a}_i = (a_{i1}, \dots, a_{i\mu})$	Production Coefficients, controlling the slope of the production function	$0.5, 2$
$\mathbf{b}_i = (b_{i1}, \dots, b_{i\mu})$	Production Exponents, controlling the curvature of the production function	$0.5, 2$
$\mathbf{d}_i = (d_{i1}, \dots, d_{i\nu})$	Distances to all other agents	$0, d^*$
$\mathbf{p}_i = (p_{i1}, \dots, p_{i\nu})$	Probabilities for the number of negotiation attempts, initiated as geometric distribution with parameter $p = \gamma$	$0, 1$
$r_i^*$	Number of negotiation attempts for the current round	$0, \nu$
$r_i$	Number of remaining negotiation attempts for the current round	$0, \nu$
<b>Agent memories and related</b>		
$R_i = [\mathbf{r}_{ij}] = (r_{ij1}, \dots, r_{ij\rho})$	Memories of time saving realised with each partner	$0, \tau$
$\mathbf{g}_i = (g_{i1}, \dots, g_{i\eta})$	List of length $\rho$ , storing the agent's most recently achieved levels of leisure	$0, \tau$
$v_{ij} = v(\bar{d}_{ij}, \bar{r}_{ij})$	Priority scores, proportional to the probability of selecting agent $j$ for negotiations	$0, 1$
$\bar{d}_{ij}$	Standardised scores indicating the other agents' proximity	$0, \gamma$
$\bar{r}_{ij}$	Standardised scores indicating the time savings realised through cooperation with other agents	$0, \gamma$
$\mathbf{u}_{ik}$	Memory of units produced	$\mathbb{N}_0^+$
$\mathbf{c}_{ik}$	Memory of associated costs	$\mathbb{R}$
$m(\mathbf{u}_{ik})$	Function to map costs to units	$\mathbb{R}$
<b>Temporary values, auxiliary functions</b>		
$\mathbf{y} = (y_1, \dots, y_\mu)$	Set of goods or associated production tasks	$\mathbb{N}_0^+$
$\mathbf{y}^c$	Current set of goods or associated production tasks	$\mathbb{N}_0^+$
$\mathbf{y}'$	Alternative set of goods or associated production tasks	$\mathbb{N}_0^+$
$f_{ij}(Y'_{ij})$	Fitness Function in GA	$\mathbb{R}$
$\hat{l}_i(Y'_{ij})$	Function of expected losses	$\mathbb{R}$
$\hat{t}_i(\mathbf{y}'_i)$	Expected time cost for an allocation of production tasks	$\mathbb{R}$
$\hat{s}_i(Y'_{ij})$	Expected time savings for an allocation of production tasks	$\mathbb{R}$

Table 7.2: Overview of parameters, attributes and functions in the Expandably Growing Specialists (EGS) model - Agent specific model aspects

### 7.1.1 Exploitation or Exploration

Every round, each agent starts with a decision about how often it plans to approach another agent as potential partner to negotiate an exchange, that it will remember as parameter  $r_i^*$ . It is possible that an agent chooses not to search for partners and live in autarky, producing solely for their own consumption (provided that their production capabilities and their own demand are in agreement). But alternatively the agent may seek to initiate negotiations, seek out partners, negotiating to divide their production tasks amongst each other and engage in exchange, in order to mutually reduce their working hours.

The decision to invest time and effort into partner search and negotiation is modelled as a random choice based on an adaptive distribution of agent-specific probabilities. These probabilities are stored in vector  $\mathbf{p}_i = (p_{i1}, \dots, p_{i\nu})$ , where each element indicates the probability with which agent  $i$  will choose to initiate the indexed number of negotiations <sup>2</sup>. This vector is initiated as a geometric distribution with parameter  $\phi = 0.7$ , which gives highest probability to choosing not to search at all (70%), but distributes the remaining probability mass (30%) across higher numbers of search attempts. Possible variations of the geometric distribution and the shape of an alternative, the uniform random distribution, are illustrated in Fig. 7.2. The chosen parameterisation reflects initially low levels of search and exchange that CSW observed in their experiments. It represents the agent's initial inclination to explore its opportunities and spend time investigating what it can achieve together with other agents in their world. Therefore this distribution reflects the agent's initial disposition towards the trade-off between exploitation and exploration discussed by March (1991). Varying the cost associated with each negotiation attempt ( $\kappa$ ), it is even possible to put a concrete price on exploration efforts and investigate how the learning algorithm responds to various conditions.

Nonetheless, this distribution serves only as a starting point. An agent will learn about the consequences of its decisions and it will tend to repeat decisions that led to favourable outcomes and refrain from decisions that led to less

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<sup>2</sup>As an arbitrary endpoint for this distribution  $\mathbf{p}_i$ , the total number of agents,  $\nu$ , was chosen. Under most settings this upper limit proved to be sufficiently high to cover all the agents' actual choices.

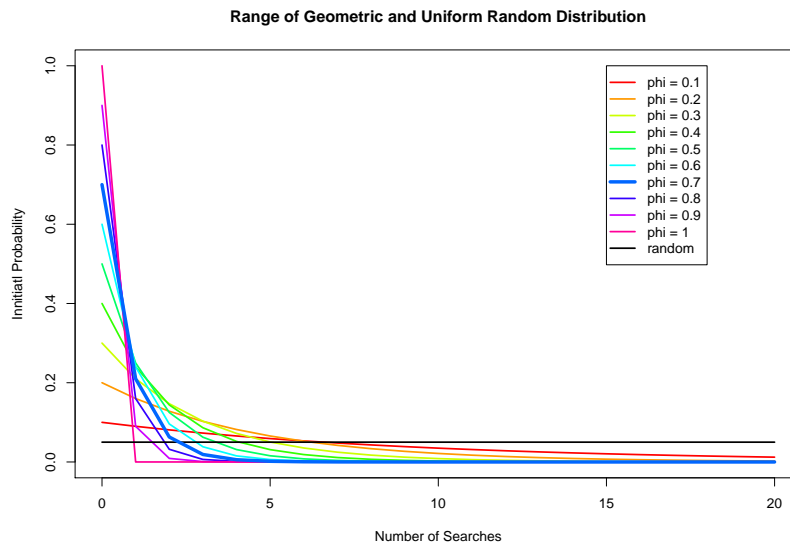


Figure 7.2: Possible shapes of geometric and uniform random distributions that could be used to initiate the agents' probabilities of choosing  $r_i^*$ , the number of negotiation attempts to be initiated this round.

favourable outcomes. The learning process that changes this distribution as the agent gains more experience is a variation of interactive reinforcement similar to the implementation in KM. It will be described in detail in Sec. 7.1.7.

So far, the implementation of this decision making procedure is likely to converge to only one value quickly. As a remedy, a further source of variation is added to the agents' decision making process: EGS features an optional variation term that randomly adds, or subtracts, one search attempt to the number of attempts selected through the standard process. This added variation is controlled by the exogenous parameter  $\varepsilon \in [0, 1]$ , which specifies the probability of such a variation to occur. Again, this parameter affects an agent's propensity to deviate from its known path and explore alternative solutions, even though their consequences are uncertain. This decision making mechanism is rather simplistic, nevertheless it combines an adaptive process of learning and exogenous parameters that can be calibrated to human decision making and their way of dealing with the trade-off between exploration and exploitation.

### 7.1.2 Searching

In the next step the agents identify a potential exchange partner. Like KM, this model is designed with realistic assumptions about the cognitive capabilities in mind. The agents are not omniscient: they know neither which would be the best partner to collaborate with, nor which would be the optimal task allocation to agree upon. Instead, they learn through experience - about themselves and their capabilities, as well as about their peers and suitable cooperation partners. EGS features two separate criteria that can influence this decision: proximity and prior experience. Hereby, the exogenous parameter  $\lambda \in [0, 1]$  controls the importance that an agent assigns to prior experience, and it is therefore referred to as the agents' *preference for loyalty*. In the model variants explored here,  $\lambda$  is set homogeneously for the entire population of agents, but it could be assigned in an agent-specific way as well. To understand the trade-off between the two choice criteria, it is necessary to first illustrate the spatial structure of the model world, as well as the agents' memory.

The world the agents interact in is a plain surface; however it features a generic representation of "distances" between each pair of agents. These distances can be interpreted as physical and/or social distances, and their practical effect is that they affect the probability of encounters between agents. Generally, agents that are more distant from each other are - all else equal - less likely to meet and interact, than a pair of agents that is closer together. The surface is wrapped around and joined at the edges, forming a torus. From the agents' perspective, the surface does not have any boundaries, while at the same time, it can be visualised conveniently on a two-dimensional computer screen. In the baseline implementation the agents are scattered uniformly and at random across this surface. Potential future extensions, include substitutes for this generic landscape, using any other spatial representation of physical distances (for example a GIS map of a city, country or continent), or suitable measures of social distance. Note that the effects of these distances need to be calibrated accordingly for the mating algorithm.

Upon initiation, the program calculates the distances between each pair of agents  $i$  and  $j$  and stores them for future reference in the agent specific vector  $\mathbf{d}_i = (d_{i1}, \dots, d_{iv})$ .

The second aspect of partner selection is the agents' memory of past interactions that serve as a proxy to estimate the prospective value of cooperation with any other agent. Each agent  $i$  maintains a list of cost saving estimates that resulted from past exchanges, for each of its partners  $j$  individually:  $\mathbf{r}_{ij} = (r_{ij1}, \dots, r_{ij\rho})$ . The length of this memory is determined by the exogenous parameter  $\rho$ .

The partner search mechanism is again modelled stochastically, using adaptive probabilities. After deciding how often each agent plans to initiate negotiations in the present round, the agents take turns in approaching each other in order to initiate negotiations. Every agent selects its target through a scoring system that combines proximity and past experience to one overall score  $v_{ij}$ . The parameter  $\lambda$  determines the weight that is given to past experiences at the expense of the weight given to distances between agents. Whenever an agent searches a new exchange partner, it calculates priority scores for the other agents with the following formula and selects its next potential partner with probabilities proportional to these scores:

$$v_{ij} = \max(0, (\lambda \cdot \bar{r}_{ij} + (1 - \lambda) \cdot \bar{d}_{ij})) \quad (7.1.1)$$

Where  $\bar{r}_{ij} \in [-\infty, \gamma]$  is a standardised score derived from the memories about past outcomes of exchanges with agent  $j$  that are currently stored in agent  $i$ 's memory. Similarly  $\bar{d}_{ij} \in [0, \gamma]$  is a standardised score for the proximity between agents  $i$  and  $j$ , derived from the distances between them. The standardisation is necessary to have distances and memories on the same scale, which depends on the arbitrary scaling factor  $\gamma$ . Let  $r_i^*$  be the highest time-saving across all other agents that agent  $i$  currently stores in its memory, and  $d^*$  the largest distance theoretically possible in the current configuration of the world, then the scores for past exchange experiences and distances between agents are calculated as follows:

$$\bar{r}_{ij} = \gamma \cdot \frac{\sum_{l=1}^{\rho} r_{ijl}}{r_i^*}$$

$$\bar{d}_{ij} = \gamma - \left( \gamma \cdot \frac{d_{ij}}{d^*} \right)$$

At the onset of the simulation, no agent has yet acquired any information about exchanges; therefore the computation of  $\bar{r}_{ij}$  is suspended. Consequently, the probabilities of encounters will depend exclusively on the distances between agents, independent of the value for  $\lambda$ . As soon as an agent obtains experience that is positive on average, the standardised scores  $\bar{r}_{ij}$  will be computed as shown and affect the partner choice according to Eq. 7.1.1.

It is possible that the selected negotiation partner is not available for new negotiations any more. In this case the (potentially costly) search attempt will be lost to the searching agent. This happens when the other partner has already gone through enough negotiations so that all the items that it demands this round are either taken care of - either being produced by others or as part of the agent's own committed production in order to realise economies of scale with other agents' orders.

### 7.1.3 Negotiating

Humans are heterogeneous in their desires and capabilities, and this is the core building block of this model. Accordingly, agents (may) differ with respect to their demand as well as their productive capabilities regarding each type of good individually. In the negotiation phase, the agents seek to find a time-efficient way to coordinate their heterogeneous demand and heterogeneous productive capabilities. None of them knows the optimal solution to this problem, and they have no certain way to find it. However, they are able to search for satisfying solutions in a creative and original way and use their knowledge about past achievements to derive sensible estimates should they have no certain knowledge about their own capabilities.

Each agent's demand is implemented as flexibly as possible. An agent  $i$  is initiated with a distinct demand vector  $\mathbf{y}_i = (y_{i1}, \dots, y_{i\mu})$ ,  $y_{ik} \in \mathbb{N}$  that specifies for each good  $k$ , how many units  $y_{ik}$  the agent wants to consume in any given round. Each unit of these demanded goods will be referred to as one *production task*. The individual goods are not substitutable for each other. Essentially this represents a fixed proportions consumption function analog to a Leontief production function (see e.g. Allen, 1968). It is similar to the one used by CSW,

although demand in EGS is bounded and not limitless as in CSW. The structure and distribution of these demand vectors can be determined exogenously. Possible variations are a random allocation of demand for each good; allocation of set demand vectors to represent certain consumer segments, or a product oriented approach that links consumption to production, modelling the modular assembly of end-products from different inputs.

In the negotiation phase, an agent needs to estimate its own production costs in order to identify comparative advantages and opportunities for exchange. Similar to consumption, production is implemented to be very flexible, facilitating to model a variety of configurations. However, while an agent is fully aware of its personal demand from the start, it first has to learn through experience what it is capable of producing at which costs. For this, each agent maintains a memory of their past production experiences that enables it to *estimate* its costs, even if it has no concrete experience for a particular number of units. Each agent  $i$  maintains records about its production experience, remembering for every product  $k$  the number of units it produced ( $\mathbf{u}_{ik}$ ) along with the associated costs ( $\mathbf{c}_{ik}$ ). Furthermore let  $y_{ik}$  be the number of units of good  $k$  that an agent  $i$  has to produce according to a task allocation  $Y$ , then the function that maps costs to units is referred to as  $m_i(y_{ik})$ .

The cost estimate  $\hat{t}_i(y_{ik})$  is then derived in one of three ways, depending on the agent's level of experience: direct reference, interpolation or extrapolation.

**Direct reference:** If  $y_{ik} \in \mathbf{u}_{ik}$ , the agent already has experience producing this number of units and can therefore reference directly:  $\hat{t}_i(y_{ik}) = m_i(y_k)$

**Interpolation:** If  $y_k < \max(\mathbf{u}_{ik})$ , the agent needs to interpolate between the two closest known points: Let  $u^- = \max(U_{ik} < y_k)$  be the largest observed production below  $y_k$  and  $u^+ = \min(U_{ik} > y_k)$  the smallest observed production above  $y_k$ . Then the expected costs have to be estimated by

$$\hat{t}_i(y_{ik}) = m_i(u^-) + (y_{ik} - u^-) \cdot \frac{m_i(u^+) - m_i(u^-)}{u^+ - u^-}$$

**Extrapolation:** If  $y_k > \max(\mathbf{u}_{ik})$ , the amount under consideration is above everything that the agent has experienced so far, then the agent will extrapolate from the largest known number of units:

$$\hat{t}_i(y_{ik}) = u_{ik}(X) \cdot \frac{m_i(\max(\mathbf{u}_{ik}))}{\max(\mathbf{u}_{ik})}$$

The cost estimates associated with any given task allocation  $Y$  are then  $\hat{t}_i(\mathbf{y}_i) = \sum_{k=1}^{\mu} \hat{t}_i(y_{ik})$

Initially,  $U_{ik}$  and  $C_{ik}$  will contain only those values that an agent produces in autarky. Only through combining its demand with the demand of others will it learn about its own capabilities, extending and updating its memory after every round.

The negotiation process simulates how the agents develop relationships with each other, learning about each other's needs and capabilities, working out together how to best coordinate their efforts. From the agents' perspective, this constitutes a creative process of solving a multidimensional optimisation problem. It also needs to be taken into account that these negotiations are generally conducted on the basis of incomplete information and with only limited cognitive capabilities. Consequently it is desirable that the solutions found here are not always optimal, but constitute merely an improvement that both parties regard as acceptable. Any implementation of this process must reflect these restrictions appropriately.

There are not many computational algorithms that are able to produce creative, but not optimal, answers to a problem like this. In EGS, this coordination problem is operationalised through a Genetic Algorithm (GA) Holland (see 1975, 1992). This machine learning algorithm is highly parallel and explores the search space of potential solutions quite effectively. It is motivated by biological metaphors about natural selection: starting with a population of candidate solutions to a problem, it simulates the evolution of new and better solutions by "breeding" new solutions from a population of old ones through selection, recombination and mutation. The GA goes through several rounds in which it produces increasingly fitter solutions to a problem at hand. For this the GA requires a fitness measure that

serves as a basis to assess the quality of any candidate. There are two ways in which a candidate solution can enter the next round: direct copying and sexual reproduction. Both are subject to fitness assessments based on the selected fitness measure. Every round, a set number of small groups from the pool of present candidate solutions are formed and their members are compared amongst each other regarding their fitness. The fittest of these solutions get to reproduce, creating a copy of themselves for the next round. Similarly, another set of new candidates is created mimicking sexual reproduction. Here, fitness assessments are again conducted on small subsets of present candidates, but in this case it is the two fittest solutions that then get to create a new candidate solution together, as a random re-combination of their own characteristics. In a last step, random variation is introduced into the this evolutionary process through a simulation of mutation. With a very low probability, each characteristic of the new generation of candidates undergoes random changes, continuously introducing a few new traits into the the pool of potential solutions every round. A GA like this is characterised by four parameters: the number of candidate solutions in every round, the cross-over rate that determines how many new candidates are created through sexual reproduction and consequently, how many through direct copying, the mutation rate and lastly the number of rounds. In EGS these values were chosen so that they are likely to produce a satisfactory solution in a short time, while not guaranteeing to identify the best solution possible. Each generation consists of a population of  $\theta = 30$  candidate solutions, the cross-over rate is  $\chi = 70\%$  and the mutation rate of  $\xi = 1\%$ . The number of rounds that the GA will go through is subject to experimentation and will be discussed in Ch. 8. Further details about the GA parametrisation will be discussed in Sec. 8.1.1.

In light of the agents' coordination task this algorithm can also be interpreted as an extensive trial and error process that follows certain rules for the the generation of new trials. A pair of negotiating agents pool all the items they currently demand and compare the expected outcomes of various combinations of task allocations between them. They develop proposals for joint production, estimate their respective outcomes to assess the proposal's fitness, and then seek to find ways to improve on what they have already. The search space of possible solutions to this problem can be quite high dimensional and potentially non-linear. Using

the binary representation of the proposed new task allocations  $Y'_{ij} = [\mathbf{y}'_i, \mathbf{y}'_j]$ , the negotiations translated into a problem suitable for the GA and the algorithm's parameters can be adjusted so that does not necessarily lead to an optimal solution but converges on a local optimum. As such, the results of the implemented algorithm provide outcomes that approximate how people *satisfice*, rather than *optimise*. This notion goes back to Herbert Simon (1957) who described human behaviour as bounded rational, trying to achieve good results with limited (i.e. not perfect) cognitive resources.

EGS uses a flexible *fitness function* that is able to evaluate numerous aspects of the alternative task allocation, going beyond the comparison of time savings alone. In the current implementation, the relevant factors are expected time savings, distributive fairness, as well as the agents' aversion to losses. To calculate the fitness of a proposed new allocation of tasks, a pair of agents  $i, j$  estimates how much time it would take each of them to perform the allocated tasks and calculate the expected cost savings of the new allocation relative to their currently held allocation of tasks  $Y^c_{ij} = [\mathbf{y}^c_i, \mathbf{y}^c_j]$ . This leads to  $\hat{s}_i(Y'_{ij}) = (\hat{t}_i(\mathbf{y}'_i) - \hat{t}_i(\mathbf{y}^c_i))$  and  $\hat{s}_j(\mathbf{y}'_{ij}) = (\hat{t}_j(\mathbf{y}'_j) - \hat{t}_j(\mathbf{y}^c_j))$ . These estimates can then be included in the fitness function as follows:

$$f_{ij}(Y'_{ij}) = \hat{s}_i(Y'_{ij}) + \hat{s}_j(Y'_{ij}) - (\hat{s}_i(Y'_{ij}) - \hat{s}_j(Y'_{ij}))^2 - \hat{l}_i(Y'_{ij}) - \hat{l}_j(Y'_{ij}) \quad (7.1.2)$$

This function represents these three components as follows: First, both agents' expected savings are added, second, a penalty term represents a notion of distributive fairness and reduces the fitness of any given solution relative to the squared difference in time savings between agents and third, loss terms  $\hat{l}_i(X)$  penalise any allocation that leads to an expected loss for an agent:  $\hat{l}_i(Y'_{ij}) = \min(0, \hat{s}_i(Y'_{ij}))$ .

The exogenous parameter  $\psi$  controls the number of rounds that the GA goes through to find a good solution. After the last of these rounds the algorithm will propose the solution with the highest fitness value and the agents will compare the expected time savings of this new allocation to their fall-back position, which would be to make no exchange at all. Only if both agents expect to save time with the new allocation will they agree to the exchange and coordinate their production accordingly. Agent  $i$  will commit to produce a selection of goods for agent  $j$  in

return for a commitment of  $j$  to produce other goods for  $i$ . The agents continue to search and negotiate as long as they have search attempts ( $r_i$ ) remaining or until they have found sources for all items that they require in the current round.

#### 7.1.4 Producing

After concluding the negotiation stage, the agents enter the production phase. Each of them compiled a list of production tasks at the end of the previous stage, describing how many units of which goods the agent has committed to produce, this is their production vector  $\mathbf{y}_i^p = (y_{i1}, \dots, y_{i\mu})$ . Each entry describes the number of units that the agent committed to produce, either for its own consumption or for an exchange with its partners.

The production procedure is a generalisation from the formulae deployed in CSW and uses a flexible structure similar to that in previous models developed here (including the SpecialNet and BusiNET). Upon initiation of the model, every agent receives two production parameters for each good,  $a_{ik}$  and  $b_{ik}$ . Together they constitute its production function and determine the time required to produce a certain number of units of a good. The general structure for production of any given good  $k$  is

$$y_{ik} = a_{ik} \cdot t^{b_{ik}} \quad \text{or} \quad t = \sqrt[b_{ik}]{\frac{y_{ik}}{a_{ik}}}, \quad (7.1.3)$$

with  $y_{ik}$  being the units of good  $k$  produced by agent  $i$ , and  $t$  being the amount of time invested. The parameters  $a_{ik}$  and  $b_{ik}$  are agent specific and may differ for each good  $k$  and they determine the slope and curvature of the production function. Sensible values are real numbers between zero and lower single digits. They may differ across goods and between agents and introduce heterogeneity of productive capabilities into the model. The effects of both parameters can dampen or enhance each other. For  $a_{ik} > 0$  and  $b_{ik} > 1$  the function's graph is a positive parabola going through the origin. If  $b_{ik} = 1$ , the function is linear and if  $a_{ik} = 0$ , an agent is incapable of producing the good in question. Every agent has a set production function for every good that exists in the model, although it is possible to set these parameters at prohibitively extreme values.

The effect of  $a_{ik}$  is dominant at low levels of production, especially when the agent produces only one unit of a good. For larger numbers of units,  $b_{ik}$  introduces economies of scale into the production process. For a good  $k$  with  $b_{ik} > 1$ , agent  $i$  will be able to reduce its average production costs when it commits to produce this good on a larger scale for other agents. For  $b_{ik} = 1$ , economies of scale are neutralised but agents still have the possibility to realise comparative advantages through exchange. There are however no economies of scope in this implementation: except for resource restrictions, the production of one type of good is independent of the others. There are no synergies possible and the skills/capabilities required to produce one good are irrelevant for the production of another.

In the production phase, each agent calculates how much time it requires to produce all the goods in  $\mathbf{y}_i^p$  by summing up its production functions (see Eq. 7.1.3) for each good  $k$ . The agent will then also calculate its leisure time, which is the difference between  $\tau$ , the number of work hours per round, and the total time required for production, minus the costs for search and negotiation ( $\kappa r_i^*$ ), if  $\kappa \neq 0$ :

$$x_i = \tau - t_i(\mathbf{y}_i) - \kappa r_i^*. \quad (7.1.4)$$

In contrast to CSW and KM, the time that agents spend on production is not fixed. In fact each agent tries to minimise the time it spends working by all means possible. It is possible that an agent has to work overtime, but it is also possible that it gains extra leisure time. While technically the transformation from time costs to leisure is redundant, this model uses leisure as the standard of comparison to highlight the self-interest that humans have in gains of efficiency: Increased efficiency benefits the individual because it needs to spend less time and effort on production. The primary consequence of this is that the individual has more time on its hands to spend in whichever way it pleases. It is one possibility to invest the time gained into the production of even more goods and gain greater economies of scale, but this is only one of many possible ways to spend the time and it is not assumed here that all the agents strive for is the maximisation of production. Other potential extensions include the production of inventories of some goods and using them as protection against future uncertainties and using them to affect future negotiations.

### 7.1.5 Learning about Production Capabilities

Analogously to Kimbrough's model, EGS represents specialisation as a process of discovery. An agent is initially unaware of its productive capabilities and has to learn about what it is capable of through trial and error and its own, direct experience. The agent's production capabilities are initially unknown, but nonetheless fixed throughout the model run. Unlike learning in the BusiNET and Network of Specialists models, an agent cannot improve its skills through experience. Such learning curve effects are a possible model extension that was deliberately omitted in the current implementation to facilitate better tractability of the model development. Through the introduction of exponents, the production function in the current EGS version has already twice the number of parameters of the previous models. The introduction of learning curve effects would add a whole new dimension to the model that could distract from the core objective of the model: understanding the coordination between agents and how it leads to specialisation and division of labour in a business network.

One could argue that this learning process will only delay the agents' coordination process for as long as it takes for them to learn about their skills and deficits. From this perspective this additional mechanism might easily appear superfluous and an unnecessary complication of the model of a business network. However, the reason for its inclusion is that such systems are path-dependent in their development - and the discovery process may forestall or promote certain developments, as agents remain ignorant to their potential because they never had the opportunity to try.

As mentioned before, each agent  $i$  maintains a memory of its past production: one list about all the units produced for each of the goods  $k$  ( $\mathbf{u}_{ik}$ ) and one for the associated costs ( $\mathbf{c}_{ik}$ ). These are the basis to estimate the potential costs in every negotiation phase. Learning about their own production capabilities is straightforward: Following the production phase, an agent compares the currently produced units  $y_{ik}$  to those already in its memory ( $\mathbf{u}_{ik}$ ). If  $y_{ik} \in \mathbf{u}_{ik}$  the agent will just replace the corresponding entry in  $\mathbf{c}_{ik}$  with the current cost  $t_i(y_{ik})$ . If  $y_{ik} \notin \mathbf{u}_{ik}$ , the agent will extend  $\mathbf{u}_{ik}$  by  $y_{ik}$  and analogously append  $\mathbf{c}_{ik}$  by  $t_i(y_{ik})$ . In the first round, the agents are initialised with knowledge about their cost of producing

one unit of every good, and - should these differ from one unit - the costs for the amount of units they require in autarky.

### 7.1.6 Learning about Partners

In the second learning step, each agent evaluates its cooperations with others regarding success and failure and then updates its memory about the value gained from exchange with each of them. These memories will affect the agent's future search and mating activities and guide it to repeat negotiations with better matching partners. Information about past exchanges are stored for every partner  $j$  in the memory matrix  $R_i = [\mathbf{r}_{ij}]$ , with individual vectors  $\mathbf{r}_{ij} = (r_{ij1}, \dots, r_{ij\rho})$ . Each  $\mathbf{r}_{ij}$  is of length  $\rho$ , which is an exogenous parameter determining the number of rounds that the agents remember. Learning about its partners, each agent will append  $\mathbf{r}_{ij}$  by an estimate of the cost savings brought about by the exchange with the respective partner and "forget" the oldest entry. These memories are initiated at zero throughout. For every potential partner  $j$  in the population that agent  $i$  did not interact with in the current round,  $\mathbf{r}_{ij}$  will still be updated with  $r_{ij1} = 0$ .

In order to single out the value of one individual exchange partner after each round of negotiations and exchanges where cooperation may have taken place with others as well, each agent performs a thought experiment. After calculating its total production time, it estimates its costs for an alternative set of production tasks  $\mathbf{y}_{\setminus j}$ , for a set of tasks that  $i$  would have produced if the exchange with  $j$  had not happened. The estimates are derived analogously to the cost estimations in the negotiation phase, only it is possible that the estimates are now different, because the agent went through a production phase in which it updated its productive capabilities.  $\mathbf{r}_{ij}$  will then be updated by appending  $r_{ij}$  and removing the oldest entry.

$$r_{ij} = \hat{t}_i(\mathbf{y}) - \hat{t}_i(\mathbf{y}_{\setminus j})$$

Over time, each agent will learn about the potential time savings to be gained from interactions with each potential partner. Depending on its preference for loyalty, an agent will seek out those agents that help it save the most time more often - and reciprocally the agent will be approached by more compatible partners

more often. Successful interactions in the past increase the probability of meeting again in the future. In this process each agent only considers its own previous outcomes. At the same time, if both parties in an exchange relation perceive each other as good matches, both of them become more likely to seek out one another and therefore both of them contribute to the establishment of their relation. The recurring interactions of agents have the potential to lead to the development of ongoing exchange relations and, on the larger scale, to the emergence of an entire exchange network.

### 7.1.7 Learning about Number of Negotiation Attempts

The last learning step relates to the number of partner search attempts that the agent will undertake (and potentially pay for) in the next round. This learning procedure is implemented as a variation of interactive reinforcement learning similar to the algorithm in KM. Each agent  $i$  maintains a probability vector  $\mathbf{p}_i = (p_{i1}, \dots, p_{i\nu})$ , where each element indicates the probability with which it will choose to initiate the indexed number of negotiations. Learning about the value of these search attempts pertains to changes made to this vector, increasing the probability for a number of searches if it leads to a good result, and reducing its probability when the result is dissatisfying. If an agent is satisfied by the results that a certain number of search attempts led to, the agent will become more likely to repeat that number of search attempts in the following round.

In order to assess the quality of a production round's outcomes and determine whether the chosen number of searches  $r_i^*$  was a good choice or not, agent  $i$  again resorts to memory. In the vector  $\mathbf{g}_i = (g_{i1}, \dots, g_{i\rho})$  it stores the past  $\rho$  levels of realised leisure, independent of the number of search attempts.  $r_i^*$  will be evaluated through comparison with the agent's mean performance over  $\mathbf{g}_i$ , i.e. all the rounds that it currently remembers. This algorithm uses a fixed increment  $\iota$  that is either added to the probability of a well performing number of searches, or subtracted from that probability when the performance is too low.  $\iota$  models the agents' speed of adaptation with which they respond to newly gained knowledge.

To ensure that the sum of probabilities in  $\mathbf{p}_i$  equals 1 after the update, all values in the vector will be standardised by dividing through the current sum of

probabilities. Once a probability in  $p_i$  reaches zero - or even falls below zero through subtraction - it will remain at zero permanently. However, depending on the model settings, it may be possible that the agent will pick that number of searches again as a result of random variation.

## 7.2 Comparing EGS and KM

EGS serves a purpose very similar to the model in Kimbrough (2011), but it is based on a different collection of mechanisms and uses different algorithms that together represent a different theory about the social mechanisms that bring about the evolution of exchange. By producing outcomes that agree with selected observations from CSW's experiments, Kimbrough (2011) demonstrates that his model may serve as a *sufficient explanation* of the processes that lead to the discovery of specialisation and exchange. KM is sufficient in the sense that it constitutes one conjunction of mechanisms (i.e. the model, or implemented theory) under which desired behaviour can be reproduced (Marks, 2007). This does not mean, however, that KM is the only model that can bring about these results. Marks (2007) argues that simulation models are proofs of existence, showing that a combination of conditions is sufficient to bring about a certain outcome. The set of *all* combinations of conditions that necessarily bring about the desired behaviour can be much wider, spanning a high-dimensional space, with no guarantee of continuity, and possibly include a large number of non-linear interactions among elements.

From this perspective, EGS is an *alternative explanation* to KM that also includes relational and social aspects of business as part of the explanation of the process of specialisation and division of labour. Despite findings in CSW that emphasise the importance of interpersonal relations in coordination of specialisation, such mechanisms are largely absent in KM. In EGS basic elements of relationship formation and maintenance are represented in the way memory of past interactions influences the agents' mating behaviour and therefore reflects the actors' activities and interactions with a higher degree of realism.

One major advancement of EGS over KM is its extended and more flexible economic framework, especially because the original consumption framework in CWS is rather inflexible by design. Even the experiments with three goods (Kim-

brough *et al.*, 2007, 2008) indicate no way in which the underlying functions could be extended further. For consumption, the third good is included multiplicatively to Leontief utility functions, which leaves no obvious way to further extend this setup. As mentioned above, the agents' demand in EGS is fully specified exogenously, represented as a fixed combination of a number of units of each good in the system. Each agent has to obtain its individual combination of goods every round. On this basis it is also possible to initiate the agents *heterogeneously* regarding their consumption preferences. Although this setup is different, a similar situation as in CSW can be simulated, yet demand in EGS is always limited and will eventually be fully satisfied.

EGS retains the essence of the production functions used in CSW, but in EGS they can easily be adjusted and extended to match new economic settings. It is part of the CSW experiment that participants can only produce two goods and have to exchange goods in order to increase their utility, yet an extension towards a system with more goods is rather straightforward, because these functions are additive. While in CSW consumption is essentially limitless and production is the limiting factor, EGS is based on the premise that demand is limited and production, while technically limitless, will have an ideal point. Under these assumptions it is possible to specify the agents' demand exogenously and have them negotiate and coordinate their production in order to produce what they want to consume with minimal costs, without using algorithms that provide only optimal solutions for negotiations and circumvent the individual agents' entire learning process.

This altered implementation also makes it possible for agents to negotiate to exchange *before* the actual production step. Their negotiations are about items from their current demand sets, which they intend to give to their partners as orders for subsequent production. In the negotiation phase, the agents attempt to rid themselves of production tasks that would incur high costs if they performed them themselves, in exchange for taking over tasks that they can perform with comparative advantage. This also differs from the setup in CSW; however it was necessary to reverse the order of production and negotiation to avoid multi-dimensional optimisation problems that model the agents' resource allocation in settings where they can produce more than two goods. Instead agents produce exactly what they negotiate, negotiate only what they need and consequently reduce waste to zero,

producing - in KM's terms - at full efficiency. In a way, production after negotiation has been observed in some of the better performing groups in the CSW experiments. The participants eventually ceased to negotiate and merely repeated their productive activities and exchanges, once they had found a satisfactory arrangement. Furthermore CSW generally found high levels of efficiency as participants quickly learned to minimise their waste. So EGS' agent behaviour does not differ too much from human behaviour in this respect.

Like KM, EGS includes heterogeneous agents that coordinate their production in a self-organised manner based on limited, local knowledge. But moreover, EGS is expandable and flexible, allowing to model a wide range of systems with various production and consumption functions, various numbers of agents and goods, a spatial structure, emergent inter-agent relationships and more flexible negotiation. The results of Crockett *et al.* (2009) and Kimbrough (2011) will be included as special cases of EGS analysis and used as a basis for model validation. EGS is modular, extensible and scalable for subsequent implementations of realistic scenarios and specific social-ecological systems. Notably, the model was built *after* surveying the relevant literature and identifying the causal mechanisms, i.e. actors, their activities, properties and constellations that drive the development of real business relationships and networks. Consequently, the agents' activities are implemented so that they mimic real human action and interaction and thereby represent a theory about the causal mechanisms that bring about (or not) specialisation and division of labour.

### **7.3 Mechanisms in EGS**

EGS covers a wide range of the mechanisms discussed in Ch. 3 - but not all of them. Also, not all of those mechanisms that are included *explicitly* with a dedicated procedure, but implicitly in the assumptions and consequences of some of the procedures and the way they are implemented. To provide a concise overview, tables 7.3 to 7.6 indicate for each identified mechanism if it is included in EGS and briefly summarises how it is implemented. There are a few mechanisms that are included only in part, and others that are not yet included, but their introduction

is anticipated and should therefore not pose insurmountable technical difficulties. Selected aspects of the model will be addressed in the following.

Learning as a way to improve one's capabilities was included in BusiNET and SpecialNet as the dominant driver of specialisation, but has been replaced in EGS by non-linear production functions that allow for genuine economies of scale. However, an agent in EGS learns in the sense that it discovers its productive capabilities as it produces - and as it produces it becomes aware that it is capable of reducing its marginal costs by producing at a higher scale. It may be arguable to what degree this represents learning. On one hand, the production function is fixed and once an agent reaches a volume, it will always be able to produce this volume at the same cost. On the other hand, the agent learns about itself and about capabilities that it is initially unaware of, potentially enabling it to reduce its marginal production costs. In a way this constitutes another form of learning, going from ignorance to full potential in one step.

The currently implemented production functions are already very flexible, allowing for the implementation of a large degree of heterogeneity between the agents and a multitude of different scenarios to investigate the effects of diverse capabilities in a population. However, the basic structure of these functions is set: they are monomial, containing only one non-zero coefficient and one exponent per good. Consequently interaction effects between goods, such as economies of scope, and also interaction effects pertaining to different growth rates for different activities cannot readily be represented with this model. Lastly, limiting effects that arise from diseconomies of scale are not included in the model, because the functions are monotonic in the margin - so that an agent ideally chooses one of two strategies: Either produce as much as possibly of the same good, or do not produce the good at all, conditional on the assigned production exponents. Note that with this implementation, the model already needs  $2 \cdot \nu \cdot \mu$  parameters for exponents and coefficients for each of the  $\nu$  agents and each of the  $\mu$  goods. Only with simple productivity profiles like the ones used in CSW or random allocations can these numbers be held at a manageable level. Any additional term in the production function would increase the total number of parameters substantially.

Search and negotiation costs may be different for different types of goods. This is one of the mechanisms that is represented less directly in EGS. While ne-

Mechanism	EGS	Implementation	References
Specialising	✓	Actors decide to undertake some activities and not others.	Smith (1776)
Learning	(✓)	Experience leads to the discovery of capabilities, but learning curve effects are not included.	Wright (1936); Yelle (1979)
Increasing scale	✓	Marginal production costs can change with scale (if $b_{ik} \neq 1$ ).	Florence (1933); Dixon & Wilkinson (1986)
Combining		Production is independent between goods.	Richardson (1972); Baldwin & Clark (2000); Baldwin (2008)
Limiting	(✓)	Marginal production costs are changing monotonously, increasing or decreasing, but upper limits to production are not yet included.	Stigler (1951); Shove (1930)
Growing		Production is independent between goods.	Boulding (1953); Penrose (1959)
Intermediating		Only direct exchange is permitted.	Hall (1949)
Outsourcing	✓	Exchange equals outsourcing.	Robinson (1931)
Coordinating	✓	Search and negotiation costs are controlled exogenously ( $\kappa$ ).	Commons (1931); Coase (1937); Williamson (1975, 1981, 1985, 1991)
Coordinating	(✓)	Search and negotiation costs depend on the pervasiveness of the production capability, but they are not directly associated with the type of product.	Richardson (1972); Baldwin & Clark (2000)
Coordinating	✓	Coordination between actors can facilitate the realisation of comparative advantages.	Ricardo (1817)
Exploring and Exploiting	✓	Agents learn to adjust their exploration efforts ( $\mathbf{p}_i$ ).	March (1991)

Table 7.3: Implementation of production and specialisation mechanisms in EGS

Mechanism	EGS	Implementation	References
Searching	✓	Partner search depends on prior contacts, distance and randomness.	Frazier (1983); Wilkinson (2008)
Defining criteria		Agents do not explicitly search for partners with certain traits.	Anderson & Narus (1991); Collis & Montgomery (1995)
Informing		No information about other potential partners is exchanged.	Havila & Wilkinson (2002); Li & Rowley (2002)
Promoting	✓	Agents can choose to invest much time in approaching others, thereby promoting their own collaborative value.	Dwyer <i>et al.</i> (1987)
Targeting	✓	Suitable partners can be identified through test purchases.	Hedaa (1996)
Assortative mating	✓	Social/Physical distance simulates similarity.	Wilkinson <i>et al.</i> (2005)
Evaluating	✓	Agents maintain records of cooperative gains realised in the past.	Anderson & Narus (1991); Day (1994)

Table 7.4: Implementation of search and mating mechanisms in EGS

gotiation itself is not associated with costs, search attempts can be set to incur a fixed cost per attempt. On one hand, this means that each search attempt, independent of the resulting exchange, will incur the same cost. On the other hand however, production capabilities do not necessarily have to be distributed equally and there may well be goods for which superior producers are rare. Consequently, the number of search attempts required to find one of these rare producers will tend to be higher and therefore it is more costly to find such a suitable exchange partner.

