Networks, organizations and knowledge

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Networks, Organizations and Knowledge

Müge Özman

Networks, Organizations and Knowledge

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Preface

For me, the whole process of a PhD is very similar to finding one's way out of a labyrinth. Every step taken leads to a new set of paths which lie ahead, and choices have to be made. In my journey through this labyrinth, at every moment, my supervisor Robin Cowan was there to guide me. He showed me alternative paths when I thought none was left, and he helped me select one when there were too many. I am grateful to him for all the assistance and guidance he provided, and for his support in my work.

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1

Introduction

This thesis is concerned with networks and how they form. Knowledge networks are the complex map of ties among individuals through which knowledge is shared, distributed and created. Knowledge networks are simply everywhere, they carry all kinds of knowledge, sometimes gossip among inhabitants in a district, sometimes a new algorithm among programmers in an industrial region, and sometimes both.

As I take it in this thesis, networks carry knowledge and they are not formed in a random way. Contrarily, individuals make intentional choices about who to connect with, usually considering their own short term and long term self interest. If all individuals in a society make this choice, what would the resulting networks look like? The difficulty in answering this question is that there is no unique answer, because the answer depends on the context of investigation, the characteristics of the population and the subject of inquiry. Different kinds of networks form in different environments, depending on different criteria that are not always observable directly to the analyst. Consider friendship networks, biological networks or the internet. They all have different rules of formation, that are sometimes governed by culture, sometimes by nature, sometimes simply technical constraints and sometimes all of these. This is precisely what makes networks complex and their analysis cumbersome. Nevertheless, the field of network analysis has been developing rapidly especially in the last 20 years, and now we are endowed with a richer set of tools to analyse networks and their evolution.

Perhaps two questions that should be answered first are, what do we mean by analysing networks, and why is network analysis relevant, apart from an intellectual curiosity directed towards a newly emerging field?

I will attempt to answer this question in the context of networks as they are taken in this thesis, and in relation to the aim of this thesis. In this thesis, I take networks both as a conceptual category and as means to represent the way organization of economic activity takes place, and also as a specific type of governance structure.

The theories of the firm have been concerned with answering two central questions that have occupied the theoretical agenda at least since Ronald Coase. Why are there firms, and what determines their boundaries? Apart from the many approaches that have addressed these questions in the past, in the last decade the rise of a new organizational form, the so-called network-based organization, has been the source of inspiration to introduce new approaches to address these questions. Network-based organizations are different from hierarchical firms; what we observe in Silicon Valley today is different from the Chandlerian corporation in many respects. In this new type of organizational form, firms no longer have concrete boundaries and neither are they self-sufficient. Instead, firms share knowledge and other resources with other firms and are usually nodes in a huge network. Networks of firms form their own cultures and rules. Within the network there are concerns for reputation which is sometimes a more critical concern than short term profitability. There is the issue of trust, where a handshake is more important than signed contracts.

According to the knowledge based theories of the firm, firms exist to integrate the knowledge of a diverse range of specialists. These specialists are *individuals* at the micro-level. But *firms* are also specialists at the macro-level, and they integrate knowledge with other firms, through many means ranging from R&D alliances, joint ventures, or simply by sharing knowledge in industrial districts through informal means. Viewed in this way, the industry is a hierarchical organization, with individuals on the bottom level of hierarchy, firms in the middle level and network of firms on higher levels. Each of these levels are essentially networks.

Network analysis is a suitable means to highlight how the boundaries between these hierarchical levels are set. By network analysis, I mean representing the industry as a network where agents are nodes and knowledge flow the links among them, and analysing the structural characteristics of these networks. In this setting, firms are clusters within which the bonds between the individuals are stronger than the bonds outside the firm. The Chandlerian corporation in such a setting would be characterised by more or less as a group

of agents tightly inter-connected but with few connections outside the group. The network-based organization would be characterised by intensive links with outsiders.

One of the features of network based industries is that they maintain variety in the industry, found in a network of specialized firms, as observed in Silicon Valley. In other cases, however, variety is found in the diversification activities of large vertically integrated hierarchies. One question that deserves attention at this point is, if the essential role of the organization is to integrate the knowledge of diverse range of specialists, then, what is the role of the knowledge base in determining the point at which internal management of variety for a single firm is less efficient than sourcing variety from an external network? To put it in a different way, how does the knowledge base of an industry influence extent of networking activities among firms in an industry?

My aim in this thesis is to explain the formation and evolution of organizations in different industrial settings. I adopt a network perspective because it offers a unique opportunity to highlight how the levels in the hierarchy of an industry are set in a dynamic manner. I take the organization to be self-organizing, mainly formed by the decisions of individuals who seek their own interests. Networks form by the decisions of many such individuals, and the structure of these networks give an insight into the organizational structure of an industry, which emerges from the bottom-up without an authority to impose a certain structure. The main motivation underlying the individual decisions is to combine knowledge with other individuals and to produce. Central to all economic activity is knowledge. But knowledge has an economic value when it is used in production, or when it is subject to exchange, which happens through networks. Individuals exchange their knowledge with others through the links they construct with them. New knowledge is mostly created by what individuals learn from others and through combining their knowledge with others. Organizations can be perceived as the manifestation of the need to combine competencies of heterogeneous individuals for increased efficiency. In this sense, all organizations are basically networks, and they shape the direction and amount of new knowledge that is generated. Therefore, the knowledge base of an industry should have an important role in explaining how organizations form and evolve. My central question is, "how do the knowledge base of industries influence the way organizations form and evolve?" In particular, what are the characteristics of the knowledge base that support the emergence of network based organizations?

In addressing this question, I perform an agent-based simulation study and take the firm and industry to be self-organizing systems. Self-organization refers to the persistence and emergence of patterns in a system, despite the

absence of authoritative planning and control. In the agent-based simulation model, there is a population of heterogeneous agents, who are knowledgeable in a diverse range of areas and a set of products for which the main input is knowledge. Agents interact with other agents to integrate their knowledge, produce together, and learn from each other. In this way networks form. The resulting network structure and knowledge growth are obviously influenced by the complexity of the products, which we define in two dimensions, characterising the knowledge base of the industry. These dimensions are breadth and depth. Breadth refers to the range of different fields that production requires. Depth refers to the dominance of certain types of knowledge, in other words the analytical sophistication of a certain subject. I analyse how the knowledge base of the products are mapped onto the organizational structures that emerge.

The outline of the chapters are as following. In the second chapter, I present a survey on networks in economic literature. This chapter covers both theoretical and empirical work on networks in many different contexts, mainly in organizational studies and game theoretic models of coalition. In the third chapter, I outline the research problem, and present the background literature in addressing this problem. Here, I overview the literature on firm boundaries and various approaches to the theories of the firm. Also in this chapter, I explain my methodological approach. The fourth chapter is devoted to an analytical model of collaboration, and presents the motives underlying knowledge integration in a simple economy with two producers. The fifth and sixth chapters include simulation models in an economy with a large population, many knowledge types and products. In the former I present the model with some restrictive assumptions and in the latter I include a detailed analysis of the effect of knowledge base on organizational structures. In this chapter, I highlight the characteristics of knowledge bases that results in network based systems on one hand, and diversified hierarchical structures on the other. The seventh chapter is composed of some empirical findings utilising the EPO/CESPRI patent database. I also perform a regression analysis to measure how breadth and depth of patents are reflected on the density of inventor networks. Finally in chapter eight I provide some concluding remarks and directions for future research.

2

A Survey of Economic Networks

2.1 Introduction

During the recent decades, there has been a growing body of theoretical and empirical research on networks in the economics literature. Because of the inherent characteristics of networks and largely because many micro and macro systems from a social, economic or technological perspective can be represented and analyzed as networks, research in this area has become largely dispersed, where different disciplines approach networks from different perspectives, while sharing many commonalities in the core as well as influencing each others' approaches. In this sense, the evolution of research on networks in economics is characterised by contributions from a diverse range of disciplines, including physics, mathematics, sociology, organization theory and management and it has now become clear that interdisciplinary work on networks has lots to offer to understand the processes behind networks and their influence. In such a setting, it is potentially quite valuable to have a coherent understanding of different approaches involved, mainly as they are used in the economics literature. In this chapter, an attempt is made to review the current literature on networks in the economics, incorporating the contributions from a diverse range of fields.

The difficulties inherent in studying networks shows itself clearly when one looks at the largely dispersed work in this area where each discipline approaches networks from a different perspective. On one hand, social network analysts focus is on the influence of social *relations* (rather than attributes of

actors) on economic and social outcomes, especially in terms of performance and behaviour. The emphasis of organization and strategy theorists is mostly on the intra and inter organizational networks as they relate to firm performance and behaviour, while physicists focus on the self-organizing processes underlying the evolution of complex networks.

The central emphasis of economists is on innovation, how networks influence innovative activity in general and the processes behind emergence of networks. In this context, work is diversified. One strand of literature focuses on inter firm networks and various forms of arrangements between firms, including strategic alliances, R&D collaborations, and many other types of interaction among firms in an industry. This literature coincides with organizational theory. Until recently, the economists' approach to networks had given *less* emphasis on the social contexts in which relations are embedded and *more* on the economic processes that are implied by and lie beneath networks. During the recent years, this restricted view on networks is being extended to incorporate the effects of social relations in network analysis. In addition during the last 20 years, networks have attracted considerable attention as a new governance mechanism. Network based industrial systems consist of firms that are intensively involved in various kinds of ongoing relations with each other and are perceived as governance mechanisms in between markets and hierarchies. These systems are usually accompanied by an increased rate of technological change, product complexity and variety, and they seem to emerge in those industries characterized by shortened product life cycles and intensified competition.

Considering the largely diversified and rich research in the area of networks, it seems inevitable, both for coherence and limitations of space, to draw a framework in which networks are covered in the current review. This survey covers the literature on *economic networks*. However, considering the convergence of approaches in many disciplines ranging from sociology to physics, the way we define an "economic network" also needs clarification. When we say economic networks, we take the network *itself* as an economic phenomena, and it connotes the idea of using the network to model economic phenomena. Vague as this may sound, it refers to drawing a distinction between networks of goods, and networks of economic actors. In the former case, which points to the literature on network externalities, the economic implications of networks, not necessarily themselves economic, is covered. Whereas in the latter case, the network itself is taken to be an economic phenomenon.

In this context, the survey is composed of two parts. The first part covers the literature on *agents in networks*. Most of the literature reviewed in this section is related to the networks of firms in an industry. Here we review topics like, how the role of agents as members of the network shapes their

behaviour and performance, how the networks are shaped by various factors like the industry, and/or the strategic and economic considerations of the diverse actors. We analyse agents in networks under two headings; industry as a network and the firm as a network. In the former we cover the role of networks in transaction cost theories, networks as they are taken in resource based views, strategic management literature, and relatedly networks as they relate to various agent-specific issues like learning and capabilities, as well as the embeddedness perspective. The first part concludes with the section on technology and networks, where we cover the literature on industry or knowledge specific characteristics and how they relate to networks of firms. Secondly we focus on *firms as networks*, and explore the literature on the internal networks in a firm and how it is related to its efficiency from various perspectives.

The second part of the paper covers *networks of agents*. This is different from the first part in that here, we focus on various modeling approaches so that the network itself is the unit of analysis. Particularly, this part is composed of two sections. In the first section, we review the literature on small world networks and scale free networks. In the second part, we focus on game theoretic network modeling papers.

2.2 Agents in Networks

In this part, our focus is on the network as a particular governance mode. The importance of perceiving an organization as a network is that it enables to explore how the pattern of *relationships* among the actors within the organization influences the actors in the network, in a direct and/or an indirect way. In particular, the majority of the literature we cover here is directly or indirectly concerned with the implications of networking on agents' performance and/or behaviour. In the first section, we take the industry as a network, and secondly we take the firm as a network.

2.2.1 *The Industry as a network*

Network-based industries are characterised by intensive interactions taking place across firm boundaries. The domain of these interactions can take countless forms ranging from legal ownership agreements to informal know how trading. A major process that accompanies the inter-firm relations is the significant knowledge flow that takes place between the actors, which is usually considered to be an important engine for innovation. These knowledge spillovers, are not only caused by formalized arrangements between firms, but may also be the result of informal communications, a concept which Allen (1983) termed

to be collective invention. As firms rely more on external collaboration, the boundaries of the firms get blurred, and the firm becomes a dense collection of communication links within a larger network through which there is continuous knowledge flow. Today in most of the industries it is possible to see networking activities among firms, and thus the extent of networking is only a matter of degree. However, the scholars working on this field have termed industries in which these networking relations are intensive in many different ways, each focusing on particular aspects but sharing many commonalities in the core.

Some examples are, business groups, Granovetter (1998) which refer to the group of firms that are bound together in some formal or informal way, which is neither complete (like the case where firms consolidated into a legal single entity) nor weak (like in short term strategic alliances); the keiretsu in Japan, chaebol in Korea are the most prominent examples. Powell et. al. (1996) use the term "networks of learning", where their emphasis is on the way networks facilitate organizational learning and act as the locus of innovation. Ring and Van De Ven (1994) and Oliver (1990) use the term "cooperative inter-organizational relationships". Many other terms have also been used, including "networks of innovators" (DeBresson and Amesse, 1991), "network organization" (Miles and Snow, 1986), "strategic network" (Jarillo, 1988), "interfirm networks" (Grandori and Soda, 1995). A somewhat more general term that incorporates not only firms but also other actors like public laboratories, research centres and regulatory bodies has been used by Callon (1998) in his term of "techno-economic networks".

Despite the many different terms used, majority of these studies investigate what Jones et. al. term to be "network governance", and who provide a unifying definition: "a select, persistent and structured set of autonomous firms engaged in creating products or services based on implicit and open-ended contracts to adapt to environmental contingencies and to coordinate and safeguard exchanges" (1997: p. 2).

The last decade has witnessed a substantial amount of theoretical and empirical research on network-based industrial systems. Underlying this rise in interest in networks are factors like the immense improvements in communication and information technologies, regional success stories like the case of Silicon Valley, and the basic understanding that social and economic interactions among actors are influential in shaping macro level outcomes in the economic sphere. The Japanese business groups (Imai, 1989; Lincoln and Gerlach, 1996; Gerlach, 1992), Silicon Valley (Saxenian, 1991, 1994), biotechnology (Powell and Brantley, 1992; Powell et. al., 1996; Arora and Gambardella, 1994; Orsenigo et. al., 1998, 2001; Walker et. Al, 1997; Riccaboni and Pammolli, 2002;

Liebeskind et. al 1996; Baum et. al, 2000; Nesta and Mangematin, 2002), fashion (Lazerson and Lorenzoni, 1999; Uzzi, 1997), chemicals (Ahuja 2000), computer and semiconductor (Saxenian, 1991, 1994; Langlois and Robertson, 1992; Stuart, 1998; Rowley et. al, 2000), automobile industry (Dyer, 1996; Dyer and Nobeoka, 2000; Nohria and Garcia Pont, 1991; Garcia Pont and Nohria, 2002), metal working (Hite and Hesterly, 2001), ICT (Riccabonni and Pam-molli, 2002), defence electronics (Harris et. al, 2000), aircraft (Frenken, 2000; Bonaccorsi and Giuri, 2001), GSM (Blankenburg et. al, 1999; Bekkers et. al, 2002), flight simulation (Rosenkopf and Tushman, 1998); steel (Rowley et. al, 2000; Madvahan et. al, 2000) have been analysed in these studies. Some other empirical work covering a range of industries are, Hagedoorn (1993, 1995, 2002); Gulati (1995, 1999); Larson (1992).

Oliver (1990) summarizes 6 motives for the establishment of interorganizational relations; a) necessity in the sense of meeting legal or regulatory requirements, b) asymmetry, referring to the potential of an organization to exercise power or control over another organization, c) reciprocity, referring to the collaboration, cooperation rather than the exercise of power (horizontal linkages rather than vertical) d) efficiency, in terms of increasing the internal input-output ratio of the organization, e) stability, as an adaptive response to environmental uncertainties, f) legitimacy, to improve reputation, image, prestige. It is important to note that the intensity of each of these in the mix of motives vary according to the type of collaborative activity and relatedly the features of the industry. For example, in uncertain and competitive environments, reciprocity and stability are important. Whereas in joint ventures, there is for sure the effect of the motive of asymmetry, where larger firms exercise organizational control over smaller firms (Kogut, 1988).

The case of Japanese networks reveals that uncertainty is greatly reduced via the information exchange within a business group (Imai, 1989). In the same way, Saxenian (1991) notes that inter-firm networks in Silicon Valley are useful in spreading the risks involved in the costly process of introducing new products to the market. The networking among firms also enhances firm's ability to respond to fastly changing market conditions (Saxenian 1994). Here, technological, financial, market and behavioural uncertainties can be distinguished, the extent being a function of the characteristics of the industry. Technological uncertainty is related with the inherent uncertainties regarding the outcome of R&D, being more severe in technologically intensive industries. Relatedly financial uncertainties are related to the costs of financing R&D, especially in sectors that require high investment costs in R&D. Demand uncertainty is related to fastly changing conditions of the market, where it is difficult to predict the market demand. In all cases, networks of innovators facilitate cop-

ing with uncertainties, by spreading costs, or by accessing new markets, or by combining firm specific scientific capabilities (see Hagedoorn, 1993).

The research on the network based organization in economics has accelerated rapidly in recent years, as it is also evident from the numerous approaches adopted by scholars, ranging from transaction cost economics, the literature on supplier usage linkages, interactive learning and sociology, organization theory and strategy (De Bresson and Amesse, 1991).¹ Nevertheless, it seems that the place of networks in the theories of firm is still vague. Today the modern theory of the firm is largely dominated by the transaction cost approach (as pioneered by Oliver Williamson). There exist various views on how networks can be placed within a transaction cost perspective, or, whether they can be placed at all.

TCE and networks

Different forms of coordinating economic exchange is based on two essential features of industrial systems: the boundary between markets and organizations; and the intra-firm organization. Neoclassical economics largely ignores both of these features, the firm being reduced to a representative profit-maximizing unit, where the boundaries of the firms are explained via economies of scale and scope. Modern theories of the firm are dominated by the transaction cost perspective, which traditionally focuses on the trade off between markets versus hierarchical structures. Firm formation in TCE view is explained by the "cost of using the price mechanism" (Coase, 1937), and firms exist to minimize the costs associated with transactions. From a TCE perspective, the network-based firm appears to be a hybrid type of organization between markets and hierarchies (Thorelli, 1986; Williamson, 1991). On the other hand, some arguments have been developed favoring the view of networks as a distinct form that cannot be explained with a market vs hierarchy view of exchange. On this view, networks have distinct characteristics regarding for example, the feature of the items exchanged, or the behavioural attributes of parties involved in transactions which makes it theoretically infeasible to handle them with the market vs. hierarchy approaches (Larson 1992; Powell 1990). Most scholars have pointed out that in the face of rapid economic and technological change, the transaction cost approach is a static cost trade-off analysis and so cannot be used to explain the dynamic gains from networks (De Bresson and Amesse, 1991; Langlois, 1989; Noteboom, 1992; Powell et al 1996).

¹See Borgatti and Foster (2003) for a review and analysis of the network paradigm in organizations.

Underlying TCE are two basic assumptions regarding the behaviour of economic agents. Firstly, agents are boundedly rational, and accordingly all complex contracts become unavoidably incomplete (Williamson, 1998a). The second behavioural assumption is opportunism, that is "self-interest seeking with guile" (Williamson, 1975). The opportunistic behaviour is important since "attenuating the ex post hazards of opportunism by ex ante choice of governance" is mainly what the transaction cost approach deals with (Williamson, 1998a: 31). But can the central behavioural assumption of opportunism be reconciled with the development of mutual trust underlying long term relations in network organizations? Several scholars have taken this issue into their research agenda. For example according to Nooteboom et. al. (1997) there is a polarization in the literature, whereby some scholars tend to focus on opportunism whereas others focus on trust, with few exceptions taking both into account. For a coherent approach to the network based organization, however, a reconciliation of both poles as to be made.

These can be related to the lack of a dynamic perspective in transaction cost approaches, as well as undermining the social contexts in which most economic relations are embedded in (Jones et. al, 1997). In other words, as the transaction relation proceeds, there can be a change in the perceived risk of opportunism, and ex-ante expectation of opportunism may be replaced by mutual trust (or mistrust) as individuals accumulate experience in a social context (Nooteboom et. al 1997). The central role of opportunism in TCE shifts the attention away from the trust as a product of embeddedness of economic relations in social contexts (Uzzi, 1997, Noorderhaven, 1996; Johanson and Mattson, 1987; Larson 1992; Jones et. al, 1997). However, one of the driving forces in network forms being the mutual trust among parties, it is likely to reduce transaction costs (Noorderhaven, 1996; Gulati et al, 2000; Uzzi 1997; Jarillo 1988). From a transaction cost perspective, the selection of partners can be related to a trade-off between the costs associated with the risk involved in finding a reliable partner, so that the risk of being exposed to opportunistic behaviour is reduced, versus the gains from access to new opportunities. In the same way, informal know how trading systems have less transaction costs (Von Hippel, 1989). This is because decisions to trade or not to trade proprietary know-how are made by individual and knowledgeable engineers, "no elaborate evaluation of relative rents or seeking of approvals from firm bureaucracies are involved" (Von Hippel, 1989: 171).

Network forms also mitigate transaction costs, making opportunism more costly due to reputation effects in a tightly bounded social environment (Gulati et. al 2000; Walker et. al, 1997; Uzzi, 1997). Jones et.al. (1997) attempt to make a reconciliation of TCE with network approach, and based on the idea that the

traditional TCE ignores social processes, they incorporate social mechanisms into a transaction cost framework.

The exclusive focus of TCE on minimisation of costs also disregards the strategy and organizational learning aspects of networking, in addition to social contexts (Eisenhardt and Schoonhoven, 1996; Powell et. al 1996). Kogut (1988) underlines the difference between a TCE approach and strategy approach to joint ventures. In particular, strategy is related with the positioning of the firm vis a vis rivals, whereas transaction cost approach focuses on the costs of transactions solely. Most of the times the motives underlying the formation of alliances is more complex than just cost considerations, and factors like transfer of know how among parties, accessing other firms' capabilities, and/or improving the firms' own capabilities via organizational learning can be quite important. These issues have been a popular research agenda, as we review below.

Organizational learning, capabilities and networks

As mentioned by Kogut (1988) for the case of joint ventures, the transaction cost perspective, strategic behaviour and organizational learning are three frameworks to be used in explaining joint ventures, and they are distinct as well as overlapping. Not only are there numerous reasons that justify collaborative activity, but also the variety of forms of collaboration, as well as the variation in the importance of motives with respect to the features of the industry (like the level of technological intensity, stage of industry life cycle, etc.) make the research field extremely fragmented. Hagedoorn (1993) provides an exploration of different motives for alliances in different sectors of the economy. He concludes that the most significant three motives are technological complementarities (more important in sectors where interrelatedness and complexity is high), market access, and reduction of the innovation period (somewhat more valid for relatively mature industries).

The resource-based view (Wernerfelt, 1984) explains networking with respect to the complementarities in firm resources. According to the literature, the most common motive for collaborative relations is the interdependence in resources. This means that firms form alliances with other firms because they are not self sufficient and they collaborate to reduce uncertainty as well as the interdependence in their resources (Pfeffer and Salancik, 1978), especially in technologically intensive industries (Hagedoorn, 1993; Orsenigo et. al 1998, 2001). The complexity and multidisciplinary character of the knowledge base are considered to be the main factors that draw firms into external collaboration in biotechnology (Arora and Gambardella, 1994; Hagedoorn 1993). In this area, the knowledge base is widely dispersed. Also the collaborations are

mostly characterized by the alliances among the large and established pharmaceutical firms and NBFs (Arora and Gambardella 1990, Pisano, 1990; Walker et. al, 1997; Shan et. al, 1994). In most cases, the complementarities among large and small firms arise from the market access opportunities offered by the former and scientific contributions of the latter.

Various authors have taken resource based perspective in different ways. For example Nohria and Garcia Pont (1991) distinguish between strategic complementary blocks, formed of firms having different strategic capabilities in the automobile industry (as further explained below). Gulati (1995, 1999) finds supportive evidence of complementarities in resources but his emphasis is more on the effects of social embeddedness as will be discussed further below. Gulati (1999) develops the concept of a "network resource" which is the value of the firm's connections. In a similar vein, Gulati et. al. (2000) emphasize that the structural patterns of relations of a firm is unique to the firm itself, and thus should be perceived as resources exclusive to the firm. Eisenhardt and Schoonhoven (1996) analyse the semiconductor industry and adopt a resource based and social perspective to understand the motives of alliances and their results show that firms in vulnerable strategic positions (emergent or growing firms, facing many competitors) tend to form more alliances, as well as firms with a socially strong management team. Hite and Hesterly (2001) analyse the different resource needs of firms in different stages of their life cycle, and analyse the network structures conducive to firms needs (we further explore the issue of network structure below). In a recent work, Miotti and Sachwald (2003) adopt a resource based perspective to investigate the effect of complementarities in resources among collaborations formed by a wider range of actors, including academic institutions, firms, rival firms, clients, etc. An overall review of existing approaches in resource based views can be found in Das and Teng (2000).

However, as Powell et. al (1996) argue, firms network with each other not only because they lack resources and need to access others, but because of exploration and exploitation of knowledge bases. In particular, their seminal work in biotechnology places the concept of organizational learning at a central place in the networks literature. Distinguishing between exploration and exploitation in organizational learning, the former refers to "experimentation with new alternatives", and the latter refers to the exercise of "refinement and extension of existing competencies, technologies and paradigms" (March, 1991: 85). Viewed in this way, "organizational learning is both a function of access to new knowledge, and the capabilities for utilizing and building on such knowledge" (Powell et. al 1996: 118). Network forms of organization enable firms to effectively explore new knowledge. Still, external collaboration is comple-

mentary to internal capabilities in the sense that they facilitate exploiting and building upon existing knowledge (Mowery and Rosenberg, 1989). Collaboration between firms not only enhances learning about new developments, but also strengthens internal competencies and thus the "locus of innovation" is found in the "networks of learning" (Powell et. al., 1996) .

Organizational learning is usually rooted in the routines developed to effectively store, transfer, and develop knowledge in firms (Nelson and Winter, 1982; Cohen and Levinthal, 1990; Malerba, 1992). There is a growing literature on organizational learning in networks. Among these, Dyer and Nobeoka (2000) perform a study of the Toyota network, and how it enhances organizational learning of its members. They underline three knowledge sharing dilemmas (resistance to share proprietary knowledge, free rider problem and maintaining efficiency at knowledge sharing provided in the network) and explore the specific processes set by the Toyota network to overcome these. Bogenrieder (2002) explores the process of sociocognitive conflict (which refers to diversity among agents and the maintenance of a social environment to resolve this) and identifies different types of social networks that foster learning in organizations under different problem solving cases. Knight (2002) distinguishes between learning networks and "network learning", and stresses the role of the network itself as a learner.

The process of innovation is a multifaceted activity requiring a series of stages starting from basic research and inventions to marketing and distribution, where many actors are involved. Taking into account many complexities involved in innovation, coordination among the actors is vital and seldom can a single firm be self sufficient in technologically sophisticated industries. Teece (1992) underlines the necessity of coordination in innovation process, and distinguishes between complementarity in assets, vertical coordination, horizontal coordination and the connections among the technologies themselves. Inter-firm relations are established not only for accessing complementary capabilities and resources, but also, the interdependencies among technologies themselves should be considered in evaluating the motives for network relations (Teece, 1992). Viewing the stages in the process, he stresses that networks among firms in various forms facilitates the innovation process and enables competitive advantage to the firms involved.

There is also a strand of empirical literature which investigates capabilities of firms in relation to networks. Among these, Mowery et. al. (1998) investigate the transfer of capabilities, where they look at firm capabilities and the level of technological similarities and complementarities before and after alliance formation. Their findings indicate that the level of technological overlap increases after alliance formation regardless of the initial motives un-

derlying alliance (i.e. whether for market access or technological). Arora and Gambardella (1994) distinguish between scientific capabilities and technological capabilities, more specifically applicable to biotechnology sector since it is highly science driven. The former is related with the ability of the firm to *evaluate* external knowledge. On the other hand the latter refers to the ability of the firm to *utilize* external knowledge. They investigate the relation between these capabilities and the value of external collaboration. Their results indicate that scientific capabilities reduce the number of collaborative agreements (since large firms become more selective) whereas technological capabilities increase the number of collaborative agreements. McEvily and Zaheer (1999) explain the differences in competitive capabilities in metal working job shops in US, with reference to their position in the network (see below). Moreover, arguments have also been developed to view network relations of a firm to be one of its capabilities (Kogut, 2000). He uses the term networks of knowledge to connote capabilities that augment the value of the firm, achieved mainly through coordination.

Firm behaviour, performance and network structure

Adopting a network perspective refers to viewing governance structures as collections of interacting agents. In Nohria's (1992) view, all organizations are networks and need to be analysed as such. The exchange relations between agents are governed by, and shaped through the network structure, and the network structure is in return shaped by these interactions (Jones. et. al, 1997; Nohria, 1992; Doreian and Stokman, 1997, Kogut, 2000). The advantages associated with adopting a network perspective and analysing the overall network structure and/or positioning of the nodes in the networks are several. Underlying these advantages is that through analysing the structure of networks, an investigation of macro level performance of the system as a function of micro level interactions can be made. Few examples are, measuring extent of knowledge diffusion as a function of the network architecture (Cowan and Jonard, 2001, 2003; Cowan et. al. 2002), or how the positioning of the firms within the network influence behaviour and performance. For example Gulati et.al. (2000), summarise the ways in which networks influence firm performance. They postulate that differential profitability of firms may be explained by structure of firms within the network. They argue how the effect of industry structure on firm performance can be explained by network concepts, mainly network structure, network membership and tie modality. Relatedly, it is argued that the network position determines how the value is distributed among the firms in the network (Kogut, 2000).

Network approach enables a dynamic analysis. This is mainly because the network perspective enables modeling the explicit mechanisms through which knowledge is endogenously created and diffused within the industrial system; particularly, by incorporating how agents learn and adapt to the environment by accumulating experience, and the aggregate level patterns that emerge by the interaction of agents. Adopting a network perspective enables modeling the dynamic processes involved in explaining how they are “socially constructed, reproduced and altered”. It is generally accepted that the state of the network in one period influences the state of the system in subsequent periods, as a result of a dynamic process of experience accumulation and learning (Garcia-Pont and Nohria, 2002; Gulati and Gargiulo, 1999; Powell et. al 1996). Network evolution is mainly the result of a systemic interaction between technological, social and institutional factors, and the emergence of networks is through self-organization, rather than being governed through exogenous events (Kogut, 2000). Imai (1989), in analysing the evolution of Japan’s industrial networks, states that “the network view is a process view in which the basic unit is not the firm or other economic agents acting in isolation but various economic agents acting in relation to each other” (Imai, 1989: 123).

A strand of literature relates social embeddedness, network structure and firm behaviour/performance, following the seminal work of Granovetter (1973, 1985). The embeddedness perspective approaches the performance or behaviour of firms with reference to the influence of social networks surrounding them. Work in this area is wide and diversified. Uzzi (1997) in his study of the New York fashion industry relates the behaviour and performance of firms to their social contexts, and highlights the paradox of embeddedness: “the same processes by which embeddedness creates a requisite fit with the current environment can paradoxically reduce an organization ability to adapt” (p. 57) mainly by decreasing diversity, reduction of non redundant ties and sometimes causing overembeddedness. He mentions the conditions under which embeddedness proves to be increasing efficiency as well as conditions under which it can turn into a rigidity, and puts forward that ties composed of a mix of arms length and embedded ties are more conducive to increased performance in the apparel industry.

The importance of social networks and embeddedness have been studied by Gulati in various years empirically. Various forms of interdependencies, or uncertainties are only few of the factors that may lead to inter-organizational collaboration and in most cases, interdependencies are necessary but not a sufficient condition (Gulati, 1998; Gulati and Gargiolo, 1999). Not all opportunities for a cooperation result in an alliance, which poses a problem for empirical work in this area. This is because being involved in a cooperative

relation involves also a decision to select the appropriate partner, and in this decision the social networks can be determining. Gulati (1995) perceives the network to be a vehicle to carry information among the members about reliability and capabilities of others (see also Shan et. al 1994), and in his empirical study in various industries he looks at with whom firms form alliances with. His results reveal that the likelihood of alliance formation depends on social networks of firms, and increases as commonly known third parties between two firms are larger. Gulati (1999) adopts a dynamic perspective, and drawing upon the data on several industries, he develops the concept of "network resource" which is the position of the firm in the network. He measures this by the centrality of the firm in the network, and analyzes how this influences a firm's future behaviour in potential alliances. According to his results central firms are most likely to enter into alliances. Tsai (2001) carries out an empirical study in petrochemicals and food manufacturing and finds that the interaction between absorptive capability and network position has a significant effect on innovative performance. Firms that have higher absorptive capabilities can make better use of central positions in networks which increases performance significantly. These imply that firms may use their collaborative agreements as a strategic move to improve their network positions, which was a question addressed by Baum et. al. (2003). In this paper, they study the Canadian investment bank networks to highlight the extent to which the structure of the network is emergent and to what extent it is shaped by strategic decisions of core and peripheral firms to improve their network positions. According to their findings, the small world properties of the network is a result of chance partnerings and "insurgent partnerings" strategies of peripheral firms, which refer to their strategy of connecting to otherwise disconnected clusters of other firms (and thus increasing their centrality in the networks).

