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Self-Organizing Inter-Firm Networks

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Abstract

Some industries are characterised by networks of small and specialized firms with porous boundaries, while in some other industries large diversified hierarchies with concrete boundaries are a more dominant form of organization. Some other industries are combinations of these. In this paper, a simulation study is performed to explore whether, and if so how the characteristics of knowledge base influences emerging organizational structures. We focus on two dimensions of the knowledge base; breadth and depth. We define breadth of knowledge base to be the number of different knowledge types required for production, while depth refers to the extent of dominance of a single type. In the simulation study, self-interested agents form pairs to integrate their knowledge and produce together under different schemes of the knowledge base. In this way networks form. Resulting network structures are analysed to gain an insight into organizational structures that emerge. Networks are also partitioned into cohesive subgroups as proxies for the firm, and their structural characteristics are analysed. The results of the simulation study reveal that, network-based industries are likely to emerge when the products in an industry are highly specialized (employing one knowledge type intensively), but still when they have some knowledge types in common, although minor in the production process. This is the case with a broad and deep knowledge base.

Key Words: Network, knowledge, firm

1 Introduction

Evidence in most industries reveals that organizational structures exhibit a wide variety. On one hand, large vertically integrated firms dominate some industries, which can be multi-product and/or multi-technology, and networks of small and specialized firms characterize some others. Ofcourse, other industries can be the combination of these. Among various organizational structures, recent years have witnessed a rise of interest in the network-based systems, where each firm is characterised with a narrow product focus, but with intensive knowledge sharing taking place across enterprise boundaries.

The industrial structures are a function of many things. Institutional factors, the stage in the industry life cycle, tacitness of the knowledge base, technological opportunities all play a role in varying degrees, and are 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 structure 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. Among these factors, one in particular deserves attention as far as this research is concerned; the various ways in which knowledge is embodied in products.

In the most general sense, the major activity of all industrial units is knowledge recombination and transfer among a heterogeneous population of actors for the ultimate purpose of production and innovation. The dynamics of these interactions among the actors are an essential factor that shapes emerging industrial structures. These interactions are influenced obviously by the various ways in which knowledge is required for production, as well as by the way knowledge is distributed among actors. Industries differ in terms of the knowledge bases that they draw upon. In some industries, products are highly specialized, drawing upon a limited number of knowledge types. Some other industries are characterized by products that use a wider scope of knowledge in their production.

The approach that is undertaken in this paper is to conceptualize the organization, both in the macro level (the industry) and in the micro level (the firm) as a self-organizing network. Within it's boundaries, an organization facilitates the transfer of tacit knowledge via the development of a common language and shared codes among its members. Our aim is to make a mapping between the characteristics of the knowledge base and the network structure that evolves through the interaction of self-interested agents. In the simulation study, the industries are classified according to two dimensions of their knowledge bases; a) the breadth of the knowledge base, which refers to the number of different knowledge types that the production requires and b) the depth of the knowledge base, which refers to the degree of dominance of only few knowledge types, getting deeper when dominance is higher. As agents interact to integrate their knowledge and produce, networks form. We analyse the resulting networks to gain an insight into the organizational structures, performing a clique analysis which partitions the resulting networks into overlapping subgroups to be used as a proxy for the firm. The extent of overlapping among cliques is used to measure the intensity of inter-firm relations.

The results reveal that when the breadth of knowledge base is wide, two industrial structures stand out. First, when depth of knowledge base is low, we see the emergence of multi-product firms, with little or no interaction taking place across their boundaries. On the other hand, when knowledge base is deep, we see the emergence of highly specialized firms and intensive relations taking place across their boundaries, which we associate with network-based industries.

The organization of the paper is as follows. In the first part, we provide a theoretical overview, covering the literature on firm boundaries in the general. Here we distinguish between network-based industries where the firms are characterised by porous boundaries, and the large hierarchies which are multi product and/or multi technology and are characterised by more concrete boundaries. Also in this part, we explain the approach undertaken in this paper, mainly how and why all organizations can be conceptualized as self organizing networks. In the second part, we present an overview of the model. The third part is devoted to the evaluation of results. Some concluding remarks follow.

2 Firm Boundaries

A central question in most theories of the firm is "what determines boundaries of firms?". This question is especially important when we consider two organizational structures that seems to dominate most industries today. On one hand, there is so-called network based industries where firms are characterised by porous boundaries and intensive interactions taking place among them. On the other hand, there are multi-product and multi-technology hierarchical structures with less interfirm interactions. These two organizational structures can be seen as extremes on a continuum of various structures. Today, in most industries networking is an essential component of business, thus it is only a matter of degree. But why in some industries we see more networking compared to others? Several explanations have been put forward in the literature. Below, first we briefly review this literature and then explain the approach undertaken in this paper.