The deliberate search activities in EGS are still limited. Memory of past exchanges, distance in the underlying space and random variation are the sole criteria for partner selection. Over time, each agent learns about superior and inferior matches, and tends to seek interactions with better matching partners, but beyond that, the agents do not engage in selective targeting, market analysis or even information gathering. However, agents can promote their availability for exchange by spending more time approaching others. If such exploration attempts lead to cooperation beneficial for both parties, this will be stored in both agents' memo-

ries and thereby increase the probability of their future collaboration. Promotion and exploration are equivalent in this implementation.

Much of the research about Markets-as-Networks shows that the social aspects of a relation have a substantial effect on the success and duration of the relation itself (cf. Wilkinson, 2008). EGS is limited to representing social relation as recurring interactions between pairs of partners, but does not explicitly represent social aspects of the actors. The model focus is on the economic aspects of division of labour and exchange. Again, the main reason for this is the added complexity that these social aspects would require. They would pose problems both with regard to the number of additional parameters, but also the validation of these social mechanisms. As the review of relevant mechanisms showed, the relevant social aspects have many dimensions, including power, dependence trust and commitment. Moreover, their effects on economic performance and cooperation are not always easily quantifiable, obstructing a concrete implementation in computer code. For all these reasons it was decided to omit social aspects of relationships for the time being, leaving room for further extensions subsequent to the analysis of the economic dynamics.

The initiation of a business relationship requires the consent of both parties. However, it only needs one of them to terminate the relationship again. In the current version of EGS relationship termination is a slow process and largely driven by unsuccessful negotiation and forgetting. It needs to be emphasised that relations in EGS are just interactions recurring over time. In the current settings, there are only three ways in which an exchange can be “prevented”: first, the agents do not approach each other for negotiations, second, one approaches the other but is refused, because the latter is not available for negotiations any more, or third their negotiation leads to the assessment that no exchange is better than any other form of cooperation. There exists however an already implemented, but not explored, model extension that adds an option for active refusal of a partner’s approach, which is equivalent to a unilateral termination of the relationship. This method allows an agent that is approached by another agent for negotiations to evaluate this approach by various criteria and then decide to enter negotiations or not. In the current implementation, these criteria are reasonably weak: with certainty an agent  $j$  is rejected when the average of remembered interaction outcomes is neg-

Mechanism	EGS	Implementation	References
Getting Acquainted	✓	Through exchanges agents learn what their partners are capable of and how they match each other.	Dwyer <i>et al.</i> (1987)
Learning	✓	Agents' memory spans the past $\rho$ rounds of interactions.	Narayandas & Rangan (2004)
Negotiating	✓	Partners negotiate exchanges, partners are equal in power.	Bergen <i>et al.</i> (1992); Mallen (1967)
Bonding		Cooperation is limited to economic aspects only.	Bitner (1995); Grönroos (1994); Narayandas & Rangan (2004)
Sense-making		Cooperation is limited to economic aspects only.	Welch & Wilkinson (2002)
Socialising		Cooperation is limited to economic aspects only.	Håkansson (1982); Heide & John (1990)
Coordinating through contracts		Contracts are not yet included.	Grossman & Hart (1980); Hart & Moore (1990); Grossman & Hart (1986); Hart & Moore (1988)
Coordinating through other arrangements	✓	Recurring successful exchanges increase the propensity for more exchanges in the future.	Osborn & Baughn (1990); Rindfleisch & Heide (1997); Palay (1984); Noordewier <i>et al.</i> (1990)
Coordinating through power		Cooperation is limited to economic aspects only.	Wilkinson (2008)
Coordinating socially		Cooperation is limited to economic aspects only.	Wilkinson & Young (1994); Iacobucci & Hibbard (1999); Huang & Wilkinson (forthcoming)
Monitoring		Monitoring is not required because agents are fully compliant to agreements.	Eisenhardt (1989)
Adapting		Relationship specific adaptations are not yet included.	Williamson (1975, 1983, 1985, 1996)
Cheating		Agents are fully compliant to agreements.	Williamson (1975, 1983, 1985, 1996)
Terminating	(✓)	A model extension allows for agents to refuse negotiation approaches by partners that led to negative experiences in the past.	Anderson <i>et al.</i> (1994); Young & Denize (1995); Halinen & Tähtinen (2002)

Table 7.5: Implementation of business dancing mechanisms in EGS

Mechanism	EGS	Implementation	References
Prioritising	✓	Order effects and demand limitations limit the agents' availability for cooperation. They follow a first come, first serve policy.	Turnbull <i>et al.</i> (1996)
Comparing	✓	Potential partners are compared on the basis of past experiences.	Anderson & Narus (1984); Anderson <i>et al.</i> (1994); Hallén <i>et al.</i> (1991)
Intermediating		Intermediation of offers is not yet included, but technically possible.	Håkansson (1982); Burt (1992, 2004)
Competing	✓	Agents compete for cooperation partners.	Balderston (1958)
Communicating		No information about others is exchanged.	Håkansson & Johanson (1988); Havila & Wilkinson (2002)
Transmitting	✓	Agents are interdependent through their limited availability for cooperation. Changes are transmitted.	Hertz (1999); Easton & Lundgren (1992); Anderson <i>et al.</i> (1994); Blankenburg-Holm <i>et al.</i> (1996); Wiley <i>et al.</i> (2009)
Clustering		Exogenous network effects are not yet modelled.	Marshall (1898, 1919)

Table 7.6: Implementation of interaction mechanisms in EGS

ative (i.e.  $\text{mean}(\mathbf{r}_{ij}) < 0$ ), and it is rejected with a probability of 50% if these memories are neutral (i.e.  $\text{mean}(\mathbf{r}_{ij}) = 0$ ). This feature is currently left for future research and can be extended flexibly by other criteria.

EGS features two ways of indirect interdependence between producers: scarcity and path dependence. These drive various implicit mechanisms about the interaction of relationships that affect the development of the business network.

Partners for collaboration are scarce in this model. An agent distinguishes between committed and negotiable production tasks, i.e. units of goods to be produced that an agent has determined to produce itself or that it is still searching to establish a source of production for. At the beginning of each negotiation round, all the units of goods that an agent wants to consume according to its consumption function are listed as negotiable production tasks. These will be the subject of

the negotiations with potential collaborators. Committed tasks are not negotiable any longer; the agent commits to produce the goods associated with these tasks personally. In the current implementation, an agent commits to perform production tasks as results of negotiations. It will commit to perform any production task that it took over from exchange partners, but beyond that it will also commit to perform its own tasks that refer to the same type of good, well realising that time savings come through economies of scale. Should there be another round of negotiations, the agent will only negotiate about those tasks that it has not yet committed to. In a sense the negotiations follow a first come, first serve principle. The first negotiation partner has the widest selection of negotiable tasks and all those that come later have content with what is left. In this sense, agents compete to cooperate. Furthermore, changes in collaboration will affect the availability of partners for other agents. Through this interdependence, the network of relations functions as a transmitter, propagating change from one relation to others.

Path dependence operates on two time scales in EGS. As mentioned before, every round the order of encounters affects the range of negotiable tasks between potential cooperation partners. On a larger scale, each agent's memory  $R_i$  affects its mating behaviour. Previous successful encounters favour future encounters with the same partner - and consequently reduce the probability of meeting others. Through this effect, the loyalty parameter  $\lambda$  inversely affects each agent's propensity to search for new, potentially better alternatives. For high values of  $\lambda$  an agent gives priority to those partners that led to satisfactory results in the past and they also compare potential partners on the same basis.

# Chapter 8

## Understanding EGS

EGS is a model of the mechanisms that bring about self-organisation of a production system and division of labour. These mechanisms include individual decision making and learning, but also social mechanisms relating to the coordination between individuals. Agents in this model need to develop both an individual focus of specialisation in production and coordination with suitable partners in order to compensate for tasks neglected in their specialisation process. From a complex systems perspective, we can anticipate the model's input parameters to have interactive and nonlinear effects and also the development of the model itself is likely to exhibit multi-dimensional interdependencies and phase-transitions.

While EGS constitutes a formal model of causal mechanisms that bring about specialisation and division of labour, its complex developments are still too comprehensive to be understood directly and in detail. Nevertheless, using systematic experimentation it is possible to simulate the model behaviour under of a variety of different combinations of input parameters. In conjunction with measurements of the model's development and outcomes, we can derive a *meta-model* of the relationships between in- and outputs. The analysis of such models is often not a straight forward exercise, but an iterative process that requires exploration, readjustments and creativity (cf. the “modelling circle” in Railsback & Grimm, 2011).

The following analysis is designed to anticipate non-linear relationships and possible phase-transitions of the model's behaviour. Therefore a strategy of cautionary crosschecking will be adopted. A combination of visual and statistical

analysis is used to explore and summarise the model's internal workings. Summary statistics such as means and standard deviations are used to characterise the state of the model concisely. However they are complemented by graphical representations of the data, including histograms and plots of time series, to verify that the aggregates capture the structure of the data adequately. Similarly, regression models are used to quantify the relationships between input parameters and output dimensions, but they are supplemented by customised graphical representations that are better able to capture non-linear relationships in the data. Lastly, an automated clustering algorithm is applied to classify the model outcomes and again a graphical representation of the clusters in the form of a parallel coordinate plot is provided to analyse the characteristics of these clusters and explain how differences in classifications come about. The entire analysis presented here is conducted using *R: A language and environment for statistical computing*, (R Development Core Team, 2011).

This chapter will present results from the analysis of the EGS model. This analysis will address two crucial issues: first, is EGS able to reproduce known behaviour from the real world, specifically the situation simulated in the CSW experiments? And second, what insights can we gain from EGS about yet unknown behaviour in the real world, i.e. can we use it to develop theories and derive hypotheses about the complex interactions in business networks and economy in general? Section 8.1 will discuss how the experimental settings in CSW are reproduced using EGS, introduce the measures selected to describe the model's performance, characterise classes of typical outcomes and relate them to the model's input parameters. After looking at selected cases in detail, this section will conclude by comparing EGS results with those from CSW experiments and KM. The second half of this chapter (Sec. 8.2) will discuss applications of EGS to situations that go beyond the settings in CSW. It will explore the effects of different sized agent populations, as well as extensions of the product space beyond a two-good economy, and it will investigate the effects of heterogeneity in production and consumption.

## 8.1 Calibrating to CSW

EGS constitutes an alternative theory to KM that uses a different combination of social mechanisms to explain the evolution of specialisation and division of labour. This section will assess to which degree the results known from the experiments in CSW can be reproduced through EGS. Of course, EGS can only serve as explanation of emergent phenomena if it is able to reproduce these phenomena. Therefore the assessment of congruence between model and reality constitutes an essential part of model validation.

Standards for the assessment of validity of agent-based models continue to be a subject of debate. Numerous validation frameworks have been proposed (e.g. Axtell & Epstein, 1994; Carley, 1996; Grimm *et al.*, 2005; Bloomquist, 2006; Leombruni *et al.*, 2006; Fagiolo *et al.*, 2007; Haefner, 2005; Marks, 2007). They diverge in focus and method, but they seem to agree that validity cannot easily be captured by a singular measures or statistic. Furthermore, most of these frameworks agree that validity is a multi-dimensional issue and needs to be assessed on a variety of levels. This thesis will follow the approach of *pattern-oriented modelling* (Grimm *et al.*, 2005; Railsback & Grimm, 2011) that assesses model validity on two basic dimensions: 1) Theoretical (or structural) validity of the mechanisms that drives the model, and 2) Output validity, pertaining to the reproduction (and eventually prediction) of multiple independent dimensions of the target phenomenon.

The comprehensive literature reviews in Ch. 3 and 4 provide the theoretical foundations of EGS and should ascertain an appropriate level of theoretical validity. Naturally, there is a trade-off regarding the comprehensiveness of any model and the depth of understanding that can be gained from its analysis. So there are many other relevant mechanisms that have not yet been included in EGS. Such possible extensions and directions for further research will be discussed in Ch. 9.

Output validity will be assessed in this section, starting out with model calibration to empirical cases that are provided through CSW's experiments. Calibration means that the model parameters are deliberately set so that they reproduce patterns observed in the real system. According to Railsback & Grimm (2011) model calibration serves three purposes: 1) If it is possible to calibrate the model so that

it reproduces known behaviour, we can be more confident to use the same model to explore what could happen in alternative scenarios and use its results for theory development and the derivation of hypotheses. 2) Calibration allows us to estimate values of parameters that we cannot evaluate directly. 3) Calibration serves as a test of a model's structural realism, especially if it is possible to calibrate a model to match a range of observations. The remainder of this section will address the following:

1. Describe the settings that approximate CSW settings in the EGS framework,
2. Define suitable dimensions to describe model outcomes,
3. Describe features of these outcomes and their relation to input parameters,
4. Identify and describe classes of similar model developments,
5. Compare EGS outcomes to results in CSW,
6. Discuss select cases on the micro-level.

### **8.1.1 Approximate CSW Settings in EGS Framework**

As mentioned in Ch. 7, there are several substantial differences between KM and EGS. These were the results of both theoretical considerations and technical constraints of EGS's more flexible and extendable production and consumption framework. The most crucial differences pertain to the consumption functions and negotiation algorithms, as well as to the introduction of more detailed relational aspects in EGS. Despite these differences, it is possible to approximate the settings in CSW and KM in EGS. The corresponding economic setup would consist of a population of  $\nu = 8$  individuals and  $\mu = 2$  goods (**R**ed and **B**lue). The agents are

divided into equal-sized groups of “odds” and “evens”, and they are assigned the original production functions used in CSW:

$$\begin{aligned}
 Red_{\text{odd}} &= 0.41t^{2.5} \\
 Blue_{\text{odd}} &= 2.25t \\
 Red_{\text{even}} &= 2.53t \\
 Blue_{\text{even}} &= 1.1t^2
 \end{aligned}$$

The only difference is that  $t$  is the actual time invested in the production of the specific good - it is independent of the time assigned to the production of the other good. An illustration of these functions as they were used originally by CSW is given in Fig. 8.1.

Consumption in EGS is implemented to be more flexible than the fixed functions in KM, able to represent cases that go beyond the two goods in CSW, while at the same time allowing for negotiation solutions that do not presuppose perfect knowledge and the capability to identify optimal results. In CWS consumption is essentially limitless and production is the limiting factor. In contrast, EGS is based on the assumption that demand is limited and production, while technically limitless, will have an upper limit, namely the production time required in autarky. Agents seek to improve through exchange and collaboration and will refrain from deals that would leave them with more work than before. As a result the agents' demand is fixed and determined exogenously in EGS.

In EGS demand is described as a fixed number of units for each good. In order to approximate CSW, it needed to be decided which level of the originally limitless consumption to approximate. CSW models consumption through Leontief preferences requiring each type of agent to desire a relatively higher proportion of the good it is producing more efficiently:

$$U_{\text{odd}} = \min(1Red, 3Blue) \quad U_{\text{even}} = \min(2Red, 1Blue)$$

Considering the different objective in EGS, it was deemed that the autarky level of consumption would be sufficient to make the case for comparison. This setting requires approximately 10 hours' work from each type of agent, as long as

**Trade-off of Production Functions in CSW and Resulting Utility in Autarchy and Optimal Specialisation**

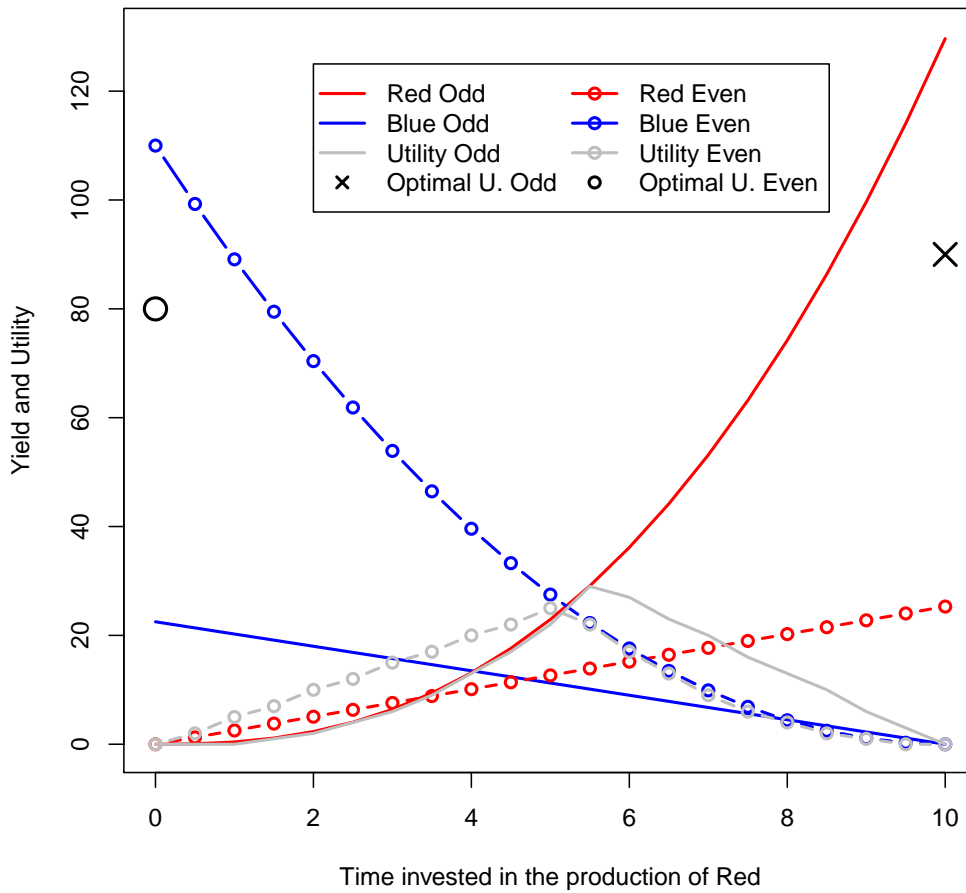


Figure 8.1: Production and utility functions in CSW. Agent types are distinguished by plain lines vs. intermittent circles. Blue and red lines indicate the production potential for Blue and Red goods respectively. Grey lines indicate the levels of utility that can be reached in autarchy, whereas the two isolated points ( $\times$ ,  $\circ$ ) indicate the optimal level of utility and production in the perfectly specialised competitive equilibrium.

they work in isolation. Nonetheless, this level of consumption already affords efficiency gains of around 40% through specialisation: In autarky odd agents produce 30*Red*, investing 5.568 hours and 10*Blue* in 4.444 hours. Even agents produce 26*Blue* in 4.862 hours and 13*Red* in 5.138 hours. In summary, odds have to spend 10.013 hours and evens exactly 10 hours working to satisfy their own demand without the help of others. Full specialisation and coordination with a matching partner would redistribute and reduce the workload. In this ideal situation odds work 6.431 hours producing 43*Red* and evens spend 5.721 hours on the production of 36*Blue*.

Possible time savings and losses that result from a range of possible task allocations between a pair of matching agents are shown in Fig. 8.2. Holding the total numbers of units constant, the agents get to negotiate the division of production tasks between them. Each of these tasks refers to the production of one unit of a good. The agents can save time, or lose time, depending on the allocation of tasks between each other. The illustrated task allocations represent a range of possible negotiation outcomes that tend to exchange tasks in a balanced way, i.e. exchanging a number of tasks for one good for a similar number of tasks for the other. The implemented negotiation algorithm is biased and tends to favour such fair solutions, but that does not mean that only these combinations of production tasks can be obtained. It is possible that an agent exchanges a few tasks for many others - and it is also possible that both agents still save time through this reallocation.

This altered implementation of demand facilitates the implementation of a much more flexible negotiation framework. Agents negotiate exchanges prior to production and then they produce exactly what they negotiated. Consequently overproduction and waste are reduced to zero. In the negotiation phase, the agents' aim is to rid themselves of production tasks that require the commitment of a relatively large amount of time, and exchange them for tasks that they can perform relatively quickly. EGS uses a genetic algorithm (GA) to model negotiation, instead of an explicit optimisation procedure like the one used in KM. This leads to a much broader range of potential negotiation outcomes and their associated mating and dancing behaviours.

The choice of suitable control parameters for GAs has been debated in both analytical and empirical investigations (see e.g. Grefenstette, 1986; Goldberg, 1989;

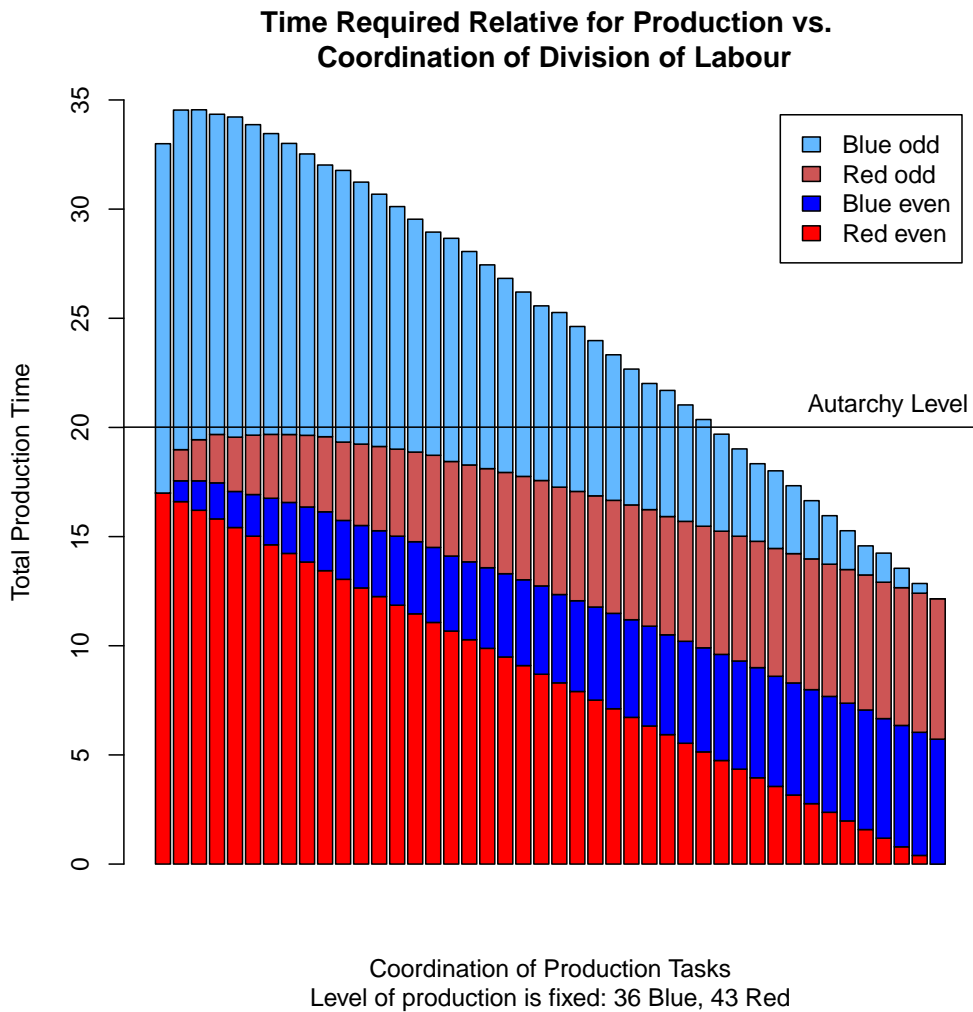


Figure 8.2: Production relative to resource allocation and coordination. In EGS the total demand is fixed and the agents are able to reduce their total work time through appropriate specialisation and coordination. The graph shows a range of possible allocations of production tasks between a pair of agents of opposite type.

Srinivas & Patnaik, 1994). The chosen settings in EGS are  $\theta = 30$  for the number of candidate solutions, the crossover rate is  $\chi = 70\%$  and the mutation rate is  $\xi = 1\%$ . These values have been found to lead to satisfactory results in a range of applications (e.g. Srinivas & Patnaik, 1994). The GA works with a small number of candidate solutions and relies strongly on mutation to introduce new aspects to the population - and with its relatively high crossover rate, introduces a high level of string disruption in the small population of solutions. The downside of these settings are that good solutions face a higher chance of being disrupted by crossover or altered by mutation; thus more importance is given to creativity of solutions than to optimisation. The relatively small number of candidate solutions reduces the calculation time but increases the risk that the algorithm prematurely converges to a local optimum. This choice is deliberate, because it is assumed that business actors in the real world are not necessarily aware of the optimal negotiation outcome and they might well settle for inferior solutions, in lack of better knowledge. The last control parameter for this GA is the number of generations  $\psi$ . This value will be one of the input parameters that are inferred during the calibration exercise here, where we explore the respective effects of  $\psi \in [5, 10, 20, 30]$ .

There are several other parameters in EGS that affect the model's behaviour, some of which do not have an explicit equivalent in the real world. This calibration step will also serve to infer suitable values for these parameters and determine how they relate to each other in affecting the model's outcomes. These parameters include  $\iota$  the increment that governs the speed of adaptation regarding the number of search attempts that an agent will undertake. The higher this value, the faster are the agents' adjustments to new information about searches. Closely related is  $\varepsilon$  which represents the degree of variation in the choice of a certain number of search attempts, specifically representing the probability of deviation from the chosen number of search attempts. It introduces some noise into this decision making algorithm and allows agents to explore new partner search strategies. Two parameters that affect the agents mating choices are  $\rho$ , the agents' memory length, and  $\lambda$ , the agents' preference for loyalty. These parameters determine how many past exchange experiences influence the agents' partner search and how strong their influence is. Lastly  $\kappa$  determines the cost associated with any one search attempt. In EGS these costs are represented in the only "currency" available: units

of time. While CSW did not include explicit search costs in their experiments, it can be assumed that their participants had to undertake efforts to find a suitable partner and negotiate an exchange, thereby incurred psychological costs. Considering the experiments' outcomes it seems appropriate to assume that in some cases, those costs were almost prohibitively high, so that some participants gave up and settled down in autarky.

In order to identify relevant parameter values while keeping the explored parameter space at a manageable size, an initial exploratory study was conducted. This study covered a larger parameter space, but only one repetition for each combination of parameters. From this exploration step, a smaller set of values was selected to be analysed in detail. A summary of these values is given in Tab. 8.1. These values are theoretically sensible and interpretable and often represent extreme cases in the continuum of possible values for each of these parameters, so that the subsequent analysis covers a wide range of possible effects and their outcomes.

Experimental parameters		Explored Values
$\nu$	Number of agents	8
$\mu$	Number of goods	2
$\psi$	Generations of the Genetic Algorithm	5; 10; 20; 30
$\iota$	Increment to adjust the probability distribution for the number of search attempts	0.1; 0.4
$\varepsilon$	Probability of deviation from the chosen number of search attempts	0; 25; 50%
$\rho$	Agents' memory length	2; 8
$\lambda$	Agents' preference for loyalty	50; 75; 99%
$\kappa$	Cost (time) per search attempt	0; 0.2; 0.4

Table 8.1: Experimental parameters in EGS that were explored and calibrated to best match the behaviour observed in CSW experiments.

## 8.1.2 Describing EGS Outcomes

A computational model like EGS simulates an entire system with its complex interdependencies and multifaceted characteristics. Pattern-oriented modelling suggests describing the state and outcomes of a simulation through a collection of

patterns that capture a range of independent dimensions of the system under consideration. These serve as both statistics to describe and summarise the model's development, and benchmarks to compare model outcomes to outcomes of the target system. In the following a variety of statistics will be introduced that are selected to describe the combination of independence dimensions of EGS. These measures are the results of an iterative process of adaptation and readjustment, just like it is described by Railsback & Grimm (2011). They address economic as well as social dimensions, and they are able to distinguish several classes of developments that EGS is capable of producing, depending on its input parameters. For each of these measures the model automatically records the mean value across all agents as well as the standard deviation throughout the population, for every round in the model.

**Specialisation:** Specialisation measures the share of production tasks for the good that the agent produces more efficiently, relative to all production tasks that the agent has taken over after negotiations. For odd agents the autarky level of specialisation is  $\frac{30}{30+10} = 0.75$ , and for even agents it is  $\frac{26}{26+13} = 0.66$ . Figure 8.3 shows a histogram summarising the levels of average specialisation that were achieved across the entire parameter space explored. The results shown are average values from the last 15 rounds of 30 repetitions per parameter combinations (more details about this aggregation will be provided in Sec. 8.1.3). The blue lines indicate the range of possible values, from 0.71 to 1. In the same plot, the red line represents a density estimate of the standard deviation of specialisation. This measure captures the spread of specialisation across agents in any one model run. It ranges from 0.03 to 0.11. This range needs to be considered in relation to the range of possible values. While a standard deviation of 0.03 indicates a reasonably homogeneous level of specialisation, a standard deviation of 0.11 in a possible range that spans only about 0.3 is quite substantial and suggests strong heterogeneity in the agent population. Also, the existence of variance in agent specialisation indicates that it is possible for individual agents to achieve full specialisation in a model run, although the average result for the population does not reach the level of complete specialisation.

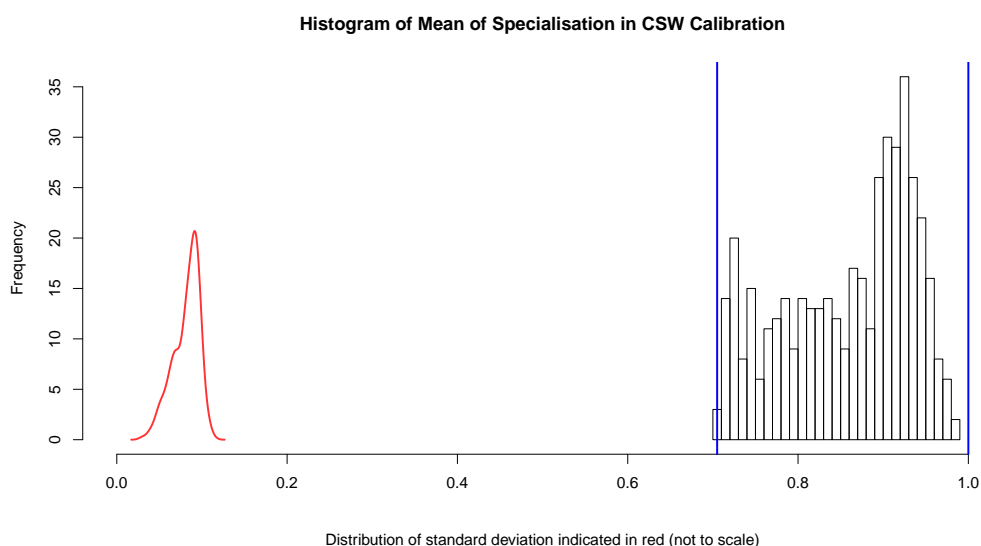


Figure 8.3: Histogram of levels of specialisation achieved in final rounds of the CSW calibration.

**Leisure:** Leisure measures the actual time-savings realised on average by agents through cooperation and exchange. Based on a 10 hour workday, leisure expresses how many of these working hours need not be spent working as a result of specialisation. The CSW production setting is designed under the assumption that participants have no interest in leisure at all. Contrastingly, the economic setup in EGS allows agents to save nearly four work hours every round through specialisation, coordination and exchange. In Fig. 8.4 these limits are indicated by the blue lines in the graph. The lowest level of average leisure, however, was found to be  $-0.037$ , indicating that agents can perform worse than in autarky. This issue will be further investigated in Sec. 8.1.5. Again, the standard deviation of leisure can reach relatively high values, indicating that there are populations where one agent realises more than two hours of leisure than other agents.

**Searches:** This measure captures the average number of search attempts for new partners in the given round of the simulation. The number of searches is an adaptive agent strategy, that characterises the way coordination and cooperation is achieved in the system. Very low numbers of searches indicate

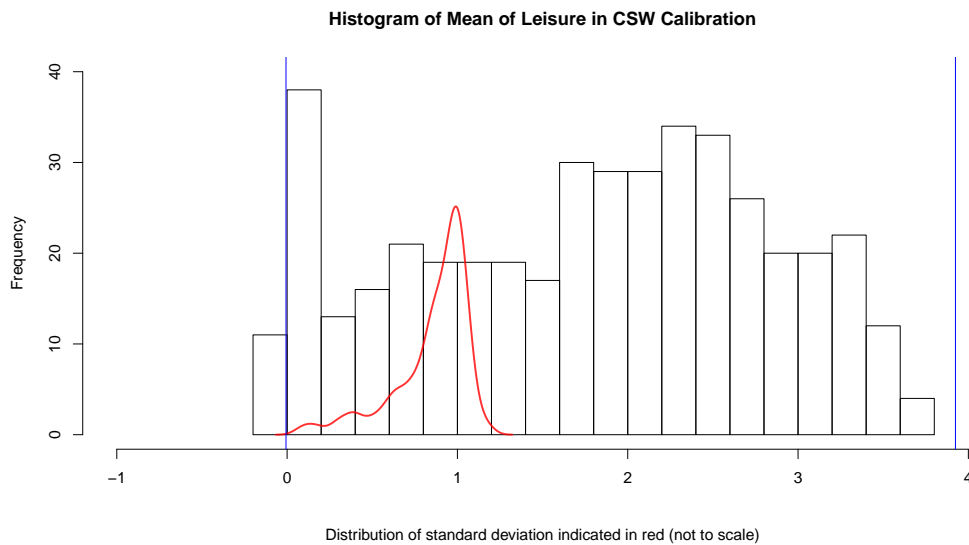


Figure 8.4: Histogram of levels of leisure achieved in final rounds of the CSW calibration.

that there is hardly any basis for exchange between agents; very high numbers of searches indicate that everyone seeks to trade with everyone else and few exclusive relationships exist. Lastly, values between 0.5 and 1 can be interpreted in the sense that agents limit themselves to a minimum number of searches and subsequent negotiations. This is particularly relevant as searches can be costly. Figure 8.5 shows that the average number of searches ranges from zero to more than four, while the median standard deviation of searches is slightly above one. Again the standard deviation can be rather high, in which case the burden of search cost would be unevenly divided between agents.

**Degree:** While searches describe the number of attempts to find an exchange partner, degree captures the number of relevant exchange partners. It is defined as the number of exchange partners that an agent still remembers in its transaction memory and that have contributed more than 10% of the agent's time savings throughout the remembered rounds. As can be seen in Fig. 8.6, the range of values lies between zero and 3.18. It must be kept in mind that the maximum number of sensible exchange relations is four: one

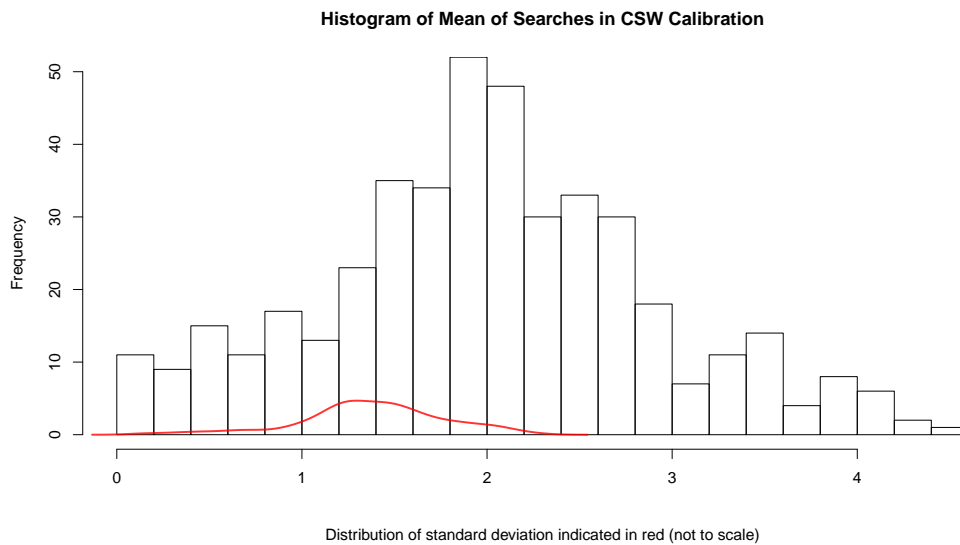


Figure 8.5: Histogram of the average number of partner searches conducted in final rounds of the CSW calibration.

with every other agent of the opposite type. In comparison with the number of searches, it becomes evident that the degree, i.e. the number of relevant exchange relations, tends to be lower than the number of searches. This means that there must be a number of model runs where agents wasted time and effort on searches that did not lead to relevant exchanges.

**Exchange:** The last dimension to describe the state and development of an EGS model run is the volume of exchanged goods, short “Exchange”. This measure summarises for every agent the total number of units outgoing and incoming due to negotiated exchange. While this number is zero in autarky, it can reach values as high as 23 in an ideal exchange between two matching agents. Figure 8.7 demonstrates that the values achieved in EGS runs cover the entire range, and even go beyond that, with a maximum of 26.32. These volumes can be the result of numerous negotiation processes with a number of partners and it does not necessarily mean that ideal exchanges were identified by any one pair of agents.

One step towards a better understanding of this model is to analyse how all these different aspects of the model relate to one another. Knowing that complex

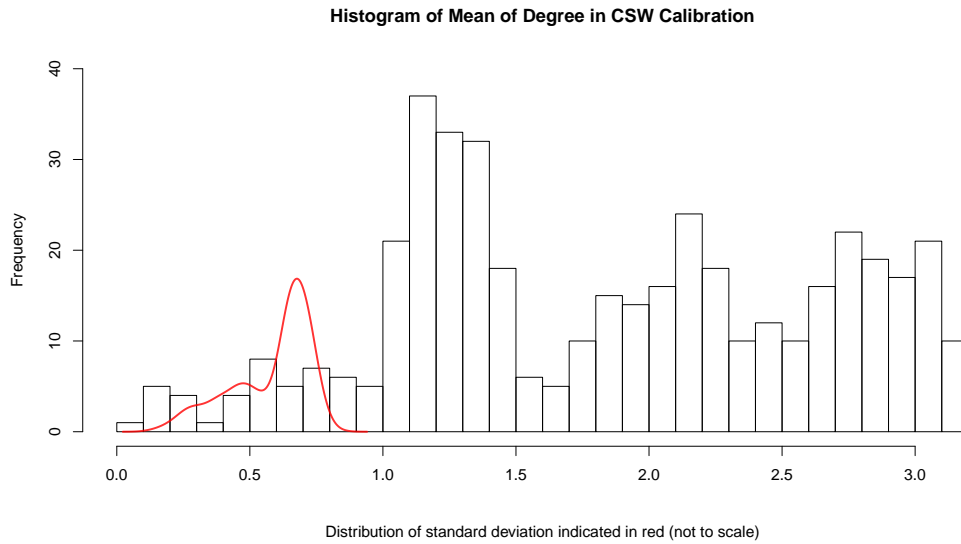


Figure 8.6: Histogram of the average number of exchange partners in final rounds of the CSW calibration.