Networks provide a feedback mechanism among the firms through time, which facilitates the spread of certain organizational forms. The concept of mimetic isomorphism was first put forward by Di Maggio and Powell (1983), and in the context of alliances Kogut (1988) mentions that this might be an important explanation. These phenomena have been studied systematically by various scholars in relation to network structure and/or embeddedness perspectives. For competitive advantage, firms imitate the behaviour of other firms, so that the emergence of certain organizational structures happens through a positive feedback mechanism conferred by networks (Garcia Pont and Nohria 2002). At the same time, the positions of firms within the network give an insight into the structural similarities among firms. More specifically, firms are found to be more likely to be influenced by other firms with similar structural locations, as revealed by their position within the network; like membership in

the same clique, or having similar centrality measures in the network. Garcia Pont and Nohria (2002), in their dynamic analysis of the automotive industry find support for the hypothesis of "local mimetism" as an important motive for alliance formation, where, as the number of prior alliances increase, the competitive pressure on *similar* firms to do the same also increases and so is their likelihood to be involved in collaboration. Partitioning the firms in the network to strategic groups (as in Garcia Pont and Nohria, 1991), they measure the effect of similarity by the local network density of strategic groups. Within a social embeddedness perspective, Galaskiewicz and Wasserman (1989) find also empirical evidence that managers tend to follow the behaviour of others in their social networks when making decisions about donations to charity organizations.

During recent years, an extensive amount of research effort has been devoted to the concepts of structural holes (Burt, 1992) and social capital (Coleman 1988), how these are reflected in the networks surrounding the firm, and how they influence performance. This discussion is usually related with the critical role of filling structural holes for firm success as put forward by Burt (1992). He argues that the competitive advantage of firms rest on their ability to fill structural holes between dense groups of firms. Low structural holes (and therefore high level of redundancy in ties) makes information exchange inefficient and thus not beneficial for competitive advantage. An opposing view on networks is Coleman's (1988) social capital concept, as identified with dense networks and compared with structural hole approach applied to biotechnology sector by Walker et. al. (1997). According to them, it is the firm's position in the network which determines its access to social capital. Burt's structural hole argument stresses the critical importance of filling structural holes to avoid redundancy in knowledge flow so that, "network positions with the highest income lie between not within dense regions of relationships" (Walker et. al. 1997). Conversely, Coleman's argument is that taking place in a dense network with cohesive ties confers competitive advantage to the firm, because coordination is improved through repeated exchange with stable partners. Social capital vs. structural holes are analogous to the strong ties vs. weak ties conceptualization of Granovetter (1973) respectively. Strong ties are usually associated with thick information exchange, efficient and effective transfer of tacit knowledge, and connote trust among the partners. In this sense, strong ties can be associated with exploitation of existing knowledge (Rowley et al, 2000). In other words, strong ties are beneficial for deepening the knowledge of the firm in specific areas (Uzzi, 1997). On the other hand, weak ties are associated with exploration, that is access to new areas of knowledge (Granovetter, 1973, Dyer and Nobeoka, 2000; Rowley et. al, 2000). These two opposing views

on the structure of networks have provoked increased attention (see Borgatti and Jones, 1998 for various ways in which structural holes and social capital is measured in networks).

Ahuja (2000) examines how the position of the firm within the network influences its innovative output with a longitudinal study in the international chemicals industry. There are two kinds of benefits that a firm acquires through networks, which are a function of its direct ties, indirect ties and structural holes it fills (connections among its partners): first of all, firms access the resources (physical, skills, knowledge) of other firms, and second, networks enhance firms access to outside developments, like a major technological innovation, or failures (knowledge spillovers). His findings suggest that structural holes have a negative impact on innovative output; indirect ties (enhancing knowledge spillovers, without costs of maintaining links) and direct ties (enhancing both access to resources and knowledge spillovers) have a positive effect on innovative output of the firm. Walker et. al (1997), measuring social capital by structural equivalence, find that in the case of biotechnology networks are characterized by persistence in network structure, and social capital is a better predictor than structural holes in the pattern of relationships.

In a similar framework, Hite and Hesterly (2001) analyse how the changing resource needs of start-ups is matched with the cohesive ties or structural holes in various stages of evolution of the firm. In particular they state that as the firm passes from the emergent stage to growing stage, the network shifts in response to changing resource needs. In the initial phases, the network structure conducive to success is more cohesive and then as the firm grows, filling structural holes becomes more critical for success. McEvily and Zaheer (1999) focus on the metal working work shops and they find evidence in favour of bridging ties in competitive advantage, which are non redundant, infrequent and geographically dispersed.

The effect of strong ties and weak ties on firm performance depends largely on the conditions surrounding the firm according to Rowley et. al.(2000), where they investigate the conditions under which strong/ weak ties and close/ sparse network are associated with firm performance. Their findings for semiconductor and steel industries reveal that weak ties are beneficial for exploration especially in uncertain technological environments, and strong ties are beneficial for exploitation, where uncertainty is low and competitive pressure is high. Dyer and Nobeoka's (2000) investigation of Toyota network also supports this argument. Gargiulo and Benassi (2000) investigate this tension empirically and stress the trade-off associated with the safety conferred by cohesive ties versus the flexibility conferred by filling structural holes. Bogenrieder (2002) focuses on organizational learning, and she stresses that the kind of social ar-

chitecture that enhances learning depends on problem situation. Specifically, depending on the type of uncertainty (goal or technical), the influence of network on learning might change, and that weak ties are valuable to enhance cognitive diversity. When both goal and technical uncertainty is high, network concentrates both on reliability of partners as well as their knowledge. As far as Nohria and GarciaPont's (1991) findings indicate, in real world industries are characterized by a mix of network structures, so neither uniformly dense nor sparse. More recently, Bekkers et. al. (2002) relate the small world perspective to structural holes versus social capital arguments empirically. Specifically, while Burt's structural hole view can be associated with more random structures where path length is approaching minimum, Coleman's social capital perspective refers to local networks with high cliquishness. Their findings find evidence of small world properties in technological alliances (see below for small world phenomena).

Among some other studies related to network structure in industries are, Riccaboni and Pammolli (2002), who perform a comparative network structure analysis in biotechnology and ICT sectors and find that the frequency distribution of firms are characterised by a power law, which indicates that these networks are scale free (see below for an exploration of scale free networks). Baum et. al (2000) analyse the performance of start-ups with respect to their alliance formation with others, and they define network efficiency by the diversity in the firms partners (universities, research institutes, rivals, etc.) Their results indicate that diversity in the partners competencies increases start up performance in most aspects.

Social embeddedness and networks

Above we have outlined a line of research in which networks are approached from a perspective in which social embeddedness is central (Uzzi, 1997; Gulati, various years, Eisenhardt and Schoonhoven, 1996; Galaskiewicz and Wasserman, 1989; Kogut and Zander, 1992; Kogut, 2000; Bogenrieder, 2002; Granovetter, 1973, 1985; McEvily and Zaheer, 1999; Walker et. al 1997; Powell, 1990; Dyer and Nobeoka, 2000; Rowley et. al, 2000; Hite and Hesterly; 2001; Larson, 1992). In most of this work, we outlined the studies in which network structure and firm performance/behaviour was linked. However, the concept of social embeddedness in networks is a widely diversified area and not in all studies explicit attention is being given to the structure of the network. In this part, we take the concept of embeddedness on its own. We focus on regional districts, as well as the line of research that underlines the significance of social contexts in economic outcomes in general.

Trust developed through interacting is a "cumulative product of repeated past interactions" (Ring and Van de Ven, 1994). As Granovetter states for business groups, whether the source of trust is kinship and family ties as in the case of Korean chaebol, or whether it is geographical proximity, there is always a "cognitive marker around which actors may construct trust relations at higher intensity than with those outside the category" (1998: 84). To the extent that knowledge is tacit and only partly codifiable, face to face interaction becomes one of the most efficient ways to provide its diffusion, and moreover sets the ground for the development of trust between parties. The embeddedness of economic relations within social relations has significant effects on knowledge creation and diffusion especially in geographical clusters. For one thing, these social networks have a positive effect on the extent of performance, and underlying them, the most significant social mechanism is trust among parties (Jones et.al, 1997). Even in cases where there is legally a binding agreement, either within geographical clusters, or among globally dispersed firms, these are accompanied with social mechanisms that permit parties to develop a common language through time so that transfer of knowledge is facilitated.

As expressed by Powell for network forms, "the entangling of obligation and reputation reaches a point that the actions of the parties are interdependent, but there is no common ownership or legal framework" (Powell 1990: 301). This is also conceptually similar to Allen's collective invention phenomena (Allen 1982) which refers to "the informal know how trading of proprietary know how between rival and non-rival firms" (Von Hippel, 1989: 157; Allen, 1983). The increased collaboration between firms in Silicon Valley and the sharing of a common culture and social context in the region enabled foreseeing the market conditions better, and this shaped the rate and direction of technological developments to a large extent. On the other hand, the firms in Route 128 were mostly self-sufficient vertical hierarchies, which were largely closed to external collaboration (Saxenian, 1994).

Kogut (2000) views the emergence of a certain network structure not only the result of characteristics of the industry, but also the result of an interplay between social and institutional norms, which applies clearly to the case of Silicon Valley (Saxenian, 1994). As stated by Almeida and Kogut (1999), diffusion within a district is a function of the combination of factors like universities, start-ups, formal alliances and informal communications as well as mobility of tacit knowledge carrying engineers. Underlying success of Silicon Valley lies the fact that the knowledge held by engineers had a highly tacit quality and the environment supports the mobility of engineers within the spatial boundaries (Almeida and Kogut 1999). Although geographically bounded,

Route 128 can hardly be considered as a regional network, and the organization structure is largely centralized in Route 128 with large established firms occupying central positions. The distinction between an industrial district and network is underlined by Lechner and Dowling (1999), where they stress that the existence of close ties among the actors and the social networks are the basis of regional networks. This distinction has important policy implications, since for the success of an industrial district not only the existence of a regional infrastructure, pooled skill, common legal and financial services are adequate; important part of success stories arises from cultural factors, and reveal the importance of social networks within regions.

Another strand of literature has approached networks from a wider context covering not only firms but research institutes, universities and government bodies as well. Among these, Kali (1999) studies the role of business networks as substitutes for the legal system in transition economies, Hite and Hesterly (2001) studies the relations of firms with regional institutes in metal working job shops, Collinson and Gregson (2003) compare the three organizations in USA, UK and Canada which were established to promote new start ups and how they interact with networks of firms and other institutions in their respective regions.

Technology and networks

Adopting a network perspective enables constructing the mutual relation between the evolution of technology and the organizational forms. According to Kogut (2000), the emergence of a certain network structure is a function of specific industry settings. In other words, what needs a more in depth analysis is the relationship between the organizational practices and the technological trajectories that accompany them in a dynamic context. Empirical research in this area includes; Powell et al (1996) and Walker et. al (1997) who find evidence of a path dependent learning process specific to biotechnology industry that shapes the network of relations among firms. Orsenigo et. al. (1998, 2001) construct a relation between the dynamics of the knowledge base in biotechnology, and the evolution of the industry and detect a close relation between the two. More specifically, their findings point to the fact that the hierarchical structure of network of firms can be perceived as an adaptive response to the hierarchical structure of the knowledge base (with more generic theories on top of hierarchy, each leading to branches applicable to specific areas). McKelvey et. al (2003) investigate the biotechnology as a sectoral system of innovation, and explore in detail the historical evolution of the network of relations, and how these were shaped by the evolution of the knowledge base, regulatory environment and the market.

Rosenkopf and Tushman (1998) examine the co-evolution of community networks and technology cycles in the flight simulation industry. They distinguish between periods of ferment where technical uncertainty is high and periods after which a dominant design emerges, that is the periods of incremental change. Their findings indicate that the intensity of relations among actors increases during the former period, and they stress the mutual relation between technology and networks. In a similar framework, Pyka (2000) focuses on emergence of informal networks and industry life cycle, and obtain similar results as Rosenkopf and Tushman. Nesta and Mangematin (2002), in their paper on biotechnology, relate the networks to the industry life cycle. Their results indicate that when uncertainty is high, firms form more collaborations mainly to exploit knowledge. In maturity, exploitation gains importance and firms revert to internal learning mechanisms.

Stuart (1998), in his analysis of the semiconductor industry makes a mapping of technological positions of the firms and analyzes how this influences future alliances. In particular while most of the studies focus on alliance patterns of already existing firms, and to explain these in terms of past experiences, Stuart's study highlights the alliance formation pattern of newly established firms by mapping them on a technological crowding network, where two firms are closer if they have overlapping competencies. His results show that both crowding and prestige tend to increase the likelihood of future alliances of firms. Stuart and Podolny (1996) also model firms technological positioning as a network, and provide a grouping of firms in Japanese semiconductor industry based on their technological positions. In a slightly different framework, Madvahan and co-authors (1998) study how specific industry events shape the structure of the network in the steel industry. They measure structure by centrality and interblock relations, and focus on industry specific events like a major technological change, entry of a powerful competitor, a change in the regulatory infrastructure, and dramatic shifts in consumer preferences. From a counter perspective, Soh and Roberts (2003) investigate the pattern of networks in data communications and utilizing social network tools they explore how network structure influences newly emerging technologies. In this framework, one of the empirical studies in the aircraft industry was made by Bonnacorsi and Giuri (2001), where they use a dynamic network time series dataset, to investigate how the structure of the vertical relation in the supplier industry shape the industry structure and market shares. In another recent approach Frenken (2000) uses Kauffman's NK model to model complementarities among technologies in the aircraft industry. Particularly in complex product systems, complementarities among the components render inter-organizational networking (or networking among the units within the firm) necessary for com-

petitive advantage and timeliness. For example, Brusoni et. al. (2001) stress the role of the firm as a systems integrator in complex product systems, specifically for the case of aircrafts. Systems integrators, while outsourcing manufacturing and design to specialized firms, maintain the system integration capabilities to coordinate a loosely coupled network organization.

Another paper linking complexity and networks is by Sorenson et. al. (2003). In this paper, they analyse the relation between the *value of access* to an original piece of knowledge (value defined in terms of the effect on knowledge reproduction) and the interdependence among components of it. They utilise patent data to depict that, when knowledge is very little or highly complex, distant or close recipients to the knowledge derive equal value from it. However, at intermediate levels of complexity, maximum benefit is achieved by closer recipients of knowledge.

Most of the papers summarised here are based on the premise that innovation is a cumulative and social process, and the interpersonal communication among scientists, engineers, or technologists play a vital role in the way knowledge diffuses. One promising avenue in the detection of these networks has been shown to be using patent data, because they provide information on co-invention and citation patterns among patents. There has been recent attempts to use patent data to detect social networks, or to apply social network concepts to patent data. For example Balconi et. al. (2004) utilize patent data to detect the structure of inventor networks formed by corporate researchers and academic inventors using Italian data.

2.2.2 *Firm as network*

A strand of research defines the firm as a communication network, and the role of the individual as an information processing unit. In most of these studies, efficiency of knowledge processing is defined with respect to speed with which information is processed, and analysis of those network structures conducive to higher performance is made. For example Bolton and Dewatripont (1994), take into account the trade-off between information processing costs and communication costs within the organization, in an analytical model. They define efficient networks in terms of minimizing labour time of information processing, and conclude that centralized structures are more efficient in firms. Dow (1990) focuses on adaptive learning within the organization, and Radner (1993) on the delay between receipt of information and decision making among managers in the organization. Keren and Levhari (1979) model optimum span of control in a hierarchical setting, and Keren and Levhari (1983) model the relationship between costs of coordination and increasing output in a hierarchies.

In a similar spirit, Qian (1994) models the optimum hierarchical structure and finds that when technological progress is absent, the wage distribution tends to become skewed where low levels of hierarchy earn less than higher levels of hierarchy.

More recent studies include, Ahuja and Carley (1999), who perform an empirical study of the emergent structure of networks in a virtual organization. Unlike traditional perception of decentralization and flexibility, their results indicate that in virtual networks specialization of a limited number of agents can result in emergence of hierarchical structures. In a study of a multiunit electronic firm, Hansen (2001) finds that both network structure and knowledge relatedness are important for effective knowledge sharing. Specifically, when knowledge is codified, links might be redundant because they still involve maintenance costs, whereas for the transfer of tacit knowledge, knowledge relatedness between agents and the shortest path between them is important for efficiency of transfer. Reagans and Zuckerman (2001) investigate the network structures in corporate R&D teams, and find that communication among *diverse* actors, as well as a dense network increases productivity.

2.3 Networks of Agents

In this part of the paper we take the global network structure to be the main unit of analysis. This is conceptually different from above, where we focused on networks in an organizational setting, and how networks effect performance or behaviour of the actors.

Not only within economics but also in many disciplines, there is a growing attention in the literature towards theorizing on the evolving structures of networks. Empirical work on the structure of real world networks is various, where a few examples are, scientific collaboration networks, movie actor networks, ecological networks, the world wide web, web of human sexual contacts, and terrorist networks. Apparently, theoretical work is developing only slowly, due to the difficulties inherent in studying networks. For one thing, most real world networks are characterized by high complexity, and these complexities are further strengthened by many factors. For example, just as a perfectly regular network in which all nodes are tied to nearest n nodes may generate complexity in the structure as it evolves, the structure of the network itself may also be complex in a static framework (Strogatz, 2001). In most real world networks, there is high level of diversity in the type of ties in terms of their weight and content, and in the nodes themselves. Also networks evolve, and so does the parameter space that defines the network itself (Strogatz, 2001).

Under these circumstances building theories to explain network behaviour is difficult since simplifications in their structure and focusing on relevant aspects (as determined by the context) of the network is inevitable, rather than covering all aspects within a unique theoretical framework. Despite all the difficulties, studying networks and how they evolve is valuable in many aspects in the economic sphere, essentially because a dynamic network perspective enables to see how economic outcomes are influenced by nature of networks and how networks influence economic processes (Kirman, 1997).

Within economics, theory of "networks of agents" can be categorized roughly under two headings, both mainly drawing upon graph theory. Firstly, most of these models explore the dynamics of networks, where self interested actors interact and result in the emergence of an overall network structure, under different mechanisms for interaction. These models are all directed towards an attempt to conceptualize and understand how the network forms and evolves, how the structure influences individual action and resulting performance of the system, the feedback mechanism conferred by the network, and the relationship between stability and efficiency of the network. The term network dynamics connotes the change of the network through time. As Doreian and Stokman (1997) point out, however, network dynamics and network evolution have different meanings. Network evolution refers to understanding the dynamics of the network via some understood process, so evolution of the network connotes understanding the rules governing the sequence of changes through time (p.5). Within social network theory, Carley and Banks (1996) provide a survey of the models that are used to examine network evolution. In doing so they distinguish between different models according to their assumption on the dominant socio-cognitive incentive to form links. Some of these models are, requirement for balance (incorporating the actors need for balance in the social environment), degree variance models (when nodes differ in their intrinsic probability to attract an edge), polarization and balkanization (society splits into discrete groups) and learning effects (where the ties strength changes).

Secondly, in static models, an overall network structure is imposed and a comparison is made between the performance of different architectures of the network. Both static and dynamic frameworks are applicable to wide range of areas besides knowledge diffusion, like political decisions, obtaining information about job opportunities, trade and exchange of goods. These areas have been studied extensively. The literature covers various research strands incorporating evolutionary game theory, statistical mechanics, percolation theory and neural networks. It is important to note that, each of the models mentioned here underline specific aspects of networks under different assumptions, which makes it difficult to compare them on a coherent basis. The models that

we summarize here are by no means exhaustive, and we focus on the distinctive qualities of each.

Here we take these models under two sections. Firstly, we focus on small world and scale free networks. Secondly, a game theoretical approach to networks will follow.

2.3.1 Small world and scale-free networks

Watts and Strogatz (1998) have been the first to systematically explore in mathematical terms what was already known to many people: that the world is small. Since then, a vast amount of research has been conducted on the so called small world networks. Small world networks are characterised by two parameters, clustering and path length. Watts and Strogatz (1998) demonstrate that the small world region lies somewhere in between a perfectly cliquish regular network with high clustering and high path lengths, and random networks with no clustering and short average path lengths. Small worlds, which lie in between these two extremes are characterised by high clustering (local connections, where nodes have ties with nearest nodes), but at the same time, via a few short cuts between distant agents, low average path lengths. As empirical work in many areas like the world wide web, scientific collaboration, movie actor networks reveal, most of the real world networks exhibit small world properties. Here we confine this survey to the application of small worlds in economics (For other areas, including physics, see Watts and Strogatz, 1998; Frommer and Pundoor (2003) for a review of three recent books on networks; Barabasi and Albert, 2000; Newman, 2000 for a review covering research on small worlds).

The application of small world phenomena in the economic sphere takes place along several dimensions. One of these is their effect on knowledge diffusion. In a simulation study, Cowan and Jonard (2001) demonstrate that small worlds outperform regular and random structures in the extent of knowledge diffusion. In a different framework, one in which the collective invention phenomena is related to the network structure, Cowan and Jonard (2003) find that small world produces highest knowledge growth, yet the most uneven distribution of knowledge among the actors. Some other examples include Wilhite (2001) where he models trade negotiations in a simulation model, and his results indicate that small world networks are more efficient in terms of the period elapsed until the emergence of an equilibrium price. Latora and Marchiori (2003) devise the concept of an “economic small world”, where they modify Watts and Strogatz framework to take into account different cases (including growing networks) where the ties among agents are weighted, and

there are costs to establishment of links. They investigate, via an analytical model, the global and local efficiency under different cost schemes. In a different framework, Blum and Dudley (2001) explore the effect of religion on economic growth between 1500 and 1750 in Europe, and in doing so, they point to the possibility that the higher growth in Northern Europe can be attributed to the small world networks of Protestants in this era.

Barabasi and Albert (2000) provide a survey on complex networks, which incorporates the state of the art developments in the theoretical literature. The survey includes a detailed account of empirical work in topology of various real world networks, as well as recent theories on random networks, small worlds, percolation theory and scale free networks. They investigate these models based on the main measures of average path length, clustering coefficient and degree distribution. In this paper, they systematically explore mathematical interpretation of scale free networks in terms of some network measures ². As it is argued in this paper, and as Barabasi (2002) also discusses, small world explanations are limited to model real world networks in some important aspects. In these models the network size is held fixed, whereas in the real world networks grow, mostly following certain rules like preferential attachment. Basically preferential attachment means popular agents attract more agents. Indeed, they have shown with the world wide web that, the degree distribution follows a power law, which means that there are a few nodes attracting majority of the nodes, and majority of the nodes have few connections. Underlying scale free networks are basically these two rules, preferential attachment, and a growing network.

Following their paper, the network literature has been witnessing an increasing interest in scale free networks. Though yet limited in the area of economics, one of the studies was made by Riccaboni and Pammolli (2002), where they compare biotechnology and ICT industries. Their results reveal that in both ICT and LS (life sciences) the frequency distribution of firm links follow a power law, and thus they are characterised by a scale free structure. In a different framework, Matutinovic (2002), constructs an analogy between ecosystems and global economy, depicts that the world trade patterns follow a power law distribution, concentrated on only a small number of industrialized countries. Baum et. al. (2003), in their study of the Canadian investment banks, question how the small world topology of the network emerges and evolves, giving emphasis to the role of strategic decisions of firms in securing network positions, and the role of chance partnering.

²See Solla de Price (1965) for the initial foundations of scale free networks.

Having outlined the recently emerging line of research in evolving structures of small and scale free worlds, a slightly more traditional approach to dynamic networks is game theory. Below we provide a review of this literature, as well as some other approaches.

2.3.2 Evolving networks: game theoretical and other approaches

In network evolution models, the rules governing addition and deletion of ties for each node is imposed in the micro level. These rules are usually based on the trade-off between the costs and benefits of forming a link. Therefore, the analysis is not being made from the planners' perspective, but from the perspective of individual incentives (Bala and Goyal, 2000). Theoretical work on evolving networks has intensified significantly during the last decade in economics.

Recent, and to a large extent one of the earliest models is that by Jackson and Wolinsky (1996). In their theoretical model, they investigate the stability and efficiency of networks, where links are non-directed, and there is a cost and benefit of forming links. According to their results, achieving stability and efficiency at the same time depends on the allocation rules of value among network members, and need not always intersect. In this framework, they apply the model to several cases. Dutta and Mutuswami (1997) extend this framework into a game theoretical model. Another model on network formation is by Jackson (2001). Here the major question is, how do individual private incentives to form or sever links in the micro level relates to the social efficiency of the resulting network structure? One of the contributions of this paper is its incorporation of different efficiency definitions, and analysis of how these align with pairwise stability (meaning the state when no two pairs have the incentive to form or sever links). His results indicate that this is largely context dependent, and individual incentives do not necessarily lead to efficiency because of factors like externalities or power based considerations. Watts (2001) extends the model of Jackson and Wolinsky (1996) to a dynamic framework and analyses the formation of efficient networks. She models non-directed communication case, where agents can also benefit from indirect links. More specifically she shows that, emergence of an efficient network depends on benefits and costs of direct and indirect links, and the process is path dependent, thus a function of the particular ways in which agents meet. Inefficient architectures are likely to form in her setting.

One of the drawbacks of these models is that agents are myopic, that is they are not forward looking. Utilizing a similar framework in a dynamic manner, Jackson and Watts (2001) investigate stability and efficiency, by modifying

the model to include random perturbations, to detect which networks formed in a deterministic setting are most stable in the face of small perturbations. Here also they introduce the concept of improving paths, where the network evolves from one state to the next with the addition or deletion of ties, by self-interested decision of the agents. They show that in this case, there is always either a cycle network (repeats itself) or a pairwise stable network. The model developed by Watts (2002) includes a repeated game with non-myopic agents. She finds that even when costs exceed benefits of forming links, circle shaped networks may form. More specifically, when agents are non myopic, circle shaped networks provide a positive and equal payoff to all members, and are supported by equilibrium, but depending on the trade-offs between costs and discounted benefits and on the order in which the game is played. Other structures may also form, but the likelihood of circle networks increase especially with the number of players.

In a slightly different framework, Bala and Goyal (2000) incorporate directed communication (one agent can decide to form a link without the consent of the other), as different from the Jackson and Wolinsky (1996) framework. Individuals form or sever links according to a cost benefit trade-off, and adjust their decisions according to the state of the current network. Thus they incorporate learning effects and investigate the equilibrium network structures. Distinguishing between one way flows and two way flows (in the former benefits accrue only to the one who connects, in the latter benefits accrue to both, and indirect benefits do not exist), in the former case, the wheel and empty, while in the latter case the star and empty are the Nash architectures.

Other recent models that incorporate learning effects within a dynamic games framework are Goyal and Vega Redondo (1999); Skyrms and Pemantle (2000). Goyal and Vega Redondo (1999) model the case where there is directed communication and links are costly. They investigate the effect of link formation and costs on individual behaviour in a coordination game. Their results indicate that unless costs are extremely high, complete network is the unique architecture. Skyrms and Pemantle (2000) model a repeated game with learning in social networks, such that the network structure emerges as a result of this process under different rules for learning.

Some other models investigate the evolution of interfirm networks in different market settings. For example, in a recent paper, Goyal and Joshi (2003) analyze network formation in oligopolies. Under different types of market competition and different cost levels (of forming links) they investigate stability and efficiency of resulting networks. In a similar framework, Goyal and Moraga (2001) model the R&D networks for different competition schemes. They look at the interactions between industry performance, network structure, stabil-

ity, social welfare and individual firm efforts in R&D when firms are forming collaborative links (binary). In this model, the costs of links are endogenously determined in the model, as different from the model developed by Goyal and Joshi (2003). Both of these models (Goyal and Joshi (2003) and Goyal and Moraga (2001)) model the collaborations between horizontally related firms. One of the models that focus on vertical collaborations have been developed by Kranton and Minehart (2000) where they investigate the efficiency of networks formed by buyers and sellers. Zirulia (2004) models the evolution of R&D networks in an oligopolistic setting and analyse the co-evolution of firm capabilities, market structure and R&D networks.

Models of cooperative games when players interact with a limited number of other players within a certain neighbourhood (local interactions) have been utilized to investigate diffusion in various contexts. These models, notably pioneering work by Ellison (1993) and more recently Morris (2000) investigate the level of threshold, (referring to the critical percentage of an agents neighbours that induces the agent to adopt an innovation) where complete standardization obtains. Morris (2000) investigates this threshold level for different local interaction systems (hierarchical network, line, lattice etc.). Chwe (2000) models a cooperative game where participation depends on what the agent knows about what her neighbours' willingness to participate is (rather than whether they participated or not), and he looks at the minimal sufficient network for collective action to occur. As for the *pace* of innovation diffusion, Young (2002) models decision making as a stochastic process whereby the probability to adopt depends on neighbours of the agent, and he models the time elapsed until the innovation diffuses throughout the society under different schemes.

The subject of social influence have also been taken into the research agendas in the context of different approaches, like neural networks (Plouraboue et. al, 1998). Their contribution is to adopt a neural network approach to model the adoption of innovations, where the strength of ties are determined by the history of communications. They introduce the concept of "learning induced criticality", which refers to the critical state of the network which leads some individuals to exhibit macroscopic influence over the network. Deroian (2002) employs a similar frame, where he highlights the pace at which diffusion takes place (namely slow diffusions) incorporating the change in the strength of ties due to similarity or dissimilarities among the actors, like the former model. Steyer and Zimmermann (2001) employ a similar framework utilizing neural networks and Hebb learning rule, and show the emergence of self-organized criticality in social networks, where a few agents can impose a strong social influence on the system. Social network approach to diffusion models uses network measures like density, centrality, structural equivalence among actors)

and on their effect on adoption decisions (Valente 1996). According to threshold models of diffusion (Valente, 1996), individuals adopt an innovation when a certain percentage of their neighbours have adopted, this threshold being different for individuals. He distinguishes between the social system as a whole and the personal networks, and points to the fact that whether an actor is an early adopter or laggard can differ according to whether one looks at the social system or the personal network.

In a recent simulation model, Cowan et. al. (2002) model an evolving network in a simulation model, where knowledge carrying agents match with each other to combine their knowledge levels (and thus innovate). The formation of networks is captured here by the analysis of cumulative frequency matrices (showing who interacted with whom, how many times). They investigate the resulting network structures within a parameter space defined by the extent of transfer of knowledge among agents. Cowan et. al (2004) explore the effects of interaction in networks compared to no-networks (no structure in communications). Their simulation results indicate that regular structures generate higher knowledge growth in industries with tacit knowledge and high technological opportunities, whereas when knowledge is codified and technological opportunities are lower, communication without any structure performs better. Hummon (2000) models *utility maximizing* agents in a simulation study, where the utility function is constructed by benefits and costs of forming or deleting ties. He investigates the resulting network architectures, using an agent based simulation approach.

2.4 Concluding Remarks

In this chapter, a literature survey of economic networks was carried out. Taking into account the largely wide and diversified literature on networks, we limited our attention to two spheres: “agents in networks” and “networks of agents”. In the first case, networks are taken in an organizational context, where the literature is concentrated mostly on inter firm networks, analysing their implications for the behaviour and/or performance of individual firms. In the second case, we focused on the strand of research that focuses on modeling aspects of networks in a global sense. More precisely, we covered theoretical models on small worlds, scale free networks and game theoretical approaches here taking the unit of analysis as the network itself.

As it is apparent from the aforementioned developments in the literature, the recent evolution of research on networks is characterized by the contributions form a diverse range of approaches, including physics, mathematics, sociology,

economics and management. In such a setting, it is quite difficult, though potentially quite valuable to have a coherent understanding of networks, which can be facilitated by forming a basis that will incorporate all these approaches, and upon which a sound and coherent theorizing on networks will be possible.

3

Firms, Networks and Knowledge

3.1 Introduction

In recent decades, the intensity of horizontal and vertical relations among firms has increased to a large extent, and this has especially been marked in the case of knowledge intensive industries. The rapid innovations and increasing product complexity in these industries have not only raised the requirements for compatibility among product components, but have also been accompanied by richer technological opportunities in these industries. These developments were preparing the grounds for intensive relations among firms, in the face of difficulties faced by a single firm to be self sufficient in serving a rapidly changing market. With these developments in the background, the role of small and flexible innovative firms in the evolution of industries has increased considerably. For example in the case of biotechnology, the network relationships are mostly dominated by arrangements between large firms and new biotechnology firms (Arora and Gambardella 1994; Walker et. al, 1997; McKelvey and Orsenigo, 2002). In the computer industry, small firms had a significant role in the opening up of new market segments and shaping the evolution of industry (Malerba et. al. 1999).

In such an environment, the requirement for large physical capital investments in most industries is losing its significance, but knowledge is becoming a central factor in influencing industry dynamics. Firms need to pursue strategies that favour external relations, not only in subcontracting components but also to share knowledge and make use of knowledge spillovers. Therefore the

well known "make or buy" decision nowadays is extended to cover not only components but also to make use of what other firms have to offer in terms of knowledge. Those firms that are not involved in firm networks risk being excluded from the market. These developments have also had an effect on intrafirm organization, which has become more flexible than the traditional organizational structure associated with mass production.