2.1 Porous Boundaries: Networks, specialization and variety

Formally, network-based industries have been defined in several ways in the literature. Referring to the same phenomena in the core, slight differences in meaning is captured by using many diverse terms. Granovetter (1998) uses the term “business groups” referring to the group of firms that are bound together in some formal or informal way, that is neither complete (like the case where firms are consolidated into a legal single entity) nor barely at all (like in short term strategic alliances); the keiretsu in Japan, chaebol in Korea being most prominent examples. Powell et. al. (1996) use the term “networks of learning”, where their emphasis is on the role of networks as the locus of innovation. Apart from these, many other terms have been used, for example, “networks of innovators” (DeBresson and Amesse, 1991) or “dynamic networks” (Miles and Snow, 1986), and strategic networks (Jarillo, 1988). Both in theoretical and empirical framework, research on these systems has been intensive, capturing a variety of aspects like role of networks in innovation and learning, in mitigating uncertainty, or research on their structural characteristics. The Japanese business groups (Imai, 1989; Gerlach, 1992), Silicon Valley (Saxenian, 1991, 1994), biotechnology (Powell and Brantley, 1992; Powell et. al, 1996; Arora and Gambardella, 1994; Orsenigo et. al., 1998, 2000; Walker et. al., 1997), Italian fashion and clothing districts (Lazerson and Lorenzoni, 1999), the computer industry (Saxenian, 1991, 1994; Langlois and Robertson, 1992), the fashion industry (Uzzi, 1997), the automobile industry (Dyer and Nobeoka, 2000) have been studied commonly among these.

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. 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).

Networks integrate the knowledge of diverse actors taking a 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 language 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 dense social linkages among the actors. 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). 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, 1982).Because of the increased variety, networks enable both rapid access to divergent types of knowledge, and increased opportunities for building internal capabilities (Powell et. al., 1996). In this way networks enhance organizational learning, by enabling exploration and exploitation at the same time (ibid.). [1] 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 (Kogut, 2000). Network based systems are mostly characterised as being self organizing, such that there is no authority to impose a certain structure, but the network of firms is the main mechanism that generates the rules underlying emerging structures.

2.2 Concrete Boundaries: Hierarchies, specialization and diversification

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. Empirical evidence in most industries shows that large firms diversify into product categories that are close to their product lines of specialization, what is termed to be corporate coherence (Teece et. al, 1994). More specifically, large firms exhibit certain coherence in their diversification portfolios. While studies of such multi-product firms shed light on why firms diversify production and why

[1] See Kogut (1988) for the role of organizational learning in joint ventures.

they do so coherently, they are mostly limited in their scope, such that their focus on product lines fails to underpin the many-to-many relation between technologies and products. 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. Based on empirical evidence in a diverse range of industries, it is accepted today that most firms extend their technological activities to a broader range of technologies, than the one/s required by their core product lines (Grandstrand and Sjolander, 1990; Grandstrand, et.al, 1997; Patel and Pavitt, 1997; Pavitt, 1998; Breschi et.al, 2002). Consequently, the difference between a multi-technology firm and a multi-product firm is essential to underline (Grandstrand and Sjolander, 1990). Just as a single product firm can have distributed technological competencies when the nature of the product is complex, so can a multi-product firm be technologically narrow. In the case of the electronics industry, Torrisi and Gambardella (1998) find that increased product focus is accompanied by increased technological diversity, which proves to yield increased performance.

Diversity and distributed technological competencies helps the firm to acquire flexibility in adapting to new technological developments, and improving current products. 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). 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).

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. (2002). They find out empirically that diversification is a function of the knowledge proximity among technologies. The closer two technologies are in terms of their knowledge bases, the more likely the firms active in one field will spread their innovation activities to the other field.

2.3 Firm boundaries and self organization

The 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 industries, and distributed to a set of small firms in other industries who interact with each other frequently? Modern economic literature has witnessed many approaches targeting this question, covered under the heading of firm boundaries.

In transaction cost theories firms exist to minimize the costs associated with transactions (Williamson, 1975). In this way, firm boundaries are reduced to the conventionally known "make or buy" decision, and the firm is involved in a trade-off between the transaction costs of buying or making. But according to many scholars, transaction cost theory is a static cost trade-off analysis that is insufficient to explain dynamic gains from networks, and that it also ignores organizational learning and strategy aspects of networking (Nooteboom et. al 1997; Eisenhardt and Schoonhaven, 1996; Powell et. al 1996). The self organizing rules beneath networks also act as a mechanism to reduce transaction costs, mainly by eliminating information asymmetry and opportunism.