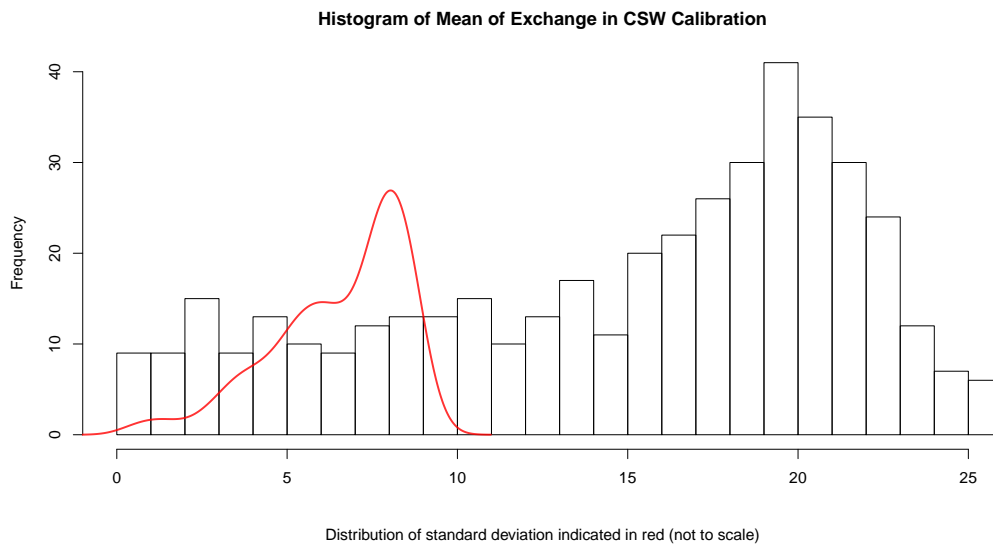


Figure 8.7: Histogram of the average volume of exchanges in final rounds of the CSW calibration.

systems can be nonlinear and highly interdependent caution is always warranted when using statistical tools that assume linear relationships. However, used carefully they can provide a useful way to summarise the large amounts of data produced by computational models, and thereby help uncover relationships between dimensions and point towards areas of interest and further investigation.

Table 8.2 on p. 234 shows the correlations between all the measures discussed above - both regarding the observed means and standard deviations in a model run. The results cover the entire range of input parameters considered for this calibration task. All mean values are positively correlated; some as low as 0.41, while other correlations come close to one. Generally, standard deviations exhibit a much lower correlation to the mean values and amongst each other - except for the average number of searches, which is highly correlated to the standard deviation.

There are several insights that can be gained from this correlation table. Considering the high correlation between leisure, specialisation and the level of exchange, both relationships are intuitive and sensible, as high leisure can only be reached through high levels of specialisation and appropriate coordination through exchange. At the same time these variables show only a loose association with the average degree, while the number of searches is still correlated with these measures, but more loosely. This may in part be a result of the nonlinear effects of costly searches. Without any searches at all, negotiations cannot be initiated, exchange is obstructed and economies of specialisation cannot be realised. Too many searches however may incur high costs and have detrimental effects on the agents' leisure. The standard deviation of leisure and the standard deviation of degree show a weak and negative correlation to their respective means. This indicates that there are at least some model runs where the discovery of specialisation and exchange does not increase heterogeneity between agents, so that the population as a whole can benefit from these developments.

### **8.1.3 Relations between Input and Output**

The analysis of agent-based models of complex systems is burdened with idiosyncratic obstacles and challenges. Output data is usually multidimensional and lon-

	∅ Leis.	sd Leis.	∅ Spec.	sd Spec.	∅ Deg.	sd Deg.	∅ Srchs.	sd Srchs.	∅ Exch.	sd Exch.
∅ Leisure	1.00	0.40	0.97	-0.09	0.41	-0.19	0.71	0.42	0.93	0.36
sd Leisure	0.40	1.00	0.47	0.80	0.56	0.34	0.48	0.57	0.55	0.86
∅ Specialisation	0.97	0.47	1.00	-0.01	0.42	-0.20	0.63	0.37	0.94	0.41
sd Specialisation	-0.09	0.80	-0.01	1.00	0.55	0.68	0.14	0.32	0.19	0.86
∅ Degree	0.41	0.56	0.42	0.55	1.00	0.62	0.56	0.45	0.65	0.80
sd Degree	-0.19	0.34	-0.20	0.68	0.62	1.00	0.13	0.25	0.07	0.66
∅ Searches	0.71	0.48	0.63	0.14	0.56	0.13	1.00	0.87	0.73	0.50
sd Searches	0.42	0.57	0.37	0.32	0.45	0.25	0.87	1.00	0.47	0.53
∅ Exchange	0.93	0.55	0.94	0.19	0.65	0.07	0.73	0.47	1.00	0.62
sd Exchange	0.36	0.86	0.41	0.86	0.80	0.66	0.50	0.53	0.62	1.00

Table 8.2: Correlation matrix of output values resulting from the calibration to CSW.

gitudinal, and the immense parameter space that needs to be explored easily multiplies the volume of produced data by a factor in the thousands. By these standards EGS is a comparatively well-behaved model: The parameter space in Tab. 8.1 requires “only” 432 different model parameterisations, because it is focussed on combinations of values that are sensible in the context of model, but also interesting in the sense that they are chosen to represent extreme and opposite cases within the range of sensible values. Another property of EGS that facilitates an easier summary of the produced data was discovered in the exploratory stage. Analysis of longitudinal EGS outcome measures suggests that model runs reach a stable level in every output dimension after about 60 rounds. On this basis it was determined that it is sufficient to terminate the model runs after 75 rounds, which would even include a buffer to ensure the essence of the run is reliably captured correctly.

Considering the amount of output data, all types of analysis will face the challenge to find a satisfactory trade-off between identifying the essence of data and discarding too much information. Too much detail in the data obstructs understanding, but too much simplification increases the danger of overlooking important aspects. Visual inspection of the numerous time-series that portray the relationships between input and output values suggests that the final state of the model can be summarised in a single value, namely an average of the measurements after 60 rounds. Figures 8.1.3 and 8.1.3 show examples of such visualisations. The four upper panels show the development of leisure throughout the model runs. They are grouped to investigate the effect of the number of GA rounds. It is clear that low numbers of GA rounds lead to low performance in terms of leisure. GA rounds can be seen as the effort that agents put into the negotiation process and these graphs clearly show that more effort leads to better performance. The three lower panels show the effects that different levels of loyalty exhibit on development of the agents’ average degree. Lower levels of loyalty lead to a higher average degree. Setting loyalty to 99 substantially reduces the variation in degrees and constricts observed values to a small range around one.

The final conceptual issue that needs to be addressed regarding the analysis of an agent-based model is the impact of the random effects on a model’s outcome. Various procedures in EGS are driven by stochastic processes so that each obser-

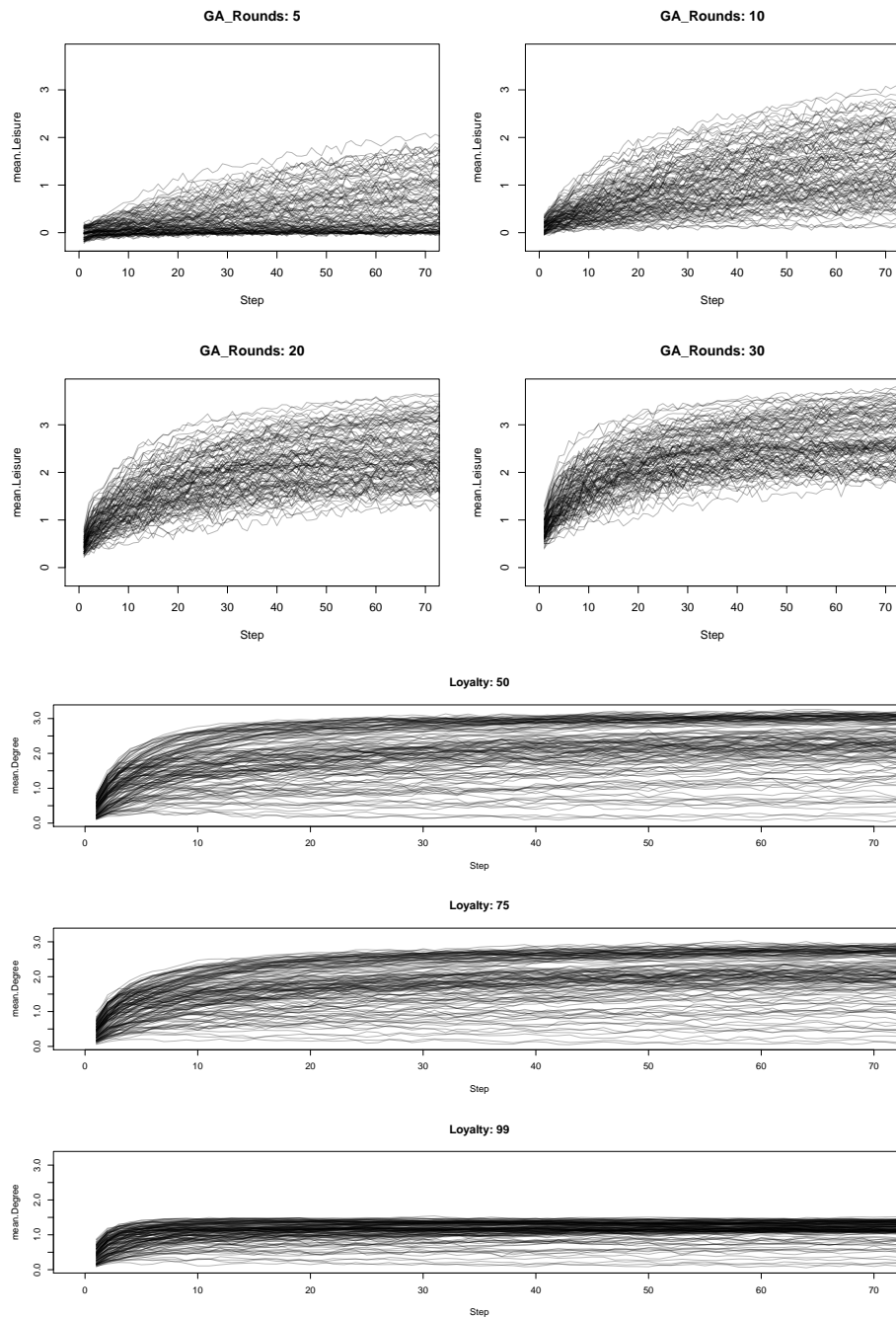


Figure 8.8: Exemplary plots of time series data recorded from EGS runs. The upper panels show the effect of the number of GA rounds on the development of leisure. The three lower panels show the effects of different levels of loyalty on the average degree of agents. Each line constitutes a time series that itself represents an average over results from 30 replications with the same input parameters.

vation of the model's trajectory in isolation could be the result of a chance event and represent an extreme outlier from the typical range of outcomes. In order to control for the impact of such chance events, 30 replications are run for each combination of input parameters and then averages over the outcomes produced are used for analysis. Consequently, the subsequent analyses will use highly aggregated data. Each parameter setting will be represented by the averages across its last 15 rounds, averaged across 30 replications of models, that each capture the averages (and standard deviations) of output variables across agent populations. In this way it is possible to characterise each model run by *six input parameters* and the *measurement of ten output values* (means and standard deviations of five aggregate statistics). The next step to understanding the internal workings of EGS is to investigate how input parameters relate to individual output values.

The identification of relationships between input parameters and several output dimensions can be addressed with statistical tools or visually. Both approaches have their advantages and disadvantages. Statistical procedures, such as regression analysis or analysis of variance, are able to quantify the relationships and impacts of input parameters. However they rely on strong model assumptions, including linearity of effects and normal distribution of the random variation. Also, the power of statistical tests depends on the sample size which is theoretically unlimited for data from computational models. Accordingly significant test results should be treated with caution. In contrast, visual analysis cannot be used to quantify the effects of parameters and it is limited regarding dimensionality of analysis, nonetheless it is much more flexible in discovering patterns and relationships that go beyond linearity.

In this section we will look at each of the output dimensions in isolation and see how they relate to input parameters, using a combination of statistical and visual tools. For clarity and brevity only selected samples of the analysis output are shown in this section. A complete overview of the analysis of each output dimension is provided in Appendix B.

The level of leisure is the first output dimension to be considered here. It captures the average time savings realised through specialisation, coordination and exchange. In an ideal situation odd agents can realise  $10 - 6.431 = 3.569$  hours of leisure, producing *43Red* and even agents can gain free time from exchange of

$10 - 5.721 = 4.279$  hours, as they are producing *36Blue*. Consequently, the average level of leisure that a matching pair can obtain in these settings is 3.924. The relationship between leisure as the dependent variable and the six input parameters as independent variables can be captured in a generalised linear regression model (Dobson, 1990; Hastie & Pregibon, 1992).

Considering that leisure is measured on a ratio scale and observations appear to be nearly normal distributed, the Gaussian family with identity link appears to be a good starting point for analysis. Stepwise model selection is used to reduce a full linear model that includes all main and all interaction effects to a model containing only the most relevant terms (see e.g. Venables & Ripley, 2002). Akaike's AIC criterion is used to identify better fitting and more parsimonious meta-models. The results of the final model are shown in Tab. 8.2.

Coefficients:	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	0.101	0.164	0.613	0.540	
Memory Length	0.046	0.009	5.101	0.000	***
GA Rounds	0.085	0.008	11.098	0.000	***
Search C.	-2.343	0.345	-6.795	0.000	***
Search P.I.	1.937	0.286	6.783	0.000	***
Loyalty	0.000	0.002	0.259	0.796	
p(E NSearch)	0.003	0.003	0.922	0.357	
Memory L.:GA R.	-0.001	0.000	-2.355	0.019	*
GA R.:Search C.	-0.011	0.017	-0.621	0.535	
GA R.:Search P.I.	-0.047	0.015	-3.086	0.002	**
Search C.:Search P.I.	-3.510	1.106	-3.174	0.002	**
GA R.:L'ty	0.000	0.000	3.353	0.001	**
GA R.:p(E NSearch)	-0.000	0.000	-1.892	0.059	
Search C.:p(E NSearch)	-0.010	0.005	-2.111	0.035	*
L'ty:p(E NSearch)	0.000	0.000	2.182	0.030	*
GA R.:Search C.:Search P.I.	0.107	0.059	1.833	0.067	

Table 8.3: Results of a generalised linear regression relating the terminal level of leisure to the collection of EGS input parameters.

The main effects of GA rounds ( $\psi$ ), memory length ( $\rho$ ) and search probability increment ( $\iota$ ) are all significant and positive, while search cost ( $\kappa$ ) is significant and negatively associated with the level of leisure. Loyalty ( $\lambda$ ) and the degree of variation in choosing the number of partner searches ( $\varepsilon$ ) do not have any signifi-

cant effect. Considering the different scales of these input parameters, the number of rounds in the GA seems to have the strongest practical main effect, then comes the negative effect of search costs, followed by the memory length and the speed of adaptation.

Furthermore, the regression analysis shows various significant interaction terms. Regarding its actual effect size the interaction effect between memory length and GA rounds is the most prominent. The associated coefficient is negative which means that the positive effect of longer memory is somewhat reduced in models with a high number of GA rounds. Also, the interaction between search cost and search probability increment is significant and negative. This means that in systems with higher search costs the positive effects of faster learning are reduced. Considering their low coefficients and consequently their minimal impact on the level of leisure the remaining interactive effects, although statistically significant, are practically negligible.

An alternative way to analyse such data is a visual analysis. Conditional scatter plots are a convenient tool to visualise relationships between multiple dimensions through repeated subdivision and systematic arrangement of the data. An example of this is Fig. 8.9 which shows plots of mean leisure versus its standard deviation. The individual scatter plots are grouped and ordered by the number of GA rounds ( $\psi$ ) and different levels of loyalty ( $\lambda$ ). Using colour coding and selected point characters it is possible to represent two more dimensions in this plot: The colour coding represents search cost ( $\kappa$ ) and the point characters visualise the increment to adjust the probability distribution for the number of search attempts, i.e. the speed of adaptation ( $\iota$ ). In summary, through partitioning of the data, colour coding and the use of different symbols these plots can visualise two dependent variables and their relations to four independent variables.

The plots displayed here are the result of visual inspection of all possible combinations of grouping variables, and present those combinations of input parameters that “explain” the largest amount of variation in the dependent dimensions. In the case of Fig. 8.9 they coincide with the set of significant main effects from the previous regression analysis.

Figure 8.9 largely confirms the findings of the preceding regression analysis. Considering only the mean of leisure (vertical axes), GA rounds appears to have

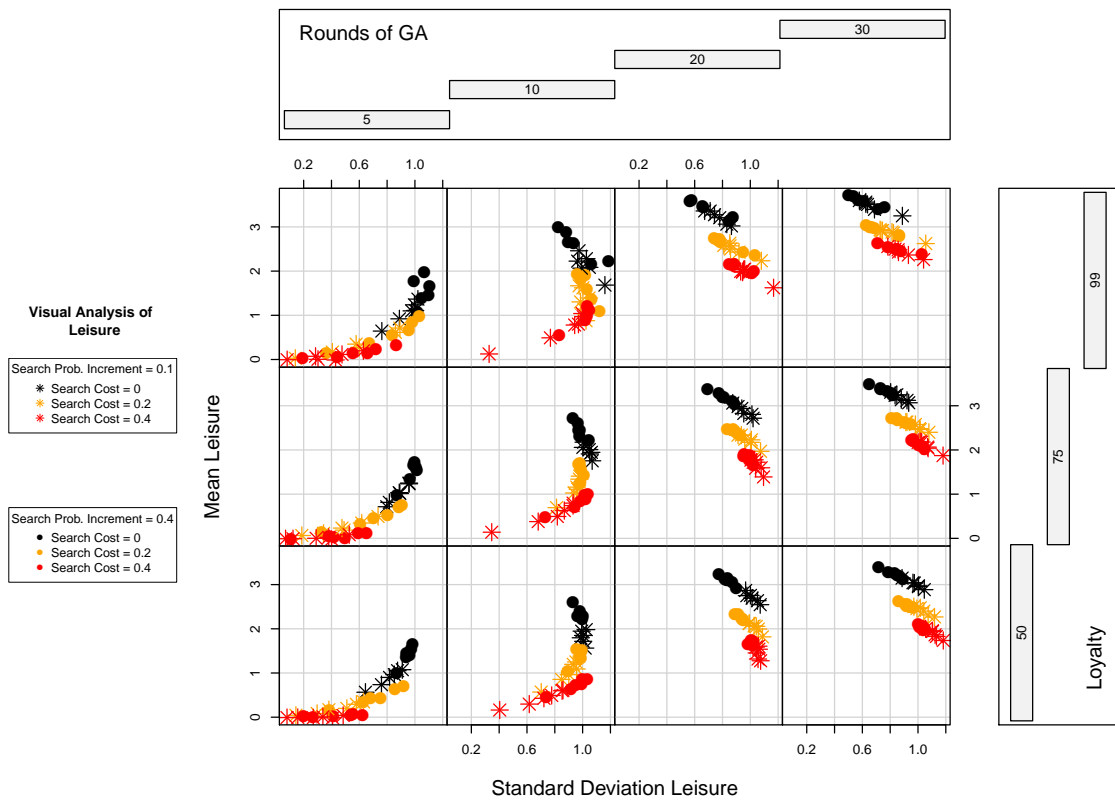


Figure 8.9: Conditional scatter plot of average level of leisure versus its standard deviation, ordered by rounds of the Genetic Algorithm ( $\psi$ ) and level of loyalty ( $\lambda$ ). The colour coding represents search cost ( $\kappa$ ) and the point characters the speed of adaptation ( $\iota$ ).

the strongest effect, reaching more than twice the level of leisure with 30 rounds compared to five rounds only. Also, search costs which are represented through colour coding have a pronounced effect. The more expensive searches for partners are, the lower the level of leisure. This is likely to be a direct effect of the search costs. Searches are necessary for cooperation and if they are set to incur costs, these costs will reduce the agents' leisure time. High search probability increments are represented through filled circles, and they persistently lead to higher outcomes in comparison to low search probability increments. Contrary to the previous regression analysis, there appears to be a positive main effect of loyalty, also. Looking at the different levels of loyalty (vertical grouping), resulting levels of leisure are higher under high loyalty and this effect is even more pronounced under higher number of GA rounds. In the regression model this was "hidden" in loyalty's interaction effects.

In addition to the mean of leisure, the conditional scatter plots also show the associated standard deviations on the horizontal axes. It becomes immediately apparent that the standard deviation is positively correlated with the mean of leisure itself. This indicates that agent populations that reach higher levels of leisure also show increased heterogeneity amongst the agents. However, for higher levels of leisure and more rounds in the GA, this association is less clear. In fact, higher preference for loyalty, but also a higher speed of adaptation regarding the number of searches, lead to a lower standard deviation and thereby to a more homogenous agent population with regard to the level of leisure attained. Search costs enhance the effect of the rounds in the GA: With fewer rounds, even lower leisure is achieved and the standard deviation is especially low when search costs are high. Contrarily, with more rounds in the GA, increased search costs lead to a greater inequality in the population.

These visual findings are confirmed by an additional regression analysis that relates the standard deviation of leisure in the agent population to the models' input parameters. Results are presented in Tab. B.2 on p. 336. All of the main effects are significant. Furthermore, there are numerous significant interaction effects. Their interactions with search costs increase the effects of all other input parameters, while they are somewhat lessened through interaction effects with GA rounds that point in the opposite direction of the main effects. These interaction

effects describe mathematically what the visualisation captures graphically: Depending on the rounds of GA and the colour coding, the clusters of points change their relative order, the input parameters interact and change their effects.

These findings can be interpreted in the following way: The main determinant of the agents' level of leisure is the effort they put into finding satisfactory negotiation results, represented by the number of GA rounds. Search costs control how easy it is for agents to achieve time savings through cooperation. Once these two main determinants of performance are set, memory length, loyalty and the probability increment determine the agents' "networking capabilities", allowing them to adjust more quickly to the economic and social setting they find themselves in, and enabling or hindering them from maintaining long lasting relations. Holding GA rounds and search cost constant, better networking always leads to better performance and it can reduce the heterogeneity in the agent population when the average level of leisure is high enough to provide for a high degree of variation amongst the agents. These findings were to be expected and thus the model is performing as it should. Nonetheless the analysis gives more nuanced insights of the interplay of the model constituents.

The correlation analysis in Tab. 8.2 shows that leisure is highly correlated with the level of specialisation and the volume of exchanges. So it is to be expected that their relationship to input parameters is similar to that of leisure. Regarding the determinants of the level of specialisation, the results from regression analysis and model selection presented in Tab. B.3 on p. 337 generally confirm this proposition. Again the model's main effects are significant, except for the effect of loyalty, and the probability of a search error, and all of them are positive except for the effect of search costs. Several interactions are found to be significant, and they largely coincide with the interactions that were significant in the model for leisure.

According to a regression model for the standard deviation of specialisation (shown in Tab. B.4 on p. 340), the main determinants of this measure of heterogeneity in the population are rounds in the GA and search cost. The latter having a negative effect on the standard deviation. There are various significant interaction effects; in fact, all parameters have a positive interaction with search costs - which means in a system with higher search costs, higher values for any of the re-

maining parameters increase the heterogeneity in specialisation. At the same time there are significant first and second order interaction effects with the number of GA rounds, indicating that in systems with many rounds in the GA, some combinations of variables have a homogenising effect on the level of specialisation.

A visualisation of these results is presented in Fig. B.2 (p. 338) and Fig. B.3 (p. 339). Visually all input parameters seem to have an effect on the level of specialisation achieved and/or its standard deviation. Therefore the results are presented in two conditional scatter plots that differ by colour coding and point characters. The non-linear relationship between mean and standard deviation of specialisation is even more strongly pronounced than in the case of leisure. Very high levels of specialisation are achieved under higher numbers of GA rounds, high level of loyalty, low search costs, high adaptation increments and a high level of errors, regarding the number of searches. Under these settings, the standard deviation, i.e. the heterogeneity between agents is minimal. The highest level of heterogeneity is reached under low loyalty, high search costs and a high number of rounds in the GA. These visualisations make it easier to interpret higher order interactions from the regression model. The non-linear relationships are clearly visible and colour coding as well as point characters make visible distinct groups of observations. Interactive effects are also clearly visible: for example, search cost has a negative effect on the standard deviation under few rounds in the GA and a positive effect under many rounds.

It becomes evident that loyalty affects a dimension of the agents' behaviour that is largely independent of the dimensions relating to specialisation and leisure. The first-order interactions between loyalty and the other parameters show that there are conditions (i.e. combinations of the remaining model parameters) where more loyal behaviour is advantageous to the agents' performance, while under other circumstances, this effect is not observable.

The volume of exchanges (see Tab. B.5 on p. 341, Tab. B.6 on p. 343, and Fig. B.4 on 342) is also highly correlated to leisure and specialisation. However, regarding the main effects, both loyalty and the probability of erroneously committing to too few or too many partner searches now have significant effects. Increased variability in the number of searches affects the volume of exchanges positively, while loyalty has a negative effect. However, there is also a signifi-

cant interaction effect between loyalty and search costs in the opposite direction. The negative effects of higher search costs as well as slower adaptation regarding the number of partner searches are relatively lower under high loyalty. This means that in high-loyalty settings, the effect of these exchange impeding factors is somewhat compensated through the agents' preference for loyalty and the associated differences in their networking behaviour.

The standard deviation of exchanged volume describes the degree of inequality in the agent population regarding the realisation of opportunities of exchange. The regression model that describes the relations of standard deviation of the exchanged volume is more complicated, because it has many significant first and second order interaction effects. As in the models above, there is a nonlinear relation influenced by the number of rounds of the GA. Under high GA rounds the positive effects of memory, search probability increment, probability of error and loyalty, as well as the negative effect of search cost are diminished. High levels of loyalty have the same effect on search probability increment and search cost. Many of these interaction effects are very small regarding their practical influence on the level of heterogeneity in exchange and therefore should not be over-interpreted.

It is not surprising to find results so similar to the previous two outcome dimensions. Only the now-significant effect of loyalty may come as a surprise. The previous marginal, but positive effects of loyalty seem to be at odds with the negative effect on the exchange volume. But herein also lies the explanation for this effect: Loyalty helps agents to establish and continue relationships with matching partners and simultaneously reduces the odds of interacting with agents that do not match. Exchange volume does not only measure the favourable exchanges, but also those that are not ideal for the agent. Loyalty helps prevent such exchanges and therefore high loyalty leads to high levels of specialisation and leisure, but a relatively lower volume of exchanges.

The average degree of agents shows a weaker correlation with the previous outcome dimensions. Detailed analysis of the relationships between input and output variables can shed some light on the reasons for this. Figure 8.10 shows the conditional scatter plots for the mean and the standard deviation of degree. It is clearly visible that in systems with high loyalty the relation of these measures

changes substantially. High loyalty almost forces the agents to have a degree of one. Also it substantially reduces the standard deviation in the population. In the associated regression analysis (Tab. B.7 p. 344 and Tab. B.8 p. 346), this is reflected in various interaction effects with loyalty for all parameters except error probability. There are also interaction effects with search cost for the error probability, memory length and the rounds of GA. Under high search costs the positive effects of all these parameters is enhanced. The main effects remain similar to the previous models: search cost and loyalty are significant and negative and the others are significant and positive.

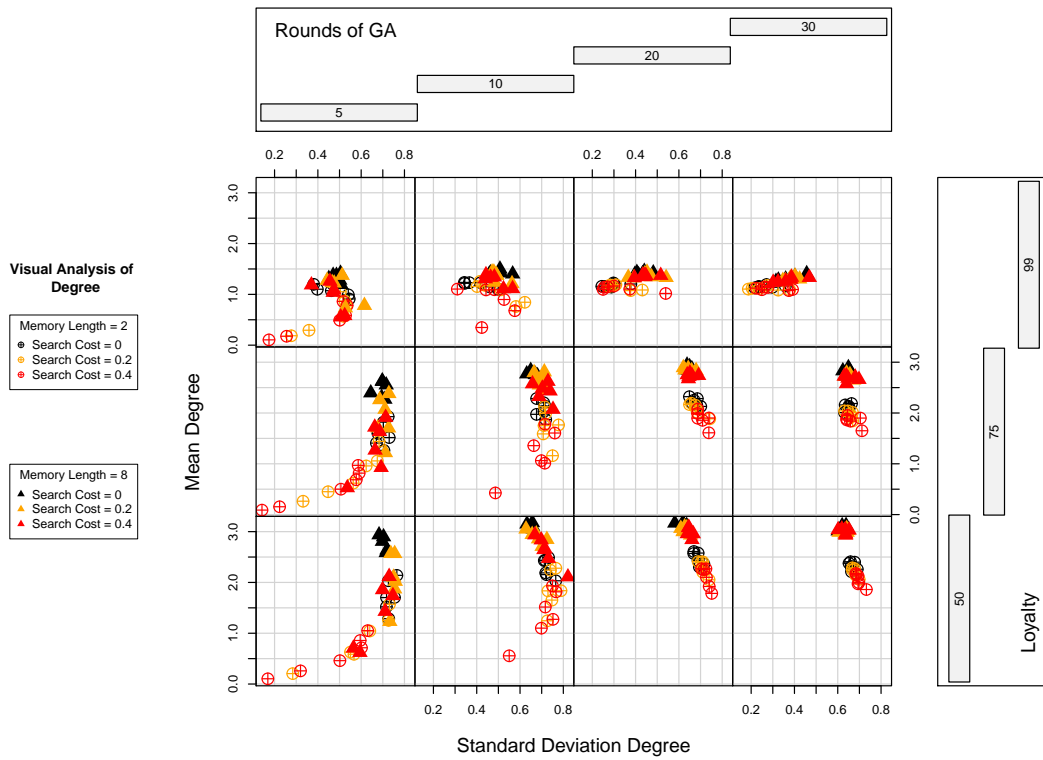


Figure 8.10: Conditional scatter plot of average level of degree versus its standard deviation, ordered by rounds of the Genetic Algorithm ( $\psi$ ) and level of loyalty. The colour coding represents search cost ( $\kappa$ ) and the point characters visualise the length of agents' memory ( $\rho$ ).

A detailed analysis of the effect of loyalty on degree and other model output dimensions will be presented in Sec. 8.1.5

The last output dimension to be investigated in this calibration phase is the average number of searches that an agent undertakes in each round. This measure indicates how much competition there is for suitable cooperation, and also how good the individual negotiation results are, as agents need to search and negotiate more of them, when they cannot negotiate satisfactory results with only one partner. Figure 8.11 shows another conditional scatter plot, grouping data by rounds of GA and search cost. This different arrangement was chosen because loyalty does not seem to have any impact on the number of searches and both search cost and the probability of making an error in determining the number of searches have a substantial effect. Means and standard deviations show a clear association, however their concrete relation is conditional on the rounds of the GA and search cost. As would be expected search costs has a strong negative effect on the number of searches. Also there is a positive effect speed of adaptation, and a clear interaction between search costs and rounds in GA. The negative effect of search cost on searches is more pronounced with fewer rounds in the GA. Slower adaptation regarding the number of searches leads to a lower number of searches, also there is a negative interactive effect with search cost. High costs and slow adaptation seem to discourage agents from searching for partners. Similarly slow adaptation together with high loyalty reduces the number of searches. Overall these results are consistent with the findings from regression analysis (Tab. B.9, p. 347 and Tab. B.10, p. 348).

To summarise, the analysis of individual output dimensions provides first insights about how EGS works. The level of leisure, specialisation and the volume of exchanges are closely related to each other and share most of their association to input parameters. This is not a surprising outcome because leisure is derived from specialisation which in turn is driven by exchange volumes. Rounds of the GA, the agents' memory and the speed of adaptation with which they adjust their choice about the number of searches are all positively associated with these output measures. Analogously, search costs have a negative impact on them. Loyalty is most closely associated with the average degree of agents, however this dimension seems to be independent of the other performance measures. Furthermore the level of loyalty seems not to be associated with the number of searches; instead the number of searches is largely determined by the search costs. This is

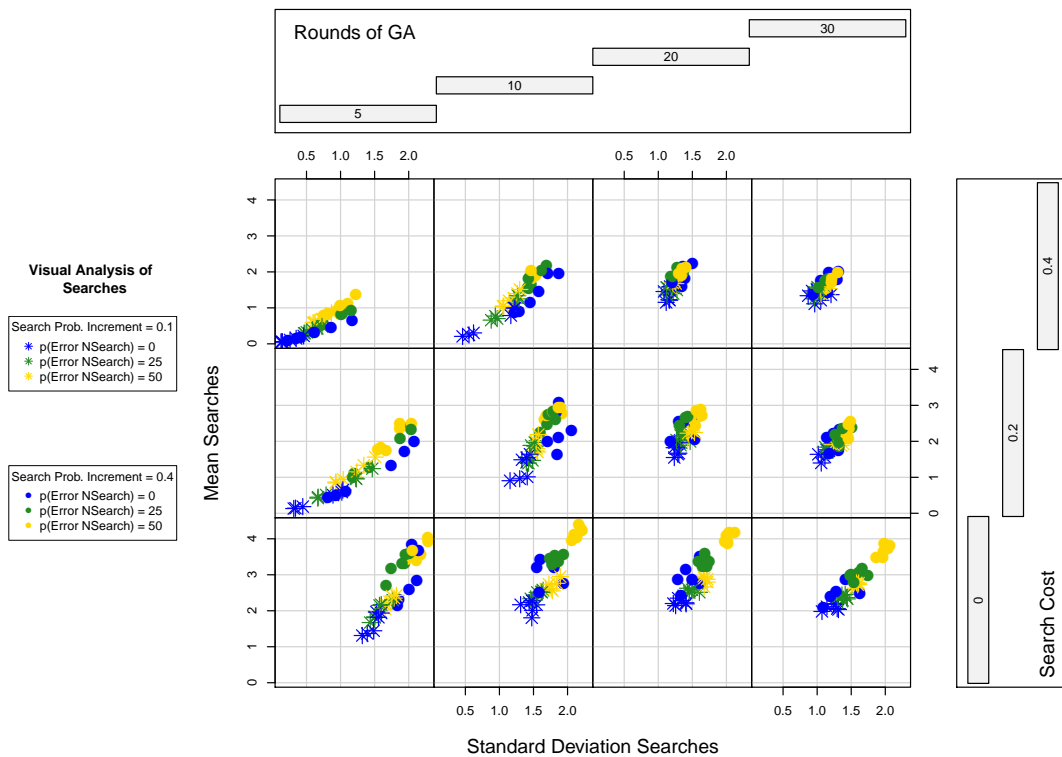


Figure 8.11: Conditional scatter plot of average number of partner search attempts versus its standard deviation, ordered by rounds of the Genetic Algorithm ( $\psi$ ) and search cost ( $\kappa$ ). The colour coding represents the probability of deviating from a chosen number of search attempts ( $\epsilon$ ) and the point characters visualise the speed of adaptation ( $\iota$ ).

interesting in so far as it shows that the agents learn very well how to deal with the specific tasks that they are confronted with.

The relative absence of effects of loyalty can be explained through the details of the current EGS implementation. It does not yet include the many mechanisms from the range of social and economic aspects that drive the development of established business relations. In the current setting of EGS loyalty is not “rewarded” directly: Negotiation works identically for all possible pairings, there are no actual efficiency gains from dealing with a more familiar partner and search costs are incorporated independently as another input parameter. The only performance benefit that can be gained through loyalty indirectly is the reduction of flawed exchanges and the resulting gains in specialisation and leisure. Moreover, the agents’ responses to the parameter search cost largely overshadow possible benefits from loyal behaviour in the current analysis. It is quite likely that the CSW setup is still too simplistic; therefore this question will be addressed in Sec. 8.2, where a selection of model future and their effects are discussed.

### 8.1.4 Clusters of Similar Model Outcomes

The next step to understanding how EGS works is to examine the relationships between output dimensions. In order to characterise typical outcomes of the model, cluster analysis can be used to classify the data into classes of similar model development. A collection of algorithms is available to identify groups of model runs that would be maximally similar within each group, but maximally different between groups. Such clustering results can then be used to characterise typical profiles of the model development and in a subsequent step relate them to typical combinations of input parameters that bring about one class or the other.

For this exploratory task is undertaken using hierarchical clustering with “Ward” linkage over a set of Euclidean distance measures (Gordon, 1999; Becker *et al.*, 1988; Murtagh, 1985). This algorithm first specifies how closely any two sets of outcome measures resemble each other, and then divides them to clusters so that individual clusters exhibit minimal variance. Considering the high correlation between several of the measured outcome dimensions, only a subset of dimensions will be used in the cluster analysis. These include means of leisure, volume exchanged, degree and searches, and also the standard deviations of leisure and searches. All these measures capture a different aspect of the model development. As in the previous section this analysis will be based on aggregate measures of the last 15 rounds of observations for an aggregate across 30 simulation runs with identical parameters.

The dendrogram that displays the results of the cluster analysis is shown in Fig. 8.12. Identifying the final number of clusters, i.e. deciding at which height to cut the tree, is a somewhat subjective decision. The dendrogram displays five clear and distinct groups down to about the cluster distance of fifty. Below a distance of fifty, the clustering algorithm quickly divides the observations into smaller and smaller groups. Anticipating that these groups would serve as a means to describe general classes of outcomes in a concise and demonstrative way, it appears to provide sufficient detail to cut the dendrogram at a level of fifty, identifying five distinct clusters. Anticipating their particular characteristics, they will be referred to as Autarkists, Bad Negotiators (BN), High Effort - High Outcome (HEHO), Networkers and Exclusive Specialists (ES).

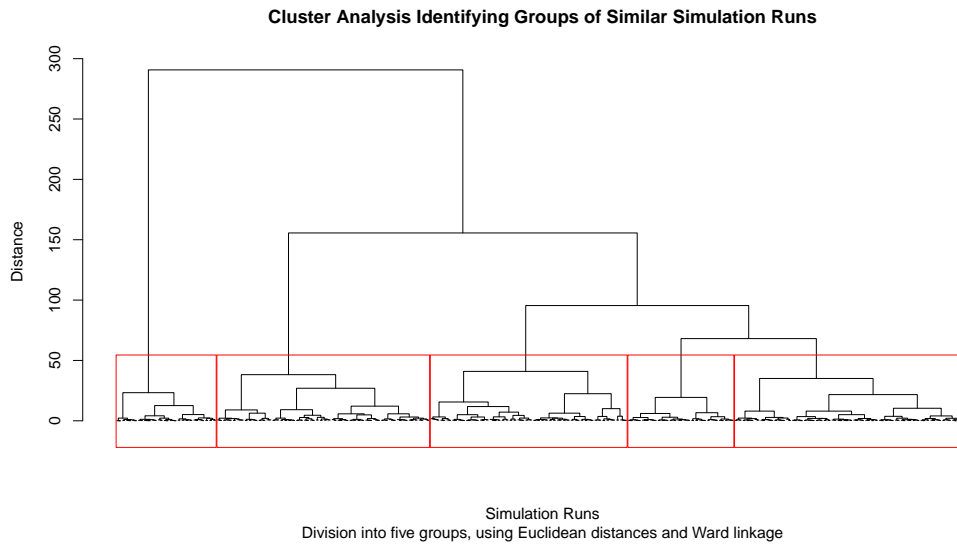


Figure 8.12: Cluster analysis, grouping simulation runs into groups of similar profiles by clustering over the dimensions of their output. The clustering procedure uses Euclidean distances between vectors of observed outcomes and the complete linkage method to join clusters.

Cluster	#	mean	sd	mean	sd	mean	mean	sd	mean
		Leis.	Leis.	Spec.	Spec.	Degree	Sear's	Sear's	Exchange
Minimum		-0.024	0.07	0.71	0.029	0.089	0.05	0.13	0.25
Maximum		3.72	1.19	0.98	0.11	3.18	4.41	2.28	26.32
Autarkists	51	0.10	0.38	0.73	0.06	0.71	0.46	0.66	2.50
BN	108	0.90	0.89	0.80	0.09	1.68	1.71	1.50	9.45
HEHO	100	2.48	0.91	0.89	0.08	2.43	3.16	1.77	19.55
Networkers	119	2.17	1.01	0.90	0.09	2.26	1.92	1.28	19.09
ES	54	2.90	0.77	0.95	0.06	1.25	2.12	1.31	19.15

Table 8.4: Number of observations and mean values for clusters of outcomes

The main characteristics and distinctive features of the identified clusters are discussed below. Table 8.4 summarises the average outcome statistics and frequency of occurrence for each of the five clusters. Parallel coordinate plots on p. 255 and p. 256 visualise outcomes associated with each cluster across all parameterisations. The clusters in focus are highlighted in red and superimposed on the remaining observations in black. The graphs clearly show the gradual progression towards better performance, both regarding leisure and specialisation. Moreover, the subtler differences between well performing clusters become apparent, e.g. their heterogeneity and the networking strategies that the agents develop to coordinate. The substantial linear relationship between many outcome dimensions becomes evident as the clusters gradually reach higher levels in the graph. However, these visualisations also show that not all relationships are linear and that there are idiosyncratic variations between clusters.

