Available online at www.sciencedirect.com
ScienceDirect
Technological Forecasting & Social Change 73 (2006) 1121–1143
Technological Forecasting and Social Change

Knowledge integration and network formation

Müge Ozman *

Bureau d'Economie Théorique et Appliquée (BETA), 61 avenue de la Forêt Noire, 67085 Strasbourg, France

Received 1 June 2005; received in revised form 30 November 2005; accepted 2 December 2005

Abstract

In this paper, we highlight how inter-firm collaboration networks are influenced by the knowledge composition of goods in an industry. For this purpose, we carry out an agent-based simulation study in which firms integrate their competencies under different knowledge-based regimes. In this way networks form. The results reveal that knowledge regime significantly influences the network structure, and interaction among firms not only is very intensive when the products are specialized but also have common knowledge among them.

Keywords: Networks; Knowledge; Learning; Agent based simulation

1. Introduction

In recent decades, the intensity of horizontal and vertical relations among firms has increased to a large extent, especially 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. These developments prepared 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. Mostly, interdependencies among products, compatibility requirements, specialization and collaboration accompany each other in these systems. Task complexity, combined with time pressure, makes cooperation among firms more efficient than vertical hierarchies [1,2].

* Tel.: +33 3 90 24 20 69; fax: +33 3 90 24 20 71.
E-mail address: ozman@cournot.u-strasbg.fr.

0040-1625/$ - see front matter
doi:10.1016/j.techfore.2005.12.007

In such an environment, knowledge has become a central factor in influencing industry dynamics. In most industries, 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. A major process that accompanies the inter-firm relations is the significant knowledge flow that takes place between the firms, 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 [3] termed to be collective invention (see also [4]). The structure of networks among firms is inevitably influenced by the competencies needed in production and the architecture of these networks yield insights into effectiveness and efficiency with which knowledge is transferred, created and also the innovative performance of firms [5–7].

There is a rich literature that addresses in a broad sense the relation between knowledge-specific characteristics and networks. Among these, studies that focus on uncertainty and industry events [8–10]; complementarities in goods [11], similarities in knowledge bases [12,13] the stage in the industry life cycle [14]; interdependence in products [15], system embeddedness and observability of knowledge [16]; hierarchical organization of knowledge base [17], characteristics of knowledge in terms of technological opportunities and tacitness [18] can be cited. Although most of these studies focus on different aspects of knowledge and networks, there has been no systematic study in the literature about how the network structure responds to different ways in which knowledge is embodied in goods in the economy as we investigate in this paper.

The question addressed in this paper is how the network structure responds to different knowledge-based regimes. The approach that is used differs from previous studies in that a dynamic network approach is adopted. The paper is composed of two parts, where firstly we present a very simple economy with two producers, two products and two types of competencies, and analyse via an analytical model, how and under which conditions producers collaborate and integrate their knowledge. In the second part, we extend the model to many producers, competencies and products. Because of the analytical complexity in this part, we perform a simulation study and analyse the collaboration dynamics in this case. Specifically, in the agent-based simulation model, self-interested actors who have competencies in different areas chose partners to integrate their knowledge and produce. Actors also learn from each other in this process, and networks form by the interactions among them. We analyse these networks and highlight the relation between patterns of interaction and knowledge base of the industry. We model the knowledge base using the concept of relatedness among products (similarity in their knowledge requirements) and the level of specialization of products. The results reveal that interaction among actors not only is very intensive when the products are specialized but also have common knowledge among them.

An important result of this paper is that we show how a simple economy with two producers behaves differently from an economy with many producers, competencies and products. In this sense, we show that the results pertaining to a duopoly case cannot be generalized to a case where there are many firms. As far as the relationship between knowledge base and networks are considered, in an economy with two producers specialization of the goods places stricter restrictions on collaboration possibilities than the case where there are many producers.

The paper is organized as follows. In the second section, we explain the main model and present some preliminary analytical results. In the third section, we present an agent-based simulation study where self-interested economic actors form networks to integrate their knowledge. We analyse the structure of resulting networks under different regimes of the knowledge base in the fourth section. Fifth section includes some empirical insights. Some discussions and concluding remarks follow in the last section.

2. The model

2.1. General

Let us consider a simple economy in which there are two producers, two goods and two knowledge types. Each of the goods requires 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_{as} measures the extent to which good a is knowledge s intensive (we assume constant returns to scale, so that $\gamma_{a1}+\gamma_{a2}=1$ for each good). To formalize, denote knowledge input by k, where k_{is} shows producer i's knowledge endowment in area s. It follows that the amount of product a that can be produced by i is given by;

$$y_a^i = \prod_{s=1,2} k_{is}^{\gamma_{as}} \qquad \text{where} \quad \sum_j \gamma_{as} = 1 \tag{1}$$

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 production. We also assume that demand is perfectly elastic so that profits increase monotonically with quantity. We take relative prices to be unity. In this production function, we consider an economy in which the main input in production is knowledge. It is important to underline that, although 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. Therefore, the amount of the final product which we consider to be immaterial depends on the knowledge it embodies. Higher levels of knowledge produce more output. An example of this sort of production function can be scientific collaborations (which can be considered to be not too much different from research collaborations among firms, to the extent that the knowledge combination process is concerned). Here, the output requires expertise of different scientists. As a result of this process the scientific paper is produced, and in this process, the contributors also accumulate new knowledge.