The knowledge-based theories of the firm (Grant, 1996; Kogut and Zander 1992, 1996; Spender and Grant, 1996; Nonaka, 1994) stress that the basic resource of the firm is knowledge and the basic activity of the firm is to create knowledge. Grant (1996) defines organizational capabilities as the firms ability to integrate the knowledge of individual specialists. This integration is mostly unique to the firm and is not imitable. Accordingly the unit of analysis is the knowledge carrying individual and the role of organizational setting is to provide incentives and motives to individuals for knowledge creation. Knowledge creation occurs in the context of the organizational rules and procedures, and the organization acts as a social mechanism to create and maintain a common language such that the transfer of tacit knowledge within the organization is easier. Thus the main function of the organization is to integrate the knowledge of the diverse actors, and create new knowledge by building on what it already has (Kogut and Zander, 1992). This is based on the idea that innovation is basically a process of knowledge recombination, and the firms' combinative capabilities determine the efficiency of this process (Kogut and Zander, 1992). Kogut and Zander (1996) stress the role of the firm as a social community, and take the boundaries in the context of identity and longing to belong to a group. Benefits of identity is that it reduces costs of communication and coordination, whereas the costs of identity is reducing variety (Kogut and Zander, 1996). As Kogut (2000) argues, internal management of variety at some point becomes more expensive than sourcing variety from an external network.

The questions that we address in this paper is, what is the role of the knowledge base in determining the point at which the internal costs of variety management becomes more expensive than networking? How does the knowledge base influence 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 prepare a suitable basis for the dominance of specialized firms with porous boundaries, or diversified hierarchies?

The approach that we undertake is to view all organizations, industries as well as firms, as self-organizing systems. In most theories of firm boundaries, the problem is analysed by making a static matching between organizational types and corresponding characteristics of the industry. However, our approach is based on the understanding that all organizations are essentially social communities formed by deliberate actions of individual actors. Underlying these actions the main motive in the individual level is integration of specialized knowledge for the ultimate purpose of production, closely in spirit to the knowledge based theories of the firm. Then, a major factor that shapes the evolution of these interactions is the knowledge requirements of production.

Through the interaction of individual actors, communities form, within which transfer and integration of tacit knowledge is easier 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. This approach, which is based on a decentralized perception of a firm, is especially suitable for the cases when there is a certain degree of institutional flexibility, such that the environment permits and motivates foundation of new firms as in the case in Silicon Valley. All these communities can be represented as networks. For example in some 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.

In the simulation study that we perform, the unit of analysis is the knowledge-carrying individual agent. Agents interact with each other for the purpose of integrating their knowledge. The main motive behind these interactions is production, and therefore the knowledge requirements of production should have a role in shaping the resulting networks. To model knowledge requirements of production, we distinguish between two dimensions of the knowledge base. First of all, some industries draw upon a wide knowledge base, utilizing many different knowledge types and specialization areas in their production. We define the breadth of the knowledge base to be the range of knowledge types that the industry draws upon. The second dimension that we focus on is the depth of knowledge base. That is the extent to which a single knowledge is dominant in production, compared to others which are minor. [2]

We then analyse the structure of the communities that evolve from the *bottom-up* by the interaction of agents. For this purpose, we use the concept of a group, as used in social network analysis. [3] Specifically, we partition the evolving networks into groups of agents, which we use as a proxy for firms. Before proceeding to the model, it is better to review the concept of a group in social networks, and explain how we use it in the current paper.

In social network analysis, 4 criterion (not necessarily overlapping) can be used to define a group, depending on the purposes of the researcher, as explained by Wasserman and Faust (1994).

1. The mutuality of ties.
2. The closeness and reachability of subgroup members
3. The frequency of ties among subgroup members
4. The relative frequency of ties among subgroup members as compared to non members.

First, the mutuality of ties refer to the fact that all the subgroup members are adjacent to each other (all of them have links with each other). The reachability perspective focuses on the reachability among the group's members, based on the idea that in a subgroup all members should be reachable, even if they don't have immediate ties with each other. The frequency of ties focus on the strength of the ties among group's members, based on the idea that each member should have a considerable strength of ties with each other. The last perspective compares within group ties to outside group ties, claiming that within group ties should be stronger among group members than outsiders. According to the aim of the research at hand, one or more of these criteria can be used to partition networks into subgroups. In some cases, cohesiveness of subgroups can be stronger, where subgroups are increasingly isolated from each other. In other cases, groups can have extensive links with outside nodes as well, reducing the extent of cohesiveness.

There are various methods to decompose a network into cohesive subgroups. Among these, one of the most commonly used is a *clique*. A clique consists of 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). For our purposes, we use the clique as a proxy for the firm, mainly because one of

[2] The breadth and depth of the knowledge base can also be interpreted as the complexity of the knowledge base, following Tunzelmann and Wang (2000), where they define breadth and depth as two dimensions of complexity in a more general context. In this paper, we explore how these dimensions are translated into the emerging network structures.