**Autarkists:** The first identified cluster of model outcomes will be referred to as Autarkists. In these model runs, agents barely benefit from exchange and they hardly realise any economies of specialisation. The average number of searches is 0.46, suggesting that the agents spend only little time searching for suitable exchange partners. The average degree is only marginally higher at 0.71, but considering that the average volume of exchange is only at 2.5, it seems that even those agents that discover exchange are unable to realise benefits from it.

**Bad Negotiators (BN):** The second cluster, Bad Negotiators, performs only slightly better in terms of leisure and specialisation than Autarkists. The number of searches is average, although there is a relatively high degree of variation regarding the number of searches. At the same time, the average of leisure, specialisation and volume of exchanges remains low, but the standard deviation of leisure suggests that there are agents that realise more than twice the amount of leisure than others. It seems the burden of searching for partners is shouldered only by a few, but they receive the bulk of its benefits as well.

**High Effort, High Outcome (HEHO):** HEHOs rank highly across most output dimensions. They spend much time searching for suitable partners and

maintain several exchange relationships at a time. The volume of exchange is high, as well as the achieved level of specialisation and, ultimately, leisure. At the same time, the standard deviations across all these dimensions are high as well, indicating that the agent populations under these parameterisations are heterogeneous regarding their efforts of search and specialisation and also regarding the degree of leisure they gain. HEHOs can be said to solve the problems that they are confronted with very well, they discover specialisation and exchange, identify suitable partners and maintain exchange relationships. Consequently, they can realise high levels of leisure.

**Networkers:** Most crucial about networkers is that they tend to have a relatively high degree but only an average level of searches. This suggests that agents in this cluster of model runs learn to build and maintain essential relations and spend their time searching for partners systematically liaising with previous successful exchange partners. These populations are highly heterogeneous populations with regard to leisure, however the average levels of leisure are confined to a range above average but below top performances. The group of Networkers includes three sub-types of classes that differ by average degree. However, there seems to be no particular correlation between the level of degree and the levels of specialisation and leisure. Contrary to HEHO, this cluster is characterised by a medium level of searches that are distributed in a relatively homogenous way across the population. Overall, Networkers are able to realise economies of specialisation and exchange but not all agents in the population manage to benefit from them. These discrepancies lead to a mediocre group performance in terms of leisure and a very high standard deviation in the distribution of leisure.

**Exclusive Specialists (ES):** Together with HEHO, Exclusive Specialists reach the highest levels of leisure and specialisation. However, populations of ES are more homogenous in terms of leisure and specialisation than HEHO. Most notably, ES have nearly the lowest variation in specialisation of all cluster groups. All agents in this cluster participate in the efficient produc-

tion of goods and realise economies of specialisation. The mean degree is very low, at only 1.25. And at the same time the number of searches as well as their standard deviation is at about the same level as that of Networkers. ES are very close to developing a minimal and efficient network of exclusive exchange relations.

Profile	GA R.	Loyalty	Mem.L.	SearchC.	Search P.I.	p(E. NS.)
Minimum	5	50	2	0	0.1	0
Maximum	30	99	8	0.4	0.4	50
Autarkists	5.59	74.67	3.76	0.34	0.19	21.47
BN	7.73	76.69	5.39	0.21	0.24	27.27
HEHO	16.00	69.08	5.72	0.04	0.34	31.85
Networkers	24.54	66.48	4.42	0.27	0.21	23.49
ES	25.56	99.00	5.33	0.17	0.26	27.78

Table 8.5: Average input values for identified clusters

Table 8.5 shows the averages of input parameters that lead to each of the clusters of outcome. Autarkists are characterised by low numbers of rounds in the GA, relatively high search costs and slower adaptation regarding the number of searches. This means that the chances of finding a good negotiation outcome are slim to begin with and the agents would have to pay a relatively high prize just to enter this unprofitable negotiation phase. Also they are relatively slow at adapting their number of searches, less likely to explore another number of partner searches and have a comparatively short memory. Overall, these settings seem to discourage the exploration and maintenance of exchange relations in almost every dimension individually and consequently the combination of such factors practically prohibits the discovery of exchange.

Bad Negotiators (BN) is the second largest cluster after Networkers. Together with Autarkists, BN constitute the group of clusters that follow exclusively from fewer rounds in the GA (i.e.  $\psi \in \{5, 10\}$ ). Networkers and ES arise almost exclusively under high rounds of the GA (i.e.  $\psi \in \{20, 30\}$ ), and HEHO seem to depend more on low search cost than on any particular level of GA rounds. BN show no other strong association with any of the other input parameters.

High Effort and High Outcome characterises a large number of simulations and this wide range may be the reason why HEHO is the only cluster that spans all possible rounds of the GA. The most obvious association of HEHO runs to input parameters is to a low level of search costs. Furthermore HEHOs are associated with a higher adaptation speed for search rounds and also a higher error rate that lets them explore other numbers of searches more quickly. Overall these are conditions that favour exploration and the discovery of exchange. Within the HEHO cluster, those runs with lower GA rounds tend to perform more poorly in terms of leisure and specialisation.

Networkers and Exclusive Specialists are clusters that almost exclusively require higher numbers of rounds in the GA. Furthermore, Networkers are brought about by relatively high search costs in combination with slower adaptation and lower error probability regarding the number of partner searches. So, despite negotiation procedures that potentially lead to superior outcomes, Networkers tend to come about when the other conditions for extensive partner search are unfavourable. The main factors to determine whether a model run with higher GA rounds develops into a Networks or a HEHO are search cost, memory length and speed of adaptation regarding searches. For networkers, these tend to be less favourable with high cost, short memory and slower adaptation.

Loyalty is the main determinant for the development of Exclusive Specialists, provided the number of rounds in the GA is high enough. ES are only possible for very high levels of loyalty ( $\lambda = 99\%$ ) and only a few high loyalty simulations turn into Networkers or HEHO. The only other input parameter that shows a weak association with the occurrence of ES is search costs, as ES tend to come about when search costs are lower.

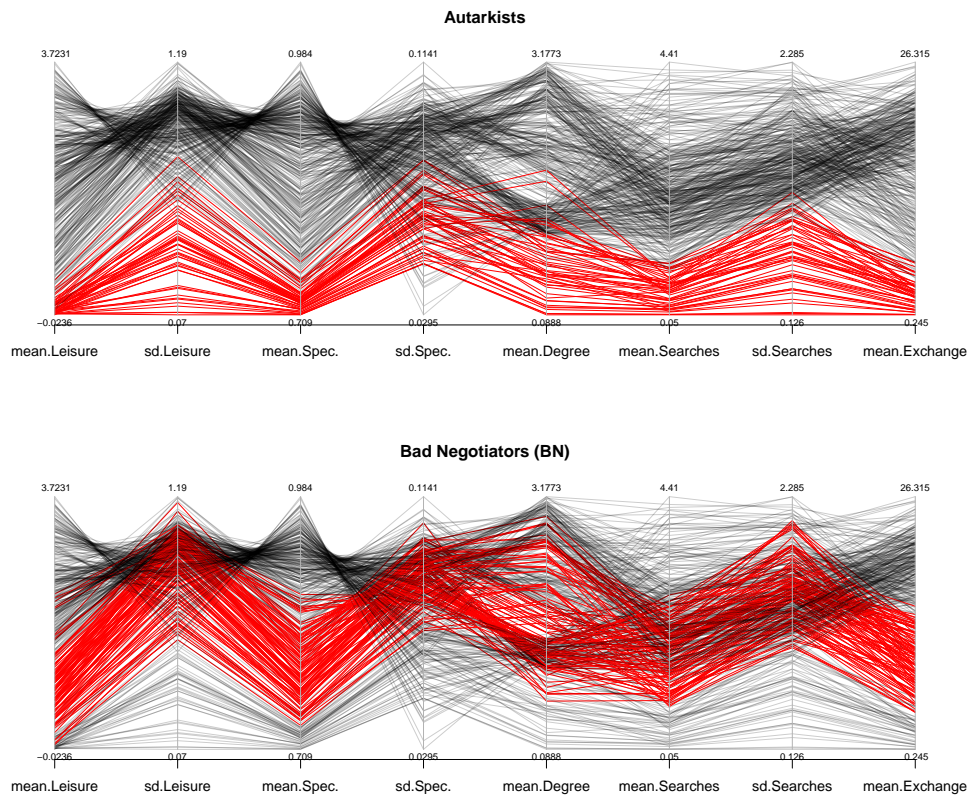


Figure 8.13: Parallel coordinate plots characterising clusters of similar model outcomes: Autarkists and Bad Negotiators.



Figure 8.14: Parallel coordinate plots characterising clusters of similar model outcomes: High Effort, High Outcome (HEHO), Networkers and Exclusive Specialists (ES).

### 8.1.5 Discussion of Select Model Aspects

One of the advantages of computer models in comparison to experiments or surveys in real world systems is that they are under full control of the researcher and can be adjusted, extended and repeated to suit the his or her needs. Should new questions arise in the course of analysis, the model can be rerun, parameters can be adjusted, and new aspects of the model can be monitored. The analysis in the preceding sections provides an overview of the selection of output measures, the impact of input parameters on the model's development, a classification of different model outcomes and how they relate to input parameters. This section will address some model aspects in greater detail. Concretely, it will quantify the strength of effects that deliberate partner selection has on output measures, give a more detailed account on the effects of different levels of loyalty, investigate the individual agents' degree of specialisation under favourable conditions, and isolate the causes for different agent performances in agent populations that exhibit a large degree of heterogeneity.

The agents' partner search strategies in the preceding analysis were based on a combination of search criteria: proximity in the social space and past exchange outcomes. Proximity is a fixed value that is set randomly upon initialisation of the model, when agents are assigned their position in space. In the abstract settings investigated here, proximity does not model a concrete equivalent in the real world, but it demonstrates the capabilities of EGS and can eventually be calibrated to represent a real social or physical environment. Social, psychological and geographic proximity are important drivers of the likelihood of meetings and the development of a relation and they can be included in EGS. In the exploration of the EGS parameter space the experimental parameter  $\lambda \in \{50, 75, 99\}$  was used to adjust the weights given to previous experience versus proximity. It has become apparent that  $\lambda = 99$  has a substantial effect on the structure of interaction, but not so much on the performance related model outcomes, such as leisure, specialisation and the volume of exchanges.

Both past experience and proximity tend to structure the agents' interactions, only they follow different criteria. However, this raises questions about the way the model responds when such structuring mechanisms are removed and substi-

tuted with random effects. The markets-as-networks perspective (Sec. 1.1) is founded on the idea that relationships matter. At the same time economic theory, even the theory of Economic Change (Sec. 2.1), or the collection of mechanisms used in KM (Sec. 6.2) hardly mentions interpersonal relation as an element of coordination in an economy.

Using EGS, it is possible to address this issue and answer the question: *do relationships matter?* Within the same economic setting and the same input parameters to control the agents' behaviour, capabilities and decision making, the experiments above are repeated - the only difference being that the structuring partner search mechanism is replaced by a random matching mechanism that is insensitive to proximity and past experiences. Instead it picks any one of the other agents at random and asks the two agents to negotiate with each other. With random matching it is impossible for agents to form relationships and avoid futile negotiations with agents that are incompatible regarding their production type.

Tables 8.6 and 8.7 illustrate the results of this experiment. In both tables results are subdivided for each cluster of previous model outcomes to show how the effects of the alternative matching mechanism differ and interact with the other parameters. In Tab. 8.6 the average outcomes for random matching ("rndm") and relational matching ("rel.") are juxtaposed and Tab. 8.7 provides percentage changes that better express the magnitude of the alternative mechanism's impact. Furthermore Tab. 8.7 provides the p-values of Student's t-tests, testing the null-hypothesis that there are no differences in means between matching mechanisms versus the alternative that there is a difference (two-sided tests).

The test results largely affirm the Markets-as-Networks perspective. Even in a setup as simple as the one used here, relationships make a difference. Leisure is significantly reduced across all clusters - even Autarkists that hardly maintained any relations at all find themselves in a situation that is worse than before. Exclusive Specialists experience the largest set-back, losing on average 42 minutes of leisure. Analogously, the level of specialisation drops significantly across clusters. Again ES face the strongest rebound, but BN, HEHO and Networkers each lose more than three per cent of their specialisation as well. Not surprisingly, the degree of agents rises throughout clusters, except for Autarkists that still face a setting where the formation of relationships is discouraged. In all other clus-

	Leisure		Specialisation		Degree		Searches		Exchange	
	mdm	rel.	mdm	rel.	mdm	rel.	mdm	rel.	mdm	rel.
Autarkists	0.04	0.10	0.72	0.73	0.82	0.71	0.43	0.46	2.44	2.50
BN	0.61	0.90	0.77	0.80	2.38	1.68	1.73	1.71	10.83	9.45
HEHO	2.12	2.48	0.86	0.89	3.19	2.43	3.26	3.16	22.73	19.55
Networkers	1.80	2.17	0.87	0.90	2.82	2.26	2.06	1.92	20.89	19.09
ES	2.20	2.90	0.89	0.95	3.09	1.25	2.43	2.12	23.21	19.15

Table 8.6: Output statistics resulting from random matching in each CSW cluster, and previous averages for comparison

	Leisure		Specialisation		Degree		Searches		Exchange	
	$\Delta\%$	p-value	$\Delta\%$	p-value	$\Delta\%$	p-value	$\Delta\%$	p-value	$\Delta\%$	p-value
Autarkists	-56.77	0.006	-0.76	0.007	+14.79	0.238	-6.53	0.549	-2.58	0.826
BN	-31.98	0.000	-3.43	0.000	+42.03	0.000	+1.17	0.802	+14.51	0.003
HEHO	-14.41	0.000	-3.87	0.000	+31.18	0.000	+2.97	0.220	+16.22	0.000
Networkers	-17.03	0.000	-3.44	0.000	+24.41	0.000	+7.39	0.007	+9.44	0.000
ES	-24.28	0.000	-6.35	0.000	+146.31	0.000	+14.69	0.001	+21.22	0.000

Table 8.7: Change through random matching on model outcomes in each CSW cluster and t-test statistics

ters, the agents' degree rises because now it is no more restricted by the matching mechanisms and depends largely on the agents' number of searches. The substantial loss of leisure is in part to be explained by an increased number of searches that may incur costs and thereby reduce the agents' leisure. However, the effect of random matching on the number of searches is significant only for those two clusters that were found to be particularly effective regarding their management of relations. Networkers and ES both exhibited relatively low levels of searches, but with random matching, adapt to this loss of stability and increase their searches.

The last dimension to be considered here is the volume of exchange. Surprisingly, these values increase substantially under random matching, for the first time developing in a different direction than leisure and specialisation. In order to solve this puzzle, we can rerun the model with suitable parameter combinations (and a fixed random seed, to exclude differences from random variation). Comparing the agents' behaviour on the level of the individual shows that random matching leads to an increase in exchanges between agents of the same production type. In these exchanges, they realise comparative advantages between each other as they exchange many goods that they can exchange efficiently against a few that cost them a lot of time. Without memory affecting their mating behaviour the agents lack the capability to distinguish between suitable partners and unsuitable ones and negotiate for acceptable solutions with every partner they come across. This myopic behaviour then causes the loss in leisure and the reduction in specialisation.

The next issue to be investigated in more detail is the effect of  $\lambda$ , the parameter that controls the agents' preference for loyal behaviour. In the previous analysis of the parameter space, only a wide grid of select values was explored, in order to keep computation time, but also the level of analysis, at a manageable level. However, results showed a sharp transition of model behaviour between  $\lambda = 75$  and  $\lambda = 99$ . Essentially,  $\lambda = 99$  forces the agents to restrict themselves to a degree of 1 or 2.

To better understand this effect, one representative setting was chosen in order to conduct a detailed analysis. Figure 8.15 shows a sample output of degree for one population of agents across one model run. The parameters are  $\psi = 20$ ,  $\kappa = 0.2$ ,  $\rho = 8$ ,  $\iota = 0.1$ ,  $\varepsilon = 25$  and  $\lambda = 99$ , which constitutes a model from

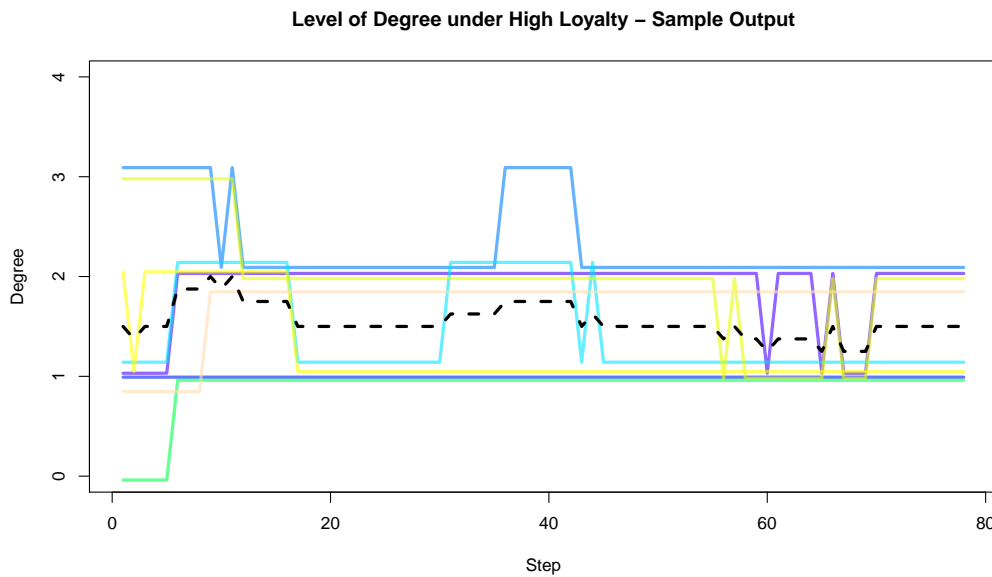


Figure 8.15: Sample output for the development of individual degree in a high loyalty model run. Individual agents' degree in colour, population average black and dashed.

the ES class. It becomes clear that there is little variation in the relationships of individual agents, after about round 18. Most of the relationships are formed in the early rounds of the model run and then persist until the run is terminated.

More detailed investigations into the effect of loyalty are conducted through another experiment. Holding  $\kappa = 0.2$ ,  $\rho = 8$ ,  $\iota = 0.1$ ,  $\varepsilon = 25$  constant, and varying  $\psi \in \{5, 10, 20, 30\}$ , the level of loyalty can be gradually increased in steps of two units, from  $\lambda = 75$  to  $\lambda = 99$ . Selected results are shown in Fig. 8.16. Again, these constitute averages over the last rounds of 30 simulation runs for every parameter combination.

The panels show that the effect of loyalty interacts with the number of GA rounds regarding the average degree, but not regarding the level of specialisation. While increases regarding specialisation are small, there is a clear negative effect of increases in loyalty regarding the average degree in the population. Also, this effect is much more pronounced under many GA rounds. From  $\lambda = 75$ , the average degree gradually declines and at about  $\lambda = 90$ , the decline accelerates

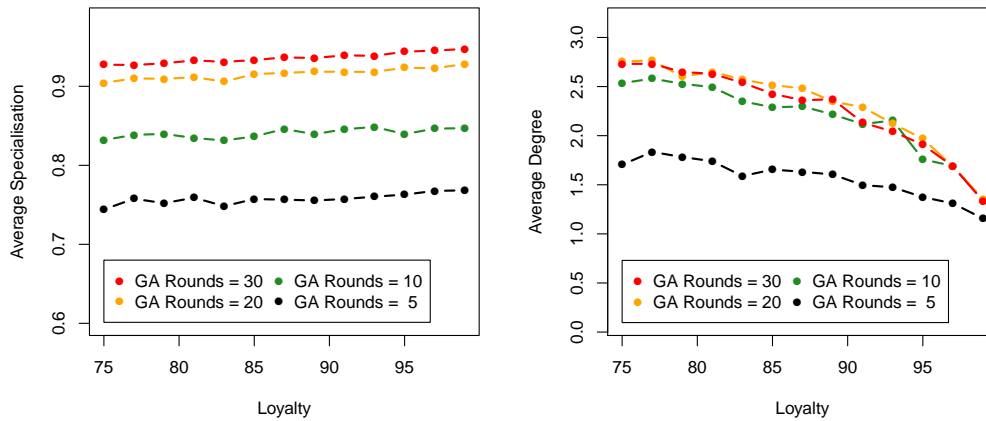


Figure 8.16: The effect of loyalty on specialisation and degree

and soon forces the average degree down to a level near one, as was demonstrated in Fig. 8.15.

These findings can be explained by looking at the details of the current EGS implementation. Loyalty affects the agents' search and mating behaviour, essentially helping them find well matching partners again in subsequent rounds. In the presence of search cost, loyal behaviour therefore can have some positive effects on the agents' overall performance. The success of negotiations that is the main determinant of the agents' level of leisure and specialisation is predominantly a result of the effort that agents devote to negotiations, namely the numbers of rounds in the GA. This version of EGS does not yet include mechanisms regarding potential efficiency gains resulting from learning and adaptation processes in business relations. Therefore, aspects related to the performance of agents are still largely independent of the agents' mating behaviour, and changes in loyalty affect only one outcome dimension.

Another question that can be addressed through in-depth analysis of individual model runs is whether or not agents are capable of full specialisation, in a system that is governed by the current collection of mechanisms. None of the population averages in the previous parameter sweep reached 100% specialisation, but this does not mean that individual agents cannot reach this level.

To further investigate the mechanisms of specialisation, a single case, i.e. a single one of those model parameterisations that led to high levels of specialisation, will be examined in isolation. By focussing on that single case, the development of specialisation can be monitored in greater detail. Concretely the selected parameter combination is  $\kappa = 0$ ,  $\rho = 8$ ,  $\iota = 0.4$ ,  $\varepsilon = 25$ ,  $\psi = 30$  and  $\lambda = 99$ . In the preceding analysis this led to model outcomes classified as Exclusive Specialist and the average level of specialisation achieved throughout the last rounds was 0.975. Under these parameters 30 repetitions are run to account for the effects of random influences. In this in-depth study, the data can be collected on the level of the individual agent, so that even more detail about the model development is captured.

The measure specialisation, as it has been used so far, is an aggregate that describes the agent's production in every round, and it is calculated as the ratio of units of the more efficient good to the total units produced in this round. To get a better understanding of how these measurements of specialisation come about, this detailed analysis will monitor individual measures for the two production tasks separately. Accordingly, two values are calculated for each agent: the first is the round's production of the good that is produced more efficiently, divided by the ideal value for the respective agent type, and the second value is the round's production of the more expensive good, divided by the agent's initial demand for that good. In Fig. 8.17 the average results from 30 repetitions are shown. In each individual model run, the agents are ranked by their ratio of producing the comparatively advantageous good. The displayed lines represent the averages of those performance classes across all 30 runs. The average of all worst producing agents are represented in yellow, the averages of all most efficiently producing agents in red, and the other ranks can be found in between, color-coded by performance. The same colour-coding is used in the lower dashed lines that describe the agent's ration of production for the good that they would ideally get rid of altogether. Splitting the specialisation measure into these two dimensions explains why full specialisation is never reached.

Figure 8.17 explains why the agents persistently failed to reach the level of full specialisation, and only came up to about a level of 98%. Two factors contribute to this result: first, there is substantial variation across the agent population - and the

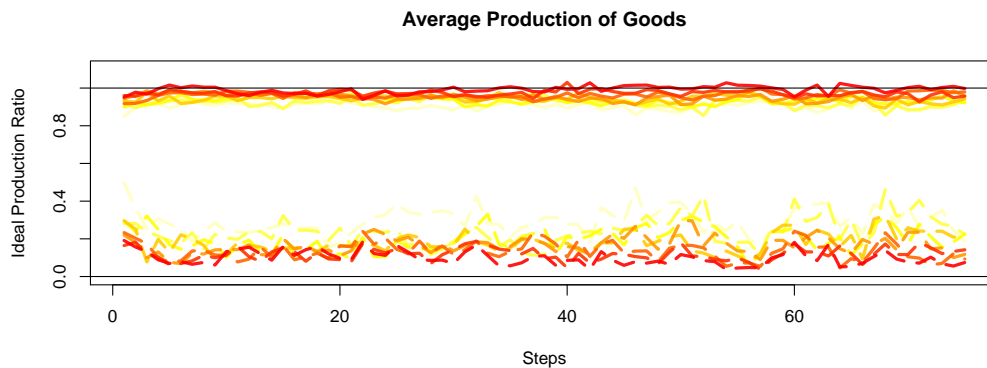


Figure 8.17: Averages of production volume to investigate the individual level of specialisation. Solid lines represent production of the more efficient good, dashed lines production of the less efficient good. The individual lines are averages over 30 repetitions.

displayed values already are averages that reduce the intra-agent variation. Still the ratio of production of the more efficient good ranges between 90% and 103%. The second factor is the substantial level of production of the least favourable good. Not only is specialisation a matter of realising economies of scale, but it also requires the successful outsourcing of unfavourable activities. In Fig. 8.17 we see that agents fail to specialise especially with regard to this second aspect. None of the averages ever reaches the level of full clearance. In addition to this, the previous, uni-dimensional measure of specialisation is more sensitive to remaining units of the inefficient good, than it is to a high level of efficient production. Sample inspection of the individual agent's production shows that it is possible and indeed common that individuals reduce their inefficient production to zero, but there are variations across time and between runs, and these prevent the aggregates to reach ideal values.

The last detailed issue about the EGS calibration to CSW settings is: how is it possible that some parameter settings lead to leisure levels below the level in autarky? Generally, the implemented decision-making rules are conservative. In autarky, a balanced population of odd and even agents reaches a level of  $-0.00648$  hours of leisure. Regardless of their negotiation outcomes, agents always have autarky as a fall-back position, and they are programmed so that they will never

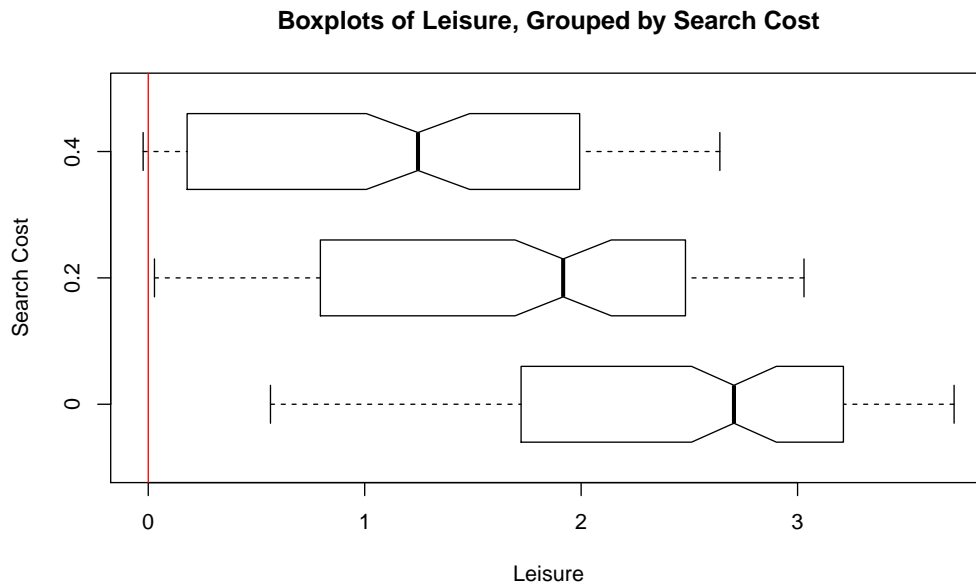


Figure 8.18: Boxplot of CSW Leisure outcomes, grouped by Search Cost

knowingly accept a negotiation outcome that is worse than the fall-back position. Consequently, after an initial phase of learning where agents discover their own capabilities and comparative advantages there cannot be a loss in leisure resulting from negotiations.

The answer lies in a combination of search cost and rounds in the GA. Out of 432 possible parameter combinations, there were seven that consistently lead to outcomes of leisure below the autarky level. Investigating the similarities between these parameter combinations it quickly becomes apparent that there are only two features that all of them have in common: search cost  $\kappa = 0.4$  and GA rounds  $\psi = 5$ . Figure 8.18 illustrates the relationship between search cost and leisure across all other parameter combinations and shows that indeed search cost reduces the level of leisure consistently.

Investigating the details of one of these under-performing parameter combinations ( $\rho = 2, \iota = 0.4, \kappa = 0.4, \varepsilon = 5, \lambda = 75, \psi = 5$ ) illustrates how such a loss of leisure can come about. Throughout the model run, the realised level of leisure is low, only occasionally reaching positive values. Also the agents quickly learn to reduce their number of searches to a minimum; in later rounds two search

attempts across the entire population become the absolute maximum. Sometimes agents actually benefit from cooperation, but more often it is the case that the lower number of GA rounds leads to negotiation outcomes that cannot compensate for losses incurred through searching. Also, given the relatively low level of interaction, the agents do not necessarily remember previous partners, because the pauses between interactions exceed the agents' memory span. As a result, they may also be unable to tell suitable partners from unsuitable ones, if they choose to search for one. While some agents remain in autarky, those few who decide to invest in relationships bear the cost and are often disappointed. These additional search costs that cannot be compensated cause the average of leisure to drop below autarky levels.

### **8.1.6 Comparison of EGS outcomes and CSW results**

The goal of EGS is to better understand how business relationships and networks facilitate the coordination of specialisation and division of labour. It does so by including relational aspects into a model of economic activities similar to the one used by CSW and KM. Moreover EGS provides a flexible framework to analyse a variety of other settings, including larger and more diverse populations and more comprehensive product spaces. While the economic behaviour of individual agents is largely driven by economies of specialisation and exogenously determined consumption functions, it is the social aspects of relationship development and maintenance that facilitate the coordination of activities between individuals. Exchanges in EGS are the results of negotiations, and these can be far from optimal, depending on the agents' compatibility, their current level of demand, the effort they put into negotiations, and also a chance element of taking the right action at the right time. Repeated interactions between the same partners constitute exchange relationships, and their success is the foundation for future interactions. In EGS agents remember the outcomes of past interactions and they use this knowledge to identify partners for future exchanges, influenced by their individual preference for such loyal behaviour. This is a basic representation of business relationships, however it is richer than the implementation in KM, where mating and dating is modelled as the adaptation of probabilities in a stochastic process. EGS constitutes one step towards comprehensive models of business relationships and networks, introducing a range of elements from the market-as-networks perspective into an economic framework.

The validity of EGS output can only be assessed through comparison with empirical data. In the absence of longitudinal data of the development of a business network, the second best way to validate EGS is to calibrate it against the result of CSW's experiments. CSW identify one critical juncture in the development of an economic system to be the transition from self-sustained autarkic production to a system of specialisation and division of labour. At this crucial point of transition, members of a society learn how to rely on each other and through their coordinated efforts achieve unprecedented economies of specialisation. With their experiments, CSW explore the origins of business networks. In

their detailed records of exchange activities and communication among participants various patterns can be identified to characterise the process of discovery of exchange and specialisation opportunities and the development of an exchange network.

The same strategy is used by Kimbrough (2011) to validate his model of the discovery of specialisation and exchange. KM focusses strongly on the individual's decision making and learning process. Kimbrough (2011) calibrates model parameters that control the agents' risk aversion and discount rate against the population's development of average efficiency and specialization over a time period that is equivalent to the CSW experiments. Kimbrough uses overall averages, but also the stratification of performance and its development over time as targets to validate his model. For validation he repeats the simulation 1800 times for each parameter combination and organises the outcomes into six groups of 300 model runs each, ordered by the realised efficiency in their final period. Through Mann-Whitney-Wilcoxon tests and bootstrapped confidence intervals he can confirm that those groups of model runs are not significantly different from the experimental results, if these are grouped by performance as well. There are two interesting points to be made about this validation strategy: first, many of the tested parameter combinations seem to match the experimental data equally well, which begs the question whether these parameters actually have any effect on the phenomenon to be explained. Second, considering computational model as the implementation of a scientific theory about an emergent phenomenon, Kimbrough's only explanation of the substantial variation across the sessions in CSW experiments must be interpreted as "random variation in combination with path dependence". The same model with the same parameter combination accounts for a population that lives near autarky as well one that nearly reaches full specialisation, only through chance events that lead to a different trajectory of model development. Despite his successes in matching experimental results longitudinally and quantitatively, Kimbrough's explanation of what happens in individual model runs is not satisfying.

EGS is built with different objectives: using the ample knowledge about the establishment and development business relationships and networks, EGS is a step to explain what could be crucial differences between populations that find

themselves persistently struggling in a state close to autarky, those that discover exchange and coordinate through multilateral gift giving, and those where specialists thrive in exclusive exchange relationships. At the same time the temporal dimension in EGS plays only a subordinate role. EGS models the development and evolution of business networks, but no claim is made about whether there is a real-world equivalent to the temporal unit of *one round* in the model. Especially, no attempt is made to match the progression of “days” in CSW experiments. After all, these were only arbitrarily chosen spans of time that merely simulated the order of weekdays in the first place.

CSW and related experiments provide a rich collection of qualitative and quantitative patterns that can serve as the basis for validation here. In the following a summary of these patterns and discussion are EGS’ success in reproducing them will be given.

The insights gained through CSW experiments can be used to assess EGS’ validity in two different ways: first, they can further inform the agents’ decision-making and the implementation of rules that govern their activities. Second a selection of aggregate patterns from the experiments can be used to assess EGS’ output validity in various dimensions.

In conjunction with the more general mechanisms identified in Ch. 3, CSW’s results provide valuable insights to the model’s calibration to this particular setting and guidelines in the identification of the relevant parameters space. CSW observe that many participants are quite adept at determining comparative advantage and also at coordinating their production and exchange activities - but others are not. The participants display much variation in their trajectories of development, regarding both their speed of development and the efficiency of their final outcomes. In EGS search costs represent such obstacles for coordination and the agents’ learning speed can be adjusted with the parameter  $\iota$ , which controls the rate of change regarding the agents’ search strategy. Also, the parameter  $\psi$  determines the agents’ efforts in negotiating and in searching for mutually beneficial cooperative solutions. Higher efforts generally lead to better results. Moreover CSW find that coordination with others is a greater obstacle to specialisation and exchange in bigger groups than finding an appropriate level of production. Considering that the model agents are unperturbed by psychological pains or stress from negotiat-

ing, such subjective costs that CSW participants may have gone through are represented explicitly through the search costs  $\kappa$ . Negotiation and problem solving in CSW experiments were often found to be far from optimal: participants satisfice rather than optimise; they rely on trial and error as a learning strategy and they learn socially through communication and imitation. EGS addresses the first two aspects: the Genetic Algorithm simulates the negotiation process as a search function for a good solution for the problem it is presented with, but it may converge on a local optimum, and considering the relatively short number of rounds that it has for its search ( $\rho \in \{5, 10, 20, 30\}$ ) it may well produce sub-optimal results. Nevertheless, if the GA finds a satisfactory solution, the agents will accept it. At the same time their learning process about the number of searches, but also the identification of suitable and unsuitable exchange partners is a process of trial and error. The last finding from CSW is that in most sessions, participants sampled the majority of other cooperation partners for a possible match, but full specialisation only occurred in stable, exclusive long-term relations. The EGS parameter  $\lambda$  can be adjusted to vary the agents' preference for exclusive relations over multilateral gift giving and therefore control this aspect of how the agents' prefer to network.

CSW's participants find various responses to the tasks set before them. While the discovery of exchange usually occurs early on in the experiment, the ability to understand comparative advantages, produce accordingly and exhaust gains from trade varies substantially across individuals within a session and across treatments. Discovering exchange does not translate into fully efficient specialisation and exchange and not everyone specialises to the full extent of their comparative advantage. Without access to the numerical data, a comparison of results from model and experiments can only be made using stylised facts (Kaldor, 1961). Such stylised facts are simplified representations of empirical findings, often a broad generalization that is true in essence but may have inaccuracies in the detail. CSW findings can be summarised in the following stylised facts:

**Specialisation** Across their experiments and treatments, CSW participants often reach a significant degree of specialisation, but the results remain inhomogeneous. CSW observe large differences between participants within a session, but also substantial divergence between individual sessions and treat-

ments. Many economies do not reach the competitive equilibrium with full specialisation and exchanges with suitable partners. Two-person economies either reach full specialisation, or remain near autarky. In some sessions, participants discover efficiencies from comparative advantages first in pairs of the same production type. These are lower, but sufficient for participants to maintain their cooperation over an extended amount of time.

**Efficiency** CSW define a measure of efficiency as the ratio of realised to competitive profit, normalised so that autarky profits equal zero. This measure is similar to the measure of leisure used in EGS analysis. CSW find a very high level of heterogeneity in efficiency across participants and treatments. Also, they often observe persistent imbalances in the terms of trade within individual pairs. In the final stages most sessions reach a state of Pareto efficiency in the following two limited senses: first, holding production decisions constant, few gains from trade remain unexploited, and second, few subjects could earn higher profits if they deviated from their chosen level of output unilaterally.

For validation of KM, Kimbrough (2011) focusses on reproducing the level of specialisation and efficiency of experimental sessions with eight participants. Figure 8.19 provides an overview of the levels and development of these six sessions. They are ordered by their level of specialisation in the last round, session 6 being the closest to autarky, session 1 coming close to the competitive equilibrium.

**Degree** Full specialisation and efficient exchange is only observed in bilateral exchange relationships, and these are typically not open to the inclusion of any third party. In some sessions only one such stable relationship is observed. These are the most substantial determinants of the high levels of specialisation and efficiency across sessions. The existence of one such exchange pair does not necessarily give impetus to the formation of other pairs. After several repetitions of exchange in a relationship, goods are exchanged on a routine basis, without further communication required. In few sessions multilateral exchange and gift giving is observed as a way to coordinate production.

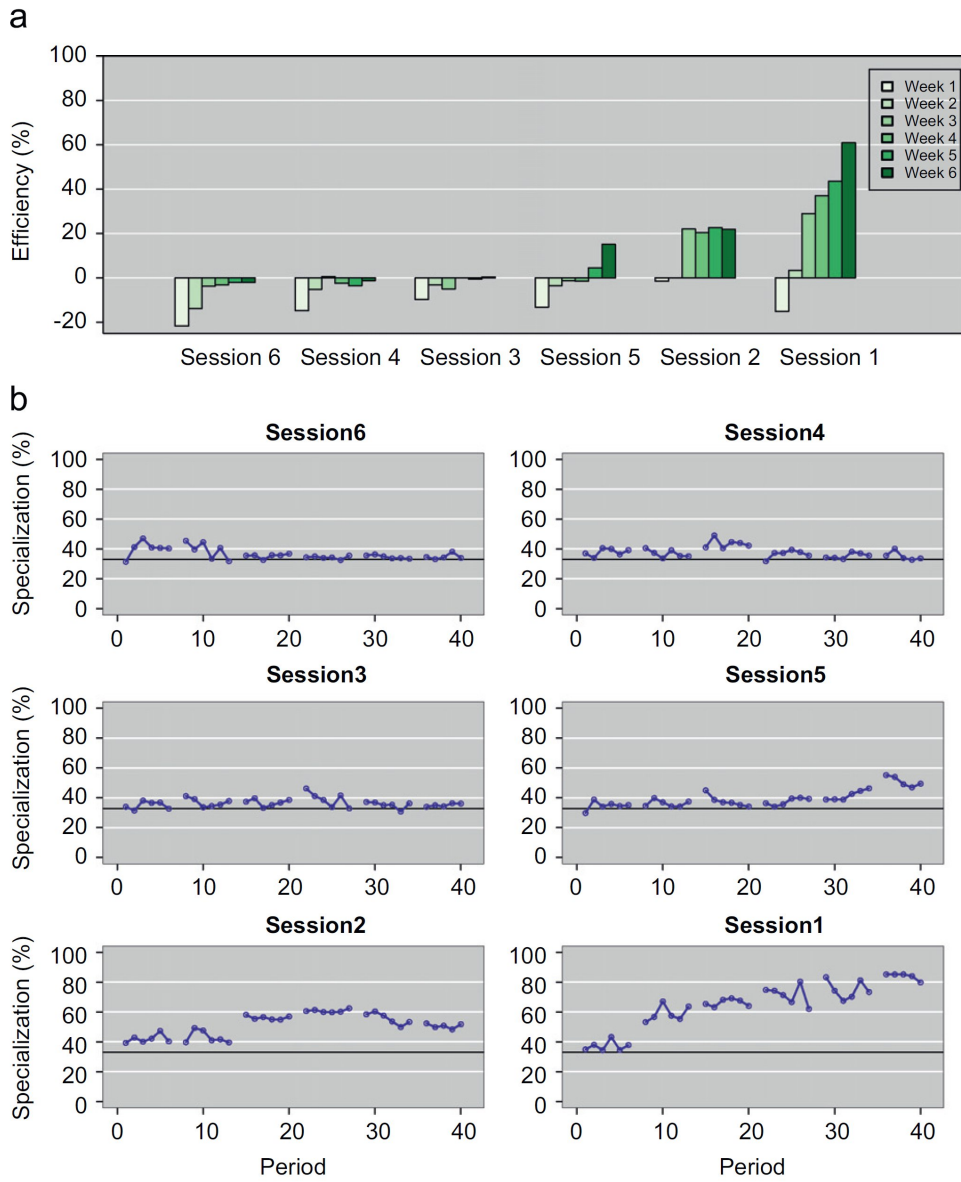


Figure 8.19: Average efficiency by week and rate of specialization by day - CSW treatment: (a) efficiency (blocks - by week) and (b) specialization, from Kimbrough (2011, p. 503)

**Searches** Partner searches are found to be largely a process of trial and error. Throughout the sessions, the majority of exchange pairings is tried at least once. The larger number of possible pairings in eight-person sessions may be associated with the lower levels of specialisation and efficiency in these sessions, in comparison with four-person economies. With the establishment of exchange relations, participants cease to search for other partners.