With all these developments in the background the systematic exploration of what is termed to be the "firm" has also changed its focus in the literature. During the last decade, knowledge has occupied a central position in the firm theories. Various concepts like tacitness of knowledge (Polanyi, 1967), absorptive capacity (Cohen and Levinthal, 1990), combinative capabilities (Kogut and Zander, 1992) attempt to capture the influence of knowledge on the way industrial activity is organized.

Industrial structure is a function of many factors, among which institutional aspects, the stage in the industry life cycle, tacitness of the knowledge base, technological opportunities all play a role in varying degrees, as also studied intensively from various theoretical perspectives. Despite controversies in the rich literature that has evolved along various branches, it is generally accepted that the evolution of industry structures is accompanied by the evolution of the interplay between a complex set of actors involved in the process of innovation, including artifacts, institutions, knowledge embodying individuals, and the market.

There is now a rich literature on two cases in which the relation and the distinction between products and technologies that underlie them deserve attention. Firstly, it is observed that large firms usually extend their production into related products, and thus efforts to characterize the behaviour of multi-product firms have intensified during the last two decades (Teece et. al., 1994 and Teece, 1982). But a distinction is usually made between a multi-product firm and a multi-technology firm, with the observation that large firms also diversify their technological competences for a variety of reasons, even though they may be specialized in a core product line (Granstrand, 1998; Granstrand and Sjolander, 1990; Granstrand et. al., 1997; Patel and Pavitt, 1997; Pavitt, 1998). One of the driving forces behind technological diversification within a firm is increased external linkages and to make use of new technological opportunities (Granstrand et.al, 1997). As we reviewed in the previous chapter, recently there has also been a growing literature on networks of small firms, each specialized in a single product with narrow technological focus, but intensive knowledge sharing taking place across enterprise boundaries. These systems are characterized by variety and specialization at the same time (Kogut,

2000), accompanied by rapidly changing market conditions, uncertainty, intensive informal know how trading and collaboration.

From this discussion it follows that variety is sometimes found in a network of specialized firms, and at other times in the diversification activities of large hierarchies. In the most general sense, the underlying reasons for this phenomena forms the starting point of the research that we undertake.

Theoretically, this inquiry has been tackled under the heading of firm boundaries in the literature. Various schools, including mainstream theories, transaction cost perspective, evolutionary theories, resource based views, and knowledge based theories address firm boundaries in different manners. But to the extent that a distinction is made between products and technologies, firm boundaries extend beyond the way they are determined by the traditional "make components or buy components" decision, but become a more complex issue encompassing two dimensions, product boundaries and technology boundaries (Brusoni et. al. 2001).

In line with this framework, this chapter provides a theoretical exploration of the aforementioned approaches. First, the literature on firm boundaries is presented, where the focus is on the transaction costs perspective, the resource based view and knowledge based theories of the firm, as well as the complementarities and the tensions among these. In exploring this literature we focus especially on the existence of firms and boundaries problems. In the second section we explore two distinct cases: in the first, firms are characterised by porous boundaries and involved in intensive interactions with each other, namely the case of network based industries. In this section, we further explore this case with respect to the issues of specialization and variety. The second case that we consider is the case of multi-product and multi-technology large firms, where we make an inquiry into the diversification strategies that firms pursue. The third section presents the research question, and the approach undertaken in this thesis to address it. More specifically, we argue that the knowledge embodied in production can have an important role in explaining the existence of firms, as well as what determines their boundaries. In this context, the approach that we follow is close in spirit to the knowledge based theories of the firm. Moreover, we contend that, to explore this issue in a systematic manner, conceptualizing the organization both at the micro level (the firm) and at the macro level (the industry) as a self organizing network is a promising avenue. For example, the firm can be seen as a cluster of knowledge carrying and creating agents. Network based systems can be expressed as small clusters of specialized individuals, with intensive links among the clusters themselves. Large firms can be characterized by bigger clusters of individual agents with few (or intensive) links among them. In short, organizations can be seen as

emergent networks of interacting agents, where the knowledge base shapes the way these interactions take place, and thus their boundaries.

3.2 Firm Boundaries

There are two central questions that lie at the heart of theories of the firm:

1. Why do firms exist?
2. What determines scale and scope of their activities (the problem of boundaries)?

Neoclassical theory reduces the firm to a representative profit-maximizing agent, being defined by a production function with the boundaries set by economies of scale and scope. Underlying such an approach is the assumption that knowledge is purely codified, and that it can be appropriately expressed as an abstract production function that also defines the firm itself. Accepting the approach of neoclassical economics to the firm, modern economic literature has been witnessing a variety of other approaches aimed to answer the two questions above. The earliest of these is the transaction costs perspective (TCE), inspired by the seminal work of Coase (1937), who explained the *existence* of firms by the “costs of using the price mechanism”. Williamson (1975, 1985) extended his analysis into a more rigorous theory. Alternatives to the transaction cost perspective came from the area of strategic management and organizational theory, known under various approaches like the competence based view of the firm, the closely related resource based view, and the knowledge-based view.

3.2.1 Transaction Cost Approach

The new institutionalist economics (NIE), according to Williamson (1998a), comes in two parts. The first part deals with the *rules of the game*, that is the institutional environment. He quotes Davis and North (1971) in defining the institutional environment as “the set of fundamental political, social and legal ground rules that establishes the basis of production exchange and distribution rules governing elections, property rights, and the rights of contract”. The second part of NIE deals with institutional arrangements. Defined to be the “arrangement between economic units that governs the ways in which these units can cooperate or compete” (1998b), the institutional arrangements correspond to the *play of the game*. Distinguishing between institutional environment and institutional arrangements, TCE holds the background conditions

constant (taking rules of the game as shift parameters), and focuses on alternative modes of governance.¹

Underlying TCE are two basic assumptions regarding the behaviour of economic agents. Firstly, agents are boundedly rational, that is "behaviour that is intendedly rational but only limitedly so" (Simon, 1997). Because of bounded rationality, all complex contracts become unavoidably incomplete (Williamson, 1998). Here, however, Williamson stresses the environmental constraints that put a limit to the rationality. In other words, at some point, where the conditions of the transaction contract become too complex or uncertain to be specified at the outset, bounded rationality becomes binding and this results in incomplete contracts. The second behavioural assumption is opportunism, that is "self interest seeking with guile" (Williamson, 1975). The opportunistic behaviour is important since "attenuating the ex post hazards of opportunism by ex ante choice of governance" is mainly what the transaction cost approach deals with (Williamson, 1998a: 31).

In the TCE, two types of governance structures are focused on; namely markets and firm contracting. The choice between the two depends on the costs associated with the exchange, so that TCE is usually considered as an efficiency based approach (Foss, 1996). In market contracting, the benefits of exchange are clearly specified, transactions are non repetitive, involve standardized products and technological stability (DeBresson and Amesse, 1991) and assets are completely distributed (Williamson, 1975), the means of communication being mainly prices. On the other hand in a pure hierarchical form, assets are tightly controlled, and the hierarchical organization is the self sufficient unit where all the transactions are internalized. Asset specificity is one of the basic tenets of the TCE. Once resources are committed under pure market exchange, irreversibility and specificity of the assets renders the parties vulnerable to possible opportunistic behaviour in the future (known as the hold-up problem). In addition, because of bounded rationality and uncertainty, future conditions surrounding the contract cannot be predicted in advance. These factors, especially when the exchanges are carried out on a more frequent basis, increase the transaction costs associated with pure market exchange. To economise on such transaction costs, firms are formed.

In the previous chapter, we explained the main criticisms directed towards TCE, mainly in the context of networks. Here, we will elaborate more on this issue in the framework of the *existence* of firms. TCE have been criticized on

¹ In the parts that follow, the approach that we undertake is similar. In particular, we assume a flexible institutional structure that does not impose constraints on the formation of firms, and we base the discussion on the criteria of economic efficiency only.

a number of issues, among which the assumption of opportunistic behaviour is the most common (Conner and Prahalad, 1996; Kogut and Zander, 1992, 1996; Holmstrom and Roberts, 1998; Madhok, 1996; Ghoshal and Moran, 1995). As we review below, these criticisms mainly came from the proponents of the resource based approach. Another area in which TCE provokes skepticism is that it does not have implications about the performance differences among firms (Conner and Prahalad, 1996; Madhok, 1996) and gives exclusive emphasis to cost considerations.

3.2.2 Resource Based and Knowledge Based Theories of the Firm

Whereas the transaction cost approach explains the existence of the firm by ex-ante fear of opportunistic behaviour, the resource-based view (RBV) explains the firm as a pool of resources of which the distribution to various uses gives the firm competitive advantage. The resource based view has its roots in the seminal work of Edith Penrose (1959), and has been extended since, especially during the last decade (see for example for initial contributions, Wernerfelt, 1984; Prahalad and Hamel, 1990). In the RBV, firm capabilities are seen as the resources exclusive to the firm, and are the main sources of sustainable competitive advantage. Wernerfelt's (1984) was one of the first studies which extended Penrose's view of firm resources. But it was not until the beginning of 90s that the RBV received significant attention in the literature. Notably with the contributions of Prahalad and Hamel (1990), Conner (1991), Barney (1991), the RBV developed among various lines, especially in a more detailed categorization of resources and their attributes as they influence the strategic advantages of the firms.

Following this line of research, the 1990s witnessed an extension of the RBV, mainly in the context of *knowledge* as the key resource unique to the firm. This line of research was mainly inspired by the seminal work of Prahalad and Hamel (1990) where they introduced the concept of "core competencies" as those resources which yield competitive advantage to the firm. Essentially, core competencies are the "collective learning in the organization, especially how to coordinate diverse production skills and integrate multiple streams of technologies" (p.81) and they yield potential access to a wide variety of markets. In this sense, the key characteristics of core competencies is that they are difficult to imitate by competitors, unlike specific technologies, since they are embedded in the coordination and learning processes within the firm. Prahalad and Hamel (1990) assert that, the value of core competencies in the organization depends on their "velocity of circulation" as analogous to money markets. Therefore flexibility in the movement of core competencies among

business units is expected to give the firm advantage in terms of exploiting existing competencies, entering into new markets, and shaping existing ones. This is closely related to the view that the boundaries of the firms are shaped by their capabilities. Specifically, Langlois (1989) builds upon Richardson (1972) and Teece (1986) and states that the complementary activities that the firm undertakes depends on its capabilities. When complementarities require tight coordination, but the firm does not possess the necessary capabilities, intermediate forms of organization may emerge like licensing and joint venture (Langlois, 1989; Richardson, 1972).

The knowledge based theories essentially take the key resource of the firm to be knowledge (Kogut and Zander, 1992; Grant, 1996; Grant and Baden Fuller, 1995; Spender, 1996; Nonaka, 1994). A common opinion shared among the proponents of the knowledge based approach is that opportunism is not a necessary assumption to explain the existence of the firm (Madhok, 1996; Kogut and Zander, 1992, 1996; Zander and Kogut, 1995; Conner and Prahalad, 1996). In other words firms can and they do exist, even when all individuals are honest.

One of the leading papers which explained the existence of a firm with reference to its knowledge pool by incorporating the tacit nature of knowledge to the RBV has been made by Kogut and Zander (1992), and which is considered to be the pioneering paper in the knowledge based view of the firm. According to Kogut and Zander (1992), firms exist because they are also social communities so that the transfer of knowledge within the organization is facilitated, drawing upon what Arrow (1974) points out about organizations: that they facilitate communication via the development of a common language. Transfer of knowledge is not the only mechanism that the organization facilitates, but the organization also develops capabilities by which the existing knowledge is combined with new knowledge and thereby innovation takes place as the recombination of knowledge. They stress that the fundamental dilemma faced by the organization is that when knowledge is codified, although it makes transfer easier, it also renders the firm vulnerable to imitation by competitors. They draw upon evolutionary theories (Nelson and Winter, 1982; Cyert and March, 1963) and contend that the creation of knowledge is largely the result of localized process of search, thus it happens in proximate technologies and the nature of knowledge growth is largely path dependent. Complementary to the combinative capabilities framework, Nonaka et. al. (2000) note the conversion capabilities of the firm in knowledge creation. They state that the basic operation within the firm is the continuous and dynamic process that converts tacit to explicit knowledge; explicit to explicit; explicit to tacit; and tacit to tacit. He states that the conversion rate determines the efficiency with which

the organization can create new knowledge, and also that the organizational framework determines the rate of this conversion. Kogut and Zander's (1996) later work, in which the firm is also seen as a social community, focuses on the advantage of the firm (over markets) in resolving a fundamental dilemma: that division of labour increases productivity, but the accompanying specialization also increases the costs of communication and coordination in market exchange. The identity conferred by the firm increases the speed and efficiency of knowledge creation and transfer.

Whereas Kogut and Zander (1992) take knowledge at the level of organization and argue that knowledge is produced in a social setting and cannot be reduced to the individual level, Grant (1996) takes knowledge to be "residing in the individual" and that the role of the organization is to integrate the specialist knowledge of its members, and thus he places the concept of coordination in the centre of the analysis. Firms exist because of the coordination they provide to integrate the specialist knowledge of individual members. Markets cannot maintain this coordination because knowledge is tacit and immobile, and production requires individual specialists. Moreover because of bounded rationality people have limited storage and acquisition capabilities, and thus they specialize.

Grant's (1996) emphasis is on the integration of knowledge, rather than transfer.² According to him, the boundaries of firms are determined by the efficiency with which knowledge is integrated in different contract mediums (market contracting, or firm) depending on the requirements of production, and type of knowledge. He states that:

"If markets transfer products efficiently, but transfer knowledge inefficiently (tacitness) vertically adjacent stages of production A and B will be integrated within the same firm if production at stage B requires access to knowledge utilized in stage A. If, on the other hand, the output of stage A can be processed at stage B without the need to access knowledge utilized in stage A, then stages A and B are efficiently conducted by separate firms linked by a market interface" (Grant, 1996: 119).

With respect to the organizational structure of the firm (i.e. centralization or decentralization), Grant argues that hierarchical organization is not suitable

²Transfer of knowledge is not necessarily an efficient way to integrate knowledge. "...the key to efficiency is to achieve effective integration while minimising knowledge transfer through cross-learning by organizational members". He also contends that "if two people have identical knowledge than there is no gain from integration- yet if the individuals have entirely separate knowledge bases, then integration cannot occur beyond the most primitive level." (p. 114)

when the knowledge resides in individuals and when tacit knowledge is not efficiently transferrable. In this sense, he supports team-based organization for efficiency of integration, and that the decision making mechanisms should be designed in such a way that decisions based upon tacit and idiosyncratic knowledge are decentralized, while decisions requiring statistical knowledge are centralized.³

The criticisms directed towards the conceptualization of the firm as solely a repository of knowledge came from Foss (1996). He contends that the contractual approach to the firm (i.e. TCE) and knowledge base theories are indeed complementary, and that the "existence of the firm" cannot be explained without reference to the concept of opportunism. He contends therefore that Kogut and Zander's (1992) analysis is a necessary but not a sufficient condition to explain firms, and that a contractual approach is required to complete the analysis. In other words, according to him there should be ownership and hierarchy so that the opportunistic behavior is controlled. He states that

"the presence of higher order principles (as Kogut and Zander argue) are not sufficient to explain the existence of the specific constellation of property rights that characterizes the firm. The argument from the contractual approach would be that because hierarchy can more successfully control opportunism/moral hazard, higher order principles are likely to emerge... hierarchy may stimulate the emergence of trust, cooperation, information exchange, and various sets of commitments..." (Foss, 1996: 472).

As far as the role of hierarchy as a coordination mechanism is considered, it seems from the above discussion that two contradictory views emerge. One of these (Grant, 1996) contends that hierarchical structures are not efficient for knowledge integration when knowledge is highly tacit. Whereas Foss (1996) points out that it is the existence of a hierarchy that maintains coordination in the firm, so that transfer/sharing of knowledge and learning processes are taking place. Whereas Grant (1996) and Kogut and Zander (1996) take the firm as a gathering of individuals for increased efficiency, Foss (1996) takes authority as central to maintain the workings of this group. What lies beneath this tension is the lack of a concrete definition of the firm, and it seems that the two approaches use different definitions. In other words, there is a confusion between explaining why firms exist at first hand, and the attributes that define a firm once it is formed (i.e. hierarchy and authority, as Foss argues).

³ Here statistical knowledge refers to quantifiable information, which can be accessed and processed efficiently by centralized means.

Similar to Kogut and Zander (1992) and Grant (1996), Conner and Prahalad (1996) also explain the "existence" of firms without using the concept of opportunism. However in their analysis authority still has a significant role. As they contend, this is because possession of control rights allows one party to manage/direct the actions of the other (as they term, "power to give direction") building upon the conceptualization of authority by Simon (1951), and this is particularly the reason that the form of organization influences the way knowledge is applied to business activity. They quote the following from Simon (1951) which describes the authority in the firm context:

"We will call our employer B (for "boss") and our employee W (for "worker"). The collection of specific activities that W performs on the job (typing and filing certain letters, laying bricks or what not) we will call his behaviour. We will consider the set of all possible behaviour patterns of W and we will let X designate an element of this set.... We will say that B exercises authority over W if W permits B to select X. That is, W accepts authority when his behaviour is determined by B's decision. In general, W will accept authority only if x_0 , the x chosen by B is restricted to some given subset (W's area of acceptance) of all possible values" (Simon, 1951: 294).

Simon (1951) describes the market contract in the following way:

"The employment contract differs fundamentally from a ... [market] contract... In the ...[market] contract, each party promises a specific consideration in return for the consideration promised by the other. The buyer (like B) promises to pay a stated sum of money: but the seller, unlike W, promises in return a specified quantity of a ... specified commodity" (Simon, 1951: 294)

Conner and Prahalad's (1996) analysis is based on boundedly rational agents. When this is the case, parties may differ in their evaluation/belief of the outcomes of certain actions, and such disputes may render negotiation difficult, even when agents are completely honest. They investigate the conditions under which firm contracting under authority is more profitable than market contracting and in doing so, they focus on two processes by which knowledge is applied to business, and by which markets are different from firms; namely knowledge substitution effect and flexibility. Under firm contracting, knowledge substitution takes place when "[B] tells [W] to do something that [W], relying on its own knowledge and that which it has managed to absorb from [B], otherwise would not do" (p. 485). And they state that what makes firm

organization different with regard to knowledge substitution is, "a primary effect of the firm organization –of the authority effect– is to cause an individual to use the knowledge of another before the former fully understands or agrees with it" and this is why, W might prefer authority, as they state, to: "economise on limited cognitive abilities". Whereas under market contracting, parties can make suggestions to each other about how to perform a job, and they are not obliged to obey these suggestions, but they can internalize and absorb the knowledge of each other, rather than being substituted, as in the case of firm authority. Conner and Prahalad (1996) state that either organizational mode can emerge, depending on which one yields a better blending of parties knowledge, at lower cost.

In their analysis, the flexibility effect refers to the acquisition/learning/growth effects of knowledge through time, in response to unforeseen events at the time the contract was agreed upon. They assert that under market contracting, there are costs of renegotiation, whereas in firm contracting the "boss" can simply give directions, without renegotiation. Therefore when there is uncertainty, firm contracting is less costly than market contracting because of the higher costs of renegotiation in the case of market exchange.

Nahapiet and Ghoshal (1998) stress the role of the firm as a mediator in which social capital is converted into intellectual capital. According to them, firms are networks that embody dense social capital, which they associate with trust, norms and sanctions, obligations and expectations, and identity and identification. In line with this, they contend that "social capital in the form of high levels of trust diminishes the probability of opportunism and reduces the need for costly monitoring processes, it thus reduces the costs of transactions" (Putnam, 1993; Nahapiet and Ghoshal, 1998, p. 245). Ghoshal and Moran (1996) develop this argument even further and claim that authority and rational control mechanisms are likely to reduce motivation and commitment in the workplace. They claim that, TCE, with its exclusive focus on the role of hierarchy in controlling for opportunistic behaviour is "bad for practice".

Madhok's approach to the existence of the firm bears a similarity with the above approaches, but she gives less emphasis to the knowledge-specific aspects of existence of the firm but takes as a basis the monitoring costs (Alchian and Demsetz, 1972). She contends that when explaining the existence of the firm, the benefits accruing to capabilities of the firm should also be taken into account. She emphasizes that "firms do not succeed (or exist) because shirking costs are lower than cheating costs, but because they *simply do certain things better*" (1996: 586).

3.2.3 Discussion of the Approaches

The knowledge-based approach is the basis upon which this thesis is constructed. In this respect, we take into account a couple of features, one of which is the concept of authority as a prerequisite for the existence of a firm (Foss, 1996; Williamson, 1975, 1985). In most of the literature that we have covered, it is seen that the existence of the firm is explained without incorporating the assumption of opportunistic behaviour, as posited by Williamson to be the underlying human attribute that leads to firm contracting. As Foss (1996) argues, it is the authority and hierarchy in the firm which maintains the workings of the firm as a community and which monitors opportunistic behaviour. However, the important question left unanswered in this discussion is whether authority is a *prerequisite* for the existence of the firm? This question forms the basis of the approach undertaken in this thesis, and we take authority as an *ex-post* mechanism that maintains coordination, but not a necessary concept to legitimize the existence and formation of firms *ex-ante*.

Conner and Prahalad (1996) build their discussion upon the fact that firm contracting by definition connotes authority (manager), and that the effect of authority on business is the knowledge substitution effect, i.e. knowledge of the boss is substituted for that of the worker, even when the worker does not internalize the knowledge of the boss (i.e. “economizing on limited cognitive abilities” of the worker).

The argument developed here also follows an efficiency perspective, as in Conner and Prahalad (1996). Specifically, we argue that the “knowledge” in their analysis can be taken in two dimensions; the first is managerial knowledge, which refers to the knowledge relevant to carry out managerial functions, namely strategic decision making and maintaining coordination within the firm. The second dimension of knowledge can be taken as technical knowledge; i.e. the knowledge embodied in specialists who accomplish particular productive tasks in the firm. We take both knowledge dimensions to be highly tacit in nature, as well as complementary. Does technical knowledge substitution increase efficiency? This conceptualization runs the risk of undermining the specialization of the worker, especially when the “shop floor” experience is concerned. Knowledge substitution can become a source of inefficiency in terms of resource allocation, to the extent that the “substituted part” of the employees knowledge is the idle part, and represents a lost economic value. For example, Madhok (1996) demonstrates a similar reasoning, in terms of monitoring costs. As she explains, when a group of individuals work on a specific task in the firm, certain routines are developed, individuals become specialized, and thus become efficient in this task. In this situation, it is costly for the

employer to learn all these routines in order to reduce monitoring costs. On the other hand, as far as the first dimension of knowledge is concerned, (i.e. managerial knowledge) efficiency can be increased when knowledge substitution takes place.

Viewed in this way, the employment contract is basically a contract to integrate the managerial knowledge of the manager, and the technical knowledge of the employee, which, essentially makes it a contract for knowledge integration in the terms of Grant (1996). Taking into account the fact that the employment contract also requires the consensus of both parties, then the authority has no effect *ex-ante* on the existence of the firm, and is there, by definition, to increase efficiency *ex-post*.

Having outlined briefly the major lines of the research on firm boundaries and firm existence, in the following sections we focus on two cases in which firm boundaries are taken to be the central issue. In one of these cases, firms are characterised by porous boundaries with intensive networking among themselves. In the second, large and diversified hierarchies are taken into account.

3.3 Porous Boundaries and Networks versus Concrete Boundaries and Hierarchies

We presented a detailed review of network based systems in the previous chapter. In this section, we revisit the issues of specialization and variety in these systems, as they constitute the building blocks upon which we base our arguments.

3.3.1 Variety and Specialization in Network Based Organizations

Usually firms in network industries are characterised as being highly specialized, and with intensive knowledge transfer taking place across their boundaries. The extent of networking among firms depends on many factors like increased product complexity, technological interdependence, specialization of each productive unit, market uncertainty, as well as rapidly changing market conditions. Mostly, interdependencies among products, compatibility requirements, specialization and collaboration accompany each other in these systems. When the nature of the products becomes too differentiated and complex, it is unlikely for a single firm to efficiently produce every component itself and to stay on the leading edge, given a dynamic market and rapid innovation. Task complexity, combined with time pressure, makes coordination among firms more efficient than vertical hierarchies (Jones et.al., 1997; Hagedoorn, 1993). Thus a feature of these systems is that they embody specialization and variety

at the same time, as opposed to a world in which markets are associated with variety and firms are associated with specialization (Kogut 2000).

The role of the network in forming a platform in which knowledge of diverse actors combine has been mentioned frequently in the literature. Increased variety also refers to a broader dispersion of knowledge among parties. When this is the case, networks of firms enable both rapid accesses to divergent knowledge categories, as well as the increased opportunities for building internal capabilities (Powell et al, 1996). As Dyer and Nobeoka (2000) state for the Toyota network "...if the network can create a strong identity and coordinating rules, then it will be superior to a firm as an organizational form at creating and recombining knowledge due to the diversity of knowledge that resides within a network" (p. 245). But as they mention, there are also costs to this variety, which is that through imitation the parties might become similar in time.

Kogut and Zander (1992) stress the role of the network to yield information on "who knows what" as well as "know how". Networks integrate the knowledge of diverse actors taking role in innovation and production with unique procedures shared and created by the firms/institutions that constitute the network. This process is facilitated by a shared culture and development of a common code of communication among parties, which reduces the costs of transferring highly tacit knowledge. One of the significant characteristics of networks is that these systems are characterized by social linkages among the actors, so that costs from opportunistic behaviour is reduced largely due to reputation effects in a tightly bound social environment. The embeddedness of economic relations within social contexts has significant effects on knowledge creation and diffusion. These social networks have a positive effect on the extent of knowledge diffusion, and underlying them the most significant mechanism is trust among parties (Jones et. al, 1997, Saxenian, 1994, Gulati 1995).

The emergence of networks is largely an endogenous process driven by the complex and dynamic interplay between institutions, products, technologies, the market and innovative actors. Network based systems are mostly characterised as being self organizing, such that there is no authority to impose a certain structure, but the interaction of firms is the main mechanism that generates the rules underlying emerging structures (Kogut, 2000). Consequently, in these industries, costs of a mechanism for authority is also mitigated, because the reputation concerns render opportunistic behaviour costly.

While in the case of networks specialization and variety co-exist at the same time, in the case of large firms variety takes a different form, usually studied under the heading of diversification.

3.3.2 Diversification: Multi-Product and Multi-Technology Firms

One of the first attempts to construct a theory of the multi-product firm has been made by Teece (1982) where he draws upon transaction cost perspective and evolutionary economics. In summary, to the extent that a specialized firm has excess resources, one of the alternatives that it faces is to diversify its product portfolio. However the decision to do so depends on the tacitness of organizational knowledge and thus the transaction costs associated with difficulties in transferring it. Combined with the fact that human capital within the organization can be used to produce a variety of related products, firms can find it more efficient to diversify into related product categories. Relatedness deserves attention here, since empirical research confirms that firms diversify into product categories that are close to their core product groups, what is termed "corporate coherence" (Teece et. al., 1994). More specifically, large firms exhibit a certain coherence in their diversification portfolios. Based on their theory of corporate coherence, Teece et. al. (1994) define firm boundaries with reference to path dependence, learning, technological opportunities and the selection environment. Both the extent of path dependence and organizational learning is a function of the technological opportunities available to the firm. The more technological opportunities available, the faster will be the learning process and the current paths may be more easily changed via breakthroughs in basic research or major innovations. The selection environment influences the extent to which unsuccessful firms exit. They point out that "coherent diversifiers" usually exist when there is rapid learning, high technological opportunities, tight selection environment and broad path dependencies (because of generic technologies).

The major organizational dimensions, as specified by Teece (1996) are level of hierarchy, scope (multi product or single product), vertical integration, culture and external linkages. Corresponding to these dimensions, he distinguishes four organization types: Multi product integrated hierarchy, high flex Silicon Valley type, virtual corporation and the conglomerate. He addresses the matching between these organization types and the type of innovation (systemic or autonomous) in the industry.

While these approaches shed light on why firms diversify production and why they do so coherently, they are mostly limited in their scope, such that their focus on product lines fail to underpin the many-to-many relation between technologies and products. The rapid rate of technological change in the second half of last century has brought with it an ever increasing dynamism in the way technologies are embodied in products, the way they converge during their evolution, and thus the way they become interdependent on each other,

which is partly reflected in the interdependencies among products themselves. The interdependence among technologies refers to the feedback effects among them, that innovations in one area consequently shape the rate and direction of innovations in other technologies (Frenken, 2000). Today it is possible to see a great deal of technological convergence in many areas, the convergence of computers and telecommunications being the most prominent example. Consequently, there is no one-to-one mapping between products and technology; just as a single technology can be used to produce a variety of products, so can a single product draw upon a variety of technologies, making the mapping many-to-many (Pavitt, 1998). Based on empirical evidence in a diverse range of industries, it is accepted today that most large firms extend their technological activities to a broader range of technologies, than the one/s required by their core product lines (Granstrand and Sjolander, 1990; Granstrand, et.al, 1997; Patel and Pavitt, 1997; Pavitt, 1998; Breschi et.al, 2003). Consequently, it is the difference between a multi-technology firm and a multi-product firm essential to underline (Granstrand and Sjolander, 1990). Just as a single product firm can have distributed technological competences when the nature of the product is complex, so can a multi product firm be technologically narrow. In the case of the electronics industry, Gambardella and Torrisi (1998) find that increased product focus is accompanied by increased technological diversity, which proves to yield higher performance.

Diversity and distributed technological competences helps the firm to acquire flexibility in adapting to new technological developments, and improving current products. Because the nature of learning in the firm is usually cumulative in nature, and is the result of localized search, firms might end up being "myopic to different technological and market contexts" (Malerba et. al, 1999). Therefore the possible destructive influence of a systemic innovation can be converted into a new source of competitive advantage depending on the firms capabilities in adopting its productive system to the requirements. For example, according to the findings of Breschi et. al. (2003), those firms that diversify into related technologies can make better use of cross technology spillovers, and are thus more likely to be persistent innovators in a given technology. The major driving forces in distributing technological competencies are, to monitor, absorb and coordinate changes in the supply chain related to current product technologies (so that the more complex products become the more is the tendency to diversify among different technologies). Second, gaining competence in a wider range of technologies is necessary to evaluate and master the technological opportunities in the industry that can be utilized to develop new products or improve existing ones (Granstrand et. al., 1997).

These have direct bearing on the boundaries of firms, such that they highlight the distinction between outsourcing production and outsourcing technology. In this sense, the domains within which firms form external linkages is now extended to two dimensions, different than narrowly perceived unique dimension of product based “make or buy” decisions. Accordingly in the determination of firm boundaries, the width of related technologies outside the firm assumes greater importance for competencies (Grandstrand et al, 1997). Taking into account the wide range of choices that the firm faces in terms of deciding on its mix, there are a number of intermediate positions between full-scale outsourcing and full-scale integration, depending on capabilities of firms.⁴

As far as the diversification strategies of firms are considered, Patel and Pavitt (1997) find empirical evidence that various firms producing similar products have similar patterns of diversification. A more detailed analysis of diversification patterns has been made by Breschi et. al. (2003). They find empirically that diversification is a function of the knowledge proximity among technologies. In other words, firms are likely to diversify into technologies that are similar in terms of their knowledge bases. Thus one of the factors that influence the extent of technological diversity is the knowledge base that technologies draw upon.

If range of technological diversity is a function of the knowledge proximity underlying technologies, then understanding the role of individuals as knowledge carriers, integrators, absorbers (which are the bases of production and innovation) is essential to explain the scope of activities of firms, both in terms of production and technological competences.

3.4 Knowledge Base and Organizational Structure of the Industry

A common motive in the literature presented above concerning firm boundaries and diversification, is to construct a relation between organizational structures and the transaction and/or knowledge specific characteristics. However, it also highlights a fuzziness related to the unit of analysis. Network based systems focus on the relations among the actors, while the literature on hierarchies

⁴Grandstrand et. al. (1997) emphasize the following intermediate forms: full scale design competence (the competence to design and test all the components produced externally); systems integration capability (the competence to integrate changes in inputs to products); applied research capability (the competence to pacify and control changes in externally produced inputs); exploratory research capability (the competence to identify and evaluate technological opportunities).

focuses on the internal structure of firms. Moreover, they are largely static in nature, matching organizational structures with innovation types and features. As Kogut (2000) states "the emergence of the structural pattern of cooperation is not the result of an abstract and static choice between market or firm, or market versus hybrid forms of governance" (ibid. 406).

We have argued above that the sense of identity conferred by an organizational setting as well as the routines established within it reduce costs of communication and knowledge transfer. Here identity can be defined as "organizational boundaries which dictate who is (and who is not) a member of the organization; by shared goals and values, and by patterns of interaction among individuals that give rise to a common language and common frameworks for action" (Dyer and Nobaoka, 2000; p. 352).