[3] See Freeman (1992) for a review of the concept of a group.

the characteristics of a clique is that there are overlaps between the cliques when a network is partitioned into cliques. Therefore, unlike various clustering algorithms, the cliques are *not* disconnected clusters, but groups of agents all connected within a clique, but also sharing common elements. In other words, an agent might belong to more than one clique. It is particularly this definition of clique that makes it useful for the purpose of this research. Increased overlap between cliques can be thought of as increased interaction among subgroups, which can be used as a proxy to measure the extent to which the system resembles a network-based industry. Here, overlap simply measures the porousness of the boundaries of subgroups.

3 The Model

3.1 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 form a uniform distribution) at period $t = 0$, showing the agent's knowledge level in each of the K types of knowledge; k^i_j 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 $k^i_j > k^i_m \; \forall m \neq j$. [4]

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 k produces singleton, the probability that he/she will produce good i is proportional to the weight of his expertise j required by the good.[5] We adopt the term $i - type$ agent if the agent produces good i. The amount that he/she produces as singleton is given by $y_i(\mathbf{k}^k)$

Each agent, in each period t, selects between producing as a singleton 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.

[4] The knowledge setting used here is first introduced by Cowan et. al (2001). Specifically, $k^i_{j,t} = k^h_{j,t}$ means that agents i and h have exactly the same knowledge in type j. If $k^i_{j,t} > k^h_{j,t}$, agent i knows everything that agent h knows in type j, and has some knowledge in addition.

[5] This means that if i am an expert in knowledge type j and if good i requires 90% of knowledge type j, the probability that i will produce good i is 90%.

Joint production happens through integration of knowledge of the two agents. When an $i-type$ agent and a $j-type$ agent form a pair, we assume they produce both goods i and j. The quantities are found as follows:

It is assumed that if two agents k and l collaborate ($i-type$ and $j-type$ respectively), their joint knowledge in category m is given by

$$k_m^{pair} = \max(k_m^k, k_m^l)\ \forall m = 1....K \tag{1}$$

When an *i-type agent* k forms a pair with a *j-type agent* l, Eq.(1) enters the production function, of both goods i and j. 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

$$y_{i,j} = \frac{y_i(\mathbf{k}^{pair}) + y_j(\mathbf{k}^{pair})}{2}$$

Therefore, agent k compares his/her singleton output $y_i(\mathbf{k}^k)$ with $y_{i,j}(\mathbf{k}^{pair})$ for 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 (2001) utilize this matching algorithm for analysing the network dynamics resulting from joint innovation by interaction and knowledge integration of agents.

After production takes place, the output that the agent generates is used to add to his current stock of knowledge. The following function is used in updating agent $k's$ stock of knowledge type m;

$$k_m^k(t) = k_m^k(t-1) + \theta_k y(t) g(t) \tag{2}$$

$$\begin{aligned} g(..) &= \delta_k(t) \quad k_m^k(t-1) > k_m^l(t-1) \\ & \frac{k_m^k(t-1)}{k_m^l(t-1)} \quad \text{else} \end{aligned}$$

where θ_k measures the combinative capability of the agent, and $\delta_k(t)$ is an uncertainty effect. Eq. (2) implies that, learning is measured by the extent to which the agent can make use of production $y(t)$. This is firstly a function of capability of the agent, as given by θ_k. Second, it is a function of the relative knowledge levels between the partners. Firstly, if agent k knows less than his/her partner, then there is only an absorption effect, that is assimilating part of the knowledge of the partner. The less the agent knows relative to his/her partner, the less is the amount he/she can benefit from the output to add to his/her knowledge, the extent of which is determined by his/her combinative capability. But depending on this capability, the agent can also leapfrog the partner after learning, even if he/she knew less in the previous period.

Secondly, if agent k knows more than his/her partner (agent l) before production, there is only an uncertainty in his ability to make use of production.[6] This is given in the first part of the function $g(..)$. In this case, there is only R&D. Here, uncertainty is given by the parameter $\delta_k(t) = \delta \pm \eta_k(t)$ which is different for 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_k, as well as the extent of uncertainty, captured by $\delta_k(t)$.

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

3.2 Production

We consider an economy in which the main input in production is knowledge. [7] We assume a Cobb Douglas production function for M goods and K knowledge types, such that the amount of good i is given by

$$y_i(\mathbf{k}) = \alpha \prod_j k_j^{\gamma_{ij}} \text{ where } \sum_j \gamma_{ij} = 1 \ \forall \ i = 1, 2, ..., M. \tag{3}$$

Here, k_j is the amount of knowledge in type j, and γ_{ij} measures the proportion of knowledge type j required to produce a unit of good i. Since there are M goods and K knowledge types, the corresponding γ values, for each good and knowledge can be represented by an MXK matrix G giving the respective parameters of the production function.