Neither CSW nor KM provide any explanation for the differences in performance within the treatment groups. As Fig. 8.19 shows, the speed of development and the ultimate level of specialisation and efficiency cover almost the entire range of possible outcomes within one treatment. The EGS results presented above cover the entire range of possible outcomes, moreover through the model relationships between different outcomes and their input parameters are revealed. Therefore EGS' results can serve as suggestions for future research directions that seek to explain the variation of outcomes by relating performance to individual traits of participants in any one experimental session.

The most obvious match between observed behaviours in CSW and the groups of model outcomes in EGS are Autarkists. Those are characterised by a low level of specialisation, low leisure (efficiency) and hardly any exchange or search attempts for potential partners. Autarkists are related to low numbers of rounds in the GA, relatively high search costs and slower adaptation regarding the number of searches. Also they are relatively slow at adapting their number of searches, less likely to explore another number of partner searches and have a comparatively short memory. These relationships raise the question whether participants that do not go beyond autarky show as much involvement and spend as much time negotiating as other participants. Maybe, the subjective search costs to those participants are higher, and they find it more stressful and demanding to negotiate with others and therefore they give up more readily.

Exclusive Specialists show very similar behaviour to those participants that settle down in exclusive exchange relationships. Not only do they commit to only one partner, reduce the number of searches to a minimum and produce a comparatively high level of specialisation, they also combine relatively high level of heterogeneity in leisure with lower levels of heterogeneity in specialisation. Looking

at the parameter values that bring about exclusive specialists, one might speculate that these participants put more effort into the negotiating process and somehow perceive search costs to be lower than the other participants. Also the relationship histories could be investigated for clues regarding participants' preferences for exclusive relationships. Relationship dimensions such as trust or commitment, the partners' sense-making or even the perceived level of switching costs could also be considered as partial explanations of the participants' behaviours.

The last type of observed behaviour in CSW is groups of near-specialists that engage in mutual gift giving and multilateral relationships. Their results coincide most closely with the group of simulation outcomes characterised as High Effort, High Outcome (HEHO). They show medium to high levels of leisure and specialisation and a very high degree that goes together with a high number of searches. HEHOs are most closely associated with a low level of search costs, a higher adaptation speed for searches and a higher tendency to explore new options. Consequently, differences in these dimensions would be the most likely candidates to investigate why some sessions develop exclusive specialists and others display mostly multilateral relations and gift giving.

Overall, EGS displays a wide range of possible types of outcomes that are themselves related to different combinations of input parameters. The range of possible outcomes includes all the types of behaviour that were observed by CSW across their range of experiments. In some settings agents learn to specialise, self-organise in exclusive relationships and coordinate division of labour; in other sessions they do not, and are forced to remain in autarky. And in-between there is a wide range of variations of different types of coordination, some of which were observed in the experiments, some of which were not. In the very specific settings of the CSW economic environment, EGS demonstrates that it is capable of reproducing empirical findings, it shows what else could be possible and it too provides a basis for future empirical research that can help us investigate the social mechanisms in terms of constellation of actors with their properties and their activities that bring about specialisation, exchange and division of labour.

## 8.2 Extending EGS

One of the primary objectives in the design of EGS is to ensure future expandability and adaptability. The goal is to make EGS suitable for both abstract exploration of its entire parameter space, but also able to model concrete scenarios where the same collection of mechanisms can be used to calibrate the model to economic and technical settings in one particular case. Should suitable data about a business network or even industry become available, the agents' production and consumption functions can be adjusted accordingly and EGS can be used to model the development and evolution of a concrete business network. For this purpose the production and consumption functions in EGS are implemented most flexibly allowing researchers to adjust the agents' demand and capability to match a wide range of situations. This section will showcase the capabilities of EGS, extending the application beyond the parameters used in KM.

The new model parameters under investigation here are the number of agents ( $\nu \in \{4, 12, 16\}$ ), and also the number of goods ( $\mu = 4$ ) as well as agent heterogeneity with regard to production capabilities and their consumption function.

### 8.2.1 Varying the Number of Agents

Experimental parameters		Explored Values
$\nu$	Number of agents	4; 16
$\mu$	Number of goods	2
$\psi$	Generations of the Genetic Algorithm	5; 10; 20; 30
$\iota$	Increment to adjust the probability distribution for the number of search attempts	0.1; 0.4
$\varepsilon$	Probability of deviation from the chosen number of search attempts	0; 25; 50%
$\rho$	Agents' memory length	2; 8
$\lambda$	Agents' preference for loyalty	50; 75; 99%
$\kappa$	Cost (time) per search attempt	0; 0.2; 0.4

Table 8.8: Experimental parameters in EGS that are used to explore the effects of different numbers of agents in the economic settings of the CSW experiments.

The first extension beyond CSW settings that is to be investigated here is varying the number of agents in the model. Leaving production and consumption functions identical to those used in the CSW setup, the number of agents is set to half ( $\nu = 4$ ) and twice its previous value ( $\nu = 16$ ). To explore the effects of these changes, the same experimental design as in the previous section is used. Table 8.8 gives an overview of the explored parameter space. Also, the same output dimensions are measured as in the previous analysis: leisure, specialisation, degree, number of searches and volume of exchanges. As before the model output covers both their mean and their standard deviation across the agent population. As before, random variation in individual model runs is anticipated and for each parameter combination 30 repetitions with varying random seeds are run. These two new experiments will be referred to as *CSW\_N4* for  $\nu = 4$  and *CSW\_N16* for  $\nu = 16$ .

The results of *CSW\_N4* are visualised on pages 278, 279 and 280. Figure 8.20 shows histograms of average output values across all five dimensions. The results from the previous CSW analysis are superimposed in a lighter shade of grey. The results show that there is not much difference between  $\nu = 4$  and  $\nu = 8$  in any of the outcome dimensions, except of course for degree. Regarding leisure, specialisation, number of searches and volume of exchanges, the different settings not only cover nearly identical ranges of outcomes, but the distributions of outcomes even display very similar shapes. None of these dimensions seem to be substantially affected by the size of the agent population. The similarity between outcomes becomes even more striking in the one dimension where the outcomes are actually dissimilar: under  $\nu = 4$  the maximally sensible number of relationships is two, whereas under  $\nu = 8$  the maximally sensible number of relationships is four. In both cases this is the number of agents of the opposite type that would be available as compatible exchange partners for any one agent. The histogram of average degree in *CSW\_N4* reflects this directly: the maximum number of relationships achieved in these models is two, much lower than the average of 3.2 achieved in the standard CSW treatment. However, looking at the shape of the frequency distribution from both experiments, the similarities are undeniable. There are some, but not many, outcomes below one, then there is a peak slightly above one, which is followed by two more, smaller, peaks just under the maximum level

and about halfway between one and the maximum. In the eight-agent setting the degree distribution is spread out more widely, reaching a maximum of 3.2, but the shape of the distribution has the same three-peak structure.

The insensitivity of results regarding the number of agents in the system can also be seen the clusters of profiles of similar model outcomes. Figures 8.21 and 8.22 show the results of a cluster analysis identical to the one in the previous section. These parallel coordinate plots are adjusted so that the individual dimension's scales match those in the previous analysis. It becomes clear that the variation regarding standard deviation of leisure and specialisation and the mean degree is much lower in CSW\_N4, but the other dimensions remain in a very similar range. It is remarkable that the cluster analysis discovers groups of similar outcomes that correspond directly to those groups that described the models with an agent population of eight (see p. 255 and 256 for comparison).

Looking at the results in the original CSW experiments, it may come as a surprise that there is no difference between larger and smaller populations. After all, CSW found that population size does have a profound impact on the levels of specialisation and efficiency and they find that sessions with four participants showed superior performance throughout. The explanation for this divergence between experiment and computational model is to be sought in the nature of the experimental treatment. A smaller population size not only reduces the number of actors in the system, it simultaneously reduces the search costs and increases the likelihood of finding a matching partner. In EGS search cost and the number of agents are two separate model dimensions and they can be controlled and adjusted independently. And in fact the previous analysis showed that search cost has a negative effect on both specialisation and leisure, so there is agreement between model and experiment. Considering that search costs and population size are conflated in the CSW experiments, the differences in outcomes can now be explained. EGS shows the same effects, but they are attributed to the parameter search cost, and in the experimental settings this aspect is manipulated only indirectly.

The next variation of the CSW settings is to increase the number of agents from eight to  $\nu = 16$ . Using the same visualisation techniques as for CSW\_N4, the results for CSW\_N16 are shown on pages 282, 283 and 284.

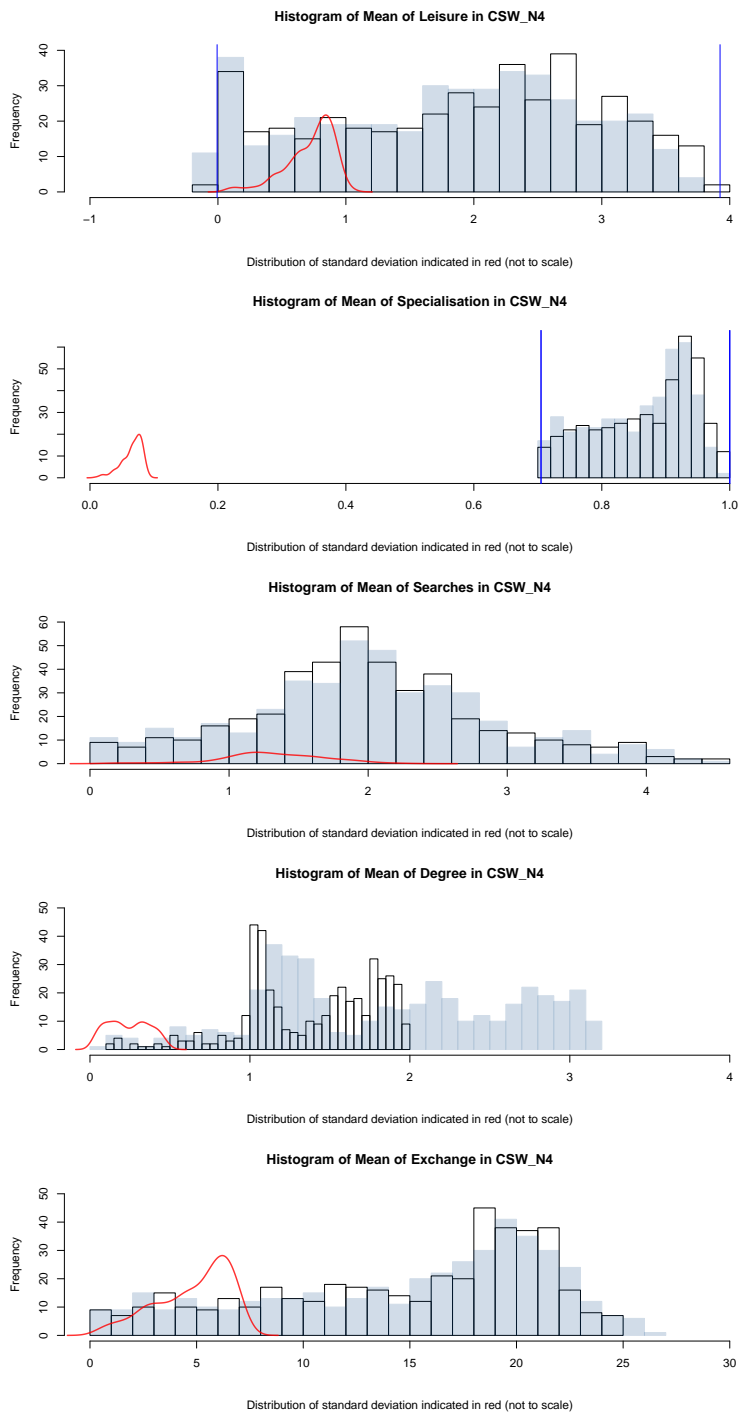


Figure 8.20: Overview of output dimensions across all parameter combination in CSW\_N4 models

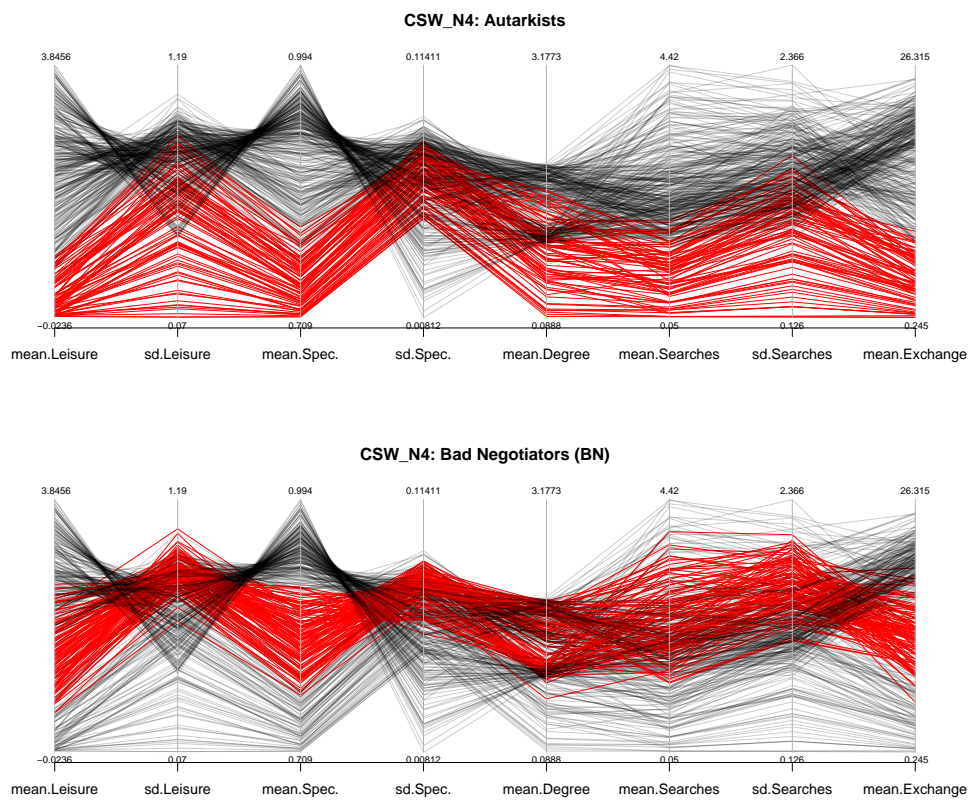


Figure 8.21: Clusters of similar outcome combinations in CSW\_N4 models: Autarkists and Bad Negotiators (BN)

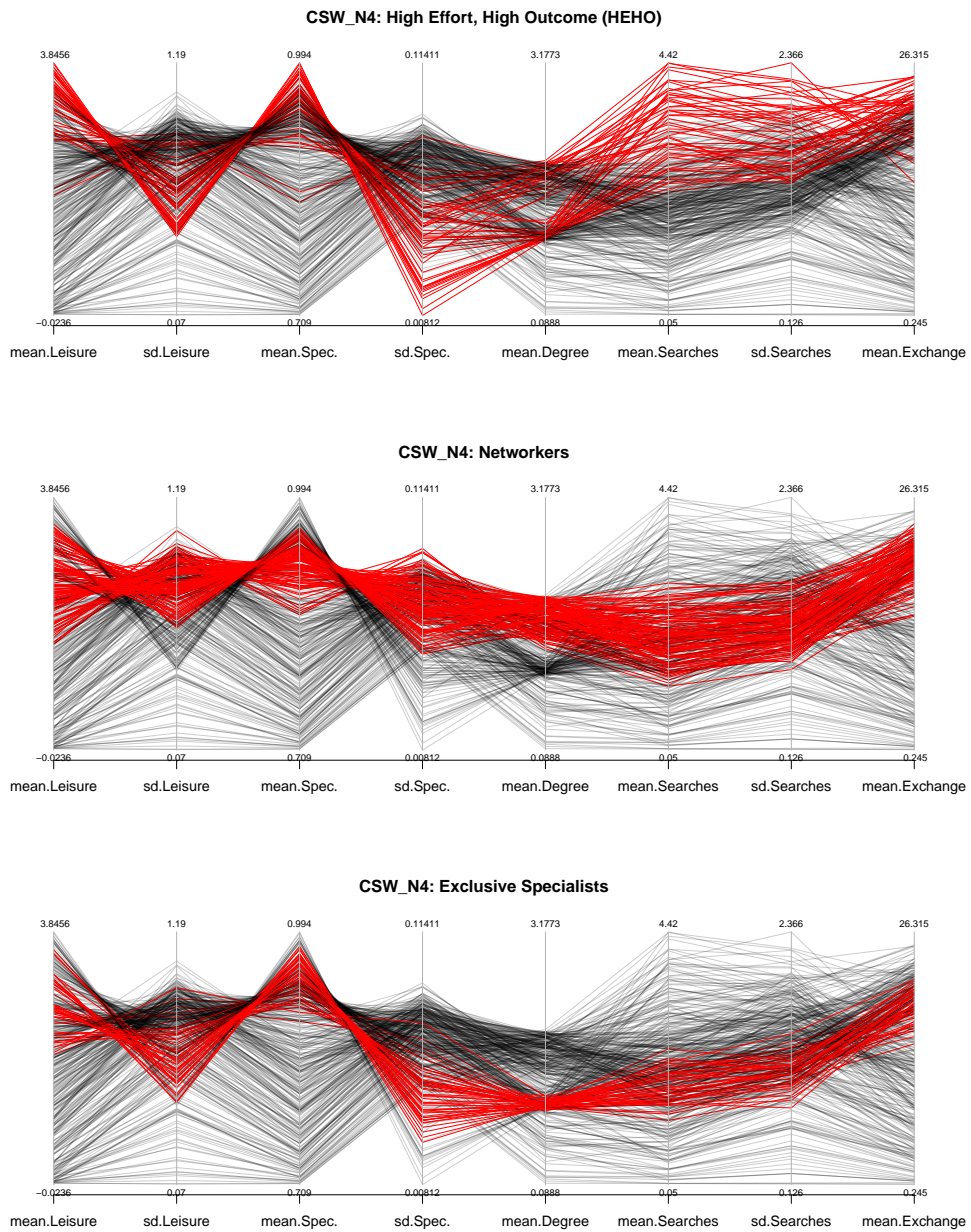


Figure 8.22: Clusters of similar outcome combinations in CSW\_N4 models: High Effort-High Outcome (HEHO), Networkers and Exclusive Specialists (ES)

In general the results confirm the findings from CSW\_N4. The number of agents in the system does not affect its development or outcomes. Figure 8.23 shows the histograms of average output values across all five dimensions. Again, the spread and shape of the histograms largely coincide with those from populations with eight agents, with the only noteworthy difference being the histogram of degree. As would be suspected, the degree in CSW\_N16 is higher than in the smaller populations. However, it still displays the three-peaked structure with peaks just above one, just below the maximum of four and right in the middle at around 2.5.

The clustering results differ slightly from the groups of similar model outcomes identified in the models with fewer agents. For CSW\_N16, the dendrogram displays a clear cut-off, at the level of the six groups instead of five before. The additional group introduces a new distinction in the cluster of Bad Negotiators. Both new clusters display lower levels of leisure and specialisation, a medium to high degree as well as an average number of searches. The new split is between those Bad Negotiators that perform very poorly and those that perform just below average. Another interesting aspect of this cluster analysis is that of the last cluster now includes those model runs that were previously identified as Exclusive Specialists but also a subset of outcome patterns that previously belonged to the group of Networkers. These two groups appear visually separate in the last cluster, but the clustering algorithm does not classify them as similar enough to the other Networkers to join them together in the preceding group. The differences between Networkers I and II lie in the standard deviations of leisure and specialisation, and also in the average degree. This recombination may well be just an artefact of the clustering algorithm and the distance measure used, but it seems like the wider range of possible degrees enhances the dissimilarities within groups, especially those that are related to a degree.

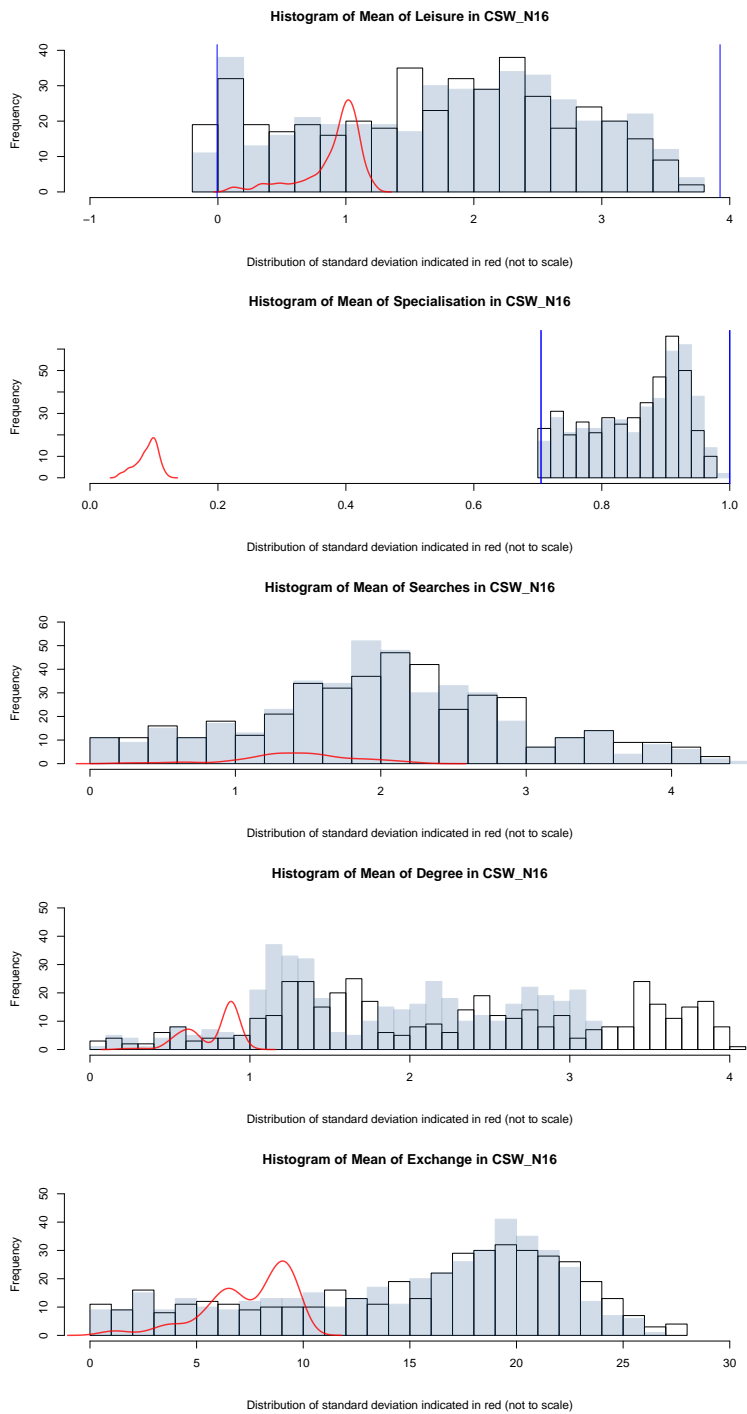


Figure 8.23: Overview of output dimensions across all parameter combination in CSW\_N16 models

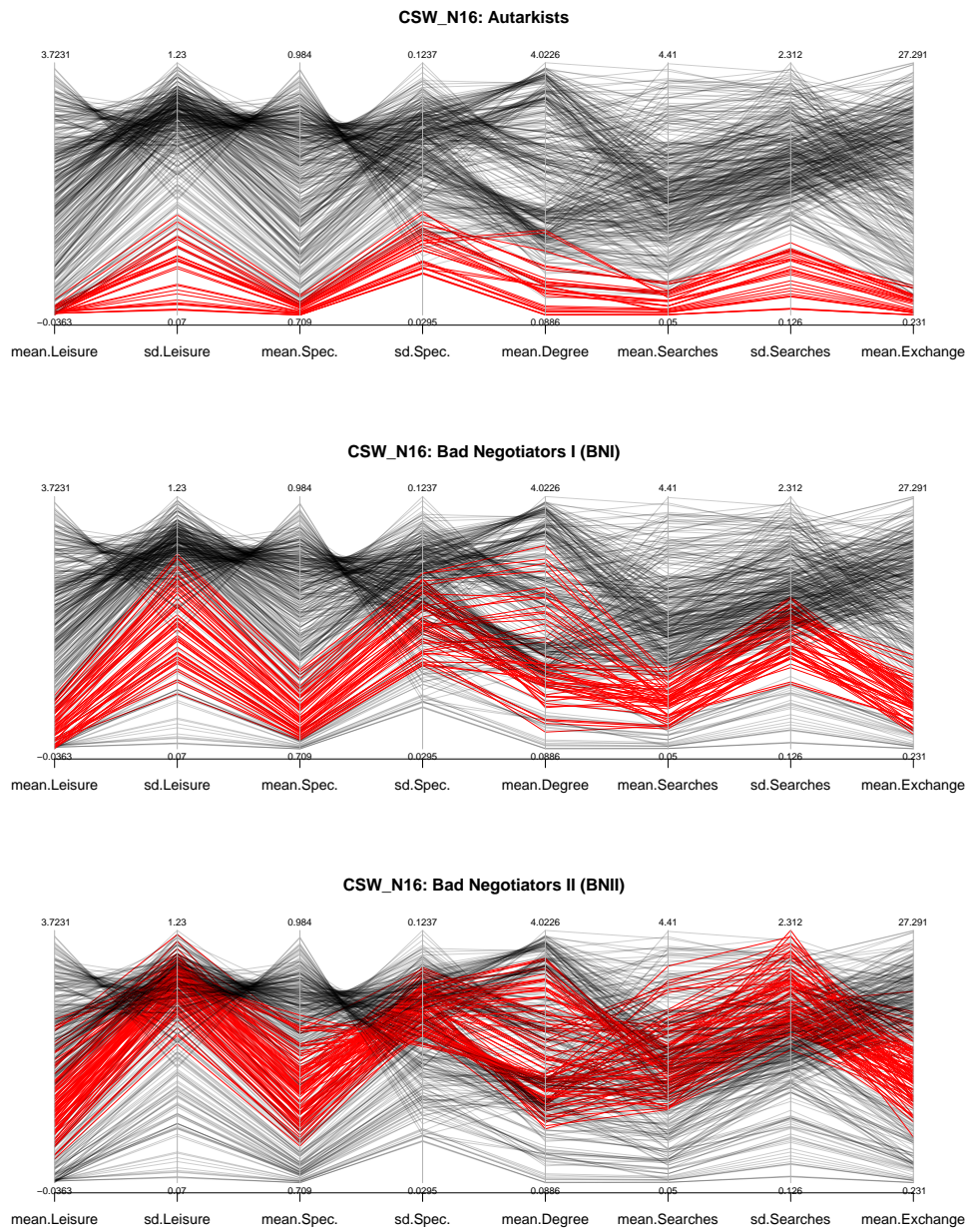


Figure 8.24: Clusters of similar outcome combinations in CSW\_N16 models: Autarkists and Bad Negotiators (BNI, BNII)

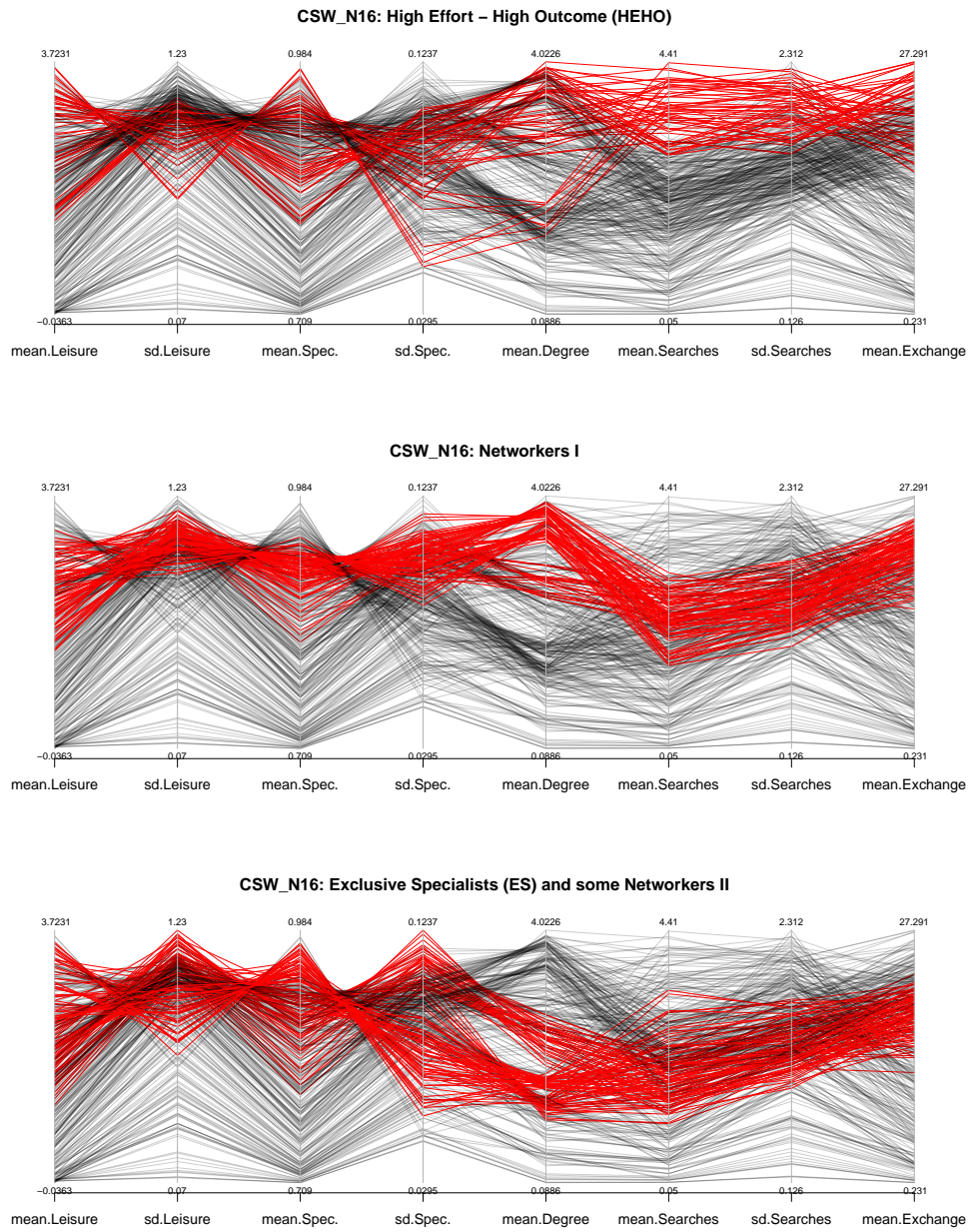


Figure 8.25: Clusters of similar outcome combinations in CSW\_N16 models: High Effort-High Outcome (HEHO), Networkers I, Exclusive Specialists and Networkers II

## 8.2.2 Varying the Number of Products

The next EGS extension to be explored here addresses the number of goods in the system. CSW simulate a very simple economy where only two types of goods are produced, exchanged and consumed. Within the flexible framework of EGS it is possible to create a multitude of different economic settings, but here we will focus on incremental changes and systematically explore how one change in the model inputs leads to changes in the model's outcomes. After varying the number of agents in the system, and learning that their number does not affect the essential characteristics of the model development, the next step is to change the fundamentals of the economic settings and introduce more goods.

This new experiment that will be referred to as ESG\_4G is run with 12 agents in every population and four goods characterising the production and consumption system. In ESG\_4G the production functions retain a structure similar to those in the CSW setting: there are still only two types of agents, one type is more efficient in producing goods A and B (type "t1"), while the other is more efficient in producing goods C and D (type "t2"). Their production functions are as following:

$$\begin{array}{ll} A_{t1} = t^{5/2} & A_{t2} = 2.4t \\ B_{t1} = t^2 & B_{t2} = 2t \\ C_{t1} = 2t & C_{t2} = t^2 \\ D_{t1} = 2.4t & D_{t2} = t^{5/2} \end{array}$$

While not identical in production efficiency, there is a clear distinction between goods. For one group of goods the agents are capable of realising economies of scale, for the others they are not.

The introduction of new products obviously requires matching adjustments of the consumption functions. Contrary to heterogeneous and unbalanced demand across agent types, as it was implemented in CSW, the updated consumption functions are homogenous and very simplistic: each agent needs to consume six units of each good every round. The agents' preference for consuming relatively more



Figure 8.26: Production functions for both agent types in EGS\_4G experiments

of the good that they can produce with comparative advantages is abolished and replaced by equal demand across all types of goods.

Figure 8.26 illustrates the production functions for each agent type, together with the units demanded in autarky and the units demanded in an efficient exchange relationship. As in CSW, the agents face a relatively simple coordination problem: type 1 should seek to produce as much of goods A and B and as little of C and D is possible, while the opposite holds for Type 2. In autarky each agent type has to spend 9.997 hours working, but through coordination and exchange a matching pair of agents can reduce their working load to 6.166 hours per round, realising 3.831 hours of leisure. The adjusted consumption functions offer more opportunities for exchanges and are therefore likely to increase the volume of exchange, on average.

Figure 8.27 summarises the results across each output dimensions, using the same kind of layered histograms as in the previous analysis. The black-and-white bars in the foreground show the results of EGS\_4G, and the shades in the background illustrate the values obtained in the standard CSW setup. The blue lines indicate the possible range of values for EGS\_4G, and the dotted lines the extreme values for the CSW settings.

The differences between settings become immediately apparent: in EGS\_4G the range of achieved leisure is much smaller and more concentrated towards the middle of the possible range, not covering nearly the entire range as in the case of CSW. Simultaneously, the level of specialisation in EGS\_4G is lower and appears to be closer to a Normal distribution, as opposed to the long-tailed distribution in CSW. Regarding the number of searches the most apparent difference is that there seem to be no model runs at all where agents choose not to search for partners. This is also reflected in the histogram of the agents' degree. As expected the volume of exchanges is increased in the new setting, and again the long-tailed distribution from CSW is turned into a much more homogenous and nearly bell curve-shaped distribution.

Overall, the new consumption and production functions seem to lead to more homogenous results across the populations of agents. Some level of exchange and specialisation occurs in all model runs, and the differences between parameterisations are less pronounced.

Further investigations concerning the relationships between input parameters and output measures indicate that the change of consumption and production functions has a substantial effect on the interplay of the remaining model aspects. By way of example the effect of input parameters on leisure will be investigated here. Table 8.9 presents the results of a stepwise model search procedure that identifies a GLM regression model to "explain" the level of leisure through the model's input parameterisation. It is equivalent to Tab. 8.3 on p. 238 for the previous CSW models. The main differences are that in EGS\_4G both the intercept and the coefficient for loyalty are much higher and statistically significant. At the same time, the other main effects that were found to be significant in the previous model remain significant, but all their coefficients and therefore their effect sizes are reduced. Also, the structure of interactive effects changes between these two models, the strongest significant effect being a positive interaction between rounds and the GA and search cost.

These results underline that there is less variation in the level of leisure produced by the model and also that the average level of leisure is higher throughout. By comparing Fig. 8.28 to Fig. 8.1.3 (p. 236) it becomes apparent how strong the loss of impact of the number of GA rounds is. Although there still are some

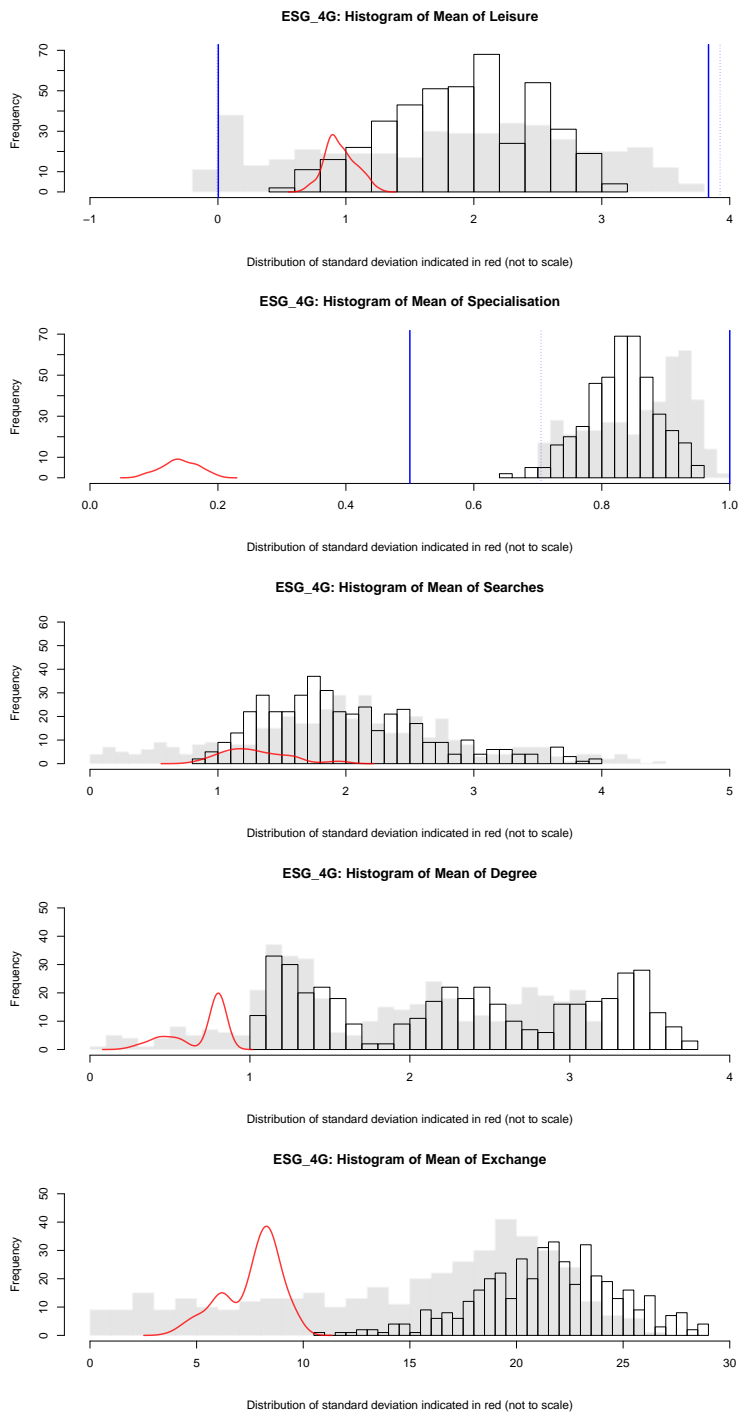


Figure 8.27: Overview of output dimensions across all parameter combination in ESG\_4G models

differences between the final levels of leisure relative to the number of rounds in the GA, these differences are no longer a matter of having all or having nothing, but more about having 1.5 or 2.5 hours of extra leisure per round.