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 $k_{22}>k_{21}$. Single 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 single case, producer 1 produces good 1, and producer 2 produces good 2.[1]

[1] 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; $k_{11}^{\gamma_{11}} k_{12}^{(1-\gamma_{11})} > k_{11}^{(1-\gamma_{22})} k_{12}^{\gamma_{22}}$ which is equivalent to $k_{11}^{\gamma_{11}+\gamma_{22}-1} > k_{12}^{\gamma_{11}+\gamma_{22}-1}$ and since $k_{11}>k_{12}$ from our assumption above, producer 1 produces good 1. Analogously, when alone, producer 2 produces good 2.

2.2. Knowledge integration

Single production is only one of the options that the producer can choose. 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 (single or joint), and selects the one that yields more output for him. For pairwise production to be realized, both producers simultaneously should find it beneficial to collaborate. The rule for knowledge integration is as follows: the amount of joint knowledge that enters the production function is maximum of what each agent knows in type s and is given by;[2]

$$k_s^{\mathrm{pair}} = \max\left(k_s^i, k_s^j\right) \quad \forall s = 1 \ldots K \tag{2}$$

Since there are two knowledge types ($K=2$), 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

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

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

Let us first take the case of producer 1. He/she has to decide between producing good 1 alone (Eq. (1)), or to produce both goods with producer 2 and get half of total production so that his/her gain in joint production is given by;

$$y_{a,b}^{\mathrm{pair}} = \frac{y_a\left(\mathbf{k}^{\mathrm{pair}}\right) + y_b\left(\mathbf{k}^{\mathrm{pair}}\right)}{2} \tag{3}$$

for a, $b=1$, 2 (goods). We 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), then collaboration 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.

The question that we address is, 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

$$k_{11} < \left(\frac{2k_{12}^{(1-\gamma_{11})} - k_{22}^{(1-\gamma_{11})}}{k_{22}^{\gamma_{22}}} \right)^{\frac{1}{1-\gamma_{11}-\gamma_{22}}} \tag{4}$$

[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.

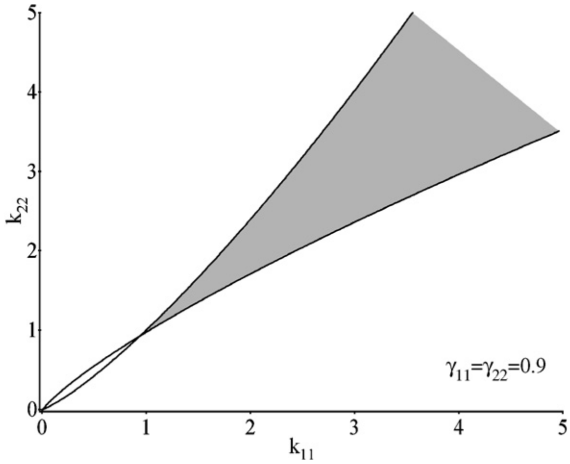

Fig. 1. Collaboration conditions for the same major knowledge levels ($\gamma_{11}=\gamma_{22}=0.9$).

For producer 2

$$k_{22} < \left(\frac{2k_{21}^{(1-\gamma_{22})} - k_{11}^{(1-\gamma_{11})}}{k_{11}^{\gamma_{11}}} \right)^{\frac{1}{1-\gamma_{11}-\gamma_{22}}} \tag{5}$$

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

Proof. See Appendix A. □

Inequalities (4) and (5) 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 Fig. 1.[3]

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 Figs. 1 and 2 show the areas in which collaboration will take place as a function of the major knowledge levels. These figures are based on inequalities (4) and (5). The intersection point of the curves is the level of minor knowledge type, which is equal to 1 in 2 and 1. 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 Fig. 1). If the initial major knowledge levels are the same (which corresponds to a 45° line in Figs. 1 and 2), 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

[3] It follows directly from Proposition 1 that, 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 $k_{22}>k_{21}$ and $k_{22}>k_{21}$: Therefore, 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 ($k_{22}>k_{21}$).

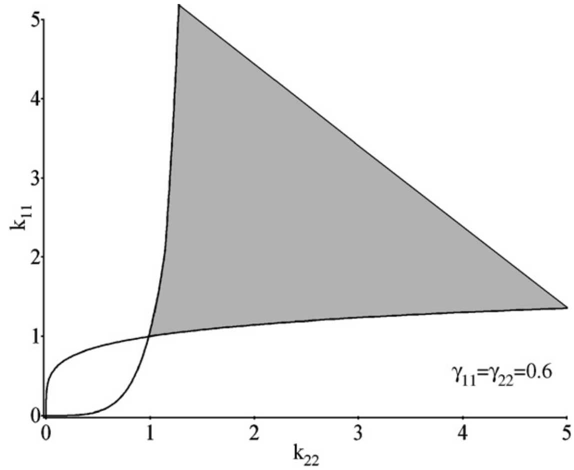

Fig. 2. Collaboration conditions for the same major knowledge levels ($\gamma_{11}=\gamma_{22}=0.6$).

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 Fig. 1, the $\gamma_{11}=\gamma_{22}=0.9$ and the