The breadth of the knowledge base is the range of different knowledge types that production of the good requires. We measure this basically by the number of coefficients in the production function greater than zero. The higher it is, the

[6] This can be thought of as the R&D uncertainty.

[7] Athough 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.

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 higher the depth. Specifically, for each product, we generate random values of $\gamma'_{ij}s$ drawn from $N \sim (\mu_{ij}, \sigma_{ij})$.[8] We plot the results in the breadth and depth space.

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.[9] More specifically, the cosine index between two products j and m is given by;

$$\cos_{mj} = \frac{\sum_{i=1}^{K} \gamma_{ji}\gamma_{mi}}{\sqrt{\sum_{i=1}^{K} \gamma_{ji}}\sqrt{\sum_{i=1}^{K} \gamma_{mi}}}$$

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 $COS(MXM)$, where cos_{ij} gives the cosine between products i and j.

4 Simulations

We perform 20 simulations for the same population of agents defined by the initial knowledge stocks. In each of these 20 simulations, a different set of goods, characterized by their production coefficients, is taken exogenously. In a single simulation, there are $M = 5$ goods and $K = 5$ knowledge types. Each of the goods are represented by a vector of knowledge input coefficients, and an accompanying breadth and depth measure. In the Appendix, an example set of goods is provided for a set of 20 simulations (since there are 20 simulations, 5 goods and 5 knowledge types in each simulation, there are 100 goods in the Appendix). Minimum breadth corresponds to a good taking 2 knowledge types as input, and maximum breadth corresponds to a product with all 5 knowledge types. We repeat this procedure (20 simulations) 10 times, each with a different population and a different set of goods. The results presented here are the averages of the measures taken over 10 simulations.

[8] An example set of goods is given in the Appendix, for various breadth and depth values. This is further explained below, in the Simulations section.

[9] See also Breschi et. al (2002) for this measure, where they use cosine index to measure relatedness between two technologies.

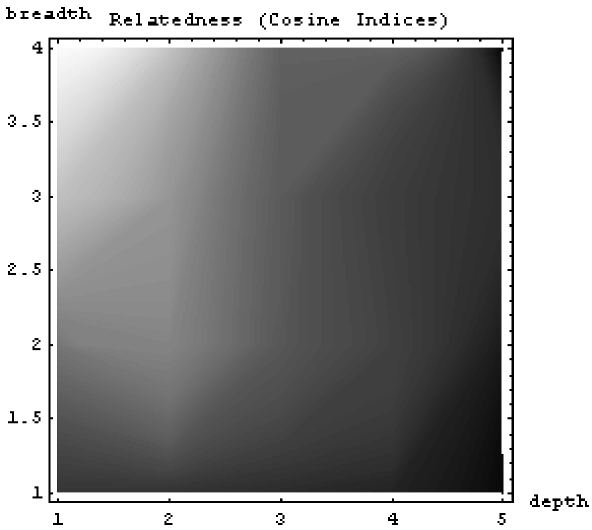

Figure 1: Relatedness among goods (average of cosine matrices)

Population consists of $N = 50$ agents. Uncertainty parameter $\delta_k(t) \in [0.95, 1.05]$ and capabilities are $\theta_k \in [0.8, 1.2]$. A single simulation consists of $T = 5000$ periods. The major aim is to make a mapping between some resulting network measures and the breadth and depth of the knowledge base.

As explained above, 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 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? This is given by the simulation results.

4.1 Network Dynamics

At each period t, an 50x50 adjacency matrix $FREQ(t)$ is constructed, where f_{ij} shows the number of times, up to period t, that agent i has formed a pair with agent j. Similar to the approach undertaken by Cowan et. al (2001), by this way it is possible to capture the dynamics of the network, contrary to the case where in a single period only the isolated pairs exist. The frequency matrix is recorded every τ periods. Therefore, when the difference between two frequency matrices Z_τ $= (FREQ(n\tau) - FREQ((n-1)\tau)$ is taken ($n = 1.....R/\tau$, where R is the total number of runs in a single simulation), $z_{ij} = 0$ implies that agents i and j has not formed a pair during the last τ runs. In the extreme case, when there are only isolated pairs and each agent matches with a unique agent and no one else, every row of Z_τ will be composed of a single τ and 0s elsewhere, which would mean there are complete isolated pairs, and during the final τ runs, every agent had matched with the same partner. In the simulations, we set $\tau = 500 \pm 10$.Taking as Z the matrix upon which the network analysis is carried out, below, the main aspects of this analysis is presented.