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	1.322	0.114	11.575	0.000	***
Memory L.	0.022	0.009	2.457	0.014	*
GA R.	0.018	0.003	5.614	0.000	***
Search C.	-3.143	0.345	-9.117	0.000	***
Search P.I.	1.652	0.320	5.160	0.000	***
Loyalty	0.004	0.001	3.372	0.001	***
p(E. NSearch)	0.002	0.002	1.030	0.303	
Memory L.:Search C.	0.075	0.024	3.106	0.002	**
GA R.:Search C.	0.028	0.004	6.571	0.000	***
Memory L.:Search P.I.	-0.079	0.026	-2.988	0.003	**
GA R.:Search P.I.	-0.010	0.005	-2.117	0.035	*
Search C.:Search P.I.	-2.045	1.062	-1.926	0.055	
GA R.:Loyalty	0.000	0.000	3.972	0.000	***
Search C.:Loyalty	-0.001	0.004	-0.278	0.781	
Search P.I.:Loyalty	-0.007	0.004	-1.883	0.060	
Memory L.:p(E. NSearch)	-0.000	0.000	-0.580	0.562	
GA R.:p(E. NSearch)	-0.000	0.000	-1.511	0.131	
Search C.:p(E. NSearch)	0.001	0.004	0.247	0.805	
Search P.I.:p(E. NSearch)	-0.007	0.005	-1.513	0.131	
Loyalty:p(E. NSearch)	0.000	0.000	2.066	0.040	*
Search C.:Search P.I.:Loyalty	0.020	0.014	1.436	0.152	
Memory L.:Search C.:p(E. NSearch)	-0.001	0.001	-1.681	0.093	
Memory L.:Search P.I.:p(E. NSearch)	0.001	0.001	1.457	0.146	

Table 8.9: Final GLM model relating the mean of Leisure to EGS\_4G input parameters

These changes need to be explained in terms of the differences between CSW and EGS\_4G setups. Considering that the production functions are still very similar in shape and structure to those in CSW, only that they now apply to four instead of two goods, the changes in model dynamics must be attributed to the changes in consumption functions. A possible explanation can be found in the mechanics of the Genetic Algorithm that simulates negotiations: when two agents meet at the beginning of a round in EGS\_4G, they both have a vector of 24 production

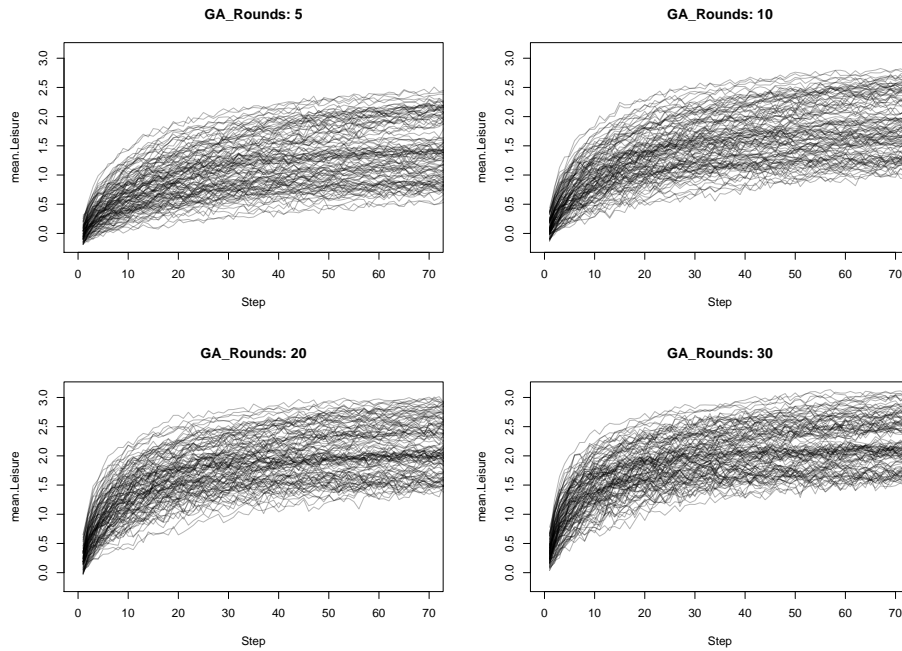


Figure 8.28: Visualisation of the development of mean leisure across all EGS\_4G runs ordered by the number of rounds in the GA.

items, 12 of which they should keep and 12 that would be better given to the partner. In CSW this ratio is 13:39, and 10:40 respectively. Taking into account that the discovery mechanism in the GA is essentially a random exploration of new candidate solutions, the odds of discovering a suitable exchange opportunity in EGS\_4G are substantially higher than in CSW. Therefore, even with low numbers of GA rounds, i.e. little negotiation efforts, agents can identify some opportunities for exchange, learn about their capabilities and economies of specialisation and eventually develop exchange relationships across all model parameterisations. In this sense the coordination task in EGS\_4G is easier than in CSW and therefore the agents show higher levels of leisure, specialisation and volume of exchange and the results across the parameter space are much more homogenous.

These changes in model dynamics are also reflected in the profiles of similar model developments that can be distilled from the data. On pages 292 and 293 the results of a cluster analysis for the range of EGS\_4G outcomes can be seen. As before Euclidean distances and Ward's agglomeration method are used,

nonetheless, the results differ in substantive ways from the profiles are identified in previous analyses. The first cluster is most similar to previous Autarkists; it is amongst the lowest in leisure, searches and specialisation, but never as low as the original Autarkists. Also, these Near Autarkists exhibit a relatively high degree. However this must be seen in conjunction with the other measures, which indicate that those relationships are of comparatively little value. The next cluster is Exclusive Specialists with more Searches (ESS) that are characterised by a higher level of performance, a relatively high number of searches combined with a relatively low degree. In these models the agents seem to revisit the same partner repeatedly to improve their negotiated exchanges. The third cluster is characterised by a high number of searches and a high degree, combined with only average levels of leisure and specialisation. A suitable characterisation would be High Effort, Medium Outcome (HEMO). Heterogeneous Loyals (HL) are the remaining model parameterisations that lead to a low degree and few searches, combined with the entire range of possible levels of specialisation and leisure. The last two groups are Networkers I that achieve mediocre outcomes in leisure and specialisation by using relatively few searches but connecting to a high number of partners. The cluster Networkers II differs through higher standard deviations of leisure and specialisation and even fewer searches.

The average input parameters associated with the groups are shown in table 8.10. The associations are similar but not identical to those of profiles identified in CSW. Near Autarkists have the lowest number of GA rounds relatively high search costs and a relatively low level of loyalty. Both ESS and HEMO are closely associated with zero search cost, fast adaptation and an increased tendency to explore new numbers of searches. But while ESS runs are brought about only at very high levels of loyalty, HEMO are characterised by very low levels. HL is associated with averages across all input parameters except for the level of loyalty. Not surprisingly, this is very high for a HL. The two Networker clusters are much more diverse regarding their inputs than their similar profiles would suggest. Both are associated with lower levels of loyalty, but Networkers I only have a medium number of rounds in the GA and low search cost, while Networkers II are associated with the opposite: many rounds in the GA and high search costs.

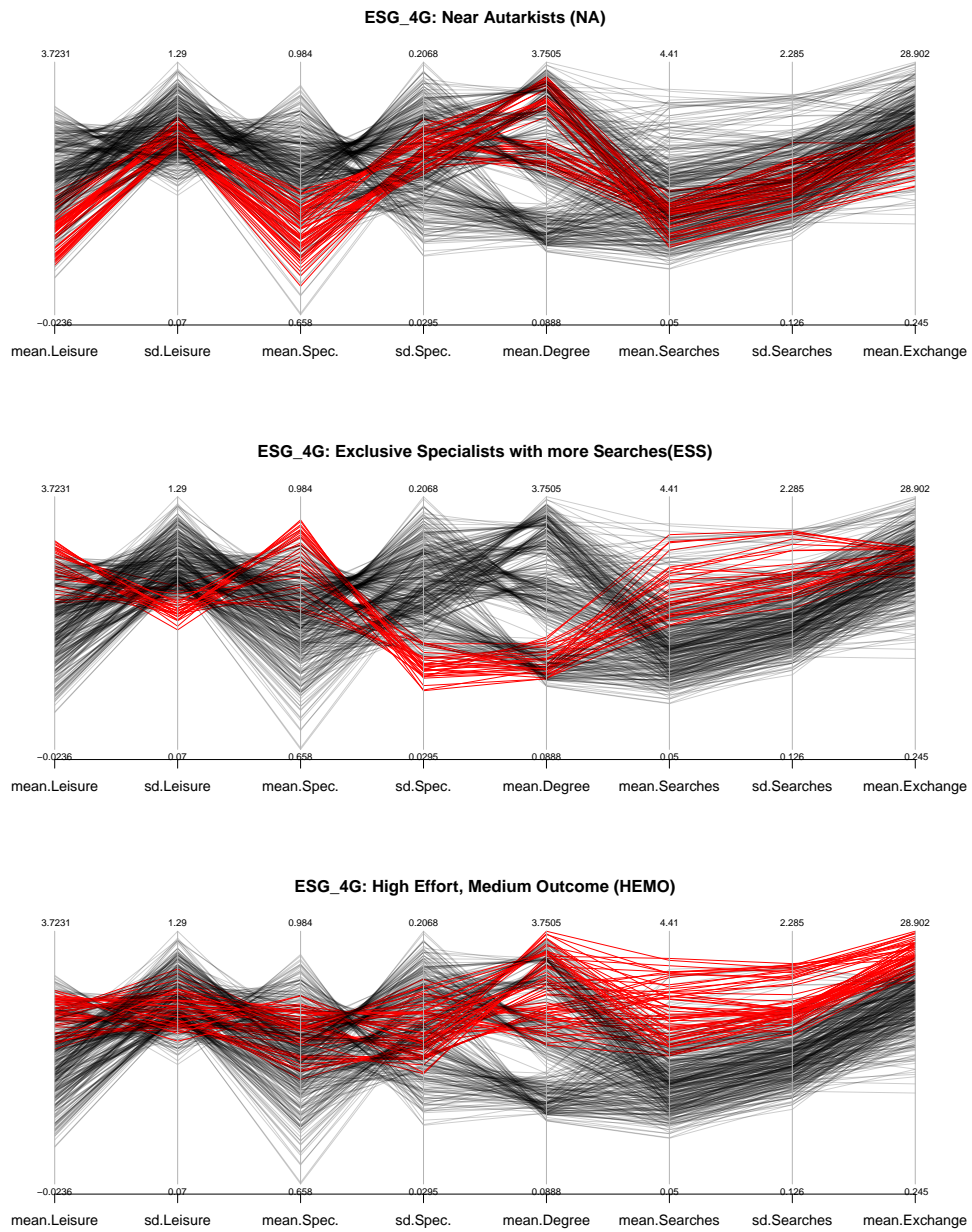


Figure 8.29: Clusters of similar outcome combinations in EGS\_4G models: Near Autarkists, Exclusive Specialists with more Searches(ESS) and High Effort - Medium Outcome (HEMO)

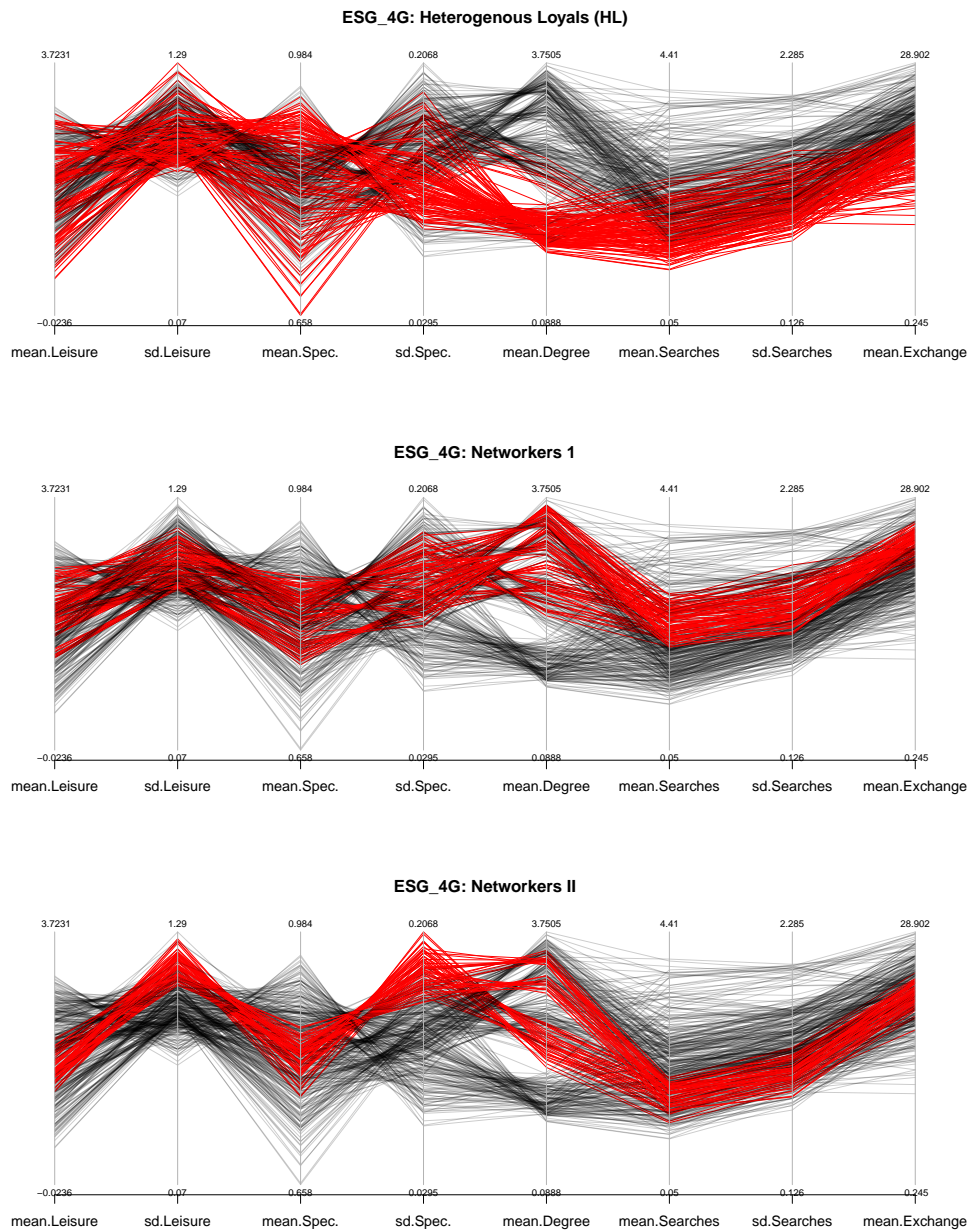


Figure 8.30: Clusters of similar outcome combinations in EGS\_4G models: Heterogenous Loyals (HL), Networkers 1 and Networkers 2

Cluster	GA_R.	Loyalty	Mem. L.	Search C.	Search P.I.	p(E. NS.)
near Autarkists	7.24	62.50	5.31	0.32	0.22	25.17
HEMO	17.12	62.29	4.75	0.01	0.31	35.85
HL	15.67	95.52	4.76	0.27	0.22	24.52
Networkers I	16.13	62.63	5.48	0.12	0.27	23.01
Networkers II	25.15	62.50	4.82	0.35	0.21	24.92
ESS	15.17	99.00	4.80	0.00	0.30	35.67

Table 8.10: Averages of input parameters for each of the clusters of similar model outcomes identified in EGS\_4G.

### 8.2.3 Increasing Production Heterogeneity

The last variation of production settings in EGS to be explored in this thesis is the introduction of heterogeneity in production. Instead of two types of agents, as in CSW and ESG\_4G, this new setting features four types of agents with different productive capabilities. It is referred to as *ESG\_4Gh*. Maintaining a total of four types of goods in the system, each agent type has a comparative advantage only regarding the production of one type of good. Consequently the most efficient level of production cannot be reached by coordinating production between only two agents but requires coordination between four agents. The production functions are similar to those used in the previous setup:

$$\begin{array}{cccc}
A_{t1} = t^{5/2} & A_{t2} = 2.4t & A_{t3} = 2.4t & A_{t4} = 2t \\
B_{t1} = 2t & B_{t2} = t^{5/2} & B_{t3} = 2.4t & B_{t4} = 2.4t \\
C_{t1} = 2.4t & C_{t2} = 2t & C_{t3} = t^{5/2} & C_{t4} = 2.4t \\
D_{t1} = 2.4t & D_{t2} = 2.4t & D_{t3} = 2t & D_{t4} = t^{5/2}
\end{array}$$

Consumption is again held homogenous to investigate the isolated effects of heterogeneity in production in this extended setting. For each type of good, each type of agent demands six units in every round. A group of four agents has the potential to coordinate their efforts so that each of them would ideally produce 24 units of their most advantageous good. While in autarky each agent would have to

spend 10.048 hours working, economies of scale, exchange and division of labour can potentially reduce their efforts to only 3.565 hours each round, saving a total of 6.483 hours per agent. The production functions and associated economies are illustrated in Fig. 8.31.

Compared to the coordination task in ESG\_4G, ESG\_4Gh is decisively more challenging. Not two but four partners are required to find the ideal allocation of production tasks, which introduces an unprecedented challenge for the agents.



Figure 8.31: Production functions for all four agent types in ESG\_4Gh experiments

The differences in production settings are reflected most obviously in the histograms in Fig. 8.32. In this case the values from ESG\_4G are shown in the background in a lighter shade of red to better illustrate the differences. Under the new settings the spread of average leisure is much wider, and better model runs achieve a higher level of leisure as well, however the models are much farther away from the ideal level of leisure than any of the preceding experiments. Similarly, the level of specialisation reaches only a maximum of 0.719% under the most favourable parameterisation. This is substantially worse than in any of the other setups, but in light of the difficulty of the task it still constitutes a considerable achievement. In those superior model runs the agents could on average, find suitable exchange partners for nearly 2/3 of the goods that they cannot produce efficiently. The number of searches now exhibits a longer tail towards the right, showing a slight increase on average, and the agents' degree is shifted by a whole unit so that the mode is now located around four. Finally, the average volume of exchanges is also slightly increased, but it never reaches the optimum of 36.

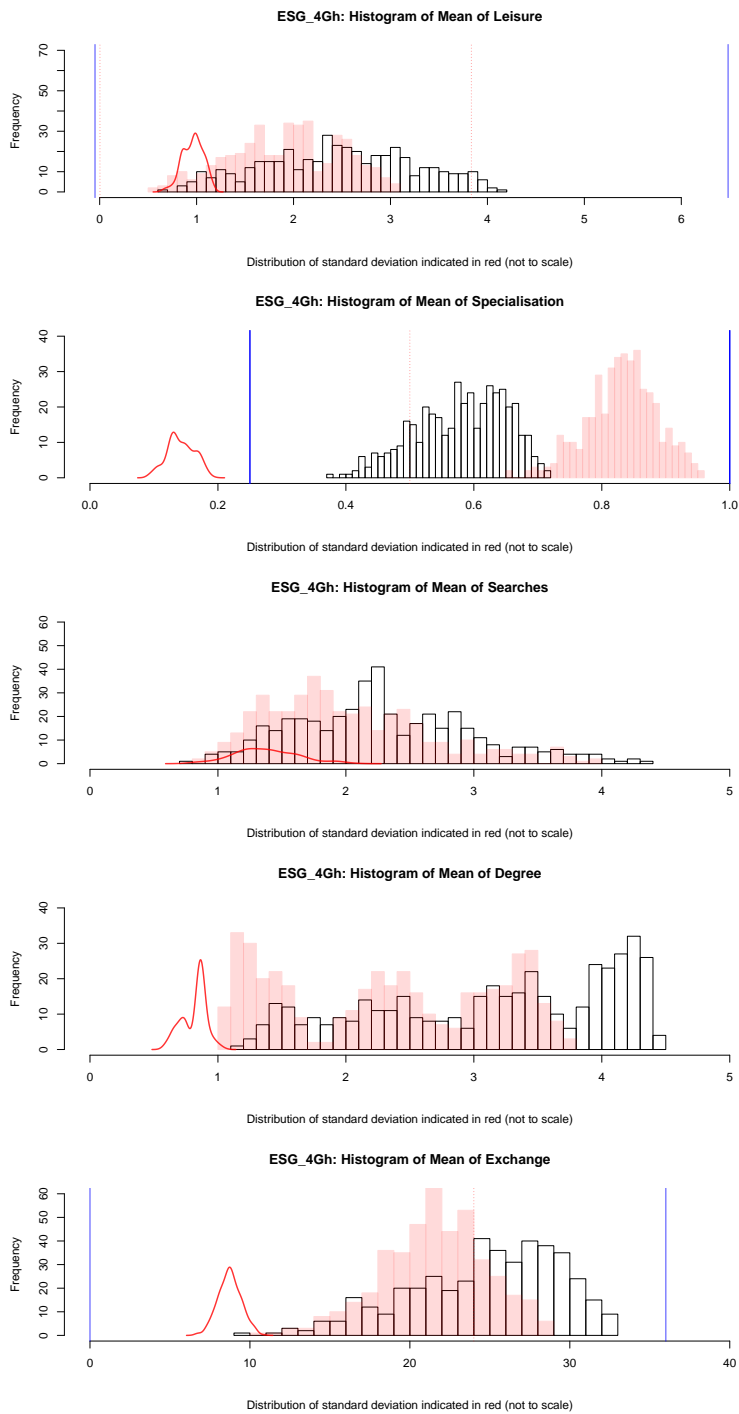


Figure 8.32: Overview of output dimensions across all parameter combination in ESG\_4Gh models

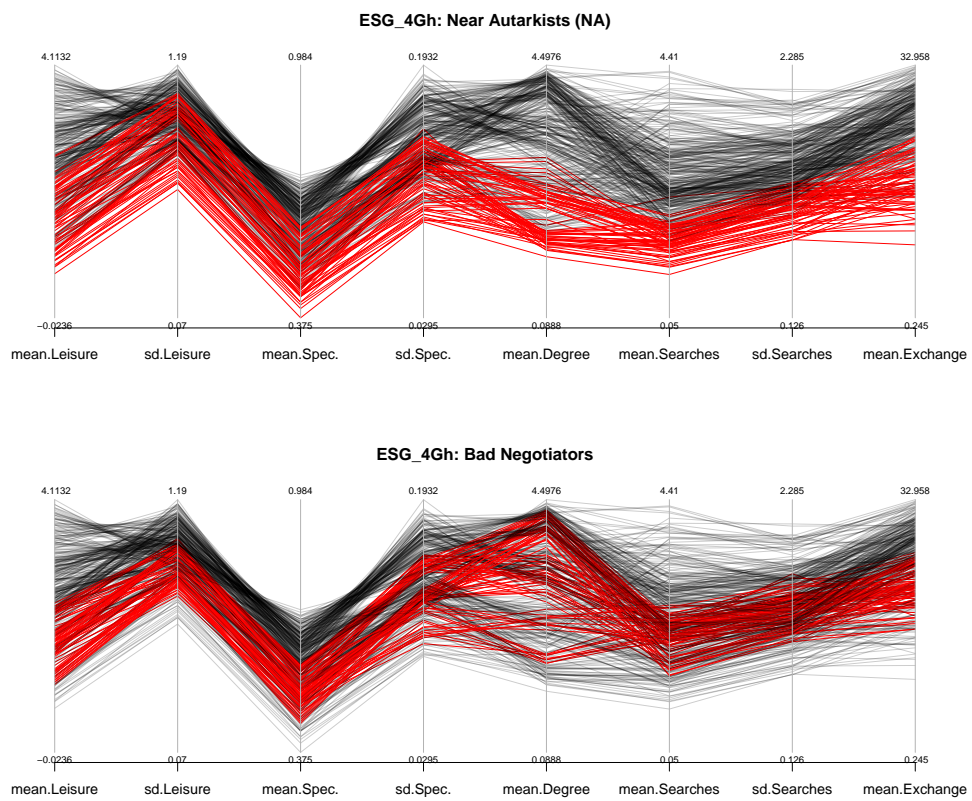


Figure 8.33: Clusters of similar outcome combinations in EGS\_4Gh models: Near Autarkists and Bad Negotiators

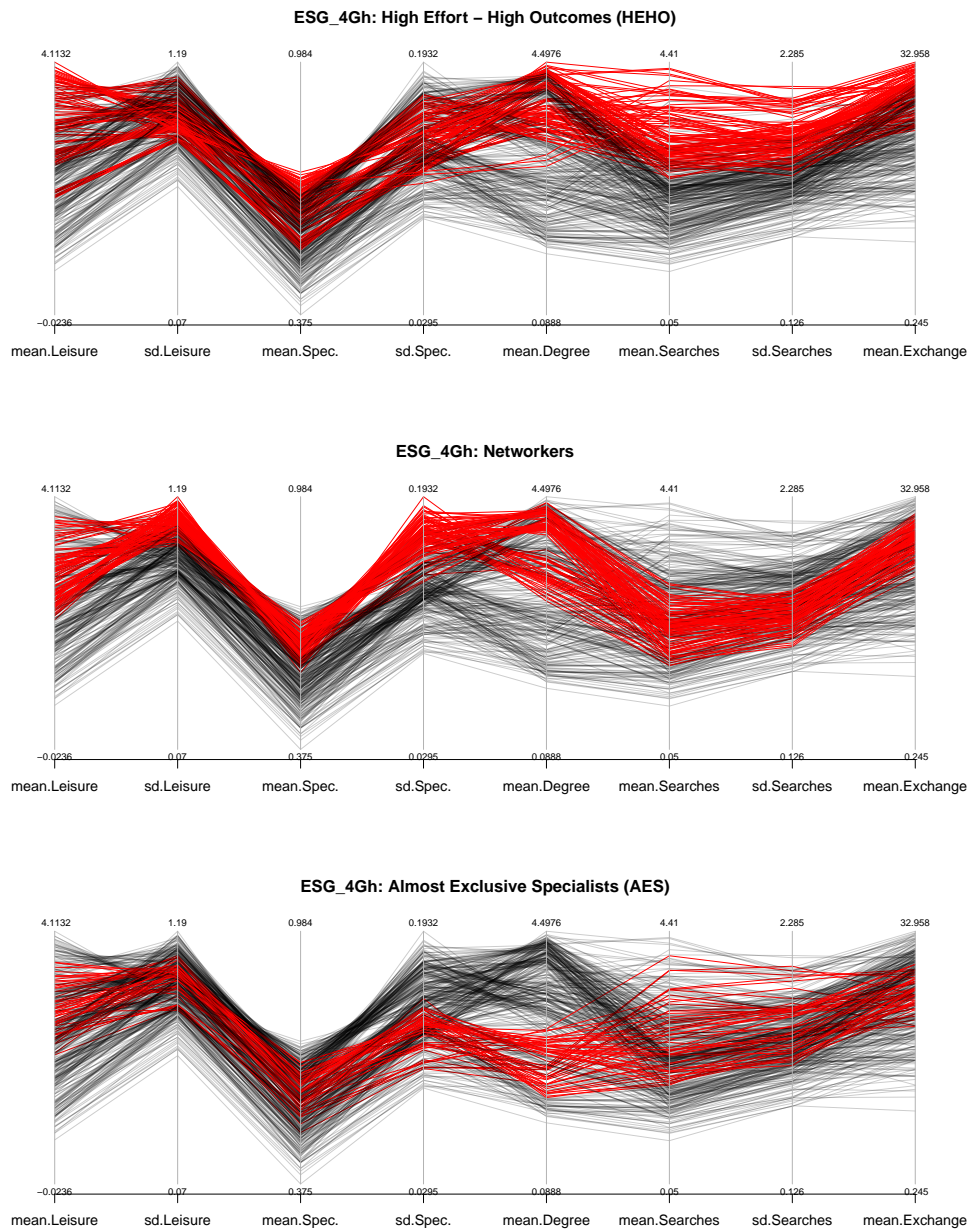


Figure 8.34: Clusters of similar outcome combinations in EGS\_4Gh models: High Effort - High Outcome (HEHO), Networkers, and Almost Exclusive Specialists (AES)

The clusters of similar model runs show patterns much more similar to those identified in CSW, than to those identified in EGS\_4G. Taking into account that the ranges of achieved - and achievable - values differ between CSW and EGS\_4Gh, we can identify Bad Negotiators, High Effort - High Outcome (HEHO), and Networkers. This time they are joined by Near Autarkists and Almost Exclusive Specialists (AES). Even agents that find themselves in settings that hinder negotiating or the maintenance of relationships do engage in interactions and occasionally come across as a favourable exchange opportunity. For AES the challenge is somewhat different because their strong preference for loyal behaviour encourages a focus on only one relationship, yet in this setting they have to engage with more than one partner to realise good exchange solutions. This challenge is reflected in their lowered performance, regarding both leisure and specialisation. For the first time exclusive specialists do not perform superior to all other groups.

Cluster	#	mean	sd	mean	sd	mean	mean	sd	mean
		Leis.	Leis.	Spec.	Spec.	Degree	Sear's	Sear's	Exchange
Near Aut'ts	53	1.58	0.88	0.49	0.12	1.85	1.39	1.06	17.68
Bad Neg's	141	1.79	0.90	0.52	0.13	3.29	2.05	1.34	21.76
HEHO	197	3.09	0.94	0.63	0.14	3.78	3.11	1.64	28.98
Networkers	225	2.80	1.08	0.63	0.17	3.72	2.15	1.28	27.30
AES	87	2.85	0.98	0.60	0.13	2.21	2.55	1.49	24.98

Table 8.11: Averages of output statistics for each of the clusters of similar model outcomes identified in EGS\_4Gh.

Looking at Tab. 8.11, these findings are confirmed. A comparison with the average outcomes for clusters in CSW (Tab. 8.4 on 250), shows that the clusters' counterparts follow the same generic patterns. The order of clusters is nearly identical across all the output dimensions. The differences are that the Near Autarkists are now much closer in performance to the other groups; Almost Exclusive Specialists have lost their leading position in terms of leisure; and lastly, the number of searches, the average degree and especially the average volume of exchanges have increased throughout. It is obvious that cooperation and exchange are much more important in this new economic setting and all of the groups adjust their behaviour accordingly.

Cluster	GA R.	Loyalty	Mem. L.	Search C.	Search P.I.	p(E. NS.)
Near Aut'ts	15.21	96.00	4.47	0.35	0.20	25.14
Bad Neg's	7.56	70.80	5.20	0.28	0.23	24.60
HEHO	15.22	63.47	4.60	0.07	0.33	32.83
Networkers	23.85	62.50	5.58	0.25	0.21	21.92
AES	19.35	99.00	5.11	0.06	0.28	28.33

Table 8.12: Averages of input parameters for each of the clusters of similar model outcomes identified in EGS\_4Gh.

In Tab. 8.12 the identified EGS\_4Gh clusters are related to the average input parameters that they are associated with, which is equivalent to Tab. 8.5 (p. 253) for CSW. These relations are not as closely matched as the model outputs. The only cluster that is clearly associated with lower GA rounds is the Bad Negotiators. While Networkers are closely associated with a higher number of GA rounds, all the other clusters now are neutral in this regard. Near Autarkists and AES only occur with high levels of loyalty, and the other clusters show no particular association with  $\lambda = 50$  or  $\lambda = 75$ . The determinant of whether a high loyalty model develops to be a Near Autarkists or AES is the level of search cost. Near Autarkists are associated with high, AES with low costs. HEHO are brought about by low search cost, and increased adaptation speed and likelihood for trying new numbers of search attempts. Within this cluster the level of leisure achieved depends on the number of GA rounds. A model is likely to develop into a Networker-type system when search costs are higher, more effort is put into negotiation and the agents have longer memory, loyalty is lower and the agents are less likely to try new numbers of searches and adapt more slowly.

### 8.3 Discussion of Findings

The EGS model is a flexible computational model of the activities of autonomous agents that are capable of producing and consuming goods and moreover have the ability to specialise in their production and to coordinate their efforts with each other over time. The agent-based model itself simulates those agents in an

artificial world and allows us to monitor their actions and interactions as they learn and adapt in the course of the model's development. The analysis presented in this chapter relates the model parameters that control some of the agents' properties and the strategies they use for interaction to a range of measurements that describe the state of the system once the agents have established and coordinated their cooperation. This analysis constitutes a meta-model, a model of the model, that seeks to summarise the complex interactions in the original model and make them more accessible and comprehensible.

This chapter covers both a calibration exercise to match EGS with the results of empirical experiments, and the description and analysis of further model extensions that showcase the flexibility and potential of EGS. In both cases the analysis follows the same pattern: 1) Describe the model outcomes in isolation, 2) Identify patterns of outcomes across the entire parameter range, and 3) Relate those patterns of outcomes to the combinations of input parameters. The differences in input parameters explain why one model run differs from the other, and the systematic exploration of the entire range of possible combinations of input parameters allows us to draw conclusions about their interactions and interdependencies.

The calibration exercise is successful in reproducing stylised facts that characterise the entire range of outcomes observed in the real world experiments. Depending on the EGS input parameters, it is possible to grow populations of agents that show the same characteristics as human subjects. EGS can produce populations that live in autarky, others where agents engage in multiple exchange relationships and still reach a high level of specialisation, and lastly it can grow populations of agents that reach a very high level of specialisation by developing exclusive exchange relations between pairs of them. The differences in input parameters that characterise these different model developments can now be used to develop hypotheses about what leads to differences in human behaviour in the real world. Furthermore, EGS produces outcomes that were not observed in the real world, including agents that seek to network, yet fail to find satisfying terms of cooperation, and other agents that maintain a relatively high number of relationships very little effort and still achieve good results in terms of specialisation and leisure. Following the categorisation of Marks (2007) a model like this is *useful*

yet *inaccurate*, and will be a matter of empirical investigation to see if there are situations where people behave as the model predicts, or if the model's predictions are wrong.

The analyses of the calibration settings and of the extensions to new settings focus on the interplay between input and output parameters. They reveal that the most important parameter to determine the average level of specialisation and leisure in a population is the amount of effort they put into negotiations ( $\psi$ ). However, the magnitude of this effect depends on the difficulty of the coordination task that the agents are facing. In a low difficulty situation, the differences are far less pronounced. The agents' preferences for loyal behaviour ( $\lambda$ ) does affect their networking behaviour, however, it is largely unrelated the agents' successes in solving coordination tasks. Only when the production settings require cooperation between several agents at the same time can a very high level of loyalty become problematic. Search cost ( $\kappa$ ) can have a prohibitive effect on the development of exchange. Yet again this is also dependent on the difficulty of the coordination task and the level of efforts that that the agents put into negotiating. Longer memory ( $\rho$ ) is positively related to the agents' degree, and their level of specialisation and leisure. Their memory of past exchanges helps the agents target suitable exchange partners more effectively and avoid wasting search negotiation time with ill-matching partners. The same holds for the speed of adaptation ( $\iota$ ), which generally leads to the establishment of more relationships and a higher number of searches for potential exchange partners. The parameter that controls the probability of trying a different number of partner searches ( $\varepsilon$ ) has the least impact on the model development. It is positively related to the average degree and the average volume of exchanges, but for future research, this value seems to be negligible.

The analysis of the workings of EGS presented here covers a range of different situations. Starting from an economy with eight agents of two types that exchange two types of goods, the model is extended in different directions. Fewer or more agents hardly affect the development of the system. Changing the demand function and introducing two more goods creates a situation where the coordination task for the agents becomes much simpler to solve. Consequently, the agents perform better in terms of leisure and specialisation, and the differences between

model parameterisations become much less pronounced. Dividing the agents into four types of producers increases the level of difficulty of coordination and poses a much bigger challenge. However, the agents adapt accordingly, increasing their cooperation efforts and investing more into searching for exchange partners. They cannot fully compensate the difficulty of the task, but still realise gains of leisure on a par with the preceding experiments.

Across all these different types of settings, the collection of patterns identified in the model outputs is surprisingly consistent. The underlying economic setting seems to determine the ranges that the individual outcome dimensions can assume, but the other input parameters control the agents' behaviours within these economic settings, and they recreate similar patterns of outcomes across all economic settings investigated here. Tables 8.13 to 8.15 show the congruence of identified clusters between CSW, ESG\_4Gh and ESG\_4G, matched by identical input parameter combinations. Looking at the match between CSW and ESG\_4Gh, there is a 61.57% agreement of model classifications between these two settings. For CSW and ESG\_4G this still reaches a level of 57.64% and lastly, ESG\_4G and ESG\_4Gh share 43.52% matches. These matches between outcomes across different settings is not perfect, but there is much more agreement than randomly assigned matches would achieve. Similar parameter combinations generate aggregate agent behaviour that produces similar patterns across various economic settings.

CSW	ESG_4Gh					total
	N. Autarkists	Bad Neg's	HEHO	Networkers	AES	
Autarkists	<b>22</b>	27	2	0	0	51
Bad Negotiators	18	<b>57</b>	24	0	9	108
HEHO	0	3	<b>68</b>	18	11	100
Networkers	13	0	19	<b>86</b>	1	119
Excl. Spec.	20	1	0	0	<b>33</b>	54
total	73	88	113	104	54	432

Table 8.13: Contingency table comparing clusters types in CSW with ESG\_4Gh

Computational models of complex adaptive systems help us better understand how emergent phenomena are brought about. EGS as an agent-based model of

ESG_4G	ESG_4Gh					total
	N. Autarkists	Bad Neg's	HEHO	Networkers	AES	
Near Autarkists	0	58	0	0	0	58
Het. Loyalists	73	26	0	0	27	126
HEMO	0	0	<b>58</b>	1	0	59
Networkers I	0	4	52	<b>37</b>	0	93
Networkers II	0	0	0	<b>66</b>	0	66
ES + Searches	0	0	3	0	<b>27</b>	30
total	73	88	113	104	54	432

Table 8.14: Contingency table comparing clusters types in ESG\_4G with ESG\_4Gh

ESG_4G	CSW					total
	Autarkists	Bad Neg's	HEHO	Networkers	ES	
Near Autarkists	<b>22</b>	36	0	0	0	58
Het. Loyalists	27	<b>36</b>	4	14	45	126
HEMO	0	4	<b>51</b>	4	0	59
Networkers I	2	24	32	<b>35</b>	0	93
Networkers II	0	0	0	<b>66</b>	0	66
ES + Searches	0	8	13	0	<b>9</b>	30
total	51	108	100	119	54	432

Table 8.15: Contingency table comparing clusters types in ESG\_4G with CSW

the development and evolution of business relationships and networks, focusing especially on the early stages of a business network where agents learn about their own capabilities, discover economies of specialisation and learn to realise these economies by coordinating their activities through cooperation and exchange. There is only one other model developed by Kimbrough (2011) that formalises the complex interplay that leads to the self-organisation of a population of independent actors to a state of specialisation, interdependence and coordination. EGS constitutes an advancement in various respects: it represents the agents' decision-making and acting more realistically, it produces a range of different model developments depending on parameters that are interpretable and have an equivalent in reality, it includes the structure of interactions and explicitly represents the emergence of an exchange network, and lastly it can be extended and adapted to a wide range of new and different settings.

EGS is one step towards a better understanding of the complexities of business relationships and networks. Although this thesis can only cover a limited number of experiments, and much research within this framework is still left undone, some new insights can already be distilled from the findings presented here. However, it needs to be considered that the lessons learned are derived from an artificial model, so the next step is to investigate them empirically, and test whether they are just a quirk of the model, or a valid aspect of human action and interaction in complex adaptive systems. Questions that need to be asked and investigated empirically after the analysis of EGS include:

- What are the individual characteristics that bring about one type of networking behaviour or another in CSW-type experiments?
- Do perceived search cost, willingness to engage in negotiations, preference for loyal behaviour, memory of past interactions and learning speed affect individuals' performances?
- Are there differences in the way people perceive the difficulty of search or coordination tasks in experiments, and if so, do these differences affect their networking behaviour?