Based on these discussions, firms and networks share an essential similarity in the sense that both of them are organizations within which transfer of knowledge is facilitated among the members. In the former, the members are employees of the firm. In the latter, the members are firms. Here we can underline the analogy between networks and firms. Both of them establish certain routines within which organizational knowledge is embedded; they form social mechanisms that shape the efficiency with which knowledge is created; they facilitate transfer of tacit knowledge within their boundaries and their evolution is governed by path dependent processes. Moreover, both firms and networks can be seen as emergent systems, to the extent that authority in the firm is taken to be posterior to the formation of the firm. This is the essential argument which enables us to take both organizations as emergent networks and analyse in the further stages, how the knowledge base influences the emergence of these organizational constructs. However, before explanation of our approach, it is better to look more closely at how and why we claim that the knowledge base of an industry can influence the emergence of different organizational structures.

It follows from our discussion in the previous sections that co-existence of specialization and variety in networks finds its close counterpart in the diversification patterns of large hierarchies. But then the question is, why do we see these activities within the boundaries of a large firm in some cases, and distributed to a set of small firms who interact with each other frequently in others? This question has been formulated in a different way by Kogut (2000) who states that internal management of variety at some *point* becomes more expensive than sourcing variety from an external network. The question then becomes, how do the existing theories on firm boundaries explain this critical level above which networking activities among firms intensify?

It is possible to address this question by considering the coherence in the diversification patterns of large firms. In other words, one point of departure to address this question is to explore the role of coherence among the products and technologies in an industry, in terms of the knowledge bases that they draw upon. The coherence in diversification patterns is a result of and also maintained by the human capital within the firm. Human capital can be used to produce a variety of related products (Teece, 1982). There is a limit, in terms of efficiency, to the breadth of different uses to which this tacit knowledge can be put, because of specialization and the path dependent nature of knowledge accumulation. This is mainly why diversifying product portfolio into related products lowers marginal costs (Teece, 1982). On the other hand, there is also a cost-increasing effect of diversification, when implemented within the firm. As the range of specialization areas increase, costs of communication (in the integration and transfer of knowledge among members) and coordination (in setting up structures to exercise authority) also increases. Therefore, only when there is a certain coherence in the knowledge bases of the products would increased diversity be cost efficient when implemented within the boundaries of a firm. On the other hand, less coherent products can increase the costs associated with coordinating variety, thus can be a factor to explain the increased networking activities among firms. Therefore we contend that coherence among the products in an industry is a factor that has an effect on the point where internal management of variety becomes more expensive than sourcing variety from an external network. This can be one of the reasons, "why specialization and variety are antithetical within the firm but define complements within a network" (Kogut, 2000, p.407).

This discussion brings one to the knowledge bases of industries. Industries exhibit differences in terms of the range of knowledge types that are utilized in production. In some industries, the knowledge base is wide, which means that production requires a broad range of different knowledge types. Other industries draw upon a narrow knowledge base. In a similar way, in some industries, a certain area of knowledge is more dominant than others, whereas in some other industries, we see a more dispersed importance of various knowledge types. Empirically, a rough picture can be deduced from patent data, by looking at the technology fields corresponding to the patents of different industries. One of these studies can be found in Patel and Pavitt (1997), where they calculate the percentage shares of different technological activities of 440 large firms in various industries (according to the percentage of patents), categorized according to the principal product group (p. 145). These measures are provided in Table 3.1. For instance, in the case of pharmaceuticals, it can be seen that Chemicals technology is very dominant, with 80% of all patents

Principal Product Group	Chem.	Non elec. mc.	Elec.	Transport	Other
Chemicals	71	16.9	8.9	0.6	2.6
Pharmaceuticals	80.2	8	2.1	0	9.7
Mining and Petroleum	57.1	34.2	6.7	0.9	1.1
Textiles	52.9	31.7	9.5	0.6	5.3
Rubber and Plastics	43.2	29.3	4.7	20.1	2.7
Paper and Wood	25.4	47.1	12.4	0.4	14.6
Food	70.6	21.9	3	0.1	4.3
Drink and Tobacco	40.8	50.3	4.6	0.3	3.9
Building Materials	30.5	51.3	10	0.9	7.3
Metals	26.8	54.9	13.9	2.1	2.2
Machinery	7.6	64.9	13.9	10.2	3.3
Electrical	7.6	21.2	67	1.3	2.8
Computers	5.2	16.3	77.3	0.2	1
Instruments	14.3	18.3	64.2	0.1	3
Motor Vehicles	3.8	44.8	20.7	28.8	1.9
Aircraft	8.1	48.5	31.2	8.3	3.9

TABLE 3.1. Percentage of Principal Product Group's Patents in Technology Field

issued in the activity (leaving 8% in non electrical machinery, 2.1% in electrical machinery, and 9.7% in other fields). On the other hand, in the case of Rubber and Plastic products, the technology base is largely distributed, 43.2% in Chemicals, 29.3% in non-electrical machinery, 20.1% in transport and 7.4% in other fields.

3.4.1 *Firms and Network-based Industries as Self-organizing Communities*

Based on our discussion in the previous sections, a couple of points stand out which prepares the basis of this thesis. Firstly, we argued that authority is a mechanism that is posterior to the formation of firms, and the main function of authority is to coordinate the integration and transfer of the knowledge of diverse actors in the firm. Secondly, we follow Kogut and Zander (1992, 1996), in their explanation of the existence of the firm as a social community within which coordination, communication and learning takes place. Thirdly, we follow Grant (1996) in his emphasis on the role of the firm as integrating the knowledge of diverse specialists. Fourth, we highlight the importance of the knowledge base of the industry in explaining how the boundaries of the firms are shaped. Against this background, the questions that we address in this thesis are: how does the knowledge base influence the structure of the firms,

in terms of specialization, diversification and networking (boundaries problem)? What types of organizational structures emerge under different knowledge bases (existence problem)? Does increased coherence among products, in terms of their knowledge bases, prepare a suitable basis for the dominance of specialized firms with porous boundaries, or diversified hierarchies?

To address these issues, the approach that we undertake in this thesis is to view all organizations, industries as well as firms, as self-organizing systems. Self organization refers to a "dynamic process by which under its own dynamics, a system spontaneously gets more organized" (Morel and Ramanujam, 1998). In the economics literature the recent decade has witnessed a surge of interest in interacting agents models, which suggests that the classical general equilibrium approach with its emphasis on the behavior of a representative agent is quite inappropriate in modeling aggregate economic and social behavior. Any attempt to explain aggregate patterns has to take into account the particular interaction structure among heterogeneous agents, and how it evolves over time. One of the aims of utilizing interacting agents models is to explain emergent global behaviour, and answer the question "why have particular global regularities evolved and persisted in the real world decentralized market economies, despite the absence of top down planning and control?" (Tsfatsion, 2001). In this thesis, we follow a similar approach, and take organizational structure to be an emergent property resulting from the interaction of knowledge embodying individuals (Morel and Ramanujam, 1998). In other words, adopting a bottom-up (Epstein and Axtell, 1996) approach, and taking the unit of analysis as the knowledge-embodying individual is a promising avenue to investigate the self-organizing process of how boundaries between micro (firm) and macro (industry) levels are set.

In most theories of firm boundaries, the problem is analysed by making a static matching between organizational types and corresponding characteristics of the industry, with a few exceptions (see for example, the "history friendly" models, Malerba et. al, 1999). However, our approach is based on the understanding that all organizations are essentially social communities formed by deliberate actions of individual actors, whether in the form of employment contracting or market exchange. Underlying these actions the main motive in the individual level is efficient integration of specialized knowledge for the ultimate purpose of both production and knowledge generation. Then, the knowledge requirements of production should have a role in shaping the evolution of these interactions. Through the interaction of individual actors for the purpose of knowledge integration and production, a ground is prepared for the formation of communities. Within these communities, transfer and integration of tacit knowledge is facilitated compared to the external environment. We take both

the *firm*, and a *network of firms* to be communities, in this sense. Specifically, firms are communities formed by individual actors, and networked systems are communities formed by individual firms. All these communities can be represented as networks, which emerge and evolve in a self organizing manner, and in the absence of an authority to impose a certain structure.

For example in vertically integrated industries, firms can be represented as large vivid clusters with little or no inter-cluster linkages. In network based industries, firms are small clusters with dense relations among the clusters themselves, the boundaries of the firms getting blurred. This approach is based on a decentralized perception of a firm which is especially the case when there is a certain degree of institutional flexibility, such that the environmental conditions favour foundation of new firms (as in the case in Silicon Valley). For this purpose, in the following chapters we carry out a simulation study of evolving networks, where networks form through the interaction of agents. We utilize social network analysis tools to investigate the structure of these networks, to gain an insight into the organizational structures that emerge.

Collaboration in a Simple Economy: Some Analytical Results

4.1 Introduction

In this chapter, we explain the main model and present some preliminary analytical results. The essence of the model captures the conditions under which producers want to collaborate with each other in a simple economy for the purpose of combining their knowledge and producing together. These conditions are included as a variety of parameters measuring the characteristics of the knowledge base and the learning capabilities of producers.

We take a simple economy with two producers, two goods, and two knowledge types. Our aim is to understand how the characteristics of the goods, in terms of their composition of knowledge, as well as the learning process, influence profit-maximising producers' decisions to collaborate.

A major engine that maintains the continuity of interactions in an industry is the transfer and integration of knowledge among producers for the purposes of production and innovation. The pattern of these interactions is largely determined by what is needed in production, in the form of physical inputs or knowledge itself. Forward and backward linkages in an industry essentially capture the first aspect, referring to the physical inputs required in production. The inter-industry relations with reference to the forward and backward linkages has been measured by the use of input-output tables which give an insight into the value of transactions among industries. However, when inter-industry and inter-firm relations based on knowledge input are considered, the picture becomes more blurred, mainly due to the inherent characteristics of

knowledge. How can the pattern of inter-industry relations based on knowledge transfer and recombination be explained? There have been several attempts in the literature, mainly based on patent data to measure the amount of knowledge spillovers within and among industries. (Verspagen et. al., 1994; Jaffee et. al., 1993). Today, we observe in most industries that the recombination of knowledge has become so significant in the value of transactions, that the extent and flexibility with which knowledge is being transferred among actors shapes the organizational structure of industries. The networks formed by interactions of many agents are shaped by the knowledge requirements of production, and the architecture of these networks yield insights into the organizational structure of an industry, in terms of centrality of some actors, or the density of network and similar measures. Since knowledge has become a central asset that shapes these interactions, the network architecture is also a function of the knowledge composition of goods. With the rising importance of knowledge in production, industrial structures are not only determined by the flow of commodities, but more importantly, by the major engine of innovation, which is knowledge recombination among actors and how knowledge is embodied in products.

4.2 The Model

4.2.1 General

Let us consider a simple economy in which there are two producers, two goods and two knowledge types. Producers decide to produce singly or jointly. Joint production occurs only when each of the producers are willing to collaborate, so that collaboration formation is bilateral. If they collaborate they learn from each other, and given their new knowledge levels they give the decision to collaborate or produce singly in the second period. Each of the goods require both types of knowledge in their production, though the intensity of use can be different. Specifically, we assume a Cobb-Douglas production function for each good, with two knowledge inputs and where γ_{mj} measures the extent to which good m is knowledge j intensive (we assume constant returns to scale, so that $\gamma_{m1} + \gamma_{m2} = 1$ for each good). To formalize, denote knowledge input by k , where k_{ij} shows producer i 's knowledge endowment in area j . It follows that the amount of product m that can be produced by i is given by;

$$y_m^i = \alpha k_{i1}^{\gamma_{m1}} k_{i2}^{(1-\gamma_{m1})} \quad (4.1)$$

We assume that there are no competing uses for the knowledge, so that its opportunity cost is zero, and producers use all their knowledge in produc-

tion. We also assume that demand is perfectly elastic so that profits increase monotonically with quantity. We also assume that relative price is unity among the products.

We assume that each of the producers is knowledgeable in both types, but is specialized in only one of them (i.e. knows one type of knowledge more than the other). Let us assume that producer 1 is expert in knowledge type 1, and producer 2 is expert in knowledge type 2, so that $k_{11} > k_{12}$ and $k_{22} > k_{21}$. Singleton production means that a producer performs the production activity by him/herself alone, utilizing his/her own knowledge in both types. Accordingly, if production is to be maximised, he/she will produce that good which uses his expertise area more intensively. We assume that good 1 is knowledge 1 intensive, and good 2 is knowledge 2 intensive, so that $\gamma_{11} > \gamma_{12}$ and $\gamma_{22} > \gamma_{21}$ (Since we assume constant returns to scale, this implies that $\gamma_{11} > 1/2$ and $\gamma_{22} > 1/2$). Then, it is straightforward to show that in the singleton case, producer 1 produces good 1, and producer 2 produces good 2. Specifically, the choice faced by producer 1 can be expressed as, $\max(y_1^1, y_2^1) = \max(k_{11}^{\gamma_{11}} k_{12}^{(1-\gamma_{11})}, k_{11}^{(1-\gamma_{22})} k_{12}^{\gamma_{22}})$. Producer 1 will produce good 1 if the following condition holds;

$$k_{11}^{\gamma_{11}} k_{12}^{(1-\gamma_{11})} > k_{11}^{(1-\gamma_{22})} k_{12}^{\gamma_{22}} \quad (4.2)$$

which is equivalent to

$$k_{11}^{\gamma_{11}+\gamma_{22}-1} > k_{12}^{\gamma_{11}+\gamma_{22}-1} \quad (4.3)$$

and since $k_{11} > k_{12}$ from our assumption above, producer 1 produces good 1. Analogously, when alone, producer 2 produces good 2.

4.2.2 Knowledge Integration and Production

Singleton production is only one of the options that the producer can chose. Otherwise, output can further be increased if both producers integrate their knowledge, produce both goods together and share the final output. In making this choice, we assume that the producer simply makes a comparison between the two cases, and selects the one that yields more output for him. Also, for pairwise production to be realized, both producers simultaneously should find it beneficial. Let us first take the case of producer 1. He/she has to decide between producing good 1 alone, or produce both goods with producer 2 and get half of total production.¹

¹We make the 50% split rule based on the following intuition. If the knowledge levels among the two producers are too different (if one of them is much more knowledgeable than the other), than collaboration

The rule for knowledge integration is as follows: the amount of knowledge that enters the production function is maximum of what each agent knows in each knowledge type.² For effective knowledge integration to occur, it should be the case that $k_{11} > k_{21}$ and $k_{22} > k_{12}$ (which states that no agent has absolute superiority in both knowledge types). When producers integrate their knowledge, the amount of knowledge that enters the joint production function is given by;

$$\text{Knowledge 1 : } \max(k_{11}, k_{21}) = k_{11} \quad (4.4)$$

$$\text{Knowledge 2 : } \max(k_{12}, k_{22}) = k_{22} \quad (4.5)$$

Here, we are interested in the conditions for the formation of a pair. In other words, for which parameter values and initial knowledge levels will the agents simultaneously prefer to produce together rather than alone?

Proposition 1 *In the initial period, two producers will form pairs if and only if the following conditions are satisfied simultaneously;*

For producer 1

$$k_{11} < \left(\frac{2k_{12}^{(1-\gamma_{11})} - k_{22}^{(1-\gamma_{11})}}{k_{22}^{\gamma_{22}}} \right)^{\frac{1}{1-\gamma_{11}-\gamma_{22}}} \quad (4.6)$$

For producer 2

$$k_{22} < \left(\frac{2k_{21}^{(1-\gamma_{22})} - k_{11}^{(1-\gamma_{22})}}{k_{11}^{\gamma_{11}}} \right)^{\frac{1}{1-\gamma_{11}-\gamma_{22}}} \quad (4.7)$$

for $\gamma_{11} + \gamma_{22} > 1$.

Proof. See Appendix ■

Inequalities 4.6 and 4.7 imply that the more is the knowledge of the other producer, the more likely will the producer himself be willing to collaborate. Below, we elaborate further on Proposition 1, in relation to Figure 4.1.

Corollary 2 *When initial major knowledge levels are the same for both producers ($k_{11} = k_{22}$), collaboration will take place in the first period if and only if*

$$k_{11} > k_{12}$$

will not take place in any case, as we demonstrate below. Therefore, the two producers should be sufficiently close to each other in their relative expertise areas if they are to collaborate. Therefore, it is reasonable to assume that they share production output equally. This rule also takes into account the fact that the relative price levels are unity.

² Here we assume that once producers decide to collaborate, then they contribute with all their endowment, in other words they reveal all their knowledge in the production.

$$k_{22} > k_{21}$$

Proof. These conditions are true by our assumptions above and follow by Proposition 1. ■

Corollary states that, if the initial knowledge levels in the major knowledge types are the same, then there will always be collaboration, since by our assumption above producer 1 is an expert in area 1 ($k_{11} > k_{12}$) and producer 2 is an expert in area 2 ($k_{22} > k_{21}$).

To make things mathematically tractable, let us assume that $k_{12} = k_{21} = 1$. Let us also assume symmetrical weights for the two products. That is to say that, $\gamma_{11} = \gamma_{22}$ and which also implies $\gamma_{12} = \gamma_{21}$. As noted above, γ_{11} measures the extent of knowledge intensiveness of the products in their respective expert types.

The shaded areas in Figures 4.1 (a) and 4.1 (b) show the areas in which collaboration will take place as a function of the major knowledge levels. Figure 4.1 is based on inequalities 4.6 and 4.7. The intuition behind the Figure 4.1 is as follows. The intersection point of the curves is the level of minor knowledge type, which is equal to 1 in both figures. Whether collaboration takes place or not depends on the major and minor knowledge levels of producers and the production parameters. Collaboration can only take place when the major knowledge levels are higher than the minor knowledge levels (that is, major knowledge levels should be greater than 1 in Figure 4.1). Corollary states that if the initial major knowledge levels are the same (which corresponds to a 45° line in Figure 4.1), collaboration will take place on the part of the 45° line greater than 1.

Collaboration does not take place in two cases. First when major knowledge types are smaller than minor levels, and second, when the difference between the major knowledge levels among the two producers is very high. This means that expertise level of one producer is too little compared to the other producer. So only within a certain limits of major knowledge levels will collaboration take place, and these limits narrow down as γ_{11} increases (In Figure 4.1 (a) the $\gamma_{11} = \gamma_{22} = 0.9$ and the area of collaboration is smaller than Figure 4.1 (b) where $\gamma_{11} = \gamma_{22} = 0.6$).

Intuitively, this is because higher γ_{11} implies lower γ_{12} , which means that the intensity of the minor knowledge type gets lower. But this means that, the contribution of the partner is lower, which is in the minor category. Therefore the partner should be high enough an expert to compensate for the decreasing weight of the minor category. Consequently, as γ_{11} increases, the area of collaboration falls as shown in Figure 4.1 (a) in comparison to Figure 4.1 (b).

(a)

(b)

FIGURE 4.1. Collaboration conditions for same major knowledge levels

To summarize, the likelihood of singleton production increases as a) γ_{11}, γ_{22} increases and b) when either partners knowledge level is too low compared to the partner him/herself, since then the higher knowing producer will not be willing to participate. These conditions are dependent on each other, which is to say that γ_{11} and γ_{22} determine the difference between the major knowledge levels that result in collaboration. The higher are these production parameters, the less difference is permitted for collaboration to take place (see Figure 4.1 (a)). This result is provided in Proposition 3.

Proposition 3 *The more specialized are the products, the closer the producers should be in their respective expertise fields for collaboration to take place initially. Similarly, the less specialized are the products, collaboration can take place even if the expertise levels are relatively different, i.e. there is a higher difference between their knowledge levels in their respective major categories.*

Proof. See Appendix ■

However, the above analysis is only confined to the first period. As productive activities continue, learning takes place, and knowledge levels are updated. In the sections below, we incorporate learning effects.

4.2.3 Learning

In the previous section, we analysed the conditions under which collaboration occurs in the initial period. In this section, we analyse the behaviour of the system in the second period, as agents gain experience in the production process and accumulate knowledge. We assume that learning takes place in both types of knowledge. It is learning by doing, and the amount learned depends upon the amount produced. Therefore, the extent that producer i learns depend on the level of producer j 's knowledge as well (assuming there was joint production in the first period). In each period, we assume agents re-consider their decision about collaborating, based on the current knowledge levels and previous period's production. If they have collaborated, they have learned from each other, and their respective knowledge levels change. The learning function by which knowledge levels are updated is as follows, given for producer i in knowledge type l (k_{il} denotes producer i 's knowledge in area l),

$$k_{il}(t) = k_{il}(t-1) + \theta_i f(t-1)g(\dots)$$

where

$$g(\dots) = \begin{cases} 1 & \text{if } k_{il}(t-1) > k_{jl}(t-1) \\ \frac{k_{il}(t-1)}{k_{jl}(t-1)} & \text{else} \end{cases} \quad (4.8)$$

where θ_i measures learning capability of the producer to add to his knowledge. Here, $f(t-1)$ is previous periods production, and learning takes place in both knowledge types. The intuition behind this learning function is as follows.

The producer learns in both areas. In his expertise area, he knows more than the partner in the previous period. In this area then, he does not have anything to learn from the partner. Therefore, the learning is only a function of last period's production level (given by $f(t-1)$), and his own capability. This is given by the condition $g(\dots) = 1$ if $k_{il}(t-1) > k_{jl}(t-1)$ in Equation 4.8.³

In the minor area, he knows *less* than the partner in period $t-1$ (since we are looking at the learning in the second period, $t-1$ refers to the initial period here). Here, partner's knowledge level is determining. The less he knows relative to the partner, the less he can learn in this category. This is because it is the partner's knowledge that is used in production, and if the producer's own knowledge in this field is comparably too little, he has limited chances to increase his knowledge in this type too much.

4.3 Collaboration in Subsequent Periods

At this point, one question of interest is, will there be collaboration in the second period once there is a collaboration in the first period? In other words, what maintains the continuity of collaborations? For clarification, we denote period 0 by $t-1$ and period 1 by t .

If there is collaboration in the first period, it follows from the learning functions that the knowledge levels in the second period are as follows:

$$k_{jj}(t) = k_{jj}(t-1) + \theta_j f(t-1) \quad j = 1, 2 \quad (4.9)$$

$$k_{ij}(t) = k_{ij}(t-1) + \theta_i f(t-1) \frac{k_{ij}(t-1)}{k_{jj}(t-1)} \quad i, j = 1, 2 \text{ and } i \neq j \quad (4.10)$$

³This is also the case if the producer has produced singly in the previous period.

Since there is collaboration in the first period, the amount that the producer receives is given by:

$$f(t-1) = \frac{\alpha}{2} (k_{11}^{\gamma_{11}} k_{22}^{\gamma_{12}} + k_{22}^{\gamma_{22}} k_{11}^{\gamma_{21}}) \quad (4.11)$$

The Same Major Knowledge Levels in $t=0$ ($k_{11}(t=0) = k_{22}(t=0)$)

This is the case where one is on the 45° line above 1, in Figure 4.1. In this case, from Equations 4.10 and 4.11, and setting $k_{11}(t-1) = k_{22}(t-1)$ major and minor knowledge grows according to;

$$\frac{k_{ij}(t)}{k_{ij}(t-1)} = 1 + \theta_i \alpha \quad \text{for } i, j = 1, 2 \quad (4.12)$$

From Proposition 1, collaboration will take place in the period $t = 1$ if and only if

$$k_{11}(t)^{1-\gamma_{11}-\gamma_{22}} > \left(\frac{2k_{12}^{1-\gamma_{11}}(t)}{k_{22}^{\gamma_{22}}(t)} - k_{22}(t)^{1-\gamma_{11}-\gamma_{22}} \right) \quad (4.13)$$

$$k_{22}(t)^{1-\gamma_{11}-\gamma_{22}} > \left(\frac{2k_{21}^{1-\gamma_{22}}(t)}{k_{11}^{\gamma_{11}}(t)} - k_{11}(t)^{1-\gamma_{11}-\gamma_{22}} \right) \quad (4.14)$$

Solving equations 4.12, 4.13 and 4.14, with the condition that $k_{11}(t-1) = k_{22}(t-1)$ we get the condition for collaboration in the second period.

Proposition 4 *Given the same initial knowledge levels, and when there is collaboration in the first period, collaboration in the second period continues if and only if the following conditions are satisfied for producers 1 and 2;*
for Producer 1;

$$\left(\frac{\Delta_2}{\Delta_1} \right)^{\gamma_{22}} + \left(\frac{\Delta_2}{\Delta_1} \right)^{1-\gamma_{11}} > \left(\frac{2k_{12}(t-1)}{k_{11}(t-1)} \right)^{1-\gamma_{11}} \quad (4.15)$$

and similarly for Producer 2;

$$\left(\frac{\Delta_1}{\Delta_2} \right)^{\gamma_{11}} + \left(\frac{\Delta_1}{\Delta_2} \right)^{1-\gamma_{22}} > \left(\frac{2k_{21}(t-1)}{k_{22}(t-1)} \right)^{1-\gamma_{22}} \quad (4.16)$$

where $\Delta_j = 1 + \theta_j \alpha$

Proof. See Appendix ■

Proposition 4 states that, the continuation of collaboration in the second period depends on the relative capabilities of producers and production parameters. To interpret these equations, let us take the case of Producer 1, as

given by Equation 4.15. By examining the sign of derivatives of the left hand side function with respect to Δ_1 and Δ_2 , we can see how capabilities of both producers influence the willingness of producers to collaborate in the second period.

Corollary 5 *Given the same initial major knowledge levels, the willingness of producer i to continue collaboration in the second period is higher when a) capability of producer j is higher and his own capability is lower and b) the producer's minor knowledge level is lower.*

Proof. See Appendix ■

The intuition behind corollary is that when the partner's learning capability level is high, he contributes more to the joint production because of a relatively higher knowledge level after learning. This results in an increased willingness of the producer to collaborate, especially the lower is his minor knowledge level (as revealed in the right hand side of Equations 4.15 and 4.16). This proposition simply states that the more capable is a producer in learning, the more attractive he will be in terms of other's willingness to collaborate with him.

Identical Capabilities

For purposes of simplicity, if we assume identical learning capabilities ($\theta_1 = \theta_2$) then we can state the following proposition.

Corollary 6 *If major knowledge levels are the same in the first period, and if the producers are endowed with identical capabilities, collaboration will continue thereafter if and only if*

For producer 1

$$1 > \frac{2k_{12}(t-1)}{k_{11}(t-1)} \quad (4.17)$$

For producer 2

$$1 > \frac{2k_{21}(t-1)}{k_{22}(t-1)} \quad (4.18)$$

Proof. Follows from Proposition 4. ■

Corollary implies that if both producers are endowed with identical capabilities, then collaboration depends on the ratio of minor to major knowledge levels. If the minor knowledge level in the beginning is sufficiently low, the producer will be willing to continue collaboration.

Different Major Knowledge Levels in the First Period

In the previous section, we analysed the conditions under which both producers were equally expert in their respective fields ($k_{11}(0) = k_{22}(0)$). How does the decision to collaborate change if the expertise levels are different in the first period, but still the condition given by proposition 1 is met, so that collaboration takes place? (this means that in Figure 4.1, one is inside the shaded area, but not on the 45° line). How does the relative knowledge differences influence the willingness to collaborate? In this section we analyse the case where major knowledge levels are asymmetric in the first period ($k_{11}(0) \neq k_{22}(0)$). Then the possibilities for collaboration in the second period is given by the following conditions. For analytical tractability we assume that the learning capabilities of producers are the same.

Proposition 7 *If major knowledge levels are different in the first period but capability levels are the same, collaboration will continue in the second period if and only if the following conditions are met for producers 1 and 2,*

For Producer 1

$$k_{11}^{1-\gamma_{11}-\gamma_{12}}(t-1) > \left(\frac{2k_{12}^{1-\gamma_{11}}(t-1)}{k_{22}^{\gamma_{22}}(t-1)} - k_{22}(t-1)^{1-\gamma_{11}-\gamma_{22}} \right) \psi \quad (4.19)$$

where

$$\psi = \frac{(1 + \theta\alpha[(\frac{k_{11}}{k_{22}})^{\gamma_{11}} + (\frac{k_{22}}{k_{11}})^{1-\gamma_{22}}])^{1-\gamma_{11}-\gamma_{22}}}{(1 + \theta\alpha[(\frac{k_{11}}{k_{22}})^{\gamma_{11}-1} + (\frac{k_{11}}{k_{22}})^{-\gamma_{22}}])^{1-\gamma_{11}-\gamma_{22}}}$$

For Producer 2

$$k_{22}^{1-\gamma_{11}-\gamma_{12}}(t-1) > \left(\frac{2k_{21}^{1-\gamma_{22}}(t-1)}{k_{11}^{\gamma_{11}}(t-1)} - k_{11}(t-1)^{1-\gamma_{11}-\gamma_{22}} \right) \phi \quad (4.20)$$

and

$$\phi = \frac{1 + \theta\alpha[(\frac{k_{22}}{k_{11}})^{\gamma_{22}} + (\frac{k_{22}}{k_{11}})^{1-\gamma_{11}}]^{1-\gamma_{11}-\gamma_{22}}}{1 + \theta\alpha[(\frac{k_{22}}{k_{11}})^{\gamma_{22}-1} + (\frac{k_{22}}{k_{11}})^{-\gamma_{11}}]^{1-\gamma_{11}-\gamma_{22}}}$$

Proof. See Appendix ■

Propositipon 7 is interpreted as follows. From Equations 4.13 and 4.14 we know that the conditions

$$k_{11}^{1-\gamma_{11}-\gamma_{12}}(t-1) > \left(\frac{2k_{12}^{1-\gamma_{11}}(t-1)}{k_{22}^{\gamma_{22}}(t-1)} - k_{22}(t-1)^{1-\gamma_{11}-\gamma_{22}} \right)$$

and

$$k_{22}^{1-\gamma_{11}-\gamma_{12}}(t-1) > \left(\frac{2k_{21}^{1-\gamma_{22}}(t-1)}{k_{11}^{\gamma_{11}}(t-1)} - k_{11}(t-1)^{1-\gamma_{11}-\gamma_{22}} \right)$$

FIGURE 4.2. Second Period Collaboration Conditions

are already satisfied since there is collaboration in the first period by our assumption. The new condition imposed by Proposition is shown by Figure 4.2. below which is the same as Figure 4.1 plus the new constraints shown by dark grey areas.

Figure 4.2 is based on the Equations 4.19 and 4.20, and the horizontal and vertical axis are the first period major knowledge levels. Since there was collaboration in the first period by assumption, we are in any point inside the light grey area (this area is the same as Figure 4.1). The second period constraints are revealed by the addition of the dark grey area. Therefore, for collaboration to continue in the second period, the first period major knowledge levels should be somewhere in the total shaded area. If in the first period there was collaboration, this means that collaboration will continue in any case in the

second period too, since the light grey area is covered by the total shaded area (light grey and dark grey).

One important question at this point is, does collaboration always continue in subsequent periods? and if not, what are the conditions under which it may cease to continue? We turn to this question in the following section.

4.3.1 Simulations

Because of the analytical complexity of the model, in this section we present some simulation results concerning collaboration and growth of knowledge in the long run.

Long Run Growth of Knowledge

What is the dynamic of knowledge growth with identical initial major knowledge levels? (From Corollary 2, we know that collaboration takes place in the first period when initial major knowledge levels are identical).

Firstly we analyse system dynamics when one of the producers has a higher capability than the other. The effect of higher capability shows itself in the higher growth rate of knowledge for this producer.⁴ But since the partner's knowledge increases at a lower rate, collaboration continues until it is no longer advantageous for the high-cap producer to collaborate.⁵ In other words, combining knowledge with a low capability producer manifests itself as lower output in subsequent periods and until a critical period in which producing alone generates higher outcome. This critical period depends on the production parameters. The higher is the importance of major type in production, the sooner this period is. The knowledge growth in this case is shown in Figure 4.3.

Figure 4.4 shows the case for the low capability producer. In this case, we see the polar opposite of the case above. Initially, growth is higher than what corresponds to his capability level. Until the point at which singleton production begins, the growth increases, thereafter there is a fall in the growth rate. The growth in the long run converges to the value that could prevail

⁴ Here we take $\alpha = 0.005$, $\theta_1 = 0.9$, $\theta_2 = 0.5$, and $k_{11}(0) = k_{22}(0) = 9$. Therefore from Eq. 4.12 the growth of knowledge of high cap producer in the first period is $1 + 0.9 * 0.005 = 1.0045$, and that of the low cap producer is $1 + 0.5 * 0.005 = 1.0025$. These values can also be seen in Figures 4.3 and 4.4 as long run knowledge growth rates.

⁵ This is because, partner's (here low cap producer) knowledge level does not grow as much as the high cap producer himself, and it is the partner's knowledge that enters production function as long as there is collaboration. Nevertheless collaboration takes place at first because in absolute value, partner's knowledge in major type is still higher than the producer. But low cap producer's capability is not enough to maintain his expertise. Therefore, after a while, the high cap producer leapfrogs low cap producer and collaboration ceases thereof.

FIGURE 4.3. Major Type, Knowledge Growth of High Capability Producer

corresponding to his capability level had he produced singleton. It is possible to see that in both cases, the more is the specialization in products, the sooner the producers shift to singleton.