4.1.1 Density

The density of the network measures the intensity of the relationships. 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. We are interested in the density of the network in the parameter space defined by breadth and depth of the knowledge base. Figure 2 shows the results obtained for the final networks, after 5000 periods, and stability in the networks is achieved.

As can be seen in Figure 2, average density in the final networks is highest in the upper right corner. In this area, both breadth and depth of knowledge base are largest. Goods utilize a wide range of knowledge types, but one of them intensively. Two areas also stand out in this figure, where density is lowest. These areas are upper left corner, and the area in which breadth of the knowledge base is lowest (the lower region in the figure). In the remaining regions, we see moderate density. We leave further elaboration on these results to the aftermath of clique analysis.

What is more important for our purposes is to understand the structure of the 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? To answer these questions, we perform a clique analysis, and partition the resulting networks into cohesive overlapping subgroups, to be used as proxies for the firm.

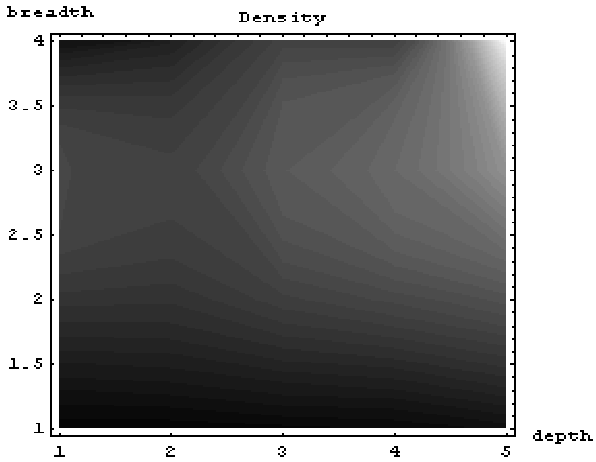

Figure 2: Final densities

4.2 Cliques

In this section, we partition the final networks that we obtained under various breadth and depth measures, into cliques.[10]

Figure 3 shows five figures. Firstly Figure 3.1 shows average product diversity in cliques. Each clique consists of a number of agents. Product diversity is measured by the weighted number of different types of goods these agents are specialized in, calculated for all the cliques seperately, and the average values taken over all cliques in a single simulation. [11] We also normalize diversity with respect to average clique size. As revealed by Figure 3.1, diversified firms exist mainly in the upper left corner. In this region, knowledge base is broad, and all types have equal weights in production, i.e. depth is low. As shown in Figure 1 this is the area corresponding to maximum relatedness among the goods. This figure shows that the cliques in the remaining regions are more focused in terms of production.

Having distinguished between product diversity and technological diversity above,

[10]To partiton the network into cliques, the software UCINET was used (Borgatti et. al., 2002).

[11]The 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 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 achiavable index. In this way we obtain exactly 2, when 2 different goods are produed with equal weight, and an index slightly smaller than 2 when the weight of one good is higher.