- Is the structure of human interactions in CSW-like settings independent of the structure of production tasks?
- How can the level of difficulty in a coordination task be quantified?
- Is the range of possible outcomes restricted and relative to the structure of a coordination task?
- What is the relation between average performance and heterogeneity in performance in human subject groups that solve the same task together?

## Chapter 9

# Conclusion and Future Research

Division of labour, brought about as a self-organising process of exchange and specialisation between individuals, is the cornerstone of our economic system. While economic theory and much of marketing thinking focuses on the individual and its decision-making within such a system, the Markets-as-Networks perspective emphasises the importance of relationships between actors and their interdependencies that result from the interconnected network of relationships. Such a network of business relationships is a Complex Adaptive System that develops dynamically over time. Moreover it exhibits emergent effects as the constellation of the individuals' actions bring about phenomena on the aggregate level that go beyond the simple sum of its parts. The individuals create and shape the network through their decisions and activities but through feedback effects the structure of the network affects the individuals' options and their possibilities. Moreover individuals engage in sense-making and strategising, responding to the situations they are facing, including the network of relations that surrounds them.

To deal with complex systems requires a different kind of thinking: more integrated, focussing on the system as a whole, including all the relevant actors and the structure of their interactions over time, and perceiving dynamics as the norm and stasis as exception. The manifold interactions and interdependencies in these networks together with their dynamic nature are posing a challenge to traditional comparative-static and variable-based methods. Nonetheless, computational modelling has been used in many other disciplines to formally represent

complex adaptive systems and to explore the mechanisms that drive their development over time. In business and marketing, such models are still rare, but there are signs that indicate this is about to change.

This thesis seeks to improve our understanding about the development and evolution of business networks as complex adaptive systems, using agent-based modelling. The model developed here is not unlike mathematical models in that it makes certain assumptions about functional forms, based on existing theory, past research and previous models and experiments. It is the formalisation of a theory about the causal mechanisms that bring about division of labour and the coordination of individuals' efforts through exchange and interpersonal relationships, making explicit the set of assumptions that are supposed to cause the phenomenon under investigation. The only difference to other mathematical models is that the interactions in an agent-based model are too complex to solve them analytically and therefore require computational experiments to understand how model parameters relate to the model's outputs. At the same time, an agent-based model is not restricted to equations that can be solved analytically and therefore it can be much more realistic than mathematical models. In an agent-based model a whole world is created *in-silico*, populated by agents that can make their own decisions and are able to act and interact with each other autonomously, following their own goals and interests. These computational agents simulate the actual activities of actual people in the actual system and in this sense an agent-based model is a causal model of the social mechanisms that bring about emergent phenomena.

This thesis is one step towards a better understanding of the evolution and dynamics of business networks the complex interdependencies that economic actors face within them. The review of the existing literature on mechanisms that drive economic action on the development of business relationships gives an overview of the plethora of mechanisms that are already known to be relevant in these systems, yet the final model presented here includes only a subset of these. Therefore, EGS should be seen as a baseline: the first model of the evolution of business networks that is built on a collection of realistic mechanisms, well understood in terms of the interactions between its parameters of the outcome that they produce, and open to further extensions, so that others can add to EGS, introduce new mechanisms and see how they affect the development of the system. EGS is

by far not the final word about the development of business networks, but it is an important benchmark and a platform for future research.

The validation of EGS was undertaken on the basis of empirical experiments about a small-scale society that had to discover specialisation and exchange. In comparison to the model that accompanied the original experiments, EGS constitutes a much richer and realistic representation of the dynamics and evolution of such a system of division of labour. It was shown that EGS can reproduce the entire range of patterns of behaviour that were observed in the experiments and it does so using realistic mechanisms about the agents' activities and decision making processes. Moreover, with the same mechanisms but with different combinations of parameters the models produced outcomes that went beyond the observed behaviour of participants in the experiments. Naturally this raises the question whether similar behaviour could be shown by human subjects under appropriate conditions.

First experiments that went beyond the settings of the empirical experiment show the potential of EGS. The number of agents, the number of goods, the type of production function and the structure of the agents' consumption - all these are aspects of the model that can be adjusted to match a wide variety of economic or technological situations. Within the scope of this thesis, it is only possible to present the theoretical foundations of the model and showcase the capabilities of this new tool in selected, abstract settings. More concrete applications will be a topic of future research, especially because they require a solid basis of data describing the concrete system to be modelled. Much still lies ahead, but the fundamental research presented here will hopefully serve as a stepping stone that facilitates empirical investigations in the future.

## **9.1 Limitations and Future Research**

EGS is the result of many discussions and much hard work, but it is only an early stage in the development of models of complex business networks - and naturally it is not perfect. There are aspects that could be improved and there are others that - with hindsight - could be implemented differently. Nonetheless it is a solid foundation for future work that is grounded in realistic mechanisms

and well understood in terms of their effects and interactions. This section will discuss EGS' current limitation but also point to directions of future research, both, within the current framework and through extensions and the introduction of new mechanisms into the model.

### **9.1.1 Research in the Existing Framework**

The current version of EGS still leaves room for much exploration and experimentation. The few analyses discussed here only scratch the surface of the wide range of possibilities offered by the current consumption and production functions. Much is still to be learned about the interplay of different structures of demand with different structures of consumption, heterogeneity in demand, and different combinations of demand and production within the population of agents. Of special interest is of course the reproduction of empirical cases that model the development of a particular business network of the time. At the point of writing this thesis, suitable longitudinal datasets seem to be unavailable, but this is likely to change in the future.

Another type of experiment that could be run directly with the current version of EGS is about the exploration of effects of heterogeneity in the agent populations regarding the parameters that control their search and exchange activities. In the preceding experiments search costs, loyalty, adaptation speed, the tendency to explore and the level of effort put into the negotiation processes were all set to identical values for the entire agent population. This need not necessarily be the case in the real world and is a likely explanation for the level of heterogeneity that CSW encountered within individual sessions of their experiments. Ideally such a computational experiment would be conducted in conjunction with empirical experiments on human subjects. Designing a sensible combination of heterogeneous agents for the computational model can be challenging, but if such a setup were calibrated to an empirical case it would constitute another strong argument for EGS' validity.

A model dimension of EGS that is currently underutilised is the spatial distribution of agents and its effects on the agents' search and mating behaviour. In anticipation of future applications the model space was implemented as a mean-

ingful aspect of the model. The distances in the model affect the likelihood of agents meeting, independent of their previous exchange experiences. They could represent actual physical distances or social distances or any other reason why one pair of agents could be more likely to meet a-priori than another. The parameter  $\lambda$  then adjusts the weights that are given to one criterion versus the other, controlling the agents' search process. Currently the locations of agents are randomised uniformly, but it could easily be adjusted to represent distances of a real-world scenario. It is possible to include actual physical distances such as the map of a city, country or continent. Also, it could be worthwhile to investigate the effects of different distributions of agents in an abstract space, for example, looking at separate clusters of agents of the same production type, and assessing the interaction of such distributions with the loyalty parameter. Ultimately, the agents could be allowed to move in space and their production functions could be made dependent on their location in the landscape. This could lead to simulating an almost realistic environment where fishing is only possible by the sea and mining is done most effectively in the mountains. EGS is ready for a scenario like this, but so far there is no concrete case to apply it to.

Further extensions of existing analyses would also be possible regarding the number of agents. So far, the investigated settings contained only a small number of agents so as to facilitate comparison with the original CSW settings and also because of computational limitations. The number of agents increases the CPU time required substantially, and wide sweeps of the parameter space cannot easily be done with many agents. However, if there were a particular case of a larger network that EGS could be calibrated to, the relevant parameter space could be narrowed down with the aid of the analysis presented here, and the validity of EGS could be assessed under these different settings.

So far, the structure and distribution of the agents' demand vectors were set to rather simplistic and generic values. Possible variations are the random allocation of demand for each good, or, for more focussed analysis, the allocation of set demand vectors to represent for example certain consumer segments. So far, the explored scenarios neglect diversity between consumers and initiate them homogeneously to better understand the effect of heterogeneous production capabilities. But of course, consumption is at least as important in a marketing system,

and it should be adapted accordingly whenever EGS is applied to the concrete case.

At this stage, the implementation of EGS includes only a few technical parameters that had to be used for the sake of implementation but carry no actual meaning in terms of the theory. These parameters include  $\phi$  which determines the initial probability distribution for the number of negotiation attempts and  $d^*$  which is the maximum possible distance between agents and is set as a parameter of the model world. Furthermore, there are parameters that control the Genetic Algorithm, including  $\theta$ , the number of candidate solutions in each generation of the GA, and the crossover rate  $\chi$  as well as the mutation rate  $\xi$ . Wherever possible, these values were set to innocuous value established in the literature, but should a future application of EGS potentially dependent on these values are more comprehensive analysis of their effects (of absence thereof) would be warranted.

### 9.1.2 Research Extending EGS

Chapter 3 identified many more mechanisms than could be implemented and sensibly analysed within the scope of this thesis. On this background EGS was built to anticipate future extensions and affords the inclusion of new mechanisms, variations of old mechanisms and experiments to explore the effects of several competing ways to implement them. Starting from the current version of EGS there are some extensions that are straightforward and easy to implement and there are others that are interesting but would require more substantial changes in the code. In order to point out more directions for future research, a brief summary and overview of these options will be given here.

A new mechanism that could be introduced into EGS straightforwardly would be *intermediation*. In the current version, negotiations are exclusively bilateral and the production tasks that are exchanged as the result of negotiations are immediately binding for the receiving agent. Currently they cannot be the subject of subsequent negotiations with others. This particular model behaviour could be changed very easily and agents would be able to negotiate across the entire range of production tasks that they hold at the time of negotiation. However, this raises the question whether agents should be able to anticipate future exchanges

with certain partners and therefore be able to quote different prices than their own production costs. A possible way out would be to allow agents to sign contracts similar to those implemented in *BusiNET*. These contracts would constitute a fixed rate of exchange of one good for another and one agent could quote its contract partners' costs in the negotiation process with a third party. While the first step of this extension would only mean changing one line of code, the second step would require profound changes in the negotiation and estimation procedures. Kimbrough *et al.* (2007) describe experiments on an economy with three goods and three spatially separated groups that can engage in exchange with each other, where each of these villages is capable to produce only two out of three goods, so "long-distance" exchange is vital. The results of these experiments would be a good starting point to validate such an extended model.

Considering the findings from the current analysis there seems to be one model aspect that should be updated in the next version of EGS: the introduction and endogenisation of *costly negotiations*. Currently, the only two types of costs that agents face are production and search costs. However, the parameter sweep indicates that the effort that the agents put into the negotiation process, i.e. the number of rounds in the GA, are essential to the success of negotiations and thereby to the success of exchange. Notwithstanding these efforts are currently gratuitous, and moreover they are treated as exogenous model parameters that agents cannot adjust. Not only does this implementation substantially slow down the model as it requires considerably more computational resources, but it is likely to be the most inaccurate representation of human behaviour to be found in EGS. An important aspect of business relations is the *adaptation and learning processes* that partners go through, getting used to each other and adjusting their expectations about each other. This learning process reduces the transaction costs and to some degree binds them together because they do not have that degree of familiarity with alternative partners. This could be a template for the next adjustment and upgrade of the current EGS version. If agents had to pay for the efforts that they put into negotiation, and if they could adjust their efforts to the prospective exchange partner they are facing, this would introduce another mechanism of relationship formation. Another extension that would necessarily have to go together with adjustable negotiation efforts would be to allow agents to remember previous ne-

negotiation results with a certain partner. They could then start from the previous negotiation results and decide for themselves how much more effort they want to put into the search for improvements. Although this might sound straightforward in theory, it would require substantial extensions to the current EGS version. Questions that need to be answered include: how do the partners determine jointly how much effort they are prepared to invest into negotiations? Who pays for these efforts? How are previous negotiation results matched with the agents' current demand that might differ from the demand in the previous round? How exactly are previous results introduced into the new GA? Do the agents have to determine their level of effort before, or in the course of the negotiation process? Considering the importance of this issue, these questions cannot be brushed away lightly. Possible alternatives should be explored with care and compared to each other and in combination with each other, and for this task the standard implementation of EGS can always serve as a benchmark. The attempts to think through how to model such mechanisms helps us to focus our analysis and understanding more sharply and this is part of their value.

So far the model does not include many of the social and technological dimensions of relationship formations that were identified in Ch. 3. EGS could be extended simply by introducing *cost savings* that are brought about by repeated interactions, simulating the learning processes that occur between any pair of exchange partners over time. The implementation in the SpecialNet model could serve as a template. Extensions like this would likely link the agents' loyal behaviour more closely to their economic performance, so that the positive effect of relationship formation is expanded to cover not only the recognition of matching exchange partners, but to actually gain from repeated interactions with a familiar partner.

Another area of future research it to explore variations of the *production functions*. Currently, the agents can be set up with heterogeneous capabilities and these capabilities then allow them to realise economies of scale, provided they coordinate their production with other agents. However, this implementation ignores learning effects and economies of scope. In the preceding models Network of Specialists and BusiNET (cf. Ch. 4), the agents learn from experience and are able to improve their capabilities as they perform a task more and more of-

ten. In these models it is the production functions' coefficients that are affected through learning, but a similar mechanisms could be applied to the exponents in EGS just as well. Through such an implementation the agents' capabilities and comparative advantages could be endogenised and become an adaptive property of the agent within the complex adaptive system. Another extension regarding the production function would be to introduce economies of scope. This would require identification of a set of interdependencies amongst the production tasks, essentially mapping out how one task relates to another and how they affect the overall level of production. While the implementation of learning does not appear to be particularly challenging, the implementation of economies of scope would require changing large parts of production system, as well as the procedures for quotes, estimates and negotiations.

A completely different aspect concerning the production function is the issue of *innovation and opportunity recognition*. In the current EGS version, the number of goods, the production functions and the demand are set exogenously. They are fixed throughout the model run. There are already several models about creativity and innovation in industrial settings, including SKIN and SEIN (Gilbert *et al.*, 2001; Ahrweiler *et al.*, 2004, 2011), that allow agents to endogenise the product space and identify new areas of production. These are big and ongoing research projects, but they may serve as templates or even offer the opportunity to merge with EGS and to explore how social dimensions interact with innovation in a self-organising system of specialists and division of labour.

A last possible extension for EGS is to *link consumption to production*. This would represent an approximation of how businesses transform a selection of inputs to a certain output and portray the production process as a sequence of activities that are assigned to the actors. This could be a step towards modelling how the modular structure of products affects the structure of the production processes associated, as discussed in Baldwin & Clark (2000) and Baldwin (2008). The interdependence of tasks and the level of coordination that is required between them is a different dimension of analysis that seeks to explain the structure of interactions between economic actors. EGS may have the potential to consolidate this product-centred view with one that focusses more on the aspects of relations

between business actors, and this is certainly another interesting field for further research.

# Appendix A

## BusiNET (Business Network Evolution Tool)

### A.1 ODD (Overview, Design Concepts, and Details)

BusiNET is an agent-based model of a dynamic business network that evolves as a self-organising system of interacting agents. The agents represent businesses that engage in production and consumption, exchange, learning and adaptation. They can establish mutually beneficial relationships that represent ongoing exchange relations. These relationships are not static, they evolve over time. Moreover they do not occur in isolation, but are embedded in a network of other relationships. Due to resource constraints these relations may affect each other directly or indirectly. The model's core feature is that relations can be joined to supply chains that connect producers and consumers through various steps of *intermediation*. The model seeks to better understand how the emergent network structure affects the agents' activities and how the structure develops dynamically over time. In the following the model is outlined according to the ODD protocol (Overview, Design concepts, Details; see Grimm *et al.* (2006, 2010).

#### A.1.1 Purpose

“Business networks” refers to the interdependent systems of intra- and inter-organisational exchange relations between firms, government agencies and other types of orga-

nizations. They are increasingly understood as examples of complex adaptive systems in which participants act on the basis of limited, local information. These systems are self-organising, which means that orderly patterns arise on the aggregate level from the micro-interactions of individuals. Moreover, research suggests that there are also feedback effects from the network structure to the development of individual relations within it. Consequently the challenge for managers and policymakers is not the management and control *of* such systems but to participate and manage *in* them.

Existing research struggles to combine the analysis of dynamic processes with an overall network perspective. The majority of existing research uses comparative-static, variable-based methods to compare business relationships. These can neither provide insights about the mechanisms that drive the system, nor about the dynamic development in the network context.

Those approaches capable of dealing with dynamics however, tend to focus on selected relationships, unable to account for the complex interrelations in the network. Examples include stage models describing the development of a relationship, case studies and descriptive characterisations of relationships. Dynamic accounts of entire networks are much more resource and data intensive which, it can be assumed, is one of the restricting factors that limit the availability of such research.

While there is little known about the feedback effects that the network structure exerts on the individual businesses, much is known about the behaviour and decision making of business in the context of relationships and networks. Reviewing existing research led to the identification of five different classes of *causal mechanisms* that drive the development of business relationships in networks over time: 1) business acting and specialising (e.g. producing, consuming, buying, selling, learning), 2) business mating (e.g. choosing, being chosen), 3) business dancing (e.g. interacting, exchanging, cooperating), 4) interconnecting mechanisms (e.g. constraining effects of other relations, comparing, accessing of resources, prioritising) and 5) other, environmental impacts (e.g. laws and regulations, transportation).

The main purpose of this simulation is to create an artificial business network that evolves dynamically over time based on the actions and interactions of the

business actors that act within it. Such a model will then allow researchers to run controlled experiments on the artificial network. Moreover, it will help to better understand the complex and adaptive interplay between individual actions, performance and network position with large-scale properties such as network structure, density or clustering.

### A.1.2 Entities, State Parameters and Scales

The simulation consists of agents that find themselves in a *social space*. Based on the distances in the social space, it is defined who can interact with whom, through the agents' *social reach*. The goods that are produced and consumed are not represented independently of the agents that hold them, but are properties of the agents, referred to as their *stock*. Agents can exchange stock with each other, in order to improve the assortment of goods they are holding. These exchanges can occur during random encounters, or in an orderly, continuous manner, governed by an exchange *contract*. When a pair of agents settle an exchange contract between each other, this contract is represented by a pair of directed links between the agents.

**Agents** Agents in this simulation represent business actors that act and interact with each other. They have several attributes that describe their current state: `Stock` is a numeric vector of length `No_Goods` that holds the amount of each good that the agent currently possesses. `Money` is an integer describing the funds currently available to the agent. `Experience` and `Specialization` are again numeric vectors: the former counts how many units of each good the agent has produced, and the latter represents the unit costs at which the agents can produce these goods. `Specialization` is the function of `Experience`. If agents are capable of remembering some of their past exchange partners, these will be stored in the list of lists `Memory`. For each good, the main list includes a sub-list of length  $\leq \text{Memory\_Length}$  containing the most recent sources. Lastly the agent attribute `Surcharge` specifies the percentage the agent adds to the cost of a service it provides to others - this can be both, production of a good or intermediation between buyer and producer.

**Space** The agents' environment is represented by social space, a torus on which agents can move freely. Its area is fixed so that it has only two effects on the simulation: first, in conjunction with the number of agents `No_Agents` it determines the average density of agents and second, in conjunction with `N_Distance` it determines the agents' distance to each other and thereby decides which agents can be reached from which position in space.

**Contracts** Contracts that regulate exchange between agents are represented as directed links. These links contain one internal parameter `usage` which monitors how many units of goods have been exchanged through this particular link, regardless of the agents' roles. They can be buyers, producers or intermediaries.

### **A.1.3 Process Overview and Scheduling**

Below is the pseudo-code for one procurement processes, executed by one randomly chosen agent at a time. This process has three phases: 1) Determining the details of the deal, 2) Executing the deal and 3) Learning from it. Detailed descriptions of each sub-procedure are given in Sec. A.1.7.

1) DETERMINING the DEAL

(how much of what comes from whom at which price)

Find\_Positions\_Of\_Minima Stock

Find\_Sources

Request\_Quotes from Sources

Select The\_Source

Select The\_Price

Select The\_Quantity

2) SETTling the DEAL

(exchange, payment, consumption)

Update\_Stock\_n\_Money

Pay

Consume

3) LEARNING

(Updating Experience/Specialization, Memory, Contracts)

Let\_Producer\_Learn

if Memory\_Length > 0 [ Update\_Memory ]

if The\_Source != self

[

    if Contracts\_Possible [ Evaluate\_Contract ]

]

The first phase starts with the act of identifying the good of which the agent has the lowest (typically 0) levels of stock. Then either the agent's neighbourhood is scanned for appropriate sources, which may include itself, or - if a contract for

that particular good is already established - the contracted agent is identified as the single source to order from.

Next, the agent requests quotes from the identified sources. If they produce themselves, they quote their own costs, or if they have established a purchasing contract with another agent, they take on the role of an intermediary and forward the request to their contracted source. In every such step agents add a fee or margin to the cost they would incur themselves (cost-plus pricing) and then forward their quote to the requesting agent. It is assumed that relationships become more efficient over time, as partners learn from each other and adapt their processing to each other's needs. This mechanism reduces the cost of intermediation. The buying agent evaluates the resulting set of quotes, choosing the one with the lowest price. At the same time the buyer determines the quantity it wants to order. This quantity depends on the current levels of stock for all goods, as well as the price offered and money available.

In the second phase, the transaction is executed. The buying agent updates its stock and money. Also it "pays" for the goods received by passing the surcharge(s) through to the producer. The processes of production and shipping are not modelled explicitly. At the end of every round the buyer consumes the stocked goods, following its consumption function.

During the third phase agents learn from their previous actions and interactions. The actual producer updates its experience by the amount it produced. The buying agent adds the source that it dealt with directly to the list of sources stored in its memory. Also, if contracting is permitted and if there is no contract established for the particular good, the buying agent evaluates the set of prices it was offered. If the best offer is substantially below the second best offer, the buyer will establish a contract with its immediate source, securing this supply for the future.

Time is not represented explicitly in the simulation. The agents act serially, one at a time going through the process of procuring one type of good and consuming their stock.

#### **A.1.4 Design Concepts**

This section gives an overview of how generic design concepts, that are common in agent-based modelling are expressed in BusiNET. Through its checklist-like character it is supposed to facilitate the comparison between different models and simulations.

##### **Basic Principles**

General concepts underlying the simulation's design come from existing research on processes in business relationships and networks. Emphasis is laid on *micro validation of the agents' behaviour*, grounded through mechanisms that have been found to be the most influential drivers of relationships.

This model is built so that some mechanisms of interaction can be added modularly, allowing researchers to examine their effects in systematic experiments. The BusiNET null-model therefore consists only of agents that are scattered randomly in the social space, producing and consuming several goods, capable to learn during the production process. Starting from this most basic settings, the following additional mechanisms can be added modularly:

- Direct exchange of goods with other agents within the social-reach,
- Ability to relocate if exchange possibilities are not satisfactory at current location,
- Cost-plus pricing for production and intermediation services,
- Remembering the last  $n$  sources for each good,
- Establishing an agreement to purchase a certain good from only one source,
- Intermediation: The ability to pass on an order for a certain good to other agents,
- Re-evaluating of contracts,
- Increasing efficiency of exchanges in mature relationships,

## **Emergence**

The implemented modules of mechanisms determine in which way the agents can act and interact with each other. The *patterns of their interactions* however are endogenous and an emergent feature of the simulation. The agents' interactions are monitored on the system - i.e. the network-level, and it is one of the main goals of this simulation to better understand the co-evolutionary relationship between the mechanisms at work and the network structure resulting from the agents' interactions. Closely related to the emergence of structure are the top-down feedback effects from this emergent network structure, back to the behaviour of the agents. It creates the individual agent's environment and with that the interaction options available to them, largely determining their path of specialisation and development.

## **Adaptation**

The agents adapt to the heterogenous and dynamic supply and demand in their local environment. They accumulate experience in producing goods and in this process specialize in the production of a subset of goods.

Another means of adaptation is the establishment of contracts with sources for a particular good. Contracts reduce the risk associated with the search process and they can also reduce the transaction costs, simulating the way business partners learn about and adapt to each other.

Lastly, the agents have the possibility to change their location within the social space. They will do so if a purchase for any given good cannot be made without losing money (i.e. at a price  $p_g > 1$ ).

## **Objectives**

The agents engage in production and exchange with the goal of maximizing the amount of goods that they can consume at the end of each procurement process. However, they are myopic in their decision making, reacting to the current environment without strategic planning or long-term goals.

## **Learning**

As discussed under *Adaptation*, the agents learn by doing. They gain experience in the production process, and this directly affects their productive capabilities, increasing their productivity for goods they produce more often. However, their overall capacity for specialisation is limited, so that excellence in the production of one good is detrimental for the efficiency of producing others.

## **Prediction**

In the course of the procurement process, the agents face four main questions: *what, from whom, at what price and how much* will they buy. While analogous decision making processes in reality almost always involve some kind of forecasting and planning, the current implementation of BusiNET reduces the associated deliberations to simple heuristics: *what* will be the good with the minimum stock level (ties are broken randomly). *From whom* is determined by the agents located within the social reach of the searching agent (and in its memory), or alternatively through an existing contract for the good in question. The *price* is determined by the lowest quote received. Determining the *quantity* is the only step that assumes more advanced cognitive capabilities. The agent seeks to spread its available funds most profitably. In order to estimate future expenditure, the agents assume that all goods will be available for the same price. Furthermore, the agents predict their future demand using a simple heuristic: they calculate the average of their current stock levels, and sum up the deficits of all the goods that are below average. The agents will then assume to allocate their total available funds proportionally amongst these goods and thus determine the quantity of the good in question that they can afford to buy.

## **Sensing**

The agents' sensing abilities are limited, given that there is no environment modelled independently of the agents. All they can do is perceive the presence of a limited number of agents that are within their social-reach and then request quotes for their services.

## **Interaction**

Exchange of goods is the only interaction the agents engage in. They first exchange information about prices and then settle the deal, exchanging goods and money. Indirect - or mediated - exchanges can occur when agents act as intermediaries between producers and consumers. An order can be forwarded through established contracts to another specialized individual. In this version of the model, the productive capacities are essentially unlimited, so that there are no direct or indirect competitive effects caused by scarcity, favouritism or prioritizing. However, agents need not offer their assistance for free, so their position in the network will affect their income, access to other agents and potential for specialisation. Future versions of the model may introduce resource constraints.

## **Stochasticity**

Processes that are influenced by random events are: uniform spatial distribution of agents upon initiation; initial levels of experience and allocation of goods; choice of direction for relocations; random selection of neighbours for the set of potential sources, should there be more than permitted by `N_number`; tie breaking in case of more than one option for minimally stocked goods or minimum prices offered.

## **Collectives**

The simulation only includes individual agents and the network that emerges from their interactions. The overall size of the market (number of agents) and the density of agents in the social space are exogenous to the simulation.

## **Observation**

Many aspects of the internal states and exchanges between agents are monitored over time, including stock levels, procured quantities and sources. Every exchange is recorded over time.

For technical reasons, the development of the simulation will be monitored in discrete rounds, the length of which is determined by the parameter `Round_Duration`. `Round_Duration` indicates the number of agents that are called to go through

the procurement process for one good. The data for exchanges is monitored for each of these steps. Internal parameters are only monitored at the end of each of these rounds.

### **A.1.5 Initialization**

At time  $t = 0$  the agents are distributed in a uniformly random way in the social space. Also, they are uniformly and randomly allocated stock levels for each good, with each individual level  $g_i \leq 1$ . Furthermore the agents are asked to consume some of their stock right away, so that at least one good will have zero stock, when the procurement processes begin. Analogously, the agents' levels of experience are randomly and uniformly set to a value  $e_i \leq 100$  units, which is directly translated into the respective levels of specialization. Memory of past interactions is initiated as empty.

### **A.1.6 Input Data**

In BusiNET the initialization, especially the location in social space, is so far not informed by external data.

### **A.1.7 Submodels**

This section will describe the submodels that represent the processes listed in Sec. A.1.3 in greater detail. These submodels drive the agents' behaviour and represent mechanisms that have been identified in the empirical and theoretical literature on business relationships and networks. A summary of all parameters relevant to BusiNET is provided in Table A.1 on p. 328.

**Find\_Positions\_Of\_Minima\_Stock:** Every agent  $i \in \mathbb{A}$  maintains an inventory list  $S_i$  with stocked levels for each of the goods  $j \in \mathbb{G} : s_{ij}$ . The Procedure `Find_Positions_Of_Minima_Stock` determines  $\arg_j \min(s_{ij})$  and returns one of the indices  $j$  with  $s_{ij} = \min(S_i)$

**Find\_Sources:** `Find_Sources` has three different modes of operation: 1) If there is no established contract, 2) if there is an established contract, 3) if

Variable name	Abbreviation	Description	Range	Unit
No_Goods	<b>G</b>	Number of goods	$\{1, 2, \dots, 14\}$	
No_Agents	<b>G</b>	Set of all goods	$\{0, 1, \dots, \mathbf{G} - 1\}$	
N_Distance	<b>A</b>	Number of agents	$\{1, 2, \dots, 1000\}$	
N_Number	<b>A</b>	Set of all agents	$\{0, 1, \dots, \mathbf{A} - 1\}$	
Memory_Length	<b>D</b>	Maximum distance for an agent to be a "neighbour"	$\{1, 2, \dots, 8\}$	
Chance_of_Disruption	<b>N</b>	Maximum number of neighbours to be considered potential sources at a time	$\{1, 2, \dots, 10\}$	
Contract_Gain	<b>M</b>	Number of past sources remembered for each good	$\{0, 1, \dots, 5\}$	
Relation_Hurdle	<b>pd</b>	Probability of considering current neighbours as potential sources although a contract is in place	$[0, 1]$	
	<b>C</b>	Factor that determines the additional efficiency gained through order-contracts	$\{0, 1, \dots, 10\}$	percent
	<b>H</b>	Minimum difference between the first and second-best prices quoted to trigger establishment of a contract	$\{0, 0.01 \dots, 0.3\}$	
<b>Internal agent parameters</b>				
Stock	$s_{ij}$	Stock of good $j$ held by agent $i$ , $i \in A, j \in G$	$\mathbb{R}^+$	
Money	$S_i$	Vector of agent $i$ 's stock of each good	$\mathbb{R}^+$	
Experience	$m_i$	Money held by agent $i$	$\mathbb{R}^+$	
Specialization	$e_{ij}$	Agent $i$ 's experience of producing good $j$ , $i \in A, j \in G$	$\mathbb{R}^+$	
	$E_i$	Vector of agent $i$ 's experience of producing each good	$[0.5, 1.5]$	
	$\mathbf{r}_{ij}$	Quantity of good $j$ that agent $i$ can produce with one unit of money, $i \in A, j \in G$		
	$R_i$	Vector of agent $i$ 's specialization regarding each good		
Surcharge	$c_i$	Surcharge of agent $i$ for production or intermediation ordered by others	$\{0, 1, \dots, 100\}$	percent
<b>Internal Order-link variables</b>				
Usage	$u_{i,k}$	Total amount of goods that have been ordered through this link by agent $i \in A$ from agent $k \in A$	$\mathbb{R}^+$	

Table A.1: Overview of parameters in BusiNET

re-evaluation of an established contract is triggered. In each of these cases the result it provides is a set of potential sources for the good in question.

1. The algorithm searches for agents that are within a distance  $D$  from the calling agent. If there are more than  $N$  such neighbours, a subset of  $N$  candidates will be selected randomly. However, if memory length  $M > 0$ , this set of potential sources is extended by the past sources remembered. Also, the calling agent itself will be included as a potential source.
2. If the calling agent has established a contract to procure the good in question, `Find_Sources` will return a set of size one, consisting only of the contracted agent.
3. Re-evaluations of established contracts occur randomly with probability  $p_d$ , whenever a purchasing contract for the good in question is established. In this case, a search for potential sources without contract is initiated. Nonetheless, the currently contracted agent will be included in the set of potential sources and can in the following step submit a competitive quote to be evaluated with the others.

**Request\_Quotes\_from\_Sources:** This procedure iterates over all agents in the set of potential sources provided by `Find_Sources`. When this set contains only the calling agent, this process can be very brief: the calling agent  $i$  reports its own costs for one unit of the good  $g$  ( $p_{ii_g} = \frac{1}{s_{ig}}$ ). When the set includes more agents this can become an extensive iterative procedure during which intermediaries forward the request through their own order-contracts until they finally reach a producer of this good. Each agent that provides a service for another agent will add its own surcharge to the quote it receives from its own source, before passing it on. At the same time, there may be efficiency gains through well-established relationships.

If neighbour  $j$  produced good  $g$  directly for the calling agent  $i$ , it would send the following quote:

$$p_{ijg} = \begin{cases} \frac{1}{s_{jg}} * (1 + c_j) * (1 - \frac{C}{u_{ij}}) & \text{if order-link } ij \text{ exists} \\ \frac{1}{s_{jg}} * (1 + c_j) & \text{otherwise} \end{cases}$$

Analogously, a producer  $k$  would report a quote  $p_{jkg}$  to intermediary  $j$  and in turn,  $j$  would quote to agent  $i$ , its predecessor in the contract chain

$$p_{ijg} = \begin{cases} p_{jkg} * (1 + c_j) * (1 - \frac{C}{u_{ij}}) & \text{if order-link } ij \text{ exists} \\ p_{jkg} * (1 + c_j) & \text{otherwise} \end{cases}$$

Note however, that only if  $i$  is the initial calling agent, is it possible that there is no contract established between  $i$  and  $j$ . Orders and requests between intermediaries can only be passed on through established contracts.

**Select\_The\_Price:** The previous procedure will yield a list of quotes in the same order as the agents in the list of potential sources. In this step, the lowest offer is selected. Ties are broken randomly.

**Select\_The\_Source:** As soon as the cheapest offer is identified, the respective agent is selected to be the actual source.

**Select\_The\_Quantity:** The quantity  $q_{ijg}$  that will eventually be ordered depends on three different factors: the buying agent's need for  $g$  relative to its needs for other goods, the agent's available money  $m_i$  and the price  $p_{ijg}$ . The agent's total need is calculated as the sum of all quantities of goods that would be required to bring their stock to the initial mean of the total stock ( $\mu(S_i)$ ). Accordingly, the relative need for  $g$  is calculated as:

$$n(g) = \frac{\mu(S_i) - s_{ig}}{\sum_{(x:s_{ix} \leq \mu(S_i))} \mu(S_i) - s_{ix}}$$

It is then assumed that all these goods would be available at the same unit price and that all available money would be split amongst them, relative to their need.

$$q_{ijg} = n(g) \cdot \frac{m_i}{p_{ijg}}$$

**Update\_Stock\_n\_Money:** The buying agent finalizes its part of the exchange.

It updates its stock

$$s_{ig}(t) = s_{ig}(t - 1) + q_{ijg}$$

and it simulates the payment by reducing its available funds accordingly:

$$m_i(t) = m_i(t - 1) - p_{ijg} * q_{ijg}.$$

**Pay:** Payment is implemented analogous to the request of quotes. Originating from the buying agent, a request to update one's finances is passed through to the producer. Each agent along the chain will retain its surcharge and make corrections for gains through established contracts. Calculations are made iteratively, on the basis of the price paid by the predecessor.

Agent  $j$  would receive from its predecessor  $i$  the information  $p_{ijg}$ , the price "paid" by  $i$ . On that basis  $j$  will update its money attribute:

$$m_j(t) = m_j(t - 1) + q_{ijg} * d_{ijg}$$

with  $d_{ijg}$  being the difference in price caused by the involvement of  $j$  in the procurement process:

$$d_{ijg} = \begin{cases} \frac{p_{ijg}}{c_j * (1 - \frac{c}{u_{ij}})} & \text{if order-link } ij \text{ exists} \\ \frac{p_{ijg}}{c_j} & \text{otherwise} \end{cases}$$

If  $j$  produced good  $g$  itself, the process will stop here. However, if  $j$  only acted as an intermediary, it will then pass on to its own source of  $g$ , with the adjusted price

$$p_{jkg} = p_{ijg} - d_{ijg}.$$

Again, note that the actual production process is not implemented, only the surcharges are passed on, assuming that where there were no production

costs, they do not have to be covered, either. This is only an implementation shortcut.

**Consume:** The agents need to consume an assortment of equal amounts of each good in conjunction, hence the good with the lowest stock level determines how much can be consumed at any given time. Through consumption stocked goods are transformed directly into money without loss:

$$m_i(t) = m_i(t - 1) + \mathbf{G} * \min(S_i)$$

**Let\_Producer\_Learn:** As there is no explicit production step, the buyer asks the producer to update its experience for good  $g$ :

$$e_{kg}(t) = e_{kg}(t - 1) + q_{ijg}$$

The agents' specialization is calculated as a shifted logistic function of the standardised experience:

$$r_{ig} = 0.5 + \frac{1}{1 + \exp\left(-\left(\frac{e_{ig} - \mu(E_i)}{\sqrt{\sigma^2(E_i)}}\right)\right)}$$

**Update\_Memory:** The buying agent adds its current direct source to the list of past sources for  $g$ . If this list exceeds the memory length  $\mathbf{M}$ , the oldest entry will be deleted, i.e. forgotten.

**Evaluate\_Contract:** Agents can commit to purchase a particular good from a set source by establishing a contract. After all transactions associated with an exchange have been completed, the buying agent will consider establishing a contract to the supplier: if the second best quote received was more than  $\mathbf{H}$ -times more expensive than the accepted price, the buying agent will establish an contract with the intention to secure this favourable source for the future.

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## Appendix B

# Reproducing CSW: Further Technical Details

This appendix contains auxiliary technical details about the validation and initial analysis of EGS in the CSW setting. The entire range of regression equations and conditional scatter plots for all output dimensions are provided here.

Coefficients:	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	0.101	0.164	0.613	0.540	
Memory L.	0.046	0.009	5.101	0.000	***
GA R.	0.085	0.008	11.098	0.000	***
Search C.	-2.343	0.345	-6.795	0.000	***
Search P.I.	1.937	0.286	6.783	0.000	***
L'ty	0.000	0.002	0.259	0.796	
p(E NSearch)	0.003	0.003	0.922	0.357	
Memory L.:GA R.	-0.001	0.000	-2.355	0.019	*
GA R.:Search C.	-0.011	0.017	-0.621	0.535	
GA R.:Search P.I.	-0.047	0.015	-3.086	0.002	**
Search C.:Search P.I.	-3.510	1.106	-3.174	0.002	**
GA R.:L'ty	0.000	0.000	3.353	0.001	**
GA R.:p(E NSearch)	-0.000	0.000	-1.892	0.059	
Search C.:p(E NSearch)	-0.010	0.005	-2.111	0.035	*
L'ty:p(E NSearch)	0.000	0.000	2.182	0.030	*
GA R.:Search C.:Search P.I.	0.107	0.059	1.833	0.067	

Table B.1: Reprint: Results of a generalised linear regression relating the terminal *level of leisure* to the collection of EGS input parameters.