In the above analysis, we took into account the case where there was collaboration in the first period. Another case of interest in terms of long run knowledge growth levels is the case where no collaboration takes place in the initial period. For this to happen, the conditions stated by Proposition 1 should be violated (outside the shaded region in Figure 4.1). If we assume that the producer who has low initial major knowledge level is the producer who has a high capability of learning, then in later periods collaboration begins, since his high capability compensates in the long run for the low initial knowledge. Thereby the high capability producer will find it beneficial at one point to form a collaboration. However in the very long run, the high capability producer will leapfrog the low capability producer and collaboration will cease again. This case is shown by Figure 4.5. On the other hand, if the low initial knowledge producer is also the low capability producer, collaboration never takes place in subsequent periods. To summarize, in the beginning the low capability producer is the one who prefers to produce alone, but in the very long run, it is the high capability producer who ceases collaboration. The period of collaboration is demonstrated by the temporary increase in growth of knowledge by both producers in Figures 4.5 and 4.6.

FIGURE 4.4. Growth of Major Knowledge, Low Capability Producer

FIGURE 4.5. Growth of Knowledge, Low Capability Producer, No Collaboration in $t=0$

FIGURE 4.6. Growth of Knowledge, High Capability Producer, No Collaboration in $t=0$

4.4 Discussion

In this chapter, we presented some analytical results of the model, taking an economy with two producers, two knowledge types and two products. The results highlight the critical role of complementarities in production. Producers will find it profitable to form a collaboration only when they will get higher production by integrating their knowledge is the basic premise of our model. We investigated the role of parameters in influencing the producers willingness to collaborate in subsequent periods.

We showed firstly the conditions for which collaboration will take place in the initial period, as given by Proposition 1. We also showed with Corollary 2 and Figure 4.1 that the closer are two producers to each other in terms of extent of expertise in their respective fields, the more are the possibilities for effective integration of knowledge (Corollary 2 gives the extreme case wherein both producers have the same level of expertise in their respective fields, which is a sufficient but not a necessary condition for collaboration). The interpretation of this result is straightforward. It states that comparable levels of expertise are more likely to result in collaboration. Take the case of a scientist expert in mathematics and another expert in networks. If a joint paper is to be written, they should have similar relative expertise levels for effective integration. We stated that the more similar are two producers in their respective knowledge

fields, the more possibilities for collaboration. But the degree of this closeness, necessary for collaboration to take place depends on the production parameters. When products are too specialized, the producers need to be even more closer to each other in their relative expertise levels.

We also analysed the conditions for collaboration in the subsequent periods. Our analysis reveals that the conditions to continue collaboration largely depend on relative knowledge levels and relative capability levels. In an extreme case where the initial relative expertise levels are the same, but when producers have different capabilities, collaboration will continue in the second period depending on relative capability levels. There is a negative relation between capability and willingness to collaborate, as we showed in Corollary 5.

Because of analytical intractability, for periods later than the second period, we carried out simple simulations to demonstrate the dynamics of the system. Even if there is collaboration in the initial period, once the capabilities of producers are different, collaboration will cease after a finite time. The period in which collaboration ceases depends on production parameters. The more specialized are the products, the sooner will this be the case.

Although this model gives a basic idea on the logic of the process and is also advantageous in terms of analytical tractability, the real world case is far more complicated than what this simple model reveals. When there are more than 2 producers in the economy, the dynamics are inevitably more complicated, since the choice set of the agent is proportional to the number of other producers, whether to produce singleton or considering all the other producers to collaborate. Moreover, once a collaboration occurs between two agents at a certain period, in the next period, the agents might collaborate with others, and collaborate with each other again in the following period. Also in this chapter we took into account the deterministic case. In real world the extent of learning is highly uncertain. When such situations are taken into account, the dynamics of knowledge and dynamics of interaction is too complex to handle with analytical tools. Therefore, we perform an agent based simulation study, which we further develop in the next chapter.

An Agent Based Simulation Model of Network Formation

In the previous chapter, we considered a simple economy with two producers. In this chapter we extend the analysis to incorporate a larger number of producers, goods and knowledge types, and we carry out a simulation analysis on the resulting interaction patterns among agents. The results reveal that the dynamics of the system change considerably with a larger number of producers, goods and knowledge types.

5.1 Complexity and Relatedness in Products

There is a rich literature that addresses in a broad sense the relation between technology / knowledge specific characteristics and networks. Among these, studies that focus on uncertainty (Hite and Hesterly, 2001; Rosenkopf and Tushman, 1998; Madhavan et. al., 1998); complementarities in goods (Mowery et. al., 1998), similarities in knowledge bases (Stuart and Podolny, 1996) the stage in the industry life cycle (Nesta and Mangematin, 2002); interdependence in products (Frenken, 2000), system embeddedness and observability of knowledge (Birkinshaw et. al., 2001); hierarchical organization of knowledge base (Orsenigo et. al., 1998), characteristics of knowledge in terms of technological opportunities and tacitness (Cowan et. al., 2004) can be cited.

The approach that we use in this model differs from previous studies in two aspects. Firstly, we take the network structure to be self-organizing. Secondly, in capturing product complexity we focus on two dimensions, namely breadth and depth. These dimensions can be used to represent the characteristics of the

knowledge bases of both high-tech and low-tech sectors in the economy, and provides a common basis upon which industries can be compared to each other. Moreover, these dimensions also permit us to derive a measure of relatedness among goods, and highlight how both complexity and relatedness influence networks among actors. As explained in Chapter 3, our aim is to highlight how the characteristics of the knowledge base influence organizational structures and firm boundaries. In this chapter we construct a simple model to see the effect of knowledge intensiveness of goods on resulting network structures and knowledge dynamics. In the next chapter we further develop the model to address the questions raised in Chapter 3.

5.2 The Model

In this thesis, organizations are taken as self-organizing clusters of heterogeneous economic actors who integrate their knowledge and competencies, and maximise their own gains. Networks form in this way, and we are interested in how the structure of these networks respond to different dimensions of complexity. In other words, the goods in the economy require various proportions of different knowledge types in their production and agents integrate their knowledge to produce these goods. This is essentially how networks form. The agents are maximising their own utility, and the interaction among a heterogeneous population of self-interested individuals result in a certain macro structure revealed by the network, which we interpret as industry structure. Such an approach is valuable in the sense that the unit of analysis is taken to be the individual, and the macro-level structure is the result of the interactions among self-interested individuals. The ultimate motivation underlying these interactions is production. Moreover, a significant amount of *new* knowledge, which builds upon existing knowledge, is generated during this process of integrating knowledge by interacting and thus the model stresses the cumulative nature of knowledge. The pattern of these interactions and the pattern of knowledge accumulation is influenced by the ways in which knowledge is embodied in goods.

To model the differences in knowledge base in a stylized form, we distinguish between two dimensions. We introduce the concepts of breadth and depth, as two dimensions characterising the knowledge base of the industry. The breadth of the knowledge base is the range of different knowledge types that production requires. We measure this basically by the *number* of knowledge inputs in the production function of each good. The higher it is, the wider the breadth of the knowledge base (in the analytical model presented in chapter 4, the

breadth of knowledge base was two, since only two knowledge types were used in production). Depth of the knowledge base refers to the degree of dominance of a few knowledge types in production. The more is a good intensive in one type and the less in other types, the deeper is the knowledge base considered to be (in Chapter 4, the depth of knowledge base is measured by γ_{11} and γ_{22}). Using these dimensions of the knowledge base, we obtain a measure of relatedness among the products.

The questions addressed are, how the breadth and depth of the knowledge base influence the network structure and knowledge growth? How are the structure of the network and knowledge growth related? How is the distribution of knowledge among actors affected by these? In the general sense, the aim of the model is to understand how these aspects of products and knowledge are reflected on the organization of production in the industry.

5.2.1 Population and interaction patterns

There are M goods, K knowledge types, and N agents in the economy. Each agent i is endowed with a knowledge vector, $\mathbf{k}^i$ assigned randomly (drawn from a uniform distribution) at period $t = 0$; k_j^i shows the level of agent i 's knowledge in type j . We define expertise of an agent to be that subject in which agent knows most. There exist a knowledge type j for all i such that $k_j^i > k_m^i \forall m \neq j$.¹

Given his/her knowledge vector, each agent in each period produces a good. But an agent can produce singleton, or integrate his/her knowledge with another agent and produce together.

If an agent i produces singly, the probability that he/she will produce good n is proportional to the weight of his expertise type j required by the good.² We adopt the term n -type agent if the agent produces good n . The amount that he/she produces as singleton is given by $y_n(\mathbf{k}^i)$.

Matching

Each agent, in each period t , selects between producing as single or producing in a pair with another agent. In making this decision, the agent's criteria is to maximise his/her output. Therefore, he makes a comparison between his/her joint output with all other agents in the economy and what he/she will produce alone. Joint production happens through integration of knowledge of the two

¹ The knowledge setting used here is first introduced by Cowan et. al (2002). Specifically, $k_{j,t}^i = k_{j,t}^h$ means that agents i and h have exactly the same knowledge in type j . If $k_{j,t}^i > k_{j,t}^h$, agent i knows everything that agent h knows in type j , and has some knowledge in addition.

² If product n uses 90% of knowledge type j , then there is 0.9 probability that agent i produces good n .

agents. When an n -type agent and a m -type agent form a pair, we assume they produce both goods n and m . The quantities are found as follows. It is assumed that if two agents i and l collaborate (n -type and m -type respectively), their joint knowledge in category j is given by

$$k_j^{pair} = \max(k_j^i, k_j^l) \quad \forall j = 1 \dots K \quad (5.1)$$

When an n -type agent i forms a pair with a m -type agent l , the joint knowledge vector, as given by Eq.(5.1) enters the production function, of both goods n and m . If we denote the joint knowledge vector by $\mathbf{k}^{pair}$ the output is shared equally among agents so that the individual output shares is given by

$$y_{n,m} = \frac{y_n(\mathbf{k}^{pair}) + y_m(\mathbf{k}^{pair})}{2} \quad (5.2)$$

Therefore, agent i compares his/her singleton output $y_n(\mathbf{k}^i)$ with $y_{n,m}(\mathbf{k}^{pair})$ with all other agents. Here, it is assumed that agents know the knowledge levels of the other agents. Every agent has a preference listing (other agents ranked according to the maximum output they can produce with him/her). In practice, pairing in the population is made in such a way that no two agents prefer each other to their current partners. As different from the marriage problem, where there are two different populations, this is termed to be the room-mate problem, where pairs are formed within a single population (Gale and Shapley, 1962). Within a similar framework as this paper, Cowan et. al (2002) utilize this matching algorithm for analysing the network dynamics resulting from joint innovation by interaction and knowledge integration of agents.

Production

We consider an economy in which the main input in production is knowledge.³ We assume a Cobb Douglas production function for M goods and K knowledge types, such that the amount of good i is given by

$$y_i(\mathbf{k}) = \alpha \prod_j k_j^{\gamma_{ij}} \text{ where } \sum_j \gamma_{ij} = 1 \quad \forall i = 1, 2, \dots, M. \quad (5.3)$$

Here, k_j is the amount of knowledge in type j , and γ_{ij} measures the intensity of good i in knowledge type j . Since there are M goods and K knowledge types, the corresponding γ values, for each good and knowledge can be represented

³Although we use the term knowledge here, it can be thought of as human capital or competence, so that it accumulates as a result of learning.

by an $M \times K$ matrix which shows the respective parameters of the production function (see below in the simulation section, matrix G).

Learning

In this model, the knowledge levels of agents are updated in every period. The learning process is learning by doing, and is the result of the experience in production. We assume that agents are myopic, so that they do not consider long term effects of learning from the partners that they select.⁴ Learning takes place as production proceeds. We also include an uncertainty term in this learning process, as the details are given in the Equation 5.4.⁵

The following function is used in updating agent i 's stock of knowledge type j :

$$k_j^i(t) = k_j^i(t-1) + \theta_i y(t) g(t) \quad (5.4)$$

$$g(t) = \begin{cases} \delta_i(t) & \text{if } k_j^i(t-1) > k_j^l(t-1) \\ \delta_i(t) \frac{k_j^i(t-1)}{k_j^l(t-1)} & \text{else} \end{cases}$$

where θ_i measures the combinative capability of the agent, and $\delta_i(t)$ is an uncertainty effect. Eq. (5.4) implies that learning is measured by how much the agent can make use of production $y(t)$. This is firstly a function of capability of the agent, as given by θ_i . Second, it is a function of the relative knowledge levels between the partners.

Firstly, if agent i knows less than his/her partner, the amount of his learning is limited by their relative knowledge levels and his/her capabilities. For example, if his learning capability is too high relative to partner, he can even leapfrog the partner.

Secondly, if agent i knows more than his/her partner (agent l) before production, there is only an uncertainty in his ability to make use of production and increase his knowledge. This is because, now there is no other partner from whom he can learn from, since he is already the expert. This is given in the first part of the function $g(t)$. In this case, this can be considered as R&D. Here, uncertainty is given by the parameter $\delta_i(t)$ which is different for

⁴We assume that a complex environment in which agents consider only the short term joint production amounts, and that they cannot predict the amount of learning that will take place in the long run because of uncertainty.

⁵Also see Equation 4.8 for an explanation of this learning function (without uncertainty).

all agents in each period. In this case, the extent to which the agent can add to his/her knowledge depends on his capability to innovate captured by the parameter θ_i , as well as the extent of uncertainty, captured by $\delta_i(t)$.

The knowledge types are updated in *all* the knowledge types that enter the production function of goods n and m , that is, if the agents i and l are n -type and m -type respectively, knowledge is updated in all subjects in which $\gamma_{nj}, \gamma_{mj} > 0, \forall j = 1 \dots K$.

5.2.2 Relatedness among products

In the literature, it is possible to find varying views on the conceptualization of relatedness among artefacts. Breschi et. al (2003) outline three of these as knowledge proximity, knowledge commonalities and knowledge complementarities. Knowledge proximities refer to the result of an intended or unintended local learning process of the firm. More precisely, firms may focus on new technologies that are similar in knowledge bases to their current competencies to make use of spillovers. Knowledge commonalities refer to the case where a firm is active in more than one technology because the same knowledge is used in them. Thirdly, knowledge complementarities refer to the case where one technology in terms of its knowledge base is complementary to another, rather than similarity. In this study, we adopt the second definition of relatedness. In other words, in this study, the increased relatedness refers to increased level of common knowledge between goods.

One of the values that we are interested is the relatedness among two goods. The production parameters can be used to derive a measure of relatedness. We assume that, the more similar is the knowledge requirements of two goods, the more related they are. We measure relatedness among two goods by the cosine of the angle between them.⁶ More specifically, the cosine index between two products n and m is given by;

$$\cos_{mn} = \frac{\sum_{i=1}^K \gamma_{ni} \gamma_{mi}}{\sqrt{\sum_{i=1}^K \gamma_{ni}^2} \sqrt{\sum_{i=1}^K \gamma_{mi}^2}} \quad (5.5)$$

Obviously, $\cos_{mn} = 1$, and if there is no common knowledge between the goods, $\cos_{mn} = 0$. Other cases fall in between the two extremes. Therefore, high cosine values indicate increased relatedness between two products, in terms of similarity in their knowledge requirements. The relatedness between

⁶See also Breschi et. al (2003) for this measure, where they use cosine index to measure relatedness between two technologies by looking at the patent IPC codes.

FIGURE 5.1. A Schematic Representation of Knowledge and Products

the goods is represented by the symmetric matrix $COS(M \times M)$, where cos_{ij} gives the cosine between products i and j .

In the following section a stylised version of the model is presented with some restrictive assumptions (see Chapter 6 for a more advanced version of the model). This version consists of a setting in which all goods have an equal number of knowledge inputs (which means that breadth of their knowledge base is the same), but with different intensities (different depth measures) in each separate simulation. We aim to highlight how the resulting interaction patterns are influenced when goods use one knowledge intensively, or when they have a more distributed knowledge base with equal shares of all goods.

To summarise, the simulation model consists of a population of agents endowed with knowledge in various types. In each period, agents form pairs, selecting their partner according to their joint production. Paired agents pool their knowledge according to Equation 5.1. They produce together according to Equation 5.3 and share total output according to Equation 5.2. In the second period, they update their knowledge levels according to Equation 5.4. Pairs are dissolved, and new pairs are formed with the updated knowledge levels.

5.3 Numerical Simulation

In this basic model, we assume that there are 5 goods ($M = 5$) and 5 knowledge types ($K = 5$) in the economy. Each of these goods uses exactly 3 of these knowledge types (breadth=3). We assume a stylized configuration about the way the knowledge is embodied in the goods. It is possible to represent this by a simple network, as Figure 5.1 demonstrates.

Figure 5.1 shows that each of the goods (shown by p) require three consecutive knowledge types, one of which, shown by the bold arrow, is used more

TABLE 5.1. Representation of the Matrix of Input Coefficients

	k_1	k_2	k_3	k_4	k_5
p_1	γ_1	γ_3	0	0	γ_2
p_2	γ_2	γ_1	γ_3	0	0
p_3	0	γ_2	γ_1	γ_3	0
p_4	0	0	γ_2	γ_1	γ_3
p_5	γ_3	0	0	γ_2	γ_1

TABLE 5.2. The Case of No Relatedness in Goods, Cosine Matrix

	p_1	p_2	p_3	p_4	p_5
p_1	1	0	0	0	0
p_2	0	1	0	0	0
p_3	0	0	1	0	0
p_4	0	0	0	1	0
p_5	0	0	0	0	1

intensively. In this way, two consecutive goods have two knowledge types in common, but what is a major input in one is only minor in the other. The relative weights of these knowledge types is the production parameters of the good. As a demonstration, the G matrix corresponding to this scheme is given by Table 5.1 where the rows and columns represent goods and knowledge types respectively, and γ_{ij} gives the weight of knowledge j in good i .⁷

Since we assume constant returns to scale, the row sums are one (i.e. $\gamma_1 + \gamma_2 + \gamma_3 = 1$). Also there is one knowledge type that is more intensively used than the others, $\gamma_1 > \gamma_2$ and $\gamma_1 > \gamma_3$. The gamma values in different simulations range between two extreme cases: on one hand, we take the case where the goods are totally distinct from each other, where they share no knowledge in common. This corresponds to the case where,

$$\begin{aligned}\gamma_1 &= 1 \\ \gamma_2 &= \gamma_3 = 0\end{aligned}\tag{5.6}$$

Corresponding to this case, the COS matrix is given by Figure 5.2.

In the other extreme, we take the case where relatedness is maximum among the products. Therefore,

⁷In Table 5.1, we do not use double subscripts for purposes of clarity, since the elements of the matrix represent the same numerical values.

TABLE 5.3. Maximum Relatedness among Goods, Cosine Matrix

	P ₁	P ₂	P ₃	P ₄	P ₅
p ₁	1	2/3	1/3	1/3	2/3
p ₂	2/3	1	2/3	1/3	1/3
p ₃	1/3	2/3	1	2/3	1/3
p ₄	1/3	1/3	2/3	1	2/3
p ₅	2/3	1/3	1/3	2/3	1

$$\gamma_1 = \gamma_2 = \gamma_3 = 1/3 \quad (5.7)$$

The corresponding COS matrix is given by Table 5.3.

This specification implies that, relatedness between two consecutive goods, i and $i + 1$ is higher than the relatedness between i and $i + 2$.⁸ The main parameter that is varied in different simulations is the production parameters that are inputs in the production function (given by Eq. 5.3 and Table 5.1). From the production parameters, we derive measures of relatedness using Eq. 5.5 computed by the average of the elements of the COS matrix. In this specification, it is easy to see that as the weight of the major knowledge type falls, the relatedness between two consecutive goods increase and this is when the goods utilize a more distributed set of knowledge inputs. On the other hand increased dominance of the major knowledge type implies that goods are less related, and we call these goods specialized goods (characterised by a deeper knowledge base).

We carry out 40 runs. In each of these runs, a different set of input coefficients are used for the 5 goods. On one extreme, we have the case given by Eq. 5.6 and on the other extreme we have the case given by Eq. 5.7. In between cases consist of parameter which yield intermediate levels of relatedness among the products. We present the results with respect to the relatedness measures, which are derived by taking the average of the cosine matrices that correspond to each set of input coefficients in different runs.⁹

In each of the runs there are 10,000 periods. The population consists of $N = 50$ agents. In each period, matching takes place, pairs form and produce

⁸To see why this is so, see Table 5.1. For example, between products 1 and 2, here are two common knowledge types, namely k_1 and k_2 so that the relatedness among them is higher than products 1 and 3 where they have only k_2 in common.

⁹As an example, in the case where $\gamma_2 = 0.99$ and $\gamma_1 = \gamma_3 = 0.005$, even though there is a certain relatedness between two consecutive goods it is sufficiently small, since only 0.5 percent of a particular knowledge type is shared between them.

according to Eq. 5.3 and agents update their knowledge according to Eq. 5.4. Frequency matrices of size 50×50 is constructed every 500 ± 10 periods (which show the number of times agents i and j have formed a pair in the last 500 ± 10 periods).¹⁰ The results are based on the frequency matrices of the last 500 ± 10 periods, when stability is obtained. The uncertainty parameter $\delta_k(t) \in [0.95, 1.05]$ and capabilities are $\theta_k \in [0.8, 1.2]$.

5.4 Results

We present the results under three parts. The first part presents network density. In the second part we carry out a clique analysis. The third part is concerned with knowledge dynamics and distribution of knowledge in the population. The interpretation and discussion of these results are given in the last section.

5.4.1 Network Density

Firstly we looked at the density of the final networks. It is given by:

$$D = \frac{\sum_{i=1}^N \sum_{j=1}^N x_{ij}}{N(N-1)}$$

where $x_{ij} = 1$ if there is an edge between i and j and 0 otherwise and N is the total number of nodes.¹¹ The denominator measures total number of available links in the network, and numerator measures the number of existing links.

Figure 5.2 depicts two results. Firstly, there is a clear negative relationship between relatedness and network density. As the relatedness among the products increase, the density of the network falls (lowest density occurring for the case of Eq. (5.7) above). Here, the density of the network measures the variety in the network. In other words, if the same agents form pairs all the time, or if production occurs mostly singly, network density is low. High network density occurs when different agents form pairs, which increases the number of links in the network. In this case, we see that highest variety occurs when there is

¹⁰The reason that we used 500 ± 10 periods is to check for cycles that might occur, and to observe the dynamics of the networks. We present the results in the last 500 ± 10 periods, to make sure that the network has stabilized.

¹¹The matrices upon which the density measures are based on is derived from the frequency matrices. When there is a link between two agents, the value is set to 1, otherwise 0. Therefore, an edge between two agents mean that they have formed a pair at least once in 500 ± 10 periods. We use the frequency values in the analysis below.

FIGURE 5.2. Network Density

little relatedness among the products (which means that agents change their partners frequently).

The second result that can be deduced from Figure 5.2 is the discontinuity observed when the products are totally unrelated, that is the leftmost point (corresponding to the case Eq. (5.6) above). Here, it is possible to see that the network density is very low, which means that when the goods are unrelated to each other, either there is singleton production (which will reduce network density), or the agents who are experts in the same type tend to form pairs all the time so that there is no variety in the network.¹² In other words, all agents will produce the goods that require most of their own expertise and if they integrate their knowledge, they do so with agents of the same type.¹³ This discontinuity is also observed in the remaining parts of the results below. Further interpretation of this case is provided in the last section where we discuss the results.

¹²In this case, producing singly is higher than other cases.

¹³Integrating knowledge with another agent of the same type will require that one agent knows one minor type better and the other agent knows the other minor type better so that there is still motivation for integration of knowledge.

5.4.2 *Clique Analysis*

There are various methods to decompose a network into cohesive subgroups.

¹⁴ Among these, one of the most commonly used is a *clique*. A clique is defined as a subset of nodes, all of which are adjacent to each other, and there are no other nodes that are also adjacent to all of the members of the clique (Luce and Perry, 1949). One of the properties of a clique is that there can be overlaps among cliques. This is to say that an actor can belong to more than one clique.

For our purposes, the clique is an appropriate measure to be used as a proxy for the firm. Firstly, it is viable to assume that the actors in a firm are likely to be all connected to each other, while some of the actors in a firm can also be connected to the actors elsewhere in the network. A clique is a useful measure for identifying these connections. Figure 5.3 demonstrates 2 cases. The cliques are specified by the circle frames. In the first case, there are four cliques, each composed of 4 actors, who are all connected to each other in their respective cliques. Here there is no overlapping among cliques, so that all of the cliques are disconnected from each other. In the second case, however, the picture is more blurred where the cliques are not disconnected anymore. In other words, there are actors who belong to more than one clique, and these actors, as intersections among the cliques, are represented within the shaded areas.

If we were to associate one of these systems with a network based system, which one would be the best candidate? In other words, it is obvious to the observer that comparison of Figures 5.3 (a) and 5.3 (b) reveals that there is hardly any networking among cliques in Figure 5.3 (a), whereas Figure 5.3 (b) demonstrates a case in which there is increased interaction among the cliques. This aspect of a clique is particularly what makes it appealing for our purposes. By partitioning networks into cliques, we have the chance to see in which cases the subgroups are relatively more disconnected, and in which cases the extent of overlapping is higher. This gives a basic and stylized intuition about the cases where network based systems are more likely to emerge as different from isolated firms. Therefore, overlap basically measures the porousness of boundaries of subgroups, or firms. We use the extent of overlap among cliques, as given by the shaded area in case (b), as a measure for networking activities among firms.

¹⁴ Identifying cohesive subgroups in social networks has long been an area of interest to sociologists and social psychologists. For a detailed discussion of various approaches in decomposing networks to subgroups, see Wasserman and Faust (1994) and for a review of the concept of a subgroup, see Freeman (1992).

FIGURE 5.3. Cliques

One of the issues of interest is the structure of the cliques. For this purpose, the resulting networks (in the final periods) were partitioned into cliques.¹⁵ Within a clique, all members are connected to each other.

Figure 5.4 shows the number of cliques detected in the final networks. The figure shows that the number of cliques fall as relatedness increases, with the exception of the leftmost point, where the goods are totally independent. This is also related to the density of the network. Increased density implies that different agents form pairs with a variety of other agents, which is reflected in the high number of cliques.¹⁶

Clique overlap analysis is made in the following way. Each clique is taken as a node itself. If c denotes the number of cliques detected for run y , then a matrix $C_y(C \times C)$ is constructed such that c_{ij} shows the number of common elements between cliques i and j . This matrix is taken to be similar to a frequency matrix such that higher c_{ij} implies that the cliques are closer to each other because of the increased number of common elements. The average of this matrix gives a measure of the extent of clique overlap. Figure 5.5 shows this measure.

¹⁵To partition the network into cliques, the software UCINET was used (Borgatti et. al., 2002).

¹⁶Theoretically, the relation between density and the number of cliques, however, is not straightforward. In the case of a complete graph, in which density is highest, there is only one clique. As links are removed, so that density falls, the number of cliques increase. However, this increase is only up to a point. As one continues to remove links, the number of cliques also start falling, and so is the density. In the case presented here, fall in density, as revealed by Figure 5.2 is accompanied by fall in the number of cliques (Figure 5.4).

FIGURE 5.4. Total Number of Cliques and Relatedness

FIGURE 5.5. Clique Overlap and Relatedness

In Figure 5.5 we can see that there is a negative relationship between relatedness and overlap density, with the exception of the discontinuity at the leftmost point where there is no relatedness. In other words, only two cases result in low density; when the goods are totally unrelated, and when the goods are too much related. On the other hand, in the in-between region, where goods are only little related, the overlap density is significantly higher, and falls gradually as relatedness increases.

Cliques and Production

Another measure that is of concern is the extent to which related products are produced within a clique. For this purpose, a relatedness index for each clique is derived taking into account the matrix of the final 500 ± 10 runs.

Each clique is composed of a particular set of agents. Each of these agents has a certain expertise level, which determines which good he produces when he forms a pair. Therefore, each agent is also characterised by a certain product. In this measure, we are interested in the extent to which the goods produced in the cliques are related to each other in terms of the similarity in the knowledge bases.

In devising the measure, the frequency of interactions among the agents in the clique should also be taken into account. Two agents in a clique might have formed a pair only once, which is sufficient to put them in the same clique, but definitely, the relatedness among the goods that they produce together should have less weight in a measure of an overall relatedness for the clique. Therefore, for each clique the total number of interactions is computed by taking into account each combination of pairs. The relatedness among the goods produced by each pair is then calculated with respect to that pair's interaction frequency. That is, a weighted average of overall relatedness is computed, where the weights are specified by the frequency of interaction. Formally, if the total number of interactions in clique m is $CTotInt$, if for any two agents i and j in the clique the frequency of their interaction is given by z_{ij} , if the two agents produce goods k and l , and if the cosine measure of these two goods are $\cos_{kl}$, then the index of relatedness in clique m is

$$rel_m = \frac{\sum_{i \neq j} z_{ij} \cos_{kl}}{CTotInt} \quad \forall i, j \in c_m$$

The aim is to compare this measure of clique relatedness for different underlying knowledge structures. However, for this purpose, one drawback of this measure is that configurations differ with respect to the average cosine values. To overcome this drawback, the *rel* index was normalized with respect to average of the cosine matrix (*avg_cos*) specific to that configuration (av-

FIGURE 5.6. Relatedness in Cliques and Product Relatedness

erage relatedness). So that, if the number of cliques obtained in a particular configuration is c , the final measure obtained for a particular run is;

$$relin = \frac{\sum_{m=1}^c rel_m / c}{avg_cos}$$

Figure 5.6 shows this measure with respect to different specialization levels of goods.

It can be seen in Figure 5.6 that the average relatedness within a clique is very high when products are totally unrelated and extremely specialized (case Eq. (5.6) above). This reveals that, only the agents producing same products form pairs, which is an expected result. As goods become less specialized and as relatedness increases, there is a downward trend in the clique relatedness. This means that diverse agents form pairs only when the goods themselves are highly related. On the other hand, when there is less relatedness, same type of agents tend to produce in pairs.

5.4.3 Knowledge Dynamics

In Figure 5.7 we present the average knowledge levels with respect to relatedness. Despite high variance, it is possible to see a slight fall in average knowledge level as relatedness increases. This also implies that high networking

FIGURE 5.7. Average Knowledge and Relatedness

(high density) also implies high average knowledge levels. Further elaboration of this point is made below in the discussions.

We also analysed the expertise levels, as Figure 5.8 shows, which we measured by the Blau index (Blau, 1977) in the final periods for each run. The weight of knowledge g in the total amount of knowledge for agent i in all types of knowledge is given by;

$$w_g^i = \frac{k_g^i}{\sum_{j=1}^K k_j^i}$$

The extent to which an agent is a specialist (the extent to which the agent knows a certain knowledge type more than the others) is measured by;

$$Exp_i = \frac{1}{1 - (\sum_{j=1}^K (w_j^i)^2)}$$

As Figure 5.8 reveals (showing the average of Exp_i taken over all agents for each run), expertise level is highest when the products are completely unrelated (case Eq. (5.6) above).¹⁷ However, it is interesting to observe that when goods are even slightly related to each other, expertise levels are significantly lower, and increases thereof. Intuitively, this can be explained by the density pattern

¹⁷Because the expertise index is extremely large in this case, it is not shown in Figure 5.8.

FIGURE 5.8. Expertise and Relatedness

as shown in Figure 5.2. When the relatedness is low, density is high (which reveals that there is high variety in the interaction patterns, i.e. different agents form pairs). When this is the case, agents learn in a wider range of knowledge types. Whereas when relatedness is high, there is low density so that same agents join for production. This implies that they learn in a limited number of knowledge types. This increases expertise levels in the population. Further interpretations are provided in the discussions below.

5.5 Remarks and Discussion

In the results section, we presented some analysis concerning the structure of networks and knowledge dynamics. To summarise, firstly it is worthwhile to mention the discontinuity observed in the patterns when there is no relatedness among the goods (Case 5.6 above). This case should be analysed separately from the other cases in which there is a certain relatedness among the goods. In this specific case, agents become very specialized (very high expertise levels), the density of networks is low and within the cliques relatedness among the products are very high. These results suggest that there is very little variety in the network. The agents either produce singleton mostly, or networking takes place among agents of the same expertise types. This is why the network density is very low. Expertise levels are very high, because there is only a

single knowledge type required in production, and agents learn in this type only. Expertise levels also do not change frequently (as observed in some cases below). Obviously, relatedness among the goods within the cliques are very high, because the same products are produced in the cliques and cliques are largely isolated from each other. However, a slight increase in the relatedness produces a completely different result as revealed in various measures as we interpret below. In the following, we focus on the cases in which goods are related to each other.

Our analysis reveal that, there is a clear negative relation between relatedness and network density (Figure 5.2). High relatedness produces low networking. Our results also reveal that both the number of cliques and overlap among them fall as relatedness increases (Figures 5.4 and 5.5). Expertise levels in the industry increase significantly as relatedness increases (Figure 5.8). The results concerning average knowledge levels (Figure 5.7) exhibit a large degree of variance which makes it difficult to arrive at robust conclusions, nevertheless there is a slight negative pattern between average knowledge and relatedness. The high variance is likely to be caused by the distribution of knowledge in the population as well as the heterogenous capability levels.

The results presented above show clearly that as goods become more related to each other, the links become more stabilized in the sense that agents tend to form pairs with the same agents throughout. On the other hand, when the goods are more specialized, there is more variety in the network. While these shed light on the general characteristics of the system, they fall short of answering the question of *why* little relatedness is accompanied with high networking? After all intuition would suggest increased interaction only when the goods are more related to each other.