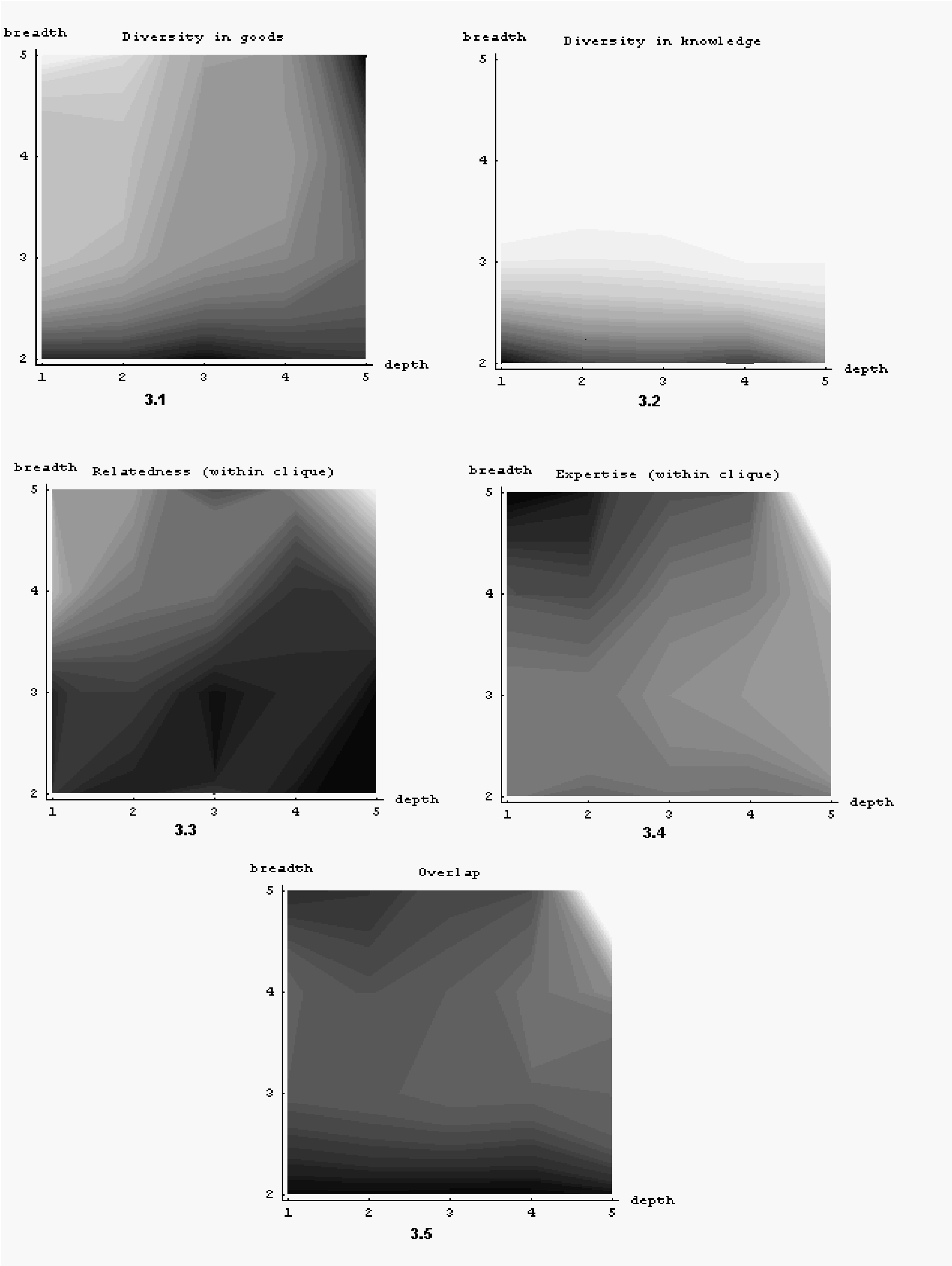
breadth
Diversity in goods
depth
3.1
breadth
Diversity in knowledge
depth
3.2
breadth
Relatedness (within clique)
depth
3.3
breadth
Expertise (within clique)
depth
3.4
breadth
Overlap
depth
3.5

Figure 3:

Figure 3.2 depicts a measure of technological diversity. We measure technological diversity 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 3.1 and 3.2 is interesting since it underlines the distinction between product diversity and technological diversity. A much wider region is characterized by technological diversity, whereas only a limited area is characterized by product diversity. Specifically, when we look at the middle regions and upper right corner, we see that these regions are relatively narrow and focused in terms of production. But at the same time, in these areas, cliques are highly diversified in terms of their knowledge bases, which we use as an implication of increased technological diversity.

Figure 3.3 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 3.3 is that in the upper left corner, where diversity is maximum (see Figure 3.1), there is also high relatedness among goods, which is not surprising, since the goods themselves are already highly related in this region. What is more interesting is that the upper right region, despite very low relatedness in the goods themselves (see Figure 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 3.1).

This observation is also confirmed when we look at Figure 3.4, which gives the within clique expertise levels. This measure is basically 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 3.1) . Conversely, in the upper right region, product diversity is low, and there is high level of specialization in knowledge. It might seem contradictory that it is also in this region that we see high technological diversity (Figure 3.2). But this implies that, the agents forming the clique are knowledgable 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 3.5. Basically, this is the measure we use for intensity of inter-clique relations. We compute this measure as follows. Take two cliques and compute