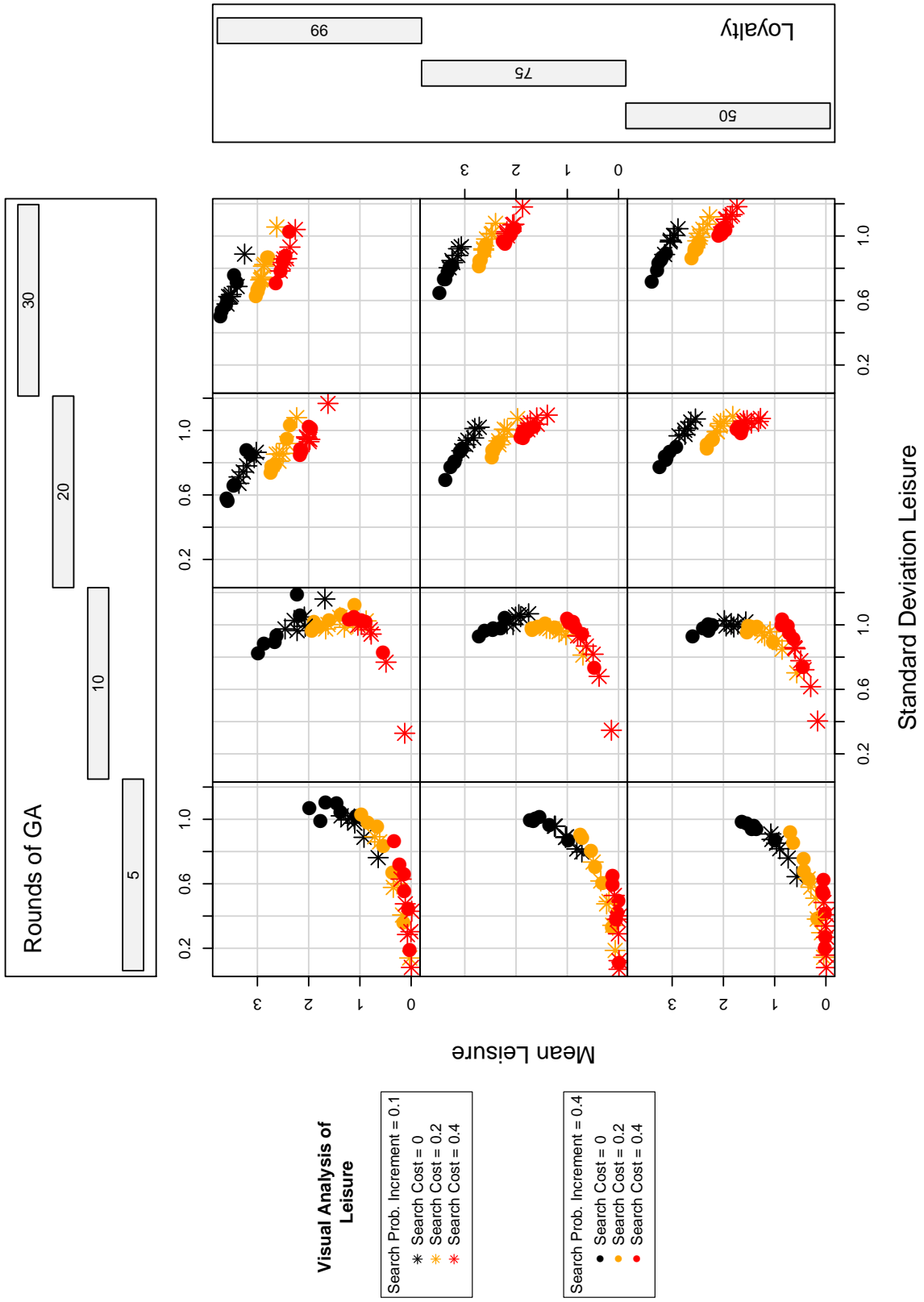


Figure B.1: Reprint: Conditional scatter plot of average level of leisure versus its standard deviation, ordered by rounds of the Genetic Algorithm ( $\psi$ ) and level of L'ty ( $\lambda$ ). The colour coding represents search cost ( $\kappa$ ) and the point characters visualise the speed of adaptation ( $\nu$ ).

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	0.394	0.094	4.176	0.000	***
Memory L.	0.028	0.009	2.945	0.003	**
GA R.	0.036	0.004	8.563	0.000	***
Search C.	-2.645	0.258	-10.261	0.000	***
Search P.I.	0.456	0.104	4.409	0.000	***
L'ty	0.004	0.001	4.545	0.000	***
p(E NSearch)	0.007	0.002	3.324	0.001	***
Memory L.:GA R.	-0.002	0.000	-3.053	0.002	**
Memory L.:Search C.	0.082	0.027	3.052	0.002	**
GA R.:Search C.	0.098	0.010	9.408	0.000	***
GA R.:Search P.I.	-0.036	0.005	-7.735	0.000	***
Search C.:Search P.I.	0.870	0.274	3.179	0.002	**
GA R.:L'ty	-0.000	0.000	-8.383	0.000	***
Search C.:L'ty	0.003	0.002	1.519	0.129	
Memory L.:p(E NSearch)	-0.001	0.000	-2.355	0.019	*
GA R.:p(E NSearch)	-0.000	0.000	-3.638	0.000	***
Search C.:p(E NSearch)	0.017	0.004	3.982	0.000	***
L'ty:p(E NSearch)	-0.000	0.000	-1.811	0.071	
Memory L.:GA R.:Search C.	-0.003	0.001	-2.194	0.029	*
Memory L.:GA R.:p(E NSearch)	0.000	0.000	1.968	0.050	*
GA R.:Search C.:p(E NSearch)	-0.000	0.000	-2.039	0.042	*

Table B.2: Final GLM model relating the *standard deviation of leisure* to the EGS input parameters

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	0.711	0.013	52.743	0.000	***
Memory L.	0.004	0.001	4.320	0.000	***
GA R.	0.006	0.001	10.444	0.000	***
Search C.	-0.218	0.019	-11.509	0.000	***
Search P.I.	0.124	0.016	7.869	0.000	***
L'ty	0.000	0.000	0.641	0.522	
p(E NSearch)	0.000	0.000	0.614	0.539	
Memory L.:GA R.	-0.000	0.000	-2.837	0.005	**
Memory L.:Search C.	0.004	0.002	1.480	0.140	
GA R.:Search C.	0.004	0.001	4.960	0.000	***
GA R.:Search P.I.	-0.002	0.001	-2.905	0.004	**
GA R.:L'ty	0.000	0.000	2.596	0.010	**
GA R.:p(E NSearch)	-0.000	0.000	-2.585	0.010	*
L'ty:p(E NSearch)	0.000	0.000	2.451	0.015	*

Table B.3: Final GLM model relating the *mean of specialisation* to the EGS input parameters

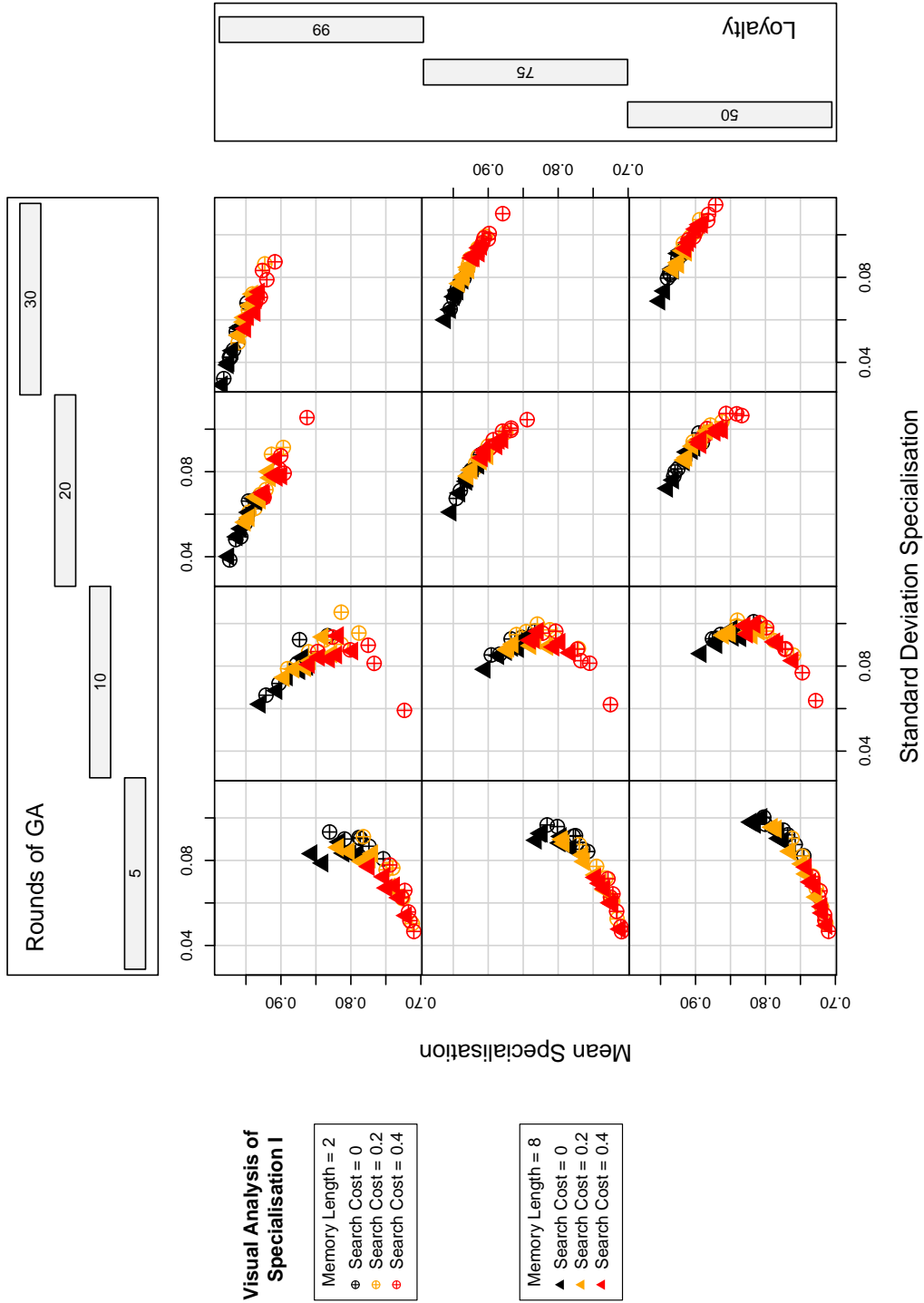


Figure B.2: First set of conditional scatter plots of average level of specialisation versus its standard deviation, ordered by rounds of the Genetic Algorithm ( $\psi$ ) and level of L'ty. The colour coding represents search cost ( $\kappa$ ) and the point characters visualise the length of agents' memory ( $\rho$ ).

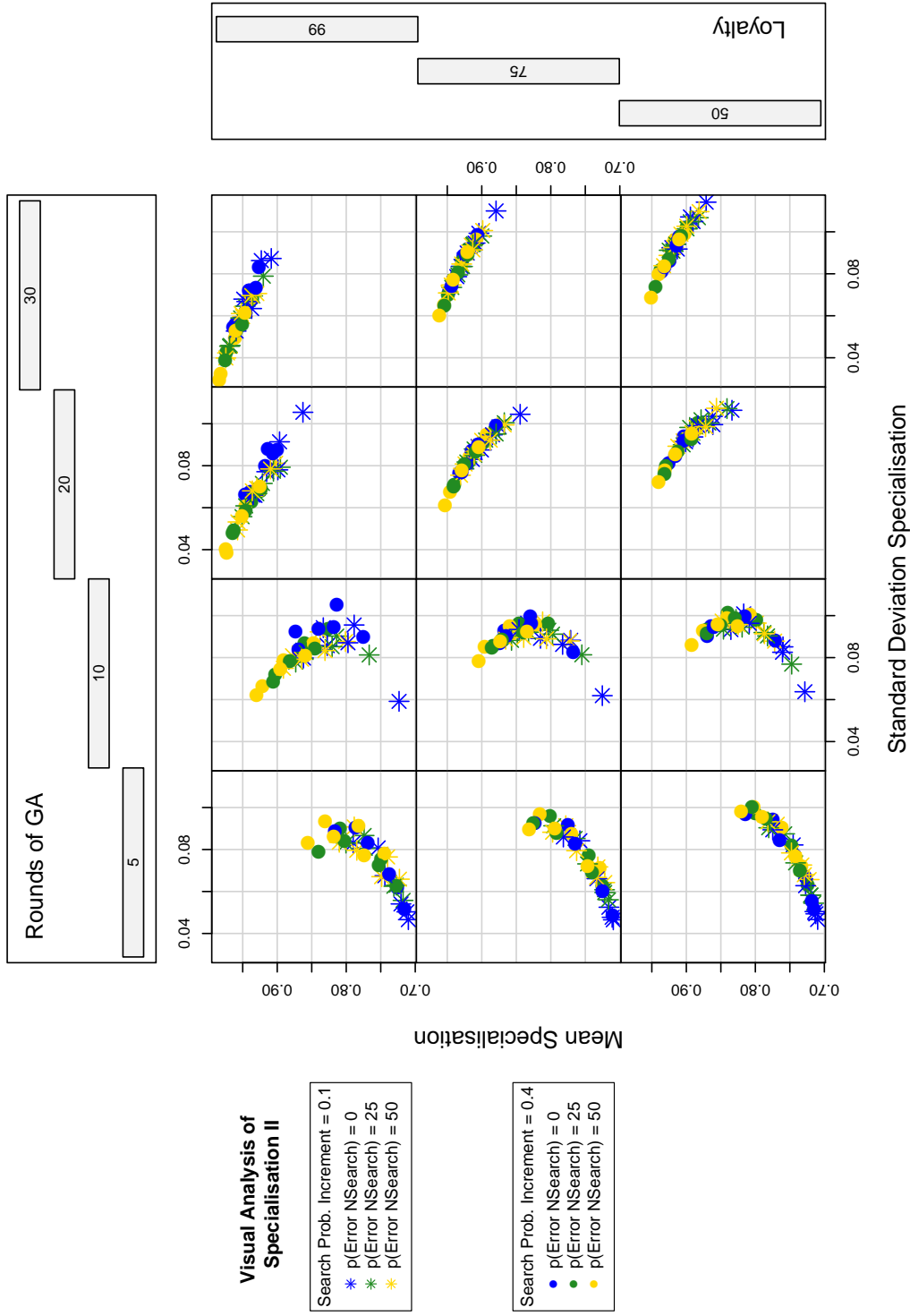


Figure B.3: Second set of conditional scatter plot of average level of volume of exchanges versus its standard deviation, ordered by rounds of the Genetic Algorithm ( $\psi$ ) and level of L'ity ( $\lambda$ ). The colour coding represents the probability of deviating from a chosen number of search attempts ( $\epsilon$ ) and the point characters visualise the speed of adaptation ( $\iota$ ).

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	0.080	0.013	6.059	0.000	***
Memory L.	-0.000	0.002	-0.008	0.994	
GA R.	0.002	0.001	2.888	0.004	**
Search C.	-0.181	0.020	-9.070	0.000	***
Search P.I.	0.045	0.026	1.717	0.087	
L'ty	0.000	0.000	0.353	0.724	
p(E NSearch)	-0.000	0.000	-0.143	0.886	
Memory L.:GA R.	0.000	0.000	0.403	0.687	
Memory L.:Search C.	0.008	0.003	2.667	0.008	**
GA R.:Search C.	0.007	0.001	7.981	0.000	***
GA R.:Search P.I.	-0.004	0.001	-3.866	0.000	***
Search C.:Search P.I.	0.055	0.017	3.239	0.001	**
Memory L.:L'ty	0.000	0.000	0.167	0.867	
GA R.:L'ty	-0.000	0.000	-2.828	0.005	**
Search C.:L'ty	0.000	0.000	3.792	0.000	***
Search P.I.:L'ty	-0.000	0.000	-0.557	0.578	
Memory L.:p(E NSearch)	0.000	0.000	0.564	0.573	
GA R.:p(E NSearch)	0.000	0.000	0.931	0.352	
Search C.:p(E NSearch)	0.001	0.001	2.817	0.005	**
Search P.I.:p(E NSearch)	0.000	0.001	0.846	0.398	
L'ty:p(E NSearch)	0.000	0.000	0.788	0.431	
Memory L.:GA R.:Search C.	-0.000	0.000	-2.639	0.009	**
Memory L.:GA R.:L'ty	-0.000	0.000	-0.804	0.422	
GA R.:Search P.I.:L'ty	0.000	0.000	1.812	0.071	
Memory L.:GA R.:p(E NSearch)	-0.000	0.000	-1.191	0.234	
Memory L.:Search C.:p(E NSearch)	-0.000	0.000	-1.281	0.201	
GA R.:Search C.:p(E NSearch)	-0.000	0.000	-1.807	0.072	
Memory L.:L'ty:p(E NSearch)	-0.000	0.000	-0.908	0.364	
GA R.:L'ty:p(E NSearch)	-0.000	0.000	-1.970	0.050	*
Search P.I.:L'ty:p(E NSearch)	-0.000	0.000	-1.420	0.156	
Memory L.:GA R.:Search C.:p(E NSearch)	0.000	0.000	1.368	0.172	
Memory L.:GA R.:L'ty:p(E NSearch)	0.000	0.000	1.481	0.139	

Table B.4: Final GLM model relating the *standard deviation of specialisation* to the EGS input parameters

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	4.841	1.711	2.829	0.005	**
Memory L.	0.385	0.101	3.815	0.000	***
GA R.	0.653	0.081	8.070	0.000	***
Search C.	-35.609	5.724	-6.221	0.000	***
Search P.I.	27.777	3.587	7.744	0.000	***
L'ty	-0.041	0.020	-2.075	0.039	*
p(E NSearch)	0.106	0.016	6.812	0.000	***
Memory L.:GA R.	-0.011	0.004	-2.841	0.005	**
Memory L.:Search C.	0.391	0.226	1.729	0.085	
GA R.:Search C.	0.680	0.297	2.288	0.023	*
GA R.:Search P.I.	-0.426	0.122	-3.506	0.001	***
Search C.:Search P.I.	-15.959	8.890	-1.795	0.073	
GA R.:L'ty	0.000	0.001	0.388	0.698	
Search C.:L'ty	0.197	0.067	2.952	0.003	**
Search P.I.:L'ty	-0.144	0.037	-3.891	0.000	***
Memory L.:p(E NSearch)	-0.003	0.002	-1.698	0.090	
GA R.:p(E NSearch)	-0.002	0.001	-3.552	0.000	***
GA R.:Search C.:Search P.I.	0.744	0.471	1.579	0.115	
GA R.:Search C.:L'ty	-0.005	0.004	-1.408	0.160	

Table B.5: Final GLM model relating the mean of *volume of exchange* to the EGS input parameters

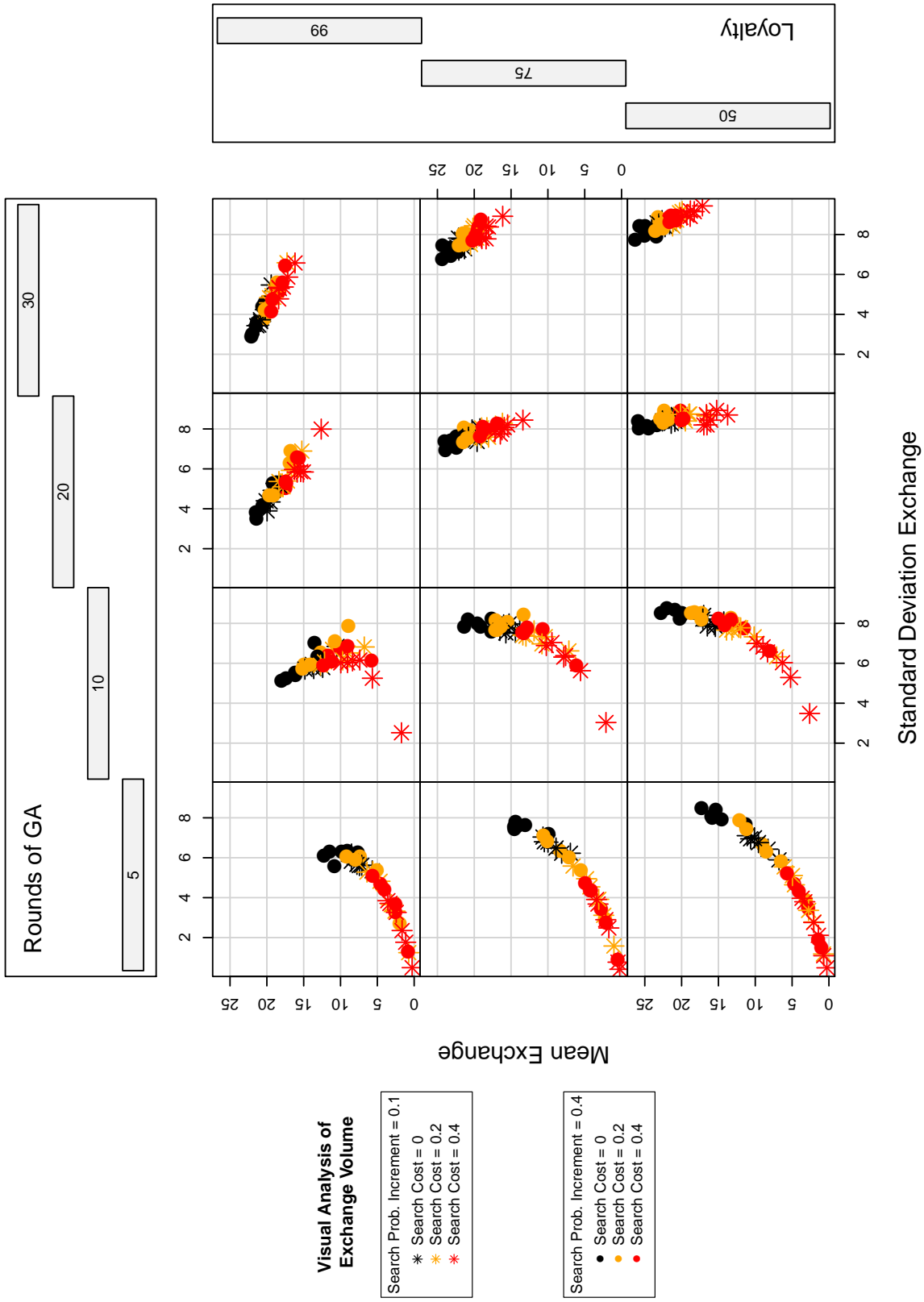


Figure B.4: Conditional scatter plot of average level of volume of exchanges versus its standard deviation, ordered by rounds of the Genetic Algorithm ( $\psi$ ) and level of L'ty ( $\lambda$ ). The colour coding represents search cost ( $\kappa$ ) and the point characters visualise the speed of adaptation ( $\nu$ ).

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	4.640	0.797	5.824	0.000	***
Memory L.	0.163	0.072	2.271	0.024	*
GA R.	0.310	0.032	9.528	0.000	***
Search C.	-20.879	1.966	-10.619	0.000	***
Search P.I.	7.432	1.577	4.713	0.000	***
L'ty	0.004	0.008	0.471	0.638	
p(E NSearch)	0.073	0.017	4.312	0.000	***
Memory L.:GA R.	-0.009	0.004	-2.455	0.014	*
Memory L.:Search C.	0.508	0.205	2.477	0.014	*
GA R.:Search C.	0.674	0.079	8.524	0.000	***
GA R.:Search P.I.	-0.219	0.036	-6.171	0.000	***
Search C.:Search P.I.	3.689	2.088	1.767	0.078	
GA R.:L'ty	-0.003	0.000	-10.258	0.000	***
Search C.:L'ty	0.066	0.016	4.186	0.000	***
Search P.I.:L'ty	-0.034	0.017	-2.022	0.044	*
Memory L.:p(E NSearch)	-0.005	0.002	-2.558	0.011	*
GA R.:p(E NSearch)	-0.002	0.001	-3.068	0.002	**
Search C.:p(E NSearch)	0.131	0.033	3.919	0.000	***
Search P.I.:p(E NSearch)	-0.029	0.019	-1.541	0.124	
L'ty:p(E NSearch)	-0.000	0.000	-3.101	0.002	**
Memory L.:GA R.:Search C.	-0.022	0.011	-2.025	0.043	*
Memory L.:GA R.:p(E NSearch)	0.000	0.000	2.299	0.022	*
GA R.:Search C.:p(E NSearch)	-0.005	0.002	-2.567	0.011	*

Table B.6: Final GLM model relating the *standard deviation of exchange* to the EGS input parameters

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	1.416	0.260	5.454	0.000	***
Memory L.	0.295	0.025	12.022	0.000	***
GA R.	0.053	0.011	4.663	0.000	***
Search C.	-6.727	0.794	-8.474	0.000	***
Search P.I.	2.348	0.473	4.961	0.000	***
L'ty	-0.008	0.003	-2.624	0.009	**
p(E NSearch)	0.005	0.003	2.034	0.043	*
Memory L.:GA R.	-0.001	0.001	-2.641	0.009	**
Memory L.:Search C.	0.068	0.032	2.122	0.034	*
GA R.:Search C.	0.208	0.041	5.050	0.000	***
Memory L.:Search P.I.	-0.051	0.035	-1.466	0.143	
GA R.:Search P.I.	-0.027	0.011	-2.530	0.012	*
Memory L.:L'ty	-0.002	0.000	-8.200	0.000	***
GA R.:L'ty	-0.000	0.000	-2.371	0.018	*
Search C.:L'ty	0.040	0.009	4.234	0.000	***
Search P.I.:L'ty	-0.015	0.005	-2.791	0.006	**
GA R.:p(E NSearch)	-0.000	0.000	-1.297	0.195	
Search C.:p(E NSearch)	0.040	0.010	3.904	0.000	***
GA R.:Search C.:L'ty	-0.001	0.000	-2.471	0.014	*
GA R.:Search C.:p(E NSearch)	-0.001	0.001	-2.743	0.006	**

Table B.7: Final GLM model relating the *mean of degree* to the EGS input parameters

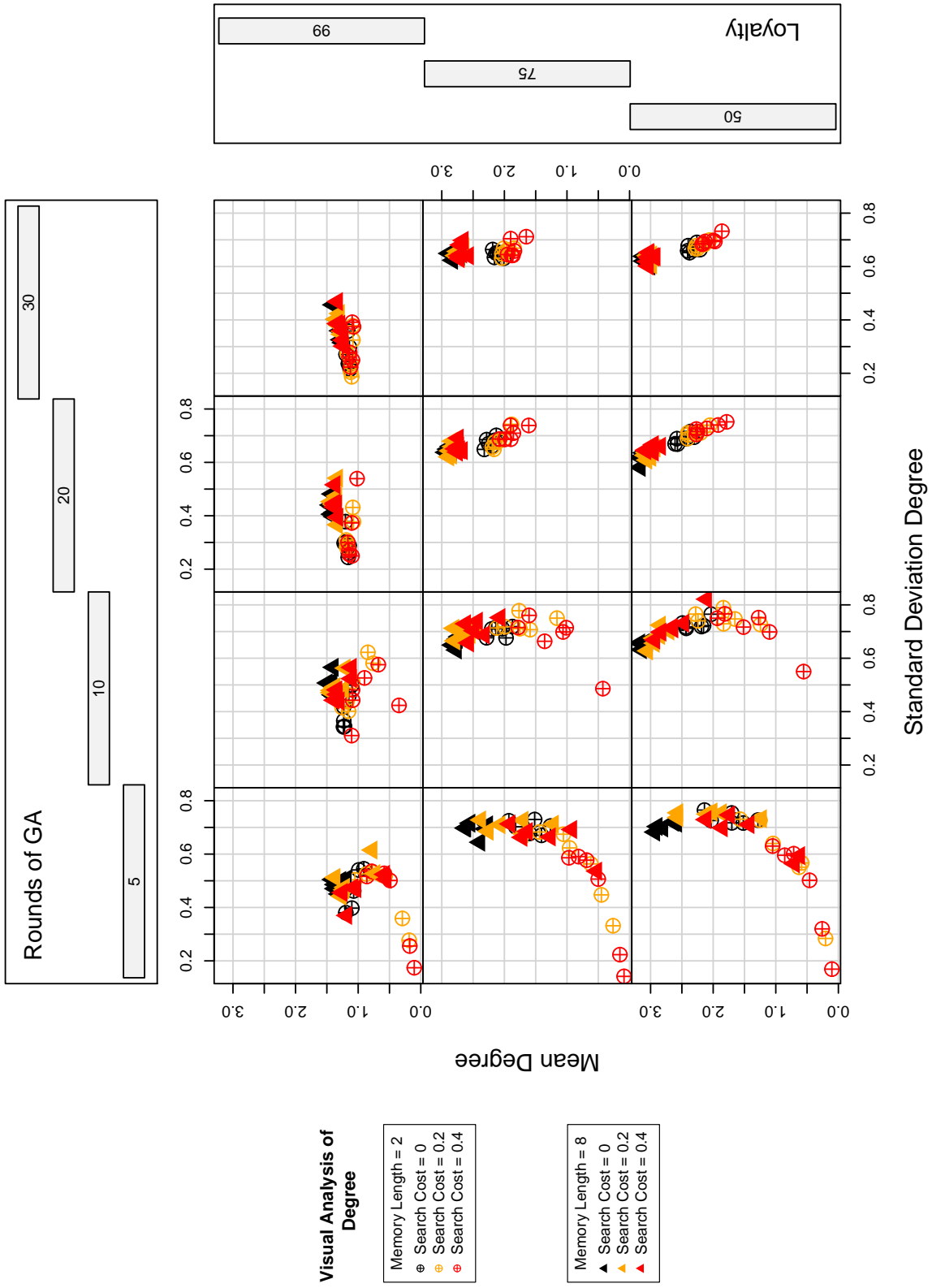


Figure B.5: Reprint: Conditional scatter plot of average level of degree versus its standard deviation, ordered by rounds of the Genetic Algorithm ( $\psi$ ) and level of  $L^*$ . The colour coding represents search cost ( $\kappa$ ) and the point characters visualise the length of agents' memory ( $\rho$ ).

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	0.850	0.129	6.566	0.000	***
Memory L.	0.006	0.022	0.274	0.784	
GA R.	0.011	0.006	1.791	0.074	
Search C.	-2.248	0.412	-5.461	0.000	***
Search P.I.	0.713	0.281	2.537	0.012	*
L'ty	-0.004	0.001	-2.413	0.016	*
p(E NSearch)	0.004	0.002	1.844	0.066	
Memory L.:GA R.	-0.002	0.001	-1.560	0.120	
Memory L.:Search C.	0.292	0.071	4.133	0.000	***
GA R.:Search C.	0.095	0.022	4.366	0.000	***
Memory L.:Search P.I.	-0.116	0.048	-2.397	0.017	*
GA R.:Search P.I.	-0.023	0.010	-2.288	0.023	*
Memory L.:L'ty	0.000	0.000	0.237	0.813	
GA R.:L'ty	-0.000	0.000	-2.122	0.034	*
Search C.:L'ty	0.014	0.005	2.865	0.004	**
Search P.I.:L'ty	-0.003	0.003	-1.093	0.275	
Memory L.:p(E NSearch)	-0.000	0.000	-0.664	0.507	
GA R.:p(E NSearch)	-0.000	0.000	-0.926	0.355	
Search C.:p(E NSearch)	0.026	0.005	4.759	0.000	***
Search P.I.:p(E NSearch)	-0.010	0.006	-1.620	0.106	
L'ty:p(E NSearch)	-0.000	0.000	-3.667	0.000	***
Memory L.:GA R.:Search C.	-0.012	0.004	-3.121	0.002	**
Memory L.:GA R.:Search P.I.	0.003	0.002	1.896	0.059	
Memory L.:GA R.:L'ty	0.000	0.000	1.202	0.230	
Memory L.:Search C.:L'ty	-0.002	0.001	-2.323	0.021	*
GA R.:Search C.:L'ty	-0.001	0.000	-2.100	0.036	*
Memory L.:Search P.I.:L'ty	0.001	0.000	1.498	0.135	
Memory L.:GA R.:p(E NSearch)	0.000	0.000	1.031	0.303	
Memory L.:Search C.:p(E NSearch)	-0.003	0.001	-3.319	0.001	***
GA R.:Search C.:p(E NSearch)	-0.001	0.000	-3.970	0.000	***
Memory L.:Search P.I.:p(E NSearch)	0.001	0.001	1.394	0.164	
GA R.:Search P.I.:p(E NSearch)	0.000	0.000	1.531	0.127	
Memory L.:GA R.:Search C.:L'ty	0.000	0.000	1.598	0.111	
Memory L.:GA R.:Search C.:p(E NSearch)	0.000	0.000	2.683	0.008	**
Memory L.:GA R.:Search P.I.:p(E NSearch)	-0.000	0.000	-1.526	0.128	

Table B.8: Final GLM model relating the *standard deviation of degree* to the EGS input parameters

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	0.855	0.362	2.361	0.019	*
Memory L.	0.064	0.036	1.753	0.080	
GA R.	0.028	0.016	1.777	0.076	
Search C.	-5.427	0.903	-6.012	0.000	***
Search P.I.	5.231	1.068	4.897	0.000	***
L'ty	0.001	0.004	0.276	0.783	
p(E NSearch)	0.010	0.010	1.075	0.283	
Memory L.:GA R.	-0.000	0.002	-0.232	0.816	
GA R.:Search C.	0.158	0.046	3.434	0.001	***
Memory L.:Search P.I.	0.237	0.125	1.894	0.059	
GA R.:Search P.I.	-0.004	0.041	-0.099	0.921	
Search C.:Search P.I.	-4.590	1.619	-2.835	0.005	**
GA R.:L'ty	-0.000	0.000	-0.057	0.954	
Search C.:L'ty	0.016	0.010	1.626	0.105	
Search P.I.:L'ty	-0.032	0.010	-3.314	0.001	**
Memory L.:p(E NSearch)	-0.000	0.001	-0.182	0.856	
GA R.:p(E NSearch)	0.000	0.000	0.379	0.705	
Search C.:p(E NSearch)	0.025	0.014	1.781	0.076	
Search P.I.:p(E NSearch)	0.013	0.032	0.404	0.687	
L'ty:p(E NSearch)	0.000	0.000	0.079	0.937	
Memory L.:GA R.:Search P.I.	-0.017	0.007	-2.584	0.010	*
GA R.:Search C.:Search P.I.	0.152	0.069	2.201	0.028	*
GA R.:Search C.:L'ty	-0.001	0.001	-1.624	0.105	
Memory L.:GA R.:p(E NSearch)	-0.000	0.000	-0.268	0.789	
GA R.:Search C.:p(E NSearch)	-0.002	0.001	-2.791	0.006	**
Memory L.:Search P.I.:p(E NSearch)	-0.004	0.004	-1.143	0.254	
GA R.:Search P.I.:p(E NSearch)	-0.002	0.001	-1.608	0.109	
Search C.:Search P.I.:p(E NSearch)	-0.093	0.036	-2.571	0.010	*
Search P.I.:L'ty:p(E NSearch)	0.001	0.000	1.753	0.080	
Memory L.:GA R.:Search P.I.:p(E NSearch)	0.000	0.000	1.707	0.089	

Table B.9: Final GLM model relating the *mean of searches* to the EGS input parameters

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	1.141	0.159	7.201	0.000	***
Memory L.	0.046	0.015	3.088	0.002	**
GA R.	0.013	0.008	1.565	0.118	
Search C.	-4.229	0.565	-7.488	0.000	***
Search P.I.	1.808	0.263	6.880	0.000	***
L'ty	-0.001	0.002	-0.559	0.577	
p(E NSearch)	0.008	0.003	2.460	0.014	*
Memory L.:GA R.	-0.003	0.001	-4.622	0.000	***
Memory L.:Search C.	0.166	0.048	3.439	0.001	***
GA R.:Search C.	0.143	0.027	5.224	0.000	***
GA R.:Search P.I.	-0.060	0.012	-5.054	0.000	***
Search C.:Search P.I.	1.022	0.695	1.470	0.142	
GA R.:L'ty	0.000	0.000	0.098	0.922	
Search C.:L'ty	0.007	0.006	1.221	0.223	
Memory L.:p(E NSearch)	-0.000	0.000	-1.100	0.272	
GA R.:p(E NSearch)	-0.000	0.000	-1.682	0.093	
Search C.:p(E NSearch)	0.030	0.010	3.061	0.002	**
Search P.I.:p(E NSearch)	-0.004	0.008	-0.489	0.625	
Memory L.:GA R.:Search C.	-0.003	0.002	-1.672	0.095	
GA R.:Search C.:L'ty	-0.000	0.000	-1.567	0.118	
Memory L.:GA R.:p(E NSearch)	0.000	0.000	3.251	0.001	**
Memory L.:Search C.:p(E NSearch)	-0.002	0.001	-2.145	0.033	*
GA R.:Search C.:p(E NSearch)	-0.001	0.000	-3.506	0.001	***
GA R.:Search P.I.:p(E NSearch)	0.001	0.000	1.819	0.070	
Search C.:Search P.I.:p(E NSearch)	-0.049	0.021	-2.265	0.024	*

Table B.10: Final GLM model relating the *standard deviation of searches* to the EGS input parameters

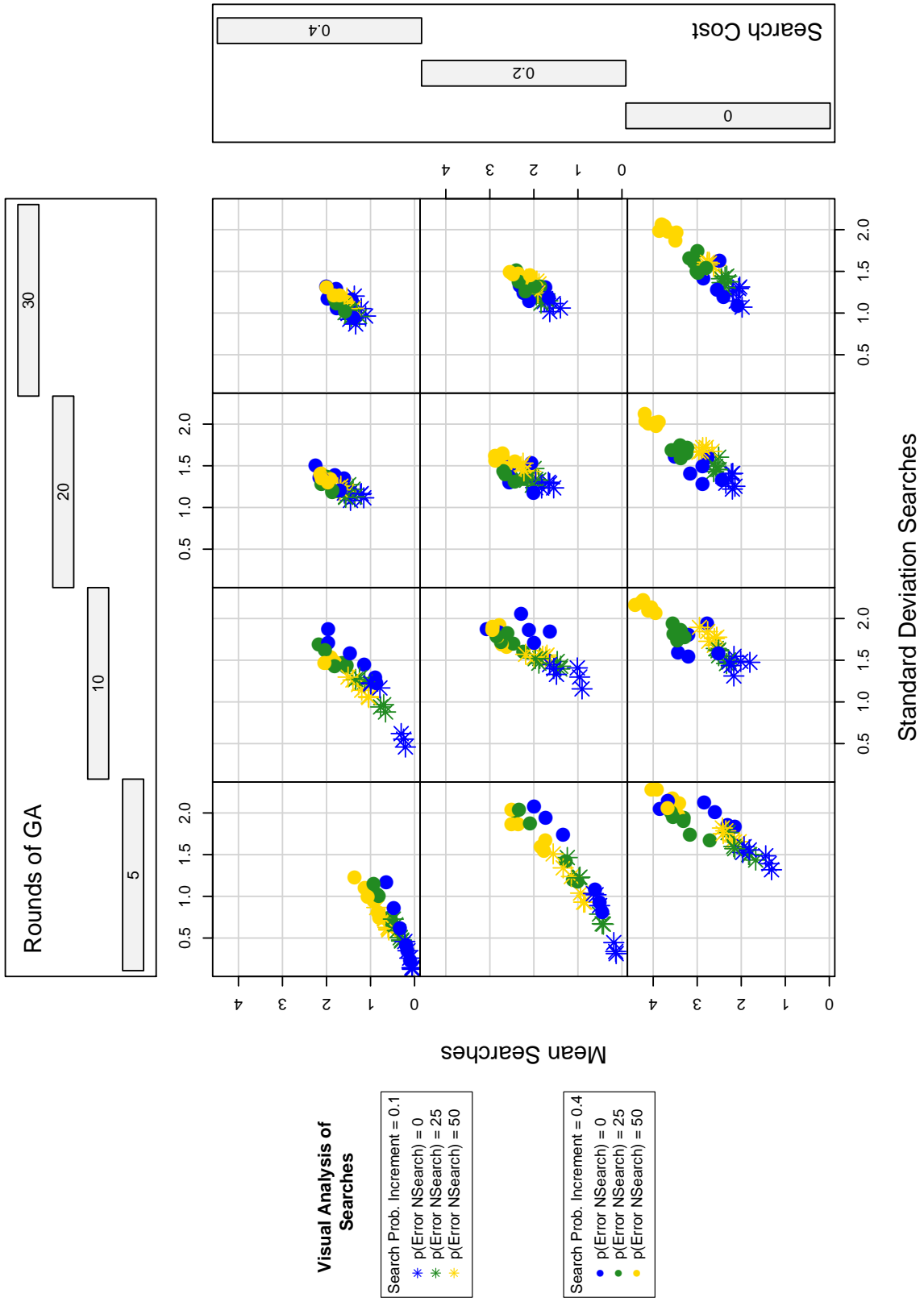


Figure B.6: Conditional scatter plot of average number of partner search attempts versus its standard deviation, ordered by rounds of the Genetic Algorithm ( $\psi$ ) and search cost ( $\kappa$ ). The colour coding represents the probability of deviating from a chosen number of search attempts ( $\varepsilon$ ) and the point characters visualise the speed of adaptation ( $\iota$ ).

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