When two goods are only slightly related, producing together with the expert of the other good enables an agent to experience the production of a good in which his own knowledge is relatively less important, but that of the other agent is very high in weight. Let us consider a hypothetical example of a good with input coefficients $\{\gamma_1, \gamma_2, \gamma_3\} = \{0.005, 0.99, 0.005\}$ and let us take two agents. Agent 1 is an expert in type 2, so that 99% of his expertise is used in joint product. Agent 2 is an expert in type 3, so that only 0.5% of his expertise is used. The final product then embodies most of agent 1's knowledge, which is in type 2. This means that agent 2's knowledge in type 2 may exhibit a large jump, compared to his initial knowledge. At the other extreme, when $\{\gamma_1, \gamma_2, \gamma_3\} = \{0.33, 0.34, 0.33\}$ both partners' expertise levels are approximately equally important in the final product, so that the increase

in knowledge is smoother than the previous case.¹⁸ To summarize, in the first case in the joint output, the weight of the partners expertise level makes significant contribution. This implies that, agents knowledge levels may make large jumps in areas that are different from their own expertise. The important question is why should this have an affect on the network density? The intuition is that, in the initial case large jumps in certain knowledge types cause frequent changes in expertise types. Referring to the example above, agent 2's expertise can change from type 3 to type 2 if he learns significantly in type 2. Then, in the next period, this will change his preference listing of other agents. In this way, there is more variety in the network, instead of the same agents interacting all the time and thus the density of the network increases. To summarize, diversity in the growth of different knowledge types also brings diversity in the choices of potential partners. If an agent's knowledge in one specific area exhibits a certain jump, then in the next period, the agent is likely to exhibit a different preference ordering of the other agents than he did the previous period. This is exactly what causes diversity and increased density in the network. We test this hypothesis by analysing the average number of times an agent's expertise changes with respect to relatedness. Figure 5.9 shows this measure. It is apparent from Figure 5.9 that the number of times expertise changes is much higher when goods are specialized. This is of course not valid when the products are totally unrelated (case (5.6) above). In that case, it is seen that the expertise *never* changes, as expected, since agents learn in only one type of knowledge.

This also explains why in Figure 5.8 the overall expertise levels are much lower when goods require more specialization and that knowledge is more distributed. Expertise areas of agents change frequently, there is more variety in the network, and this results in learning in a wide range of fields so that the knowledge of an agent becomes more distributed in different fields. On the other hand, when there is high relatedness among goods, the increase in knowledge levels are smoother, and proportional to initial levels, with less likelihood of large jumps in other knowledge levels than the expertise areas. As a result, total expertise levels are higher, since learning takes place in the same knowledge types all the time and expertise fields don't change frequently.

If our reasoning outlined above holds true, than large jumps would be expected in certain knowledge categories of the agents (compared to other knowledge types), when products are highly specialized. A large jump in a certain

¹⁸Let us think of two scientists A and B writing a joint paper. The paper requires very little of B's specialization, whereas very advanced level of A's. Unless the knowledge of B is very low in A's expertise, his knowledge in this area will increase more, compared to the case where little of A's knowledge is used.

FIGURE 5.9. Frequency of Change in Expertise and Relatedness

category would be reflected in large standard deviation among growth in all categories for each agent. The data were analysed to test this hypothesis. For each agent, and in each 500 periods, the standard deviation of knowledge growth among different categories were recorded. More specifically, $\Delta k_j^i(n\tau)$ denotes the growth in knowledge type j of agent i from period $(n-1)\tau$ to $n\tau$. If $\sigma_i^{n\tau}(\Delta k)$ denotes the standard deviation in growth of different knowledge types for agent i in period $n\tau$ ¹⁹, then when there is little relatedness and high specialization we would expect a high value of standard deviation among the average taken for all agents, that is;

$$\frac{\sum_i \frac{\sum_{n=1}^{20} \sigma_i^{n\tau}(\Delta k)}{20}}{N}$$

This is shown in Figure 5.10, where the overall trend exhibits a downward movement as goods become more related. There is still one drawback associated with this measure. That is high standard deviation might also be caused by extremely high values a small number of times. To understand the source of the high standard deviation in the case of low relatedness, the number of times the standard deviation was higher from a pre-specified value was computed for all simulations. Figure 5.11 confirms the reasoning, such that the

¹⁹Since there are 10,000 periods in each run, there are a total of 20 windows of observation (10,000 / 500).

FIGURE 5.10. Standard Deviation in the Growth of Knowledge

number of times the standard deviation was above a pre-specified value is much higher, that is, large jumps in knowledge growth occur more *frequently* in the population when there is little relatedness.

An interesting result that was obtained in this model is related to the clique analysis. It was explained above that when goods are specialized, relatedness is higher within the cliques (as revealed by Figure 5.6). This is accompanied with more distributed knowledge in actors and increased density in inter-clique relations. On the other hand, as specialization in goods decreases, cliques are composed of more diverse actors (as revealed by Figure 5.6) which is accompanied with stability; i.e. same actors tend to link all the time and less networking among the cliques (Figure 5.5). Moreover, as Figure 5.8 shows, the extent of expertise increases. While the model assumptions are highly restrictive, these results seem to support the reasoning underlying network based systems. In these systems, high networking yields increased innovation, firms are more specialized, while intensive links among themselves.

The assumptions in this version of the model are highly restrictive. For one thing, it is unreasonable to expect that all the products in the industry have the same structure in terms of the diversity and level of the knowledge they embody. Secondly in this model, we look at the effect of depth when breadth is held fixed, therefore capturing complexity in only one dimension. In the next

FIGURE 5.11. Frequency of Large Jumps in Knowledge Growth

chapter, we release these assumptions and incorporate changing breadth. How do networks and knowledge evolve when both breadth and depth is changed?

Network Dynamics: Effect of Breadth and Depth of Knowledge Base

In the previous chapter we presented a basic simulation model. In this model some restrictive assumptions were made regarding the way knowledge is embodied in goods (in particular, each good used exactly three types of knowledge in production). In this chapter we present a more advanced version of the model by relaxing some of these assumptions.

In the literature, complexity in the knowledge base have been taken in various ways. One of the commonly used frameworks is related to the number of components and interdependence among them (Simon, 1969; Zander and Kogut, 1995; Kauffman, 1993). Wang and Tunzelmann (2000) define two dimensions of complexity as breadth and depth. Complexity in depth refers to “analytical sophistication of a subject which becomes complex because of the cognitive difficulty in pushing the particular matter to its logical extremes” (p.806). Whereas complexity in breadth refers to “the range of areas that have been investigated to develop a particular subject”. In short depth is concerned with the level of sophistication and breadth is concerned with the level of heterogeneity. Defined in this way, product complexity in breadth refers to the embodiment of a larger number of components/assemblies which makes up a product, whereas depth dimension refers to the degree of cognitive complexity embodied in these components. Therefore changes in complexity in one dimension does not necessarily influence complexity in the other.

We take these two dimensions of complexity to describe how knowledge is embodied in products. How does the complexity of products in these two dimensions map into the structure of networks among economic actors? In other

words, how are the networks of economic actors influenced by the complexity in products? What can be inferred about the organizational structure with respect to the knowledge bases? How do the characteristics of the knowledge base influence the specialization and diversification patterns of firms?

In this version of the model, we also model the impact of innovation on network structure. In this setting, we model innovation as a change in the breadth and/or depth dimensions of knowledge base. In other words, a process innovation can be modelled as changing the breadth, depth, or both dimensions of the knowledge base. The questions that we address are, how does the knowledge growth and network dynamics respond when there is an exogenous innovation, and what is the effect of the nature of innovation? Our results reveal that innovation has a significant impact on the growth of knowledge and network structure in the periods following it, but the precise dynamics depend on the *nature* of innovation. Specifically, highest knowledge growth and network density results when the innovation increases both the breadth and depth of the knowledge base. This result has implications for the innovation strategies pursued by firms, in the sense that it highlights how networks and knowledge growth are influenced by moving from one point to another in the breadth and depth space, and that not all types of innovations increase growth of knowledge in the long run.

6.1 Goods and Knowledge Configuration

In this chapter, the structure of the model is the same as in the previous chapter with regard to the functions employed. However, we use a different configuration of goods. There are $M = 5$ goods and $K = 5$ knowledge types. Each of the goods is characterised by a vector of knowledge input coefficients, and consequent breadth and depth measure.

For any good, the breadth of the knowledge base is the range of different knowledge types that its production requires. We measure this by the number of coefficients in the production function that are greater than zero. Goods with minimum breadth use only two types of knowledge inputs, and goods with maximum breadth use 5. The higher it is, the wider the breadth of the knowledge base. Depth refers to the dominance of a single knowledge type in the production of the good. We measure this by the standard deviation of the coefficients. The higher the standard deviation among the coefficients, the deeper the knowledge base.¹

¹See Appendix for the derivation of the knowledge input coefficients that are used in simulations, and an example set of input coefficients.

6.2 Simulations

To recall the dynamics of the model, population consists of agents who are knowledgeable in a diverse range of knowledge types. In each period, each agent makes a preference listing of all other agents in terms of decreasing joint output. Matching takes place and pairs form in this way. Paired agents integrate their knowledge and produce together. After production, their knowledge levels are updated and pairs dissolve.

We perform 36 runs. In each of these runs there are 5000 periods. In a single run, a certain knowledge-good configuration is taken exogenously. In the Appendix, an example set of goods is provided for a set of 36 runs.² In each of the runs, the same population is used (same initial knowledge stocks and capabilities). Minimum breadth corresponds to a good taking 2 knowledge types as input, and maximum breadth corresponds to a good utilizing all 5 knowledge types.³

We repeat this procedure (36 runs) 20 times. In each of the 20 repetitions, we use a different population. The results presented below are the averages taken over the 20 repetitions.

The population consists of $N = 50$ agents. The uncertainty parameter $\delta_k(t) \in [0.95, 1.05]$ and capabilities are $\theta_k \in [0.8, 1.2]$. A single run consists of $T = 5000$ periods. What can we infer about the network characteristics in the breadth and depth space?

6.2.1 Relatedness among goods

One of the values that we are interested is the relatedness among two goods. For this purpose, we use the cosine index, as explained in detail in the previous chapter. We assume that, the more similar is the knowledge requirements of two goods, the more related they are.

Obviously, $\cos_{jj} = 1$, and if there is no common knowledge between the goods, $\cos_{mj} = 0$. Other cases fall in between the two extremes. Therefore, high cosine values indicate increased relatedness between two products, in terms of similarity in their knowledge requirements. The relatedness between the goods is represented by the symmetric matrix $COS(M \times M)$, where $\cos_{ij}$ gives the cosine between products i and j .

²Each of these matrices is an input to a single run (5 goods, 5 knowledge types). There are 36 matrices, which makes 36 runs.

³See Appendix, bottom matrices show the goods that take 2 inputs, top matrices show goods that take 5 inputs.

FIGURE 6.1. Relatedness Among Goods in the Breadth and Depth Space

Relatedness among goods (i.e. cosine indices) are derived from the production parameters. For each set of goods in the breadth and depth space, we calculated the average of the cosine matrices. Figure 6.1 gives these measures. It is easy to see that relatedness among the products are highest with highest breadth and lowest depth (upper left corner), which is expected. Because in this area, all the goods utilize all the 5 knowledge types in equal weights.

As breadth increases, relatedness increases, as depth increases, it decreases. The question is how the network and knowledge evolves in the breadth and depth space?

6.2.2 Network Dynamics

In this section, we present the analysis of final networks. In the simulation runs we take into account the networks obtained in the final 500 ± 10 periods, when stability is achieved. The results presented below are the average values of these final networks taken over the 20 repetitions.

Density

The density of the network measures the number of connections per agent.⁴ It is given by,

⁴Density measures how "crowded" the network is with respect to connections between different pairs, also see Chapter 4 for a definition.

FIGURE 6.2. Network Density in the Breadth and Depth Space

$$D = \frac{\sum_{i=1}^N \sum_{j=1}^N x_{ij}}{N(N-1)}$$

where $x_{ij} = 1$ if there is an edge between i and j and 0 otherwise and N is the total number of nodes. We are interested in the density of the network in the parameter space defined by breadth and depth of the knowledge base. Figure 6.2 shows the results obtained for the final networks, in the last 500 ± 10 periods when stability in the networks is achieved.

As can be seen in Figure 6.2, average density in the final networks is highest in the upper right corner. In this area, knowledge base is broad and deep. Goods utilize a wide range of knowledge types, but one of them intensively. Two areas also stand out in this figure, where density is low. These areas are upper left corner, and the area in which breadth of the knowledge base is lowest (the lower region in Figure 6.2). In the remaining regions, we see moderate density. It is interesting to observe that network density does not increase monotonically. From lowest breadth onwards, as breadth increases, the effect of depth on density rises. In other words, as one goes up in Figure 6.2, the depth has a more pronounced effect on density. When breadth is maximum, we see a big difference between high depth and low depth regions, where the high depth region is characterised by maximum density.

FIGURE 6.3. Knowledge, Breadth and Depth

6.2.3 Knowledge Dynamics and Expertise Levels

In this section we investigate the knowledge dynamics in the breadth and depth space. Figure 6.3 shows the average knowledge for all simulations with respect to depth of knowledge base. It can be seen that increased depth increases the average knowledge significantly. Also the effect of depth on knowledge is more pronounced when breadth of knowledge base is higher (this is also the case for density, as mentioned above). The largest knowledge accumulation occurs when depth and breadth are at the maximum which also corresponds to the area where density is maximum (see Figure 6.2).

Figure 6.4 shows individual expertise. We measure the expertise levels by the Blau index, the details of which were presented in the previous chapter. It can be seen that expertise falls monotonically as breadth increases. But when breadth gets higher, we see that effect of increasing depth is to reduce expertise as can be seen in the upper parts of the Figure 6.4.

Perhaps a more realistic measure of the expertise indices can be obtained by normalizing with respect to the breadth of knowledge base. This is because, as breadth of knowledge base increases, there are more areas that the agents learn, which tends to reduce expertise. Therefore we also computed a normalized measure of expertise, as given in Figure 6.5. In this Figure, we see that expertise falls breadth increases, but only until a point; this is to say that when breadth

FIGURE 6.4. Expertise Index

is too large, agents become more experts despite having many different areas in which they learn.

What is more important for our purposes is to understand the structure of the networks and cohesive subgroups. What kind of clustering activities take place, and what do the cliques look like in the breadth and depth space? What can we infer about specialization and diversity in these cliques, as well as overlap among them? How is the structure of networks mapped in the breadth and depth space? To answer these questions, we perform a network analysis and a clique analysis, and partition the resulting networks into cohesive overlapping subgroups to be used as proxies for the firm.

6.2.4 Cliques

In this section, we partition the emergent networks that we obtained under various breadth and depth measures, into cliques.⁵

Firstly Figure 6.6 shows average product diversity in cliques. Each clique consists of a number of agents each of whom produces one type of good. Product diversity is measured by the number of different types of goods a clique produces weighted by the number of clique members producing it and the average taken over all cliques in a single run.⁶ We also normalize diversity

⁵To partition the network into cliques, the software UCINET was used (Borgatti et. al., 2002).

⁶The weighted average is taken by using the Blau index (Blau, 1972). For example, if a clique consists of two *i*-type agents and one *j*-type agent (3 agents), then the weight of good *i* is higher than that of good *j*

FIGURE 6.5. Normalized Expertise Index

FIGURE 6.6. Product Diversity in Cliques

FIGURE 6.7. Knowledge Diversity in Cliques

FIGURE 6.8. Product Relatedness within Clique

FIGURE 6.9. Expertise within Clique

FIGURE 6.10. Overlap Among Cliques

with respect to average clique size. Figure 6.6 shows this measure.⁷ As it can be seen, diversified firms exist mainly in the upper left corner. In this region, knowledge base is broad, and all types of knowledge have equal weights in production, i.e. depth is low. As shown in Figure 6.1 this is the area corresponding to maximum relatedness among the goods. This figure shows that the cliques in other regions are more specialized in what they produce.

Having distinguished between product diversity and knowledge diversity above, Figure 6.7 depicts a measure of knowledge diversity. We measure this by the *number* of knowledge types that are greater than a 20% of average knowledge in the clique. This is generated from the final knowledge vectors of the agents forming the clique. The comparison between Figure 6.6 and 6.7 is interesting since it underlines the distinction between product diversity and knowledge diversity. Most of the regions that are specialized in terms of production are characterised by high knowledge diversification.

Figure 6.8 shows within clique relatedness. We compute this measure as follows. We calculate the relatedness among the goods produced in each clique (i.e. if two *i-type* agents and one *j-type* agent are members of a clique, the relatedness in this clique is $(\cos_{ii} + \cos_{ij} + \cos_{ij})/3$). A few observations in Figure 6.8 is that in the upper left corner, where diversity is maximum (see Figure 6.6), there is also high relatedness among goods, which is not surprising, since the goods themselves are already highly related in this region (Figure 6.1). What is more interesting is that the upper right region, despite very low relatedness in the goods themselves (see Figure 6.1), is characterized by cliques that produce goods which are highly related (which implies that usually the same goods are produced within a clique, or there is very little diversity, which is also evident from Figure 6.6).

This observation is also confirmed when we look at Figure 6.9, which gives the within clique expertise levels. This measure is the standard deviation of all knowledge levels of all agents in a clique, normalized with respect to the mean knowledge in the clique. It is possible to see in the upper left region that knowledge specialization is low, which is also the region where product diversity is high (see Figure 6.6). Conversely, in the upper right region, product diversity is low, and there is high level of expertise building. It might seem contradictory that it is also in this region that we see high knowledge diversity (Figure 6.7).

therefore diversity in this clique should be lower than one in which there is one *i-type* and one *j-type* (equal weights). Blau index is given by, $(1 - \sum weight^2)$. To make values comparable, we multiply this by number of goods divided by the corresponding maximum achievable index. In this way we obtain exactly 2, when 2 different goods are produced with equal weight, and an index slightly smaller than 2 when the weight of one good is higher.

⁷The values are the averages for all 20 simulations.

But this implies that, the agents forming the clique are knowledgeable above a critical level (20%) in many areas, but in general an average clique is still characterized by high knowledge expertise. In other words, a diverse range of other areas are known considerably, but still relatively less than the expertise subject.

What is more interesting for the purposes of our analysis is the overlap figure, given by the Figure 6.10. Basically, this is the measure we use for intensity of inter-clique relations. Overlap is defined as the number of agents common to a pair of cliques. We report the average over all possible pairs of cliques. Looking at Figure 6.10, we see that one region stands out with maximum overlap among cliques. This is the region, with broadest and deepest knowledge base, which we associate with network industries. This region is characterized by low product diversification, high specialization, high knowledge diversification, and high overlap among cliques.

6.2.5 *Summary*

To summarize our findings, we decompose the breadth and depth space into four regions. This is given in the Figure 6.11.

In the first region goods have narrow knowledge bases. Consequently, many pairs of goods have no knowledge in common, i.e. a cosine index of zero. Therefore, the average relatedness among goods is also low (Figure 6.1). As a result there is little reason for diverse agents to form pairs. Our results here reveal that, integrating knowledge with an agent who produces a related good is more likely than two agents joining to produce goods that have no knowledge in common. Instead, there is very little variety in pairs, and same agents integrate with the same ones throughout. As a result, average product diversity in a clique is quite low (Figure 6.6), because same types of agents come together. In addition, firms' knowledge is highly specialized (Figure 6.7). If goods draw upon a narrow knowledge base, and if the same types of agents form pairs, then they learn in a limited number of knowledge types, and no learning takes place in other knowledge types. This increases specialization. In this region, overlap is also low. This is also because of the narrow knowledge base. There is hardly any basis for increased inter-clique overlap, if there is no common knowledge among goods. In other words, agents have no relevant knowledge to contribute to each others production.

Region 2 is characterized by moderate knowledge breadth. This region is a transition from a narrow base to the widest base, after which the depth begins to influence the network structure.

FIGURE 6.11. Industrial Structures in the Breadth and Depth Space

When the knowledge base is at its broadest, we observe the emergence of two distinct regions; 3 and 4, corresponding to shallow and deep knowledge bases respectively. In region 3, breadth is wide, and depth is low. This implies that the goods are closely related to each other (Figure 6.1). It is in this region that high product and knowledge diversification, low knowledge specialization, and high good relatedness accompany each other. These characteristics suggest that this is the region of multi-product firms. Also in this region, inter-clique relations are not intense: cliques are more cohesive and isolated implying that firm boundaries are not porous. Why do we observe this pattern here?

An important point is that in this region, network density is quite low. In this sense, this region also resembles region 1, where the same pairs form repeatedly throughout the simulations. But the difference here is that different types of agents come together (agents producing different goods can form pairs here, since all the goods use the same knowledge types in similar amounts, which is to say that good relatedness is very high, as shown in Figure 6.1), as revealed by high product diversity. This is in contrast to the pattern in region 1, where typically agents of the same type interact.⁸ When the goods in an industry are closely related to each other, there is a certain rigidity in interactions such that the same agents (of different types) tend to come together all the time. In region 3, within clique relatedness of goods is quite high despite significant product diversification in a clique. Paradoxical as this may seem, it is because of the fact that goods themselves are highly related as seen in Figure 6.1.

Finally, the structures that emerge in region 4 resemble network industries. In this region, we observe high firm specialization, knowledge diversification and low product diversity together with high inter-clique overlap. Moreover in this region, despite very low relatedness among the goods themselves (Figure 6.1) at the aggregate level, goods produced inside cliques are highly related to each other, which is also evident from the high product focus.

A wide and broad knowledge base underlines the importance of complementarities in network systems. All goods draw upon a common knowledge base, but a major input in one good is only a minor input in another. When the knowledge base is deep, (meaning when goods are specialized), but still draw upon a wide knowledge base, they are related (since they all utilize same set of knowledge types) but only weakly. The specialization subject of one good is only a minor input in another good. This decreases the value of the relatedness index, while commonality ensures all goods are more or less related to each other. Here in this region, we see that complementarities are more sig-

⁸One of the reasons that not only the same types but also the same agents interact in this part is because of the stable matching algorithm.

nificant than other regions, and there are increased gains from integration of knowledge.

When regions 1 and 4 are compared, both regions are characterized by low relatedness in goods. One might expect at first glance that this is a factor which might trigger intensive networking, because it underlines the importance of complementarities in knowledge base. However, low relatedness in region 1 is because of a narrow knowledge base. In region 4, it is because of high depth. It is when the knowledge base is broad and deep that we see efficient integration of knowledge, and emergence of network industries, as seen in region 4.

According to Mowery et. al. (1998) there is an inverted-u relation between cognitive distance among actors and gains from integration. They carry out an empirical study to show that if the knowledge overlap is too high among firms, there is nothing to be gained. If too distant, there is limited cognitive ability to understand. In this chapter, we consider the structure of the goods explicitly, and explain how the distance between two goods in knowledge space is mapped onto the interactions among agents who embody the knowledge the produce these goods. We find that if goods are too distant, then there is little networking. If the goods are too close, there is also less networking. Only at an in-between distance among goods do we see intensive networking.

6.3 Innovation

To this point, the set of goods have been defined exogenously and do not change within a run. However, we did not look at system dynamics when there is innovation that changes the structure of the goods in terms of the knowledge they embody. In this section we investigate network and knowledge dynamics when there is an innovation which changes breadth or depth of the goods in the economy. To analyse this, we repeated the above simulations by imposing a change in the structure of the goods in the randomly selected period. The simulation run covers 10,000 periods.⁹ Every 500 ± 10 periods, the frequency matrices (showing who interacted with whom and how many times in the last 500 ± 10 periods) are recorded. The results below show the densities of these networks. We also recorded knowledge growth and expertise levels every 500 ± 10 periods. We investigate the following types of innovation in terms of their effect on goods:

1. Depth increasing innovation: This type of innovation occurs when the weight of a certain knowledge type in production increases. In other words, the

⁹We took the random innovation period to be 5000 ± 100 periods after the initial period.

FIGURE 6.12. Knowledge Growth Effect of a Depth Increasing Innovation

product becomes more intensive in the use of a certain knowledge type. This can occur in two cases in the framework of our model, with a wide knowledge base and with a narrow knowledge base. In both cases, less of other knowledge types and the more of a certain type is utilized. What is the effect of this type of innovation on knowledge growth? Figure 6.12 shows this measure. It can be seen that the extent of knowledge growth depends on the breadth of knowledge base. When the knowledge base is wide, the effect of a depth increasing innovation is to increase the growth of knowledge. Whereas when the breadth is narrower, knowledge growth falls.

Figure 6.13 shows the influence on expertise levels. It can be seen that depth has only very little effect on expertise, consistent with Figure 6.5 above.

Is there a relation between the network density, knowledge growth and expertise? For this purpose, the Figure 6.14 demonstrates the network density in response to a depth increasing innovation. It is seen that network density increases only when the breadth of knowledge base is wide. Otherwise, density remains constant except a temporary period of increase.

2. Depth Reducing Innovation: This type of innovation in our model occurs when the weight of a dominant knowledge type in production is reduced and knowledge base becomes more distributed. In this case, the innovation can occur in two cases, first when breadth of knowledge base is wide and second when breadth is narrow. Figure 6.15 show the knowledge growth, in both cases,

FIGURE 6.13. Expertise Effect of a Depth Increasing Innovation

FIGURE 6.14. Network Density Effect of a Depth Increasing Innovation

FIGURE 6.15. Knowledge Growth Effect of a Depth Reducing Innovation

the influence of a depth-reducing innovation is to reduce knowledge growth, the effect is more pronounced when the knowledge base is narrower.

Figure 6.16 shows that reduction of depth has no effect on expertise. However the same does not hold true for density. When depth reduction occurs in a wide knowledge base, network density increases (this corresponds to a move from Region 4 to 3 in Figure 6.11).

To summarize, our results reveal that the influence of increased depth on knowledge and networks depends on the breadth of knowledge base, but for expertise levels where depth has no influence. When the knowledge base is narrow, knowledge growth falls.

As far as density is concerned, our previous results are confirmed. In other words, as long as breadth is wide, increasing depth results in an upward jump in network density. However, when the innovation is depth reducing, the opposite effect does not take place. In other words, when the network density is high in the beginning, it remains high, although from a simple examination of static results a depth reducing innovation should be expected to produce a fall in network density (A move from region 4 to 3 in Figure 6.11). This shows that there is path dependence in the system when the initial network density is high, it continues to be high despite the effect of a density-reducing innovation.

3. Breadth Increasing Innovation: This type of innovation occurs when new knowledge types are included in the production of a good. This type of

FIGURE 6.16. Expertise Effect of a Depth Reducing Innovation

FIGURE 6.17. Network Density Effect of a Depth Reducing Innovation

FIGURE 6.18. Knowledge Growth Effect of a Breadth Increasing Innovation

innovation can occur in two cases, firstly when a certain knowledge type is dominant in production (i.e. when depth is high) and second when the depth is low, that is when the knowledge base is distributed. Figures 6.18 and 6.19 below show knowledge growth and expertise in the two cases.

Figure 6.18 shows that the effect of a breadth increasing innovation depends on the depth of the knowledge base. When knowledge base is deep, increasing breadth increases the growth rate of knowledge temporarily. When the knowledge base is distributed, inclusion of new knowledge types reduces the growth rate of knowledge. It is seen that the growth effects are only temporary and the previous growth rates are achieved soon after the innovation. However, these temporary changes in growth rates influence the knowledge levels.

With a broader knowledge base, Figure 6.19 shows that expertise falls in both cases, which is an expected consequence because new knowledge types are included. However, the extent of fall in expertise depends on the depth of knowledge base; when knowledge base is distributed, expertise falls less than the case when knowledge base is deep. Figure 6.20 shows the effect on network density. We see that only with a deeper knowledge base the network density increases significantly in response to this type of innovation, otherwise only a temporary rise in network density is observed.

4. Breadth reducing innovation: Breadth reducing innovation occurs when the knowledge base gets narrower, some of the knowledge types are

FIGURE 6.19. Expertise Effect of a Breadth Increasing Innovation

FIGURE 6.20. Network Density Effect of a Breadth Increasing Innovation

FIGURE 6.21. Knowledge Growth Effect of a Breadth Reducing Innovation

eliminated. Therefore complexity in the breadth dimension is reduced. Figures 6.21 and 6.22 show knowledge growth and expertise respectively in this case.

Contrary to the breadth increasing innovation, this time knowledge growth falls, regardless of the depth of knowledge base. Therefore, reducing the number of knowledge types has an effect of reducing knowledge growth significantly but only for a short period. Following the innovation, it is seen that the knowledge growth is lower than the previous rates.

It can be seen that the effect of a breadth reducing innovation is to increase expertise levels in both cases when depth is both high and low. Figure 6.23 shows network density in this type of innovation. It can be seen in the figure that the network density reduces considerably in response to a breadth reducing innovation, the effect being more pronounced when knowledge base is deeper.

5. Combination Cases:

Apart from the breadth and depth increasing/reducing innovations, an innovation can also influence both breadth and depth simultaneously. Therefore, here we focus on four such cases, as Figures 6.24, 6.25 and 6.26 show the effect on knowledge growth, expertise and network density of all these.

When an innovation is both depth and breadth increasing, then the knowledge base expands, and at the same time becomes more distributed. This means that more knowledge types are included in production and their weight

FIGURE 6.22. Expertise Effect of a Breadth Reducing Innovation

FIGURE 6.23. Network Density Effect of a Breadth Reducing Innovation

FIGURE 6.24. Knowledge Growth Under a Combination of Change in Breadth and Depth

in production becomes more or less equal. It can be seen in Figure 6.24 that this is the only case where there is an increase in the knowledge growth in the period of innovation, which is revealed by a sudden increase, and settles down thereafter, though at a higher level than growth before innovation. Interestingly, in all other cases, knowledge growth falls. This is in compliance with the results above, whenever either breadth or depth reduces, knowledge growth falls.

Figure 6.25 shows the expertise levels in the population corresponding to the four types of innovation. It can be seen that it is mainly the breadth of the knowledge base which determines the effect on expertise, and depth has no effect on expertise levels. Only when breadth of knowledge base expands, expertise falls (higher levels of this measure correspond to reduced expertise and more distributed knowledge of the agents). Contrarily, when breadth of the knowledge base gets narrower, the influence is to increase expertise, which is an expected result. This is also in compliance with our results above. We saw that in the case of depth innovations, the expertise levels were not influenced. It was in the case of breadth innovations that major changes in expertise levels were observed.

Figure 6.26 shows the network density for the four type of innovations. Two cases stand out. One of these is when knowledge base expands and gets deeper.

FIGURE 6.25. Expertise Effect of Combined Changes in Breadth and Depth

From above, this is the region that we have associated with network industries. This significantly increases the network density.

One important observation is the case of breadth decreasing and depth decreasing innovation. In this case knowledge base shrinks and gets more distributed as well. The system starts with a high network density. After the innovation, network density reduces significantly.

This shows that, the initial dynamics of the system can be determining in what happens thereof. But this is not always the case: here we can look at two cases above, depth reducing and breadth reducing innovation (see Figures 6.17 and 6.23 above). When depth is reduced in the high breadth area (from region 4 towards region 3 in Figure 6.11 above) then networking continues to be intensive. However, when the innovation is breadth reducing (from region 4 towards region 1 in Figure 6.11 above) then network density falls immediately. When the two cases occur simultaneously (breadth reducing and depth reducing in Figure 6.26 then the breadth reducing effect is dominant in determining the outcome, that is to say that network density falls down, despite the possible increasing effect of shrinking depth.

FIGURE 6.26. Network Density Under a Combined Change in Breadth and Depth

6.4 Concluding Remarks

In this chapter, we focused on the dynamic processes that lead to the emergence of network based systems. These systems are characterized by specialized firms with intensive inter-firm relations, which blurs the boundaries of firms. In exploring the dynamics of these industries, we aimed to answer the question, what characteristics of knowledge base lead to networked industries? We defined two dimensions of the knowledge base; breadth and depth. Breadth of the knowledge base is the range of knowledge types that the industry draws upon. Depth of the knowledge base is the extent to which a few knowledge types are dominant in production. Based on these dimensions, we computed a measure of relatedness among goods. Relatedness is highest when knowledge base is wide and depth is low. Relatedness is low when either knowledge base is narrow, or when knowledge base is wide and deep.

Based on the simulation study of a population of knowledge carrying agents who chose other agents with whom to integrate their knowledge and then produce, we analysed the dynamics of the networks that emerge from these interactions. Specifically, we analysed the resulting network structures under various regimes of breadth and depth of knowledge base.

We then partitioned the resulting networks into cohesive subgroups. Social network analysis offers a wide range of possibilities to partition networks into

cohesive subgroups, according to various criteria. Among these, we used the concept of a clique, and partitioned the resulting networks into cliques. We used the clique as a proxy for the firm, and under various knowledge base regimes, we analysed the structural characteristics of the cliques. The results highlight three regions of interest. First, when breadth of knowledge base is narrow, what emerge are specialized firms with high product and knowledge focus, and with relatively weak inter-firm relations. As breadth gets wider, we see the emergence of two distinct regions. In one of the regions, the knowledge base is shallow. This means that all goods utilize the same types of knowledge in similar amounts, and thus relatedness among goods is high. Here, we see multi product firms, which are technologically diversified, but inter-firm relations are not intensive. The last region is the one in which network industries are likely to emerge. Here, the knowledge base is broad and deep. Firms are specialized, they are technologically diversified, but still they have high product focus. Only in this region do we see intensive inter-firm relations.

Our results tend to be consistent with most theories of the firm. The literature on multi-product firms underline coherence in patterns of production, which, in our model, corresponds to high relatedness among goods, and we observe this in the region that we associate with multi-product firms. On the other hand, technological diversification is a common phenomenon in most of the firms that we observe today, as revealed by a recent and rich literature. One of the motives underlying technological diversification is to coordinate the changes in the supply chain, as well as gaining competence in a diverse range of fields to utilize technological opportunities. These imply that technological diversification is associated with increased external collaborations for firms. We use knowledge diversity in the firms as a measure for technological diversification. As our results reveal, the knowledge base of the industry can be determining here, in the sense that only if it is broad and deep do we see technological diversification and increased networking at the same time. In this case, we also see increased product focus despite high technological diversification, and we claim that this is the area in which network based industries are likely to emerge.

One important result that we obtained is concerned with the effects of innovation on knowledge and network dynamics. Here we showed that, if innovation is modeled as a change in breadth/depth or both dimensions of knowledge base, its effect largely depends on the interaction between breadth and depth. In other words, we cannot isolate the effect of depth or breadth on network and knowledge. There is also a path dependent effect of an innovation on network density: when the knowledge base is wide and deep, a depth reducing

innovation does not reduce the network density, despite we would expect so from the results presented above.

Our results concerning the influence of innovation have implications for innovation strategies pursued by firms. Not all types of innovations result in higher knowledge growth and more interaction among actors. Moving from one point to another in the breadth and depth space has differential impacts on knowledge growth, expertise and network density, which should be taken into account.

Breadth and Depth of Main Technology Fields: An Empirical Study

Recently, work on technological change has emphasized the importance and implications of different nature of knowledge bases of both industries and firms in terms of their effect on innovative performance (Nesta and Saviotti, 2004) and organizational structure (Orsenigo et. al, 2001; Dosi and Hobday, 1999; Prencipe, 2000; Brusoni and Prencipe, 2000). Research in this area suggests that in some industries, products and processes have become more complex, as well as there appears to be increased convergence in some market segments which obviously influences the efficient choice of organizational structure. For example the literature on complex product systems stresses the importance of the harmony between complexity in products and organization structure. In addition, an expanding area of research is concerned with the characteristics of the knowledge base of firms as well as industries, drawing a distinction between technology and product boundaries (Brusoni and Prencipe; 2000; Brusoni et. al 2001).

For the case of pharmaceuticals, Brusoni et. al (2004) measure the breadth and depth dimensions of the knowledge bases of largest firms, and conclude that the profiles of specialization are significantly different among firms. Nesta and Saviotti (2004) analyse the diversity and coherence (where diversity and coherence are used in a similar framework as breadth and depth) of knowledge base of pharmaceutical firms and conclude that both have a positive and significance influence on innovative performance of the firm.

The simulation model presented in previous chapters is largely abstract in nature, which permits us to apply it to a wide range of contexts in which the

essential argument can be tested. One of these essential arguments as revealed by our results is that, the density of the networks formed by economic actors is higher when goods are both specialized and at the same time draw upon a wide knowledge base. In this chapter, our aim is to apply this model in the real world to show the differences in the knowledge bases of main technology fields and also to test empirically the effect of breadth and depth on network density. We aim to answer questions like, which technology fields draw upon a wide knowledge base? How do the characteristics of knowledge bases influence the density of networks among actors? To address these, we take the patent to be a product, and position 30 main technology fields in the breadth and depth space by utilizing the EPO/CESPRI database. We construct a measure of breadth and depth for each patent taken in the period 1978-2000 according to technology field. The first part of the chapter is concerned with the description of how breadth and depth measures are derived. We measure breadth by the range of different technology fields that a patent includes in its IPC (International Patent Classification) list. The depth of the patent is measured by the extent to which a patent draws upon a certain field more intensively than others, also measured by using the IPC list of the patent. We present how breadth and depth has evolved through time in these technology fields. We also position the patents taken by 40 largest firms (in terms of the patents granted) in two knowledge intensive sectors biotechnology and telecommunications, in the breadth and depth space and highlight that not only technological fields, but also firms differ in terms of their knowledge bases.

In the second part of the chapter, we test empirically the validity of the simulation results by a simple regression model, in which we take the product to be a patent. We carry out a regression analysis of the density of firm-based inventor networks and firm-based breadth and depth measures. More precisely, we analyse how the density of inventor networks is influenced by the breadth and depth dimensions of patents. The results confirm our simulation results and reveal that there is a significant interaction effect of the breadth and depth of patents on the density inventor networks, such that highest network density occurs when both breadth and depth are at their maximum.

7.1 Breadth and Depth of Main Technology Fields

In this section, we present our analysis of breadth and depth of 30 main technology fields, the evolution of breadth and depth in selected knowledge intensive technology fields, as well as an analysis of the breadth and depth dimensions of largest firms in two sectors, namely biotechnology and telecommunications.

FIGURE 7.1. Number of Patents in the Database

7.1.1 Data

We use the EPO/CESPRI database which includes all the patents granted by the EPO between the years 1978 and 2000. We include 668,947 patents, excluding those that do not have a secondary IPC code. A patent document is a rich source of information, since it contains information on the relevant technology codes related with the subject matter of the patent, which is given by the 8-digit IPC code. A patent document is assigned a main IPC code, as well as secondary codes. The patents in the sample are partitioned into 30 main technology fields based on their main IPC codes. This classification has been prepared by Fraunhofer Gesellschaft-ISI (Karlsruhe), Institut National de la Propriété Industrielle (INPI-Paris) and Observatoire des Sciences et des Techniques (OST, Paris) and it is mainly composed of an allocation of IPC codes into technology fields. The distribution of patents in the sample period, according to technology fields are given in Figure 7.1.

Before proceeding with the explanation of the breadth and depth indices, it is useful to briefly mention the structure of the IPC system.

7.1.2 Structure of International Patent Classification (IPC)

In the IPC system, there are 8 sections revealed by the first digit of the code; classes, which are revealed by the first 3 digits, which are in turn divided

into subclasses; and groups, as revealed by the first 6 digits. An example is A21B01/06. In this example, A is the section which is covered under the heading of human necessities. A21 is the class (baking) and A21B is the subclass (bakers ovens, machines or equipment for baking). A21B01 is the group level and A21B01/06 is the subgroup level, which corresponds to bakers ovens heated by radiators. Each patent granted by the EPO has a main IPC code, and secondary codes. To calculate the breadth and depth measures, we utilize the IPC list of the patent in both main and secondary codes. The main IPC code of the patent is used to assign the patent to one of the technology fields, and the secondary codes are used to measure the breadth and depth dimensions of the patent in terms of its coverage.

7.1.3 Breadth

The breadth of the patent measures the width of different technology fields that the secondary IPC list of a patent in a certain technology field covers. The more the different types of technology fields a given patent extends to, the wider its knowledge base taken to be. For this purpose, we use several different measures, to test for robustness of our results.

The first measure is based on a direct count of the number of secondary IPC codes of a patent in different technology fields, other than its own technology field (patents own technology field is given by its main IPC code). Formally, let $I = \{1, \dots, 30\}$ represent the 30 technology fields, and $\Gamma_{ij} = \{k \in I \setminus \{j\} \mid x_i(k) = 1\}$ represent the set of technology fields of the IPC list of the patent i which is in technology field j , and $x_i(k) = 1$ if the patent has an IPC code in field k . Then the breadth of this patent is given by $b_{ij} = \# \Gamma_{ij}$. The breadth of the technology field is the average of the breadth over all patents in this technology field;

$$B_j = \frac{\sum b_{ij}}{N_j}$$

where N_j is the total number of patents in technology field j .

One disadvantage of this measure is that it assigns an equal weight to all the technology fields with respect to their relatedness. In other words in devising a breadth measure, one should take into account the relative relatedness between the technology field of the patent and the other technology fields that it covers. For example, the technology fields biotechnology and pharmaceuticals are relatively more related to each other than pharmaceuticals and electrical engineering. In this case, if in the IPC code of a pharmaceuticals patent there exists an IPC code that belongs to electrical engineering, this field should have

FIGURE 7.2. Weighted and Direct Count Breadth Measures for 30 Main Technology Fields

a higher weight in the breadth, than an IPC code which belongs to biotechnology. In the second measure that was developed, we took into account the relatedness among technology fields, based on the relatedness measures devised by Breschi et.al. (2003). Here, the relatedness among technology fields is calculated based on the citation rates.

For a patent i in technology field j , weighted breadth is:

$$b_{ij} = \sum_{k \in I} x_i(k)(1 - R_{jk})$$

where R_{jk} is the relatedness between fields j and k .¹

Figure 7.2 reveals that, the technology fields are significantly different from each other in terms of their breadth measures. In most fields, the breadth measure increases when we weight with respect to relatedness, with the exception of biotechnology and organic chemistry where the breadth measures decrease, mainly due to the fact that although the patents in these fields have a significant average number of IPC codes in other technology fields, these are mainly in highly related areas. Overall, it can be seen that the relative breadth of fields remain constant even when adjusted for relatedness, which basically

¹See Breschi et. al (2003) for the matrix of relatedness weights among 30 technology fields.

confirms the robustness of our breadth measures. In the rest of the chapter we use the weighted measures.

7.1.4 Depth

The depth measure is conceptually less straightforward than breadth. Depth of a patent refers to the extent to which the patent is specialized in a certain field. Therefore, a patent may have both high breadth and high depth, if, for example, it draws upon a wide range of different aggregated fields (which will be reflected in the breadth measure), but also in a certain aggregate field it utilizes a high number of detailed fields.

The first measure of depth that we employ is based on the number of IPC codes of the patent which are the same as the technology field of the patent itself. Formally, let $I = \{1, \dots, 30\}$ represent the 30 technology fields. If patent i is in technology field j , $\Gamma_{ij} = \{k^j \in I \mid x_i(k^j) = 1\}$ represent the set of IPC codes of the patent which is in technology field j , ($x_i(k^j) = 1$ if the patent has a secondary IPC code in field j), namely its own technology field as revealed by the main IPC code. Then the depth of this patent is given by $d_{ij} = \# \Gamma_{ij}$. The depth of the technology field j is the average of the breadth over all patents;

$$D_j = \frac{\sum d_{ij}}{N_j}$$

where N_j is the total number of patents in technology field j . Therefore, the depth measures the extent to which the patent is concerned with its own technology field. Although this measure provides a rough idea on the analytical sophistication of the patent, a more precise measure should take into account the structure of the IPC codes themselves. In other words, the IPC list of the patent may include many IPC codes from the same technology field, but would this mean that the patent is “deep”? Within its own technology field, the patent may still be drawing upon different knowledge types rather than exploiting a certain knowledge unit in depth. To capture this, we made a more detailed analysis of the specific IPC codes of the patent.

An important point here is that two IPC codes can differ in many levels, including section level (e.g. **A01N57/12** and **B03B01/10**), class level (**A01N57/12** and **A02L01/00**), subclass level (**A01N57/12** and **A01L01/10**), group level (e.g. **A01N57/12** and **A01N47/10**), subgroup level (**A01N57/12** and **A01N57/09**). This hierarchical categorization gives an idea about the extent to which the subject matter of the patent is exploiting a certain field in depth. In particular, a high number of IPC codes in lower levels of hierarchy implies that the more

refined the subject matter of the patent is. Let us consider two extreme cases. In high levels of hierarchy, A01N57/12 and B03B01/10 differ in the section level, if the patent includes these two codes at the same time in its IPC list, it means that it draws upon two very different knowledge areas. On the other hand, in the IPC list of the patent, if we see A01N57/09 and A01N57/12 at the same time, the patent draws upon one specific knowledge type in detail, with many aspects of it, namely the area A01N57. According to this approach, the repetition of lower hierarchy levels reveal increasing depth of the patent.

Taking this into account, we weighted the above depth indices, with respect to an index of dominance that was calculated on the 6 digit level. As mentioned above, we define the depth of the knowledge base to be the dominance of some knowledge types in the patent. For this purpose, we construct a depth index, that measures the extent to which the patent is specialized, e.g., relying intensively on a small number of subjects.

To construct an index of depth, we calculated the frequency that each subgroup repeats in the IPC list of the patent, and thus the percentage of this subgroup. We assume that the higher is the weight of particular subgroup, the deeper is the patent.

To calculate a measure of dominance of a certain subgroup, we utilize the Blau index (1977). For a patent i in technology field j , The index is calculated as follows:

$$w_{ij} = 1 - \sum a_{ik}^2$$

where a_{ik} is the proportion of a certain subgroup k in patent i . Higher values of the Blau index indicate that all knowledge types are utilized in similar proportions, whereas smaller values indicate the intensive use of some knowledge types over others. Therefore, *lower* values indicate a *deeper* knowledge base (more specialized). One disadvantage associated with this index is that depending on the breadth of the patent, the maximum and minimum of the index is different, so that the index cannot be used as it is to compare patents of different breadth measures. This is to say that, when there are a higher number of different subclasses, then this will be reflected in a larger possible maximum value of the index. To be able to make the depth measures comparable, we divide the depth measures obtained by the number of items in the IPC list of the patent. We use these depth measures as weights in the number of technology fields in the same area as the patent, given above by d_{ij} . In other words, we are not only concerned with the extent to which the patent draws upon knowledge in its own technology field, but also the extent

FIGURE 7.3. Weighted and Direct Count Depth Measures for 30 Main Technology Fields

to which a certain subject matter is utilized in depth by the patent. The final depth measure for technology field j is given by;

$$D_j = \frac{\sum d_{ij}(1 - w_{ij})}{N_j}$$

The Figure 7.3 demonstrates weighted and non-weighted depth measures for each technology field.

As can be seen in the figure, there are significant differences among technology fields in terms of the depth of patents, and the relative depth measures are robust with respect to the two measurement techniques. In the section below, we place the technology fields in the breadth and depth space.

7.1.5 Breadth and Depth

Figures 7.4 and 7.5 show the breadth and depth of the 30 technology fields by direct count and weighed techniques respectively. It can be seen that the results in both methods are very robust, and the relative position of technology fields preserve their position in the breadth and depth space. Biotechnology is markedly different from other fields in terms of having the highest breadth and depth measures.

It is possible to see in these figures that technology fields are significantly different from each other with respect to their breadth and depth measures.

FIGURE 7.4. Breadth and Depth of 30 Main Technology Fields- Direct Count

FIGURE 7.5. Breadth and Depth of 30 Main Technology Fields, Weighted

TABLE 7.1. List of Technology Fields

1	Electrical Engineering
2	Audiovisual Technology
3	Telecommunications
4	Information Technology
5	Semiconductors
6	Optics
7	Control Technology
8	Medical Technology
9	Organic Chemistry
10	Polymers
11	Pharmaceuticals
12	Biotechnology
13	Materials
14	Food Chemistry
15	Basic Materials Chemistry
16	Chemical Technology
17	Surface Technology
18	Materials Processing
19	Thermal Processes
20	Environmental Technology
21	Machine Tools
22	Engines
23	Mechanical Elements
24	Handling
25	Food Processing
26	Transport
27	Nuclear Engineering
28	Space Technology
29	Consumer Goods
30	Civil Engineering

FIGURE 7.6. Evolution of Breadth in Selected High Tech Fields

Few observations stand-out from these figures. The results seem to be very robust to the measure used which confirms the relative position of technology fields with respect to each other in the breadth and depth space whether we use direct counting or weighting. Biotechnology and organic chemistry stand out in terms of highest breadth and depth. Telecoms and semiconductors have very low breadth measures.

7.1.6 Evolution of Breadth and Depth 1978-2000 (30 Main Technology

Fields)

Figures 7.6 and 7.7 present the evolution of breadth and depth in time for selected technology fields.

A general pattern is that for most fields, the breadth measures remains more or less stable, with the exceptions of telecoms, biotechnology and organic chemistry. For the telecoms, the knowledge base seems to have become more focused (fall in breadth and increase in depth), while the opposite holds true for biotechnology and organic chemistry where the knowledge base expanded. For the depth measures, it is possible to see that nearly in all fields, the depth increases, which is a consequence of the increased specialization in most knowledge-intensive sectors.

FIGURE 7.7. Evolution of Depth in Selected High Tech Fields

7.1.7 Breadth and Depth of Largest Firms

In this section, we perform an analysis of the patents held by the largest firms in biotechnology and telecoms. For this purpose, we assign the patents to the firms, and calculate the average of breadth and depth measure for the largest firms in biotechnology and telecoms. Formally, if patent i is taken by firm j , and if the corresponding breadth and depth of patent i are b_{ij} and d_{ij} , the breadth and depth of firm j is given by:

$$b_j = \frac{\sum_i b_{ij}}{n_j} \quad (7.1)$$

$$d_j = \frac{\sum_i d_{ij}}{n_j} \quad (7.2)$$

where n_j is the total number of patents taken by firm j in the period 1978-2000. The Figures 7.8 and 7.9 show our results for the two sectors biotechnology and telecoms.

7.2 Breadth, Depth and Density of Inventor Networks: A

FIGURE 7.8. Breadth and Depth Measures of the Largest Biotechnology Firms

FIGURE 7.9. Breadth and Depth Measures of the Largest Telecommunications Firms

Regression Analysis

In the previous two chapters, an agent based simulation study was performed in which actors performed joint production by integrating their knowledge. We analysed the structure of networks that emerge from these interactions under different regimes of the knowledge base. In this model, we focused on the emergence of various network structures. At the same time, we found that both breadth and depth of the knowledge base influences the overall network density, and there is also an interaction effect such that density is highest where both breadth and depth are at their maximum levels. More specifically, the effect of both breadth and depth depends on the level of the other variable.

In this section, we perform an empirical study by focusing on the relation between network density and the breadth and depth measures. We take the essential arguments behind the simulation model as the basis of this model, but apply it in a different framework than the industrial structures. In particular, we take the product as a patent, and the inventors in a firm as the producers of it. The general abstractness of our simulation model makes it very suitable to apply its general premises at different levels of aggregation. Our aim in this regression analysis is to understand the influence of the breadth and depth of patents on the inventor network densities. Therefore, we apply the model on a different level of aggregation, such that the average breadth and depth measures for a firm are taken as explanatory variables (as given by Equations 7.1 and 7.2), and the density of inventor network in the firm is taken to be the dependent variable.

Each of the patents has an inventor list. In the firm-based network constructed, a link between inventors i and j exist when both of these inventor names appear in the same patent. In this way, a network of inventors is constructed for each firm in our sample.

Breadth of a firm measures the range of different kinds of technology fields of the patents held by the firm. The depth of the firm measures the extent to which the patents held by the firm is specialized in a certain field. The intuition behind our model is as follows. It is possible to assume that in large firms which constitute our sample, inventors are specialized in different technology fields, and participating in the same patent refers to an integration of different areas of specialization by these inventors.² Hypothetically let us consider that a certain firm has patents in a range of different technology fields. If we consider

²In particular, this is expected to be the case when the patent draws upon a wide range of different technology fields (when the breadth is high). As explained below, otherwise a high depth patent can be considered the joint efforts of inventors specialized in similar fields.

a single patent taken by the firm, a large breadth implies that various types of technology fields are contained in the subject matter. In this case, then, we can expect a larger number of inventors to have contributed to this patent, which increases the number of links among *diverse* types of inventors in the network.

Taking this in the background, what can we infer about the interaction effect between breadth and depth on their joint effect on network density? In other words, how does the density contribution of a high breadth firm change with its depth? For this case, consider a patent high in depth. Higher depth means that a patent is utilizing intensive knowledge mainly in its own technology field. In this case, there is a high degree of specialization in a certain area, which requires a high degree of tacit knowledge transfer among inventors specialized in similar fields. In other words, in this case we can expect a high degree of cliquishness among the actors of the same specialization field which increases network density.³ In this case, instead of a diverse range of inventors participating (as in the case of breadth), similar inventors participate more frequently who are all specialized in similar technology fields.

To summarise our discussion above, both breadth and depth individually is expected to have a positive effect on network density. In particular, breadth increases network density because it requires joint efforts of different types of inventors, and depth increases network density because it requires a highly cliquish structure in which inventors of the similar fields need to integrate their knowledge.

Combining these two arguments concerning the individual effects of breadth and depth on density, we can infer that the density of the network within the firm will be higher when both breadth and depth is high. In other words, when depth is high, which reveals a richness in interaction among specialists of the same area (and thus high cliquishness), an increase in breadth will incorporate different specialists into the network which will tend to increase the density of the network. The opposite holds true for the high breadth patents. When breadth is high, increased depth will have a more pronounced effect on density. Combining these arguments, we can set the following hypothesis.

Hypothesis: The network density depends on the combined effect of breadth and depth. The positive effect of breadth on network density will be more pronounced for higher values of depth, and the positive effect of depth on network density will be more pronounced when the breadth is high.

³High cliquishness refers to the case where, if two actors are linked, the other actors with whom they are linked separately are also linked to each other, thus increasing the network density.

Dep. Variable:	Density /	NoInv				
Ind. Variable	Mod 1	Mod 2	Mod 3	Mod 4	Mod 5	Mod 6
Intercept	0.0017** (2.03)	0.0014 (1.966)	-	0.0013* (1.69)	-	-
Breadth	-0.003* (-1.87)	-0.0025 (-1.70)	-	-0.0026* (-1.73)	0.0007*** (6.11)	-
Depth	-0.0014** (-1.97)	-0.0012 (-1.69)	-	-0.0012 (-1.56)	-	0.0003*** (5.58)
Int. Effect	0.0029** (2.23)	0.0026 (2.04)	0.0005*** (6.16)	0.0025* (1.89)	-	-
NoEmploy	-	7.94e-10 (1.13)	1.0E-9 (1.63)	-	-	-
NoPatent	-9E-8*** (-3.04)	-1.17E-7 (-3.17)	-3.6E-8*** (-3.3)	-	-8.7E-8*** (-3.12)	-9.5E-8*** (-3.09)
Adj R ²	0.35	0.37	0.5	0.21	0.45	0.41

*t-statistics in paranthesis

TABLE 7.2. Regression Models

One disadvantage associated with taking directly density as the dependent variable is that, it causes a problem in terms of the comparability of different firms. This is because the total number of inventors in each firm in the sample is different, and a higher number of total inventors may result in lower density measures. To take into account this effect, we ran a different set of regressions in which we took the dependent variable to be the normalized density measures, obtained by dividing the density by the total number of inventors in the firm, therefore obtaining a measure of density per inventor. In the second set of simulations, we performed regressions for the two technology fields separately.⁴ The control variables used are the number of patents and the employee figures.

Table 7.2 shows the aggregate regression results. In some of the models, we excluded the intercept term, since it was insignificant. In the models 5 and 6, we included breadth and depth only with the control variable number of patents. It can be seen that in both models, the coefficients of the breadth and depth are positive and significant. This means that, absent interaction effects, both breadth and depth has a positive influence on network density. The first four models include interaction effect. In this case, the coefficients of breadth

⁴Two firms in the sample are excluded because they are outliers, Incyte and Genencor, whose density measures were significantly higher than others (and the breadth and depth measures of Incyte is also significantly different from other firms).

Dep. Variable:	Density / NoInv			
Ind. Variable	Biotech 1	Biotech 2	Telecom 1	Telecom 2
Intercept	-	-	0.01** (2.83)	0.01** (2.72)
Breadth	-0.0009 (-1.28)	-0.0006 (-1.09)	-0.029** (2.74)	-0.03** (-2.59)
Depth	-0.0004* (-1.77)	-0.0002 (-1.16)	-0.011** (-2.81)	-0.01** (-2.7)
Int. Effect	0.0016** (2.27)	0.0014** (2.20)	0.027** (2.75)	0.025** (2.63)
NoPatent	-	-5.2E-7** (-2.66)	-	-5.5E-8* (-1.72)
NoEmploy	-	-	-	-
Adj. R ²	0.43	0.5	0.19	0.27

TABLE 7.3. Biotechnology and Telecommunications Regression Models

and depth are negative, whereas the coefficient of the interaction effect is positive and significant. A positive interaction coefficient and negative variable coefficients point to the fact that breadth (depth) has a positive influence on network density for higher values of depth (breadth). In particular, we can depict this argument by taking the derivatives and finding the threshold values of variables.

$$\frac{d(\text{density}_j)}{d(\text{breadth}_j)} = -0.0025 + 0.0026(\text{depth}_j)$$

$$\frac{d(\text{density}_j)}{d(\text{depth}_j)} = -0.0012 + 0.0026(\text{breadth}_j)$$

It can be seen that for depth >0.96, the density of the network increases with an increase in breadth. For values of depth smaller than the threshold, the breadth has a negative effect on network density, although small in absolute terms because of the counter-effect of depth. In other words, the effect of breadth on network density depends on the level of depth, and unless depth is absolutely small, the effect is positive.

The same observation holds true for the effect of depth on network density. For very small values of breadth (critical threshold of 0.47) the effect of depth on network density is negative, but small in absolute terms. The positive effect rises with increasing values of breadth. These point to the fact that breadth has a positive effect on network density, which is more pronounced for higher levels of depth.

Table 7.3 gives the regression results separately for the two industries. It can be seen in Table 7.3 that in the case of biotechnology the signs of coefficients of breadth and depth are negative and the interaction effect is positive as expected. In the second model, the R^2 is higher, and in this model, the signs of breadth and depth are negative but not significant. The sign of interaction effect is positive and significant in accordance with the aggregate model. For the case of telecoms, the results are very strong, such that in both models the signs of breadth and depth is negative and interaction effect is positive and all coefficients are significant. The employment figures are included in some of the models, but since the effect was not significant, it was not included in others shown here.

To summarize, in the models that we have analysed, the higher is the breadth (depth) the lower is the negative effect of depth (breadth) on network density. After the threshold levels are passed, the higher is the breadth (depth) the higher is the positive effect of depth (breadth) on network density which confirms our initial hypothesis that the effect of breadth and depth on network density is significant and is positive for higher values of the other variable. As far as the separate industries are concerned, the effect of breadth and depth is significant in the case of telecoms, whereas they are not as significant in biotechnology. However, in both cases, there is a positive and significant interaction effect coefficient. These empirical results are in accordance with the simulation model presented in the previous chapters.

Conclusions

In the first chapter, I provided an introduction to the topics raised in this thesis. In the second chapter, I presented a survey of literature on economic networks. The aim of this chapter was to highlight the rising importance of networks in economic literature, and to draw a framework of the fields which use network analysis. One issue of confusion commonly encountered is that networks in economics are both used as a conceptual tool to view systems, and also they point to a particular form of governance structure, which is the so-called network based organization. This survey covers both of these, because the theoretical problem that I address is concerned with the emergence of network-based organizations, and the method that I undertake is to use network analysis as a tool to view organizations.

In the third chapter, I presented the central arguments in this thesis. I focused on a growing literature on two organizational structures. In the first, there is intensive knowledge sharing among a network of small and specialized firms. These systems are characterized by variety and specialization at the same time accompanied by rapidly changing market conditions, uncertainty, intensive informal know-how trading and collaboration and the boundaries of the firms get blurred. Networks integrate the knowledge of diverse actors taking role in innovation and production. If there is inertia or stability in the network, this process is facilitated by a shared culture and development of a common code of communication among parties, which reduces the costs of transferring highly tacit knowledge. The emergence of networks is largely an endogenous process driven by the complex and dynamic interplay between institutions,

products, technologies, the market and innovative actors. In this sense they are characterized as being self-organizing, such that there is no authority to impose a certain structure, but the interaction of firms is the main mechanism that generates the rules underlying emerging structures.

While in the case of networks specialization and variety co-exist at the same time, in the case of large firms variety takes a different form, usually studied under the heading of diversification. The diversified hierarchical structure is the second type of organization that I covered in chapter three.

From these observations, it can be seen that variety is sometimes found in a network of specialized firms, and at other times in the diversification patterns of large hierarchies. The underlying reasons for this phenomena forms the starting point of this thesis. The question is, why do we see these activities within the boundaries of a large firm in some cases, and distributed to a set of small firms who interact with each other frequently in others? The question then becomes, how do the existing theories on firm boundaries explain this critical level above which networking activities among firms intensify?

Taking these in the background, I presented the various theories of the firm in Chapter three. The two central questions that most theories of the firm focus on are, why do firms exist and what determines their boundaries. Traditional approaches to these consist of neoclassical theory and transaction cost economics. While both of these have their strengths, they have been criticized by scholars on a number of issues. Some of these are their behavioural assumptions, like homogeneity of actors, opportunism, and perfect rationality. More recent theories consist of the resource-based view of the firm, and the knowledge-based theories. This thesis is very close in spirit to the knowledge-based theories of the firm. According to this approach, firms exist to integrate the knowledge of a diverse range of specialists, and their boundaries are determined by the knowledge requirements of production. In this chapter, I discussed all these approaches in detail, also covering their criticisms directed towards the TCE approach.

There are four main building blocks upon which I base my thesis. Firstly, authority is a mechanism that is posterior to the formation of firms, and the main function of authority is to coordinate the integration and transfer of the knowledge of diverse actors in the firm. Secondly I follow Kogut and Zander (1992, 1996), in their explanation of the existence of the firm as a social community within which coordination, communication and learning takes place. Thirdly, I follow Grant (1996) in his emphasis of the role of the firm as integrating the knowledge of diverse specialists. Fourth, I emphasize the importance of the knowledge base of the industry in explaining how the boundaries of the firms are shaped.

Against this background, the questions that I address in this thesis are how the knowledge base influences the structure of the firms, in terms of specialization, diversification and networking? What types of organizational structures emerge under different knowledge bases? Does increased relatedness among products, in terms of their knowledge bases, prepare a suitable basis for the dominance of specialized firms with porous boundaries, or diversified hierarchies?

To approach these problems, I adopt a network perspective, and view all organizations as emerging networks. In this sense, both network based industries, and firms themselves are seen as self organizing networks of interacting agents. In a network representation, firms can be visualized as clusters of economic agents, who interact with each other more frequently than they do with outsiders. Network based systems would consist of such clusters where the linkages among clusters are also intensive.

In the fourth chapter, I presented the skeleton of the model, and gave some analytical results concerning collaboration among two producers in a two-good economy. The essential factors that determine collaboration among producers are as follows. Collaboration depends on capabilities of producers, and their relative knowledge levels. Since collaboration will only take place when both parties are willing to do so, there is a space of relative knowledge levels which will result in collaboration. The more specialized are the goods, the closer producers should be to each other in their respective expertise types to form partnerships. I also incorporated effects of learning in the analytical model. However, the analytical model that I present here is too simple to permit general conclusions. Firstly, the dynamics of the system changes considerably when we take into account a large number of producers. Moreover learning takes place in every period that may change the dynamics of the system in unexpected ways in future periods. Thirdly, the analytical model is largely deterministic in nature whereas in the real world there is uncertainty. Finally with only two products, it is difficult to model adequately the characteristics of the knowledge base. In the following two chapters, I carry out an agent based simulation study to incorporate these.

The aim of the model is to highlight the effect of the characteristics of the knowledge base on interaction patterns among producers. To model the knowledge base, I develop the concepts of breadth and depth. Breadth refers to the range of different knowledge types that the production requires. Depth refers to the extent to which a single knowledge type is used more intensively than others in the good. Using the concepts of breadth and depth also permits me to model the relatedness among products in the economy with respect to the similarities in their knowledge levels. For example, when two goods utilize

the same types of knowledge in exactly the same amounts, then they are highly related. If one good is very intensive in a certain knowledge that is only minor for another one, then relatedness is low.

In Chapter five, I carried out a simple simulation study, in which the breadth is held constant (every product takes a input three knowledge types) but in which the intensity of use is different. Depending on the depth, I analyzed the structure of resulting networks. My findings in this chapter reveal that, when depth is high, that is when the goods are using intensively a certain knowledge type, but a major input in one is only minor in the other, the network is denser. High depth also means that there is little relatedness among goods in terms of the similarities in their knowledge bases. As products utilise a more even distribution of knowledge types, relatedness among them increases, and at the same time the intensity of interactions fall.

I carried out a more realistic and detailed simulation in Chapter six. Here, the analysis is extended to cover the influence of both breadth and depth in a two dimensional space. I found that highest network density occurs when breadth and depth are both highest. In this chapter, I used social network analysis tools to decompose the resulting networks into subgroups to be used as proxies for the firm. The clique is an appropriate subgroup for my purposes mainly because cliques overlap. Taking clique as the firm permits to measure the extent of networking among firms by measuring the overlap among cliques.

I analysed the structure of cliques in the breadth and depth space, in terms of their specialization, diversification in goods and knowledge, overlap among them, and expertise. I found that high breadth and high depth region is characterised as having firms with high specialization, low diversity, and high overlap. This region can be associated with network based industries. In this region, goods are related but not too much. Another region of interest is where relatedness among goods is very high (high breadth and low depth). In this region, the cliques are characterised by high degree of diversification, very low overlap and low expertise. I associate this region with multi-product and multi-technology hierarchical structures having more concrete boundaries.

What are the implications of the simulation results? In chapter three, I argued that the relatedness among the products in an industry influences the point at which diversified hierarchies or networked small firms emerge. Too much variety increases costs of communication inside the firm, whereas diversification lowers marginal costs when human capital can be put to produce a variety of related products. I argued that the knowledge base of an industry, then, should influence the structure of firms in terms of their diversification, specialization and networking. In other words, I argued that the boundaries of the firms is a function of the characteristics of the knowledge base.

My simulation results confirm this reasoning. When the products are too similar to each other in terms of their knowledge bases, multi-product firms are more efficient. In another extreme, when there is no similarity in goods at all, there are specialized firms and no networking among them also. Only when the relatedness among the products are at an intermediate level do we see specialized firms which are involved in significant networking.

The nature of the simulation model is highly abstract, which makes it possible to apply it in different contexts than the original context in which it is developed, namely industrial structures. To test the essential arguments developed in the model, in the final chapter I carried out an empirical study using the EPO/CESPRI database. In this analysis, I took a patent to be a product that is produced by integrating the knowledge levels of different specialists. I positioned 30 main technology fields into the breadth and depth space. I also analysed the effect of breadth and depth on the network density. Particularly, I constructed a relation between the density of firm-based inventor networks and breadth and depth measures of patents held by these firms in biotechnology and telecommunications. I found that the effect of both breadth and depth on network density depend on the level of the other. The higher the breadth (depth) of a firm, the more positive is the effect of depth (breadth) on network density. These results point to the fact that the firms with highest breadth and depth measures have highest inventor network densities in accordance with the arguments I developed in my simulation model.

The arguments developed in this thesis should not be seen as the only explanation for the emergence of diversified hierarchies or network-based systems. Obviously, there are many factors that influence structure of organizations, as a huge literature reveals, ranging from institutional factors, demand side effects, cost considerations, firm strategies and many more. Therefore, my results do not point to an 'if and only if' explanation of organizations. But the aim of a model is not to model the world with all its complexities, rather, to be able to isolate the effect of the theme of inquiry. In a world in which knowledge is in the core of both business and academia, and in which networks are the main mechanism through which knowledge diffuses, the impact of knowledge bases on network structure deserves a central role.

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Appendix A

Proof of Propositions in Chapter 4

Proposition 1 *In the initial period, two producers will form pairs if and only if the following conditions are satisfied simultaneously.*

$$k_{11}^{1-\gamma_{11}-\gamma_{22}} > \frac{2k_{12}^{(1-\gamma_{11})} - k_{22}^{(1-\gamma_{11})}}{k_{22}^{\gamma_{22}}}$$

$$k_{22}^{1-\gamma_{11}-\gamma_{22}} > \frac{2k_{21}^{(1-\gamma_{22})} - k_{11}^{(1-\gamma_{22})}}{k_{11}^{\gamma_{11}}}$$

for $\gamma_{11} + \gamma_{22} > 1$.

Proof. To be able to find this we need to look at the indifference function for both producers, which shows the critical production levels at which the producers are indifferent between producing singleton or together. Let us consider producer 1 first. The indifference equation is given by

$$\underbrace{\alpha k_{11}^{\gamma_{11}} k_{12}^{\gamma_{12}}}_{\text{producer 1, good 1, singleton}} = \frac{1}{2} \alpha \left[\underbrace{k_{11}^{\gamma_{11}} k_{22}^{\gamma_{12}}}_{\text{paired, good 1}} + \underbrace{k_{11}^{\gamma_{21}} k_{22}^{\gamma_{22}}}_{\text{paired, good 2}} \right] \quad (\text{A.1})$$

In the same way, indifference condition for producer 2 is given by

$$\underbrace{k_{21}^{\gamma_{21}} k_{22}^{\gamma_{22}}}_{\text{producer 2, good 2, singleton}} = \frac{1}{2} \left[\underbrace{k_{11}^{\gamma_{11}} k_{22}^{\gamma_{12}}}_{\text{paired, good 1}} + \underbrace{k_{11}^{\gamma_{21}} k_{22}^{\gamma_{22}}}_{\text{paired, good 2}} \right]$$

Rearranging terms for producer 1 we get the following indifference condition

$$k_{11}^{\gamma_{11}} k_{22}^{\gamma_{12}} - k_{11}^{\gamma_{11}} k_{12}^{\gamma_{12}} = k_{11}^{\gamma_{11}} k_{12}^{\gamma_{12}} - k_{11}^{\gamma_{21}} k_{22}^{\gamma_{22}}$$

The interpretation of the equation is straightforward, which represents the trade-off faced by producer 1. The LHS shows the *net* gain in producing good 1 as a pair. This is equal to producing good 1 as a pair, less the opportunity cost which is producing good 1 singleton. The RHS shows, on other hand, the *net* loss from producing as a pair. This is equivalent to what producer 1 could have produced singleton, less the additional good 2 he gets by collaborating. If the RHS of equation A.1 is greater then the LHS, producer will prefer singleton. Therefore the condition for collaboration is given by

$$\alpha k_{11}^{\gamma_{11}} k_{12}^{\gamma_{12}} < \frac{\alpha k_{11}^{\gamma_{11}} k_{22}^{\gamma_{12}} + \alpha k_{11}^{\gamma_{21}} k_{22}^{\gamma_{22}}}{2}$$

Rearranging terms we get the condition for producer 1's willingness to collaborate:

$$k_{11}^{1-\gamma_{11}-\gamma_{22}} > \frac{2k_{12}^{(1-\gamma_{11})} - k_{22}^{(1-\gamma_{11})}}{k_{22}^{\gamma_{22}}}$$

$$k_{11} < \left(\frac{2k_{12}^{(1-\gamma_{11})} - k_{22}^{(1-\gamma_{11})}}{k_{22}^{\gamma_{22}}} \right)^{1/(1-\gamma_{11}-\gamma_{22})}$$

■

Proposition 3 *The more specialized are the products, the closer the producers should be in their respective expertise fields for collaboration to take place initially. Similarly, the less specialized are the products, collaboration can take place even if the expertise levels are relatively different, i.e. there is a higher difference between their knowledge levels in their respective major categories.*

Proof. Consider Proposition 1. It was stated that, the condition for collaboration is:

$$k_{11}^{1-\gamma_{11}-\gamma_{22}} > \frac{2k_{12}^{(1-\gamma_{11})} - k_{22}^{(1-\gamma_{11})}}{k_{22}^{\gamma_{22}}}$$

which shows producer 1's willingness to collaborate. Dividing both sides by $k_{22}^{1-\gamma_{11}-\gamma_{22}}$ we get

$$1 < 2\left(\frac{k_{12}}{k_{22}}\right)^{1-\gamma_{11}} - \left(\frac{k_{11}}{k_{22}}\right)^{1-\gamma_{11}-\gamma_{22}} = f(.) \quad (\text{A.2})$$

and if $\frac{k_{11}}{k_{22}} = 1$ as we stated in Corollary 2, the condition than becomes

$$1 < \left(\frac{k_{12}}{k_{22}}\right)^{1-\gamma_{11}}$$

which is true by assumption therefore collaboration will take place for sure as stated by Corollary 2. On the other hand, when initial knowledge levels are

not the same (any point in the shaded area in Figure 4.1 but not the 45° line) the smaller is k_{11} compared to k_{22} , then according to the rightmost term in A.2 γ_{11} (or γ_{22}) should be small to validate the inequality. Formally, taking the derivative of the right hand side of the inequality with respect to γ_{11} (for simplicity assume $\gamma_{11} = \gamma_{22}$)

$$\frac{df(\cdot)}{d\gamma_{11}} = 2 \left(\ln \frac{k_{11}}{k_{22}} \right) \left(\frac{k_{11}}{k_{22}} \right)^{1-2\gamma_{11}} - 2 \left(\ln \frac{k_{12}}{k_{22}} \right) \left(\frac{k_{12}}{k_{22}} \right)^{1-\gamma_{11}} < 0 \text{ for } \frac{k_{11}}{k_{22}} < 1$$

and

$$\frac{df(\cdot)}{d(k_{11}/k_{22})} = \frac{1}{(\frac{k_{11}}{k_{22}})^{2\gamma_{11}}} (2\gamma_{11} - 1) > 0$$

Therefore, the smaller is k_{11}/k_{22} , the smaller will be $f(\cdot)$, to counter-effect this, γ_{11} should be small which will increase $f(\cdot)$ so that possibility for collaboration will increase. This is shown by the comparison of Figures 4.1(a) and 4.1(b). Therefore even if producer 1 knows much less than producer 2 in his expertise field, if the goods are less specialized collaboration will still take place. ■

Proposition 4 *When there is collaboration in the first period, collaboration in the second period continues if and only if the following conditions are satisfied for the first and second producers respectively.*

For producer 1

$$\left(\frac{\Delta_2}{\Delta_1} \right)^{\gamma_{22}} + \left(\frac{\Delta_2}{\Delta_1} \right)^{1-\gamma_{11}} > \left(\frac{2k_{12}(t-1)}{k_{11}(t-1)} \right)^{1-\gamma_{11}} \quad (\text{A.3})$$

where $\Delta_1 = 1 + \theta_1\alpha$ and $\Delta_2 = 1 + \theta_2\alpha$

For producer 2

$$\left(\frac{\Delta_1}{\Delta_2} \right)^{\gamma_{11}} + \left(\frac{\Delta_1}{\Delta_2} \right)^{1-\gamma_{22}} > \left(\frac{2k_{21}(t-1)}{k_{22}(t-1)} \right)^{1-\gamma_{22}} \quad (\text{A.4})$$

Proof. Let us take the case for producer 1. The new knowledge levels in period 2 (we denote period 2 by t), as given by the learning functions 4.7 are;

$$k_{11}(t) = k_{11}(t-1) \left[1 + \theta_1\alpha/2 \left(\frac{k_{11}^{\gamma_{11}}(t-1)k_{22}^{\gamma_{12}}(t-1) + k_{11}^{\gamma_{21}}(t-1)k_{22}^{\gamma_{22}}(t-1)}{k_{11}(t-1)} \right) \right]$$

$$k_{22}(t) = k_{22}(t-1) \left[1 + \theta_2\alpha/2 \left(\frac{k_{11}^{\gamma_{11}}(t-1)k_{22}^{\gamma_{12}}(t-1) + k_{11}^{\gamma_{21}}(t-1)k_{22}^{\gamma_{22}}(t-1)}{k_{22}(t-1)} \right) \right]$$

$$k_{12}(t) = k_{12}(t-1) \left[1 + \theta_1\alpha/2 \left(\frac{k_{11}^{\gamma_{11}}(t-1)k_{22}^{\gamma_{12}}(t-1) + k_{11}^{\gamma_{21}}(t-1)k_{22}^{\gamma_{22}}(t-1)}{k_{22}(t-1)} \right) \right]$$

when $k_{11}(t-1) = k_{22}(t-1)$ the new knowledge levels are

$$k_{11}(t) = k_{11}(t-1)(\Delta_1) \quad (\text{A.5})$$

$$k_{22}(t) = k_{22}(t-1)(\Delta_2) \quad (\text{A.6})$$

$$k_{12}(t) = k_{12}(t-1)(\Delta_1) \quad (\text{A.7})$$

where $\Delta_1 = 1 + \theta_1\alpha$ and $\Delta_2 = 1 + \theta_2\alpha$

Condition for collaboration in period t is given by Proposition 1 to be

$$k_{11}^{1-\gamma_{11}-\gamma_{22}}(t) > \frac{2k_{12}^{(1-\gamma_{11})}(t) - k_{22}^{(1-\gamma_{11})}(t)}{k_{22}^{\gamma_{22}}(t)} \quad (\text{A.8})$$

Inserting Equations A.5, A.6 and A.7 into Equation A.8 and the condition $k_{11}(t-1) = k_{22}(t-1)$ and arranging terms we get

$$k_{11}^{1-\gamma_{11}-\gamma_{22}} \Delta_1^{1-\gamma_{11}-\gamma_{22}} > \left(\frac{2k_{12}^{1-\gamma_{11}}(t-1)\Delta_1^{1-\gamma_{11}}}{k_{11}^{\gamma_{22}}(t-1)\Delta_2^{\gamma_{22}}} \right) - k_{11}^{1-\gamma_{11}-\gamma_{22}} \Delta_2^{1-\gamma_{11}-\gamma_{22}}$$

dividing both sides by $k_{11}^{1-\gamma_{11}-\gamma_{22}}$ and arranging terms yield:

$$\left(\frac{\Delta_2}{\Delta_1} \right)^{\gamma_{22}} + \left(\frac{\Delta_2}{\Delta_1} \right)^{1-\gamma_{11}} > \left(\frac{2k_{12}(t-1)}{k_{11}(t-1)} \right)^{1-\gamma_{11}}$$

for Producer 1. The same procedure yields the condition for Producer 2. ■

Corollary 5 *Given same initial major knowledge levels, the willingness of producer i to continue collaboration in the second period is higher when capability of producer j is higher and his own capability is lower.*

Proof. By proposition 4, the condition for collaboration for producer 1 is given by

$$v^1(\Delta_1, \Delta_2) = \left(\frac{\Delta_2}{\Delta_1} \right)^{\gamma_{22}} + \left(\frac{\Delta_2}{\Delta_1} \right)^{1-\gamma_{11}} > \left(\frac{2k_{12}(t-1)}{k_{11}(t-1)} \right)^{1-\gamma_{11}} \quad (\text{A.9})$$

To evaluate the influence of capabilities of both producers on the satisfaction of this condition, we take derivatives of $v^1(\Delta_1, \Delta_2)$ with respect to Δ_1 and Δ_2 .

$$\frac{\partial v^1}{\partial \Delta_2} = \frac{\gamma_{22}}{\Delta_1} \left(\frac{\Delta_2}{\Delta_1} \right)^{\gamma_{22}-1} + \frac{1-\gamma_{11}}{\Delta_1 \left(\frac{\Delta_2}{\Delta_1} \right)^{\gamma_{11}}} > 0$$

Therefore the higher is the capability of producer 2, the more likely that willingness of producer 1 to collaborate will increase since it increases v^1 . In the same way,

$$\frac{\partial v^1}{\partial \Delta_1} = \frac{\Delta_2(\gamma_{11}-1)}{\Delta_1^2 \left(\frac{\Delta_2}{\Delta_1} \right)^{\gamma_{11}}} - \frac{\gamma_{22}}{\Delta_1} \left(\frac{\Delta_2}{\Delta_1} \right)^{\gamma_{22}} < 0$$

which states that the lower is producer 1's own capabilities the more he will be willing to collaborate. ■

Proposition 7 *If major knowledge levels are different in the first period but capability levels are the same, collaboration will continue in the second period if and only if the following conditions are met for producers 1 and 2,*

For Producer 1

$$k_{11}^{1-\gamma_{11}-\gamma_{12}}(t-1) > \left(\frac{2k_{12}^{1-\gamma_{11}}(t-1)}{k_{22}^{\gamma_{22}}(t-1)} - k_{22}(t-1)^{1-\gamma_{11}-\gamma_{22}} \right) \psi \quad (\text{A.10})$$

where

$$\psi = \frac{(1 + \theta\alpha[(\frac{k_{11}}{k_{22}})^{\gamma_{11}} + (\frac{k_{22}}{k_{11}})^{1-\gamma_{22}}])^{1-\gamma_{11}-\gamma_{22}}}{(1 + \theta\alpha[(\frac{k_{11}}{k_{22}})^{\gamma_{11}-1} + (\frac{k_{11}}{k_{22}})^{-\gamma_{22}}])^{1-\gamma_{11}-\gamma_{22}}}$$

For Producer 2

$$k_{22}^{1-\gamma_{11}-\gamma_{12}}(t-1) > \left(\frac{2k_{21}^{1-\gamma_{22}}(t-1)}{k_{11}^{\gamma_{11}}(t-1)} - k_{11}(t-1)^{1-\gamma_{11}-\gamma_{22}} \right) \phi \quad (\text{A.11})$$

and

$$\phi = \frac{1 + \theta\alpha[(\frac{k_{22}}{k_{11}})^{\gamma_{22}} + (\frac{k_{22}}{k_{11}})^{1-\gamma_{11}}]^{1-\gamma_{11}-\gamma_{22}}}{1 + \theta\alpha[(\frac{k_{22}}{k_{11}})^{\gamma_{22}-1} + (\frac{k_{22}}{k_{11}})^{-\gamma_{11}}]^{1-\gamma_{11}-\gamma_{22}}}$$

Proof. We follow the same method as in Proposition 4, but without imposing the condition $k_{11}(t-1) = k_{22}(t-1)$ and setting $\theta_1 = \theta_2$. In this case the new knowledge levels are

$$\begin{aligned} k_{11}(t) &= k_{11}(t-1)[1 + \theta\alpha/2 \left((\frac{k_{22}(t-1)}{k_{11}(t-1)})^{\gamma_{12}} + (\frac{k_{22}(t-1)}{k_{11}(t-1)})^{\gamma_{22}} \right)] \\ k_{22}(t) &= k_{22}(t-1)[1 + \theta\alpha/2 \left((\frac{k_{11}(t-1)}{k_{22}(t-1)})^{\gamma_{11}} + (\frac{k_{11}(t-1)}{k_{22}(t-1)})^{\gamma_{21}} \right)] \\ k_{12}(t) &= k_{12}(t-1)[1 + \theta\alpha/2 \left(\frac{k_{11}^{\gamma_{11}}(t-1)}{k_{22}^{\gamma_{11}}(t-1)} + \frac{k_{11}^{\gamma_{21}}(t-1)}{k_{22}^{\gamma_{21}}(t-1)} \right)] \end{aligned} \quad (\text{A.12})$$

setting $n = \theta\alpha/2 \left(\frac{k_{11}^{\gamma_{11}}(t-1)}{k_{22}^{\gamma_{11}}(t-1)} + \frac{k_{11}^{\gamma_{21}}(t-1)}{k_{22}^{\gamma_{21}}(t-1)} \right)$ and $m = \theta\alpha/2 \left((\frac{k_{22}(t-1)}{k_{11}(t-1)})^{\gamma_{12}} + (\frac{k_{22}(t-1)}{k_{11}(t-1)})^{\gamma_{22}} \right)$ and inserting these into the condition stated by Proposition 1 and rearranging terms we get

$$k_{11}^{1-\gamma_{11}-\gamma_{12}}(1+\Delta m)^{1-\gamma_{11}-\gamma_{12}} > \left(\frac{2k_{12}^{1-\gamma_{11}}(1+\Delta n)^{1-\gamma_{11}}}{k_{22}^{\gamma_{22}}(1+\Delta n)^{\gamma_{22}}} - k_{22}^{1-\gamma_{11}-\gamma_{22}} \right) (1+\Delta n)^{1-\gamma_{11}-\gamma_{12}} \quad (\text{A.13})$$

and

$$k_{11}^{1-\gamma_{11}-\gamma_{12}} > \left(\frac{2k_{12}^{1-\gamma_{11}}(1+\Delta n)^{1-\gamma_{11}-\gamma_{22}}}{k_{22}^{\gamma_{22}}(1+\Delta m)^{1-\gamma_{11}-\gamma_{12}}} - \frac{k_{22}^{1-\gamma_{11}-\gamma_{22}}(1+\Delta n)^{1-\gamma_{11}-\gamma_{12}}}{(1+\Delta m)^{1-\gamma_{11}-\gamma_{12}}} \right)$$

yields

$$k_{11}^{1-\gamma_{11}-\gamma_{12}}(t-1) > \left(\frac{2k_{12}^{1-\gamma_{11}}(t-1)}{k_{22}^{\gamma_{22}}(t-1)} - k_{22}^{1-\gamma_{11}-\gamma_{22}} \right) \psi$$

where

$$\psi = \frac{(1 + \theta \alpha [(\frac{k_{22}}{k_{11}})^{-\gamma_{11}} + (\frac{k_{22}}{k_{11}})^{\gamma_{22}-1}])^{1-\gamma_{11}-\gamma_{22}}}{(1 + \theta \alpha [(\frac{k_{22}}{k_{11}})^{-\gamma_{11}} + (\frac{k_{22}}{k_{11}})^{-\gamma_{22}}])^{1-\gamma_{11}-\gamma_{22}}}$$

■

Appendix B

Appendix to Chapter 6

Figure B.1 shows an example set of input coefficients (G matrices). Figure includes 36 matrices, which are used for 1 run. Each matrix is composed of 5 rows and 5 columns, where the rows represent goods and columns represent knowledge types, so that g_{ij} is the knowledge j intensity of good i . Going in the right direction increases the depth of knowledge base, and going in the up direction increases breadth of knowledge base. It can be seen that in the topmost right matrix, all goods utilize all knowledge types, but one of them intensively, which corresponds to maximum breadth and maximum depth. Topmost left matrix shows the case where all goods use all knowledge types in more or less equal amounts, which corresponds to maximum breadth and minimum depth of knowledge base.

B.1 Derivation of Production Parameters

The breadth of the knowledge base is the range of different knowledge types that production requires. We measure this basically by the number of inputs in the production function greater than zero. The higher it is, the wider the breadth of the knowledge base. Let us denote the number of inputs greater than zero for a product i by n , and the knowledge input coefficients by γ_{ij} , where $j = 1, \dots, K$. Each of the parameters are taken from a population such that $\gamma_{ij} \sim N(\mu_{ij}, \sigma_{ij})$. What we are interested in is the mean and standard deviation of the sample when n of the γ s are aggregated (so that each of the γ 's is from a different population, and we find the mean and standard deviation of the

0.2	0.27	0.19	0.19	0.19	0.14	0.14	0.21	0.20	0.30	0.12	0.17	0.16	0.13	0.42	0.14	0.45	0.15	0.16	0.10	0.07	0.17	0.01	0.60	0.15	0.07	0.08	0.05	0.70	0.10	0.01	0.07	0.05	0.07	0.80	0.02	0.89	0.03	0.04	0.02	0.01	0.97	0.01	0.01	0.01	0.01	
0.21	0.22	0.17	0.21	0.19	0.14	0.18	0.15	0.22	0.31	0.30	0.34	0.09	0.09	0.18	0.17	0.11	0.12	0.13	0.48	0.07	0.02	0.21	0.12	0.59	0.11	0.08	0.06	0.66	0.08	0.12	0.07	0.79	0.01	0.02	0.03	0.04	0.04	0.87	0.03	0.02	0.01	0.02	0.95	0.01		
0.20	0.21	0.23	0.15	0.20	0.18	0.36	0.16	0.13	0.17	0.15	0.13	0.19	0.12	0.41	0.12	0.12	0.23	0.10	0.42	0.17	0.06	0.03	0.59	0.15	0.09	0.07	0.70	0.05	0.10	0.03	0.07	0.09	0.06	0.75	0.03	0.04	0.86	0.03	0.04	0.97	0.01	0.01	0.01	0.02	0.01	
0.24	0.20	0.24	0.16	0.16	0.31	0.19	0.19	0.17	0.14	0.15	0.17	0.13	0.10	0.42	0.08	0.07	0.45	0.28	0.11	0.15	0.09	0.02	0.60	0.13	0.04	0.67	0.09	0.11	0.09	0.00	0.04	0.08	0.14	0.74	0.02	0.04	0.02	0.04	0.88	0.01	0.01	0.96	0.01	0.01		
0.23	0.19	0.21	0.14	0.23	0.16	0.20	0.18	0.30	0.15	0.26	0.32	0.06	0.11	0.25	0.15	0.14	0.13	0.47	0.11	0.58	0.17	0.15	0.09	0.01	0.04	0.06	0.14	0.70	0.06	0.05	0.01	0.78	0.07	0.09	0.02	0.03	0.03	0.89	0.01	0.00	0.01	0.97	0.02			
0.24	0.21	0.30	0	0.26	0.24	0.21	0.35	0.20	0	0.27	0	0.09	0.42	0.23	0	0.14	0.12	0.39	0.35	0.26	0.58	0	0.03	0.13	0.12	0	0.13	0.09	0.65	0	0.75	0.11	0.09	0.06	0.05	0	0.00	0.06	0.87	0.01	0	0.95	0.02	0.02		
0.26	0.21	0	0.26	0.27	0	0.19	0.23	0.26	0.32	0	0.29	0.41	0.07	0.22	0.11	0	0.14	0.39	0.36	0.59	0.18	0	0.12	0.12	0.11	0.65	0.09	0.15	0	0.07	0.12	0	0.73	0.08	0.04	0.01	0.91	0	0.04	0.04	0.02	0	0.01	0.94		
0.21	0.28	0.27	0.24	0	0.25	0	0.18	0.31	0.25	0.44	0.27	0.23	0.05	0	0.17	0.16	0	0.16	0.50	0.12	0.09	0.54	0.26	0	0.07	0.15	0.65	0.13	0	0.75	0.06	0.10	0.09	0	0.07	0.84	0.06	0	0.01	0.02	0	0.96	0.02	0.00		
0	0.20	0.29	0.28	0.23	0.18	0.20	0	0.36	0.26	0	0.35	0.31	0.21	0.13	0.51	0.15	0	0.17	0.17	0	0.24	0.55	0.06	0.15	0.10	0.12	0.10	0.68	0	0.08	0.05	0	0.79	0.08	0.04	0.00	0.83	0.03	0	0.95	0	0.01	0.01	0.04		
0.25	0.27	0	0.22	0.26	0.24	0.25	0	0.18	0.33	0	0.09	0.29	0.24	0.38	0	0.17	0.16	0.19	0.48	0.14	0.17	0.16	0.53	0	0.68	0.13	0.10	0	0.10	0.73	0.04	0.11	0	0.12	0.08	0.01	0.82	0	0.09	0.02	0.03	0.93	0.02	0		
0.35	0.33	0	0	0.32	0.24	0.33	0	0	0.43	0.18	0.42	0.40	0	0	0.50	0.15	0.35	0	0	0.22	0.21	0.58	0	0	0.14	0.66	0.19	0	0	0.09	0.16	0.75	0	0	0.10	0.80	0	0	0.09	0.06	0	0	0.10	0.84		
0.31	0.36	0	0.33	0	0	0.33	0.41	0.26	0.40	0	0.41	0.19	0	0	0.20	0.31	0.50	0	0	0	0.49	0.45	0.05	0	0.20	0.65	0.15	0	0	0.24	0.72	0.04	0	0.11	0.08	0.80	0	0	0.89	0.03	0.08	0	0			
0	0.31	0.34	0.35	0	0.25	0.32	0	0	0.43	0	0	0.29	0.44	0.27	0	0.50	0	0.15	0.34	0	0.27	0	0.60	0.14	0	0.64	0	0.20	0.16	0.14	0	0.11	0.77	0.12	0	0	0	0.11	0.77	0.12	0	0	0.06	0.92	0.02	
0.39	0	0	0.30	0.31	0.32	0.41	0	0	0.27	0.27	0	0.47	0.25	0	0.49	0	0.16	0	0.35	0.10	0	0.35	0	0.55	0.65	0	0.19	0	0.15	0.14	0.14	0	0.72	0	0	0.11	0	0.10	0.79	0	0	0.07	0.92	0.01		
0.32	0.33	0.34	0	0	0.37	0.32	0	0.31	0	0.39	0	0.23	0.38	0	0	0	0.23	0.53	0.24	0	0	0.49	0.46	0.06	0	0	0.16	0.19	0.64	0	0.18	0.73	0	0.10	0.10	0	0.06	0	0.83	0.07	0	0.03	0.90	0		
0.50	0.50	0	0	0	0	0	0	0.55	0.45	0.60	0.40	0	0	0	0.37	0.63	0	0	0	0	0	0.32	0.68	0	0	0.30	0.69	0	0	0	0.25	0	0	0.75	0	0	0.18	0	0	0.82	0	0	0.08	0.92	0	0
0	0.53	0	0.47	0	0.45	0.55	0	0	0	0	0.58	0.42	0	0	0.38	0	0	0.62	0.65	0	0	0	0.35	0.30	0.70	0	0	0	0	0.24	0	0.76	0	0	0	0	0.15	0.85	0	0.90	0.10	0	0			
0.52	0	0.48	0	0	0.47	0.53	0	0	0	0.41	0	0	0.59	0	0	0.38	0.62	0	0.34	0.65	0	0	0	0	0	0	0	0	0	0	0.32	0.68	0	0	0.25	0.76	0	0.10	0	0	0.90	0	0.93	0	0.07	0
0	0.46	0	0.54	0	0.41	0.59	0	0	0	0.40	0.59	0	0	0	0.39	0	0	0.61	0	0.33	0	0.67	0	0	0	0	0.29	0.71	0	0	0	0.75	0	0	0.25	0	0	0.17	0.83	0	0	0	0	0.06	0.94	
0.51	0	0	0.49	0	0	0	0	0.45	0.55	0	0	0.59	0	0	0	0	0.40	0	0.61	0	0	0	0.32	0.68	0	0	0.28	0.72	0	0	0	0	0	0	0	0	0	0	0.16	0.84	0	0	0.06	0	0.94	0

Depth

Breadth

aggregated population). The mean and standard deviation of the aggregated population is what we use as the breadth and depth measures. The mean of the aggregated population is $\sum \gamma_{ij}/n = 1/n$. Take the case of $n = 2$, as an example. This means that there are two inputs in production. The mean will be $1/n$, because we assume constant returns to scale. The input vectors of two goods as an example, are $(0.49, 0, 0, 0, 0.51)$ and $(0, 0, 0.99, 0.01, 0)$. We measure breadth by $n = 1/\mu$, which is equal to $1/0.5 = 2$ in this case.

We measure depth by the standard deviation of this aggregated sample. To illustrate, let us take a good i with $n = 3$ and maximum depth. Here, the good takes three γ s as input, let us assume these are knowledge types $j = \{1, 3, 4\}$. Because we have maximum depth, one of the knowledge types is more dominant than others, say type $j = 3$. We draw γ_{i3} randomly from a normal population with mean $\mu_{i3} = 0.95$ and standard deviation $\sigma = 0.05$. The other coefficients γ_{i1} and γ_{i4} , as an example, are drawn randomly from populations $\sim N(0.01, \sigma)$ and $\sim N(0.04, \sigma)$. When these three populations are aggregated, the mean is $\mu_i \simeq 0.33$ (so that breadth is equal to $n = 1/0.33 = 3$) and standard deviation is $\sigma_{\max}$, which we take to be the depth of knowledge base. If we have a good with $n = 4$, and maximum depth, we draw the coefficients from four different populations in such a way that the combined population standard deviation is $\sigma_{\max}$ as well. Following this procedure, we generate the matrices in Figure B.1. Those matrices which have the same depth measure have the same standard deviation of the aggregated populations.

Netwerken, Organisaties en Kennis (Summary in Dutch)

Dit proefschrift behandelt economische netwerken en hun ontstaan. Netwerken hebben de afgelopen twintig jaar veel aandacht gekregen in de economische wetenschap. Deze interesse in netwerken is niet alleen gericht op patronen die ontstaan in een systeem van interacterende agenten, maar heeft ook geleid tot een nieuwe organisatievorm: de 'netwerkorganisatie' (*network-based organization*). In dit type organisatie hebben bedrijven geen vastomlijnde grenzen en kunnen niet autonoom opereren. In plaats daarvan delen bedrijven hun kennis en andere bezittingen met andere bedrijven en vormen ze knooppunten in een netwerk.

Het hoofdonderwerp van dit proefschrift is de opkomst van de netwerkorganisatie. In het bijzonder is onderzocht hoe het 'kennisreservoir' (*knowledge base*) van een bedrijfstak van invloed is op het ontstaan van organisatievormen en dan vooral van netwerkorganisaties. De hier gevolgde aanpak is gebaseerd op de veronderstelling dat alle organisaties netwerken zijn die zichzelf organiseren. Een bedrijfstak bestaat uit bedrijven op macroniveau en individuen op microniveau. Beide niveaus kunnen als netwerk worden gerepresenteerd. Op beide niveaus trachten de agenten (bedrijven cq. individuen) hun kennis te integreren teneinde verbeteringen in productie te bewerkstelligen.

Tegen deze achtergrond is een 'agentgebaseerde simulatie' (*agent-based simulation*) verricht, waarbij egoïstische agenten hun kennis integreren terwijl hun kennisreservoirs verschillen van karakter. In het bijzonder wordt er een onderscheid gemaakt tussen de breedte en de diepte van een kennisreservoir. Dit proefschrift geeft antwoorden op de volgende vragen: Hoe beïnvloedt de manier waarop een product kennis kan overdragen de structuur van netwerken gemaakt door agenten en wat kunnen we door het analyseren van netwerken afleiden over organisatiestructuren?

Dit proefschrift bevat ook een empirische studie, waarin de kennisreservoirs van de belangrijkste technologiegebieden worden geanalyseerd. Daarnaast is het effect getest van kennisreservoirs op de karakteristieken van netwerken van uitvinders in de biotechnologie en telecommunicatie.

About the Author

Müge Ozman was born in Ankara, Turkey. She studied Industrial Engineering at Middle East Technical University in Ankara, after which she obtained her MSc. Degree from the Economics department of the same University. After graduation she worked as an engineer in various manufacturing companies. In 1999, she came to the Netherlands and commenced her doctoral studies on economics of innovation and technical change, at the Maastricht Economic Research Institute on Innovation and Technology (MERIT). In 2000, she started working on the PhD project on networks and knowledge at MERIT. The present dissertation is the report concerning the findings of this research. She is currently carrying out her post doctoral study at Bureau d'Économie Théorique et Appliquée (BETA), in Université Louis Pasteur, Strasbourg.