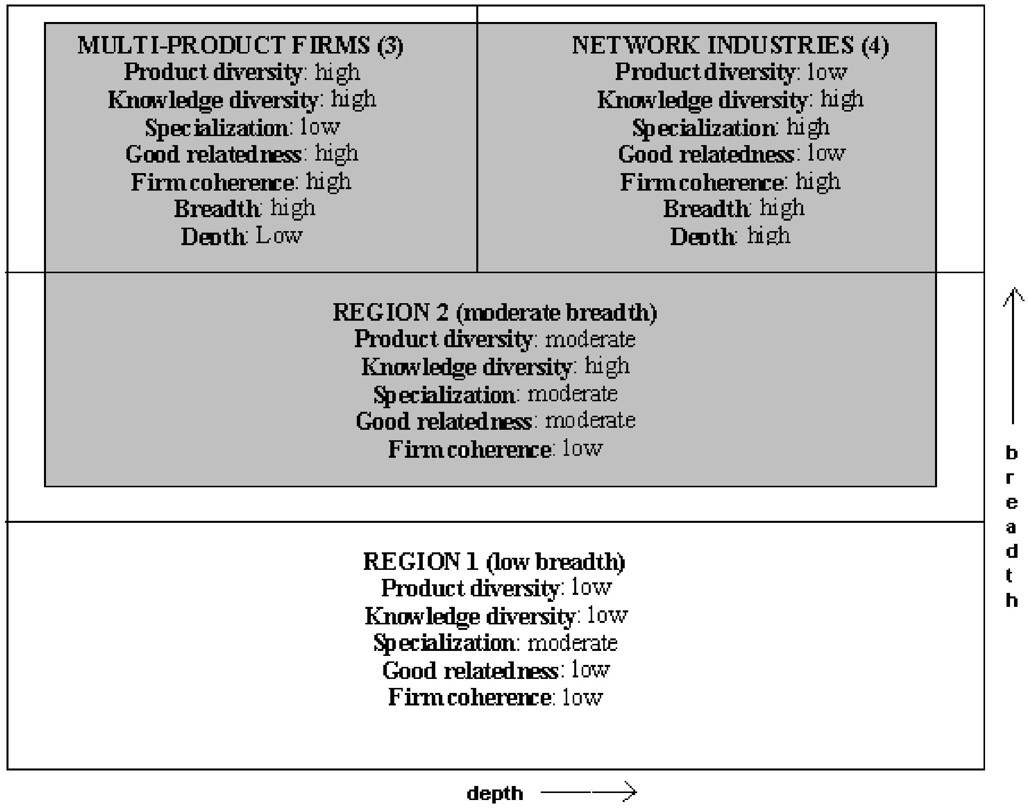

Figure 4: Categorization of industries in the depth and breadth space

the number of common members. We perform this for all clique pairs, and take the average. Looking at Figure 3.5, 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 technological diversification, and high overlap among cliques.

4.3 Summary

To summarize our findings, we decompose the breadth and depth space into four regions. This is given in the Figure 4.

Region 1 characterizes a very narrow knowledge base. As a consequence of this, some pairs of goods have no knowledge in common, i.e. a cosine index of zero. Therefore, the relatedness among goods is also low, as implied by Figure 1. This is why, there is hardly any scope for diverse agents to form pairs. 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, because same types of agents come together. Specialization is quite high, as a direct result of these. 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, and reduces technological diversification. 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 produced by most. In other words, agents have no relevant knowledge to contribute to each others production. These results are also in accordance with the low knowledge diversity in this area, as give in Figure 3.2.

We define region 2 to be a transitory region, characterized by moderate breadth. This region is a transition from narrow base to widest base, after which the depth begins to influence the network structure. When breadth of the knowledge base is wide enough, we observe the emergence of two distinct regions; 3 and 4. In region 3, breadth is wide, and depth is low. This implies that the goods are highly related to each other, as also seen in Figure 1. It is in this region that both product and technological diversification, low specialization, high relatedness (coherence) accompany each other. We claim that this region constitutes multi-product firms. In this region, inter-clique relations are not intensive, cliques are more cohesive and isolated. 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 same pairs come together mostly throughout the simulations. But the difference here is that, different types of agents come together (an *i-type* agent and a *j-type* agent can come together since they both utilize same knowledge types in nearly same amounts), as revealed by high product diversity. This is contrary to the pattern in region 1, where mostly same types interact. When the goods in an industry are too much 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 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.

Finally, we call region 4 network industries. In this region, high firm specialization together with technological diversification and low product diversity accompanies high inter-clique overlap. Moreover in this region, despite very low relatedness among goods themselves, we don't see the effect of this inside the cliques. The goods produced inside cliques are highly related to each other, which is also evident in the observance of a high product focus.

A wide and deep 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 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 very little. The specialization subject of one good is only a minor input in another good. This decreases the absolute 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 significant 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 knowledge base is wide and deep do we see efficient integration of knowledge, and emergence of network industries, as shown by region 4.

One of the issues of interest is the shaded region. We call this region technological diversifiers. It is interesting to see that only part of this region is network-based, and another part of it is multi-product firms.

5 Concluding Remarks

In this paper, 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; the 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 to integrate their knowledge and maximise output, we analysed the dynamics of the networks that emerge from these interactions. Specifically, we analysed the resulting network structures under various schemes of breadth and depth of knowledge base. The results revealed that network density is highest in the region characterized by a broad and deep knowledge base, where relatedness among goods is low.

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 schemes of knowledge base, we analysed the structural characteristics of the cliques. The results highlight three regions of interest. First, when breadth of knowledge base is narrow, specialized firms with high product and technological focus exist, and inter-clique relations are not intensive. As breadth gets wider, we see the emergence of two distinct regions. Both regions are characterized by a broad knowledge base. In one of the regions, knowledge base is not deep. 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 so intensive. The last region is the one in which network industries are likely to emerge. Here, 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 in compliance 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, 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. However, as our results reveal, 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.

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Figure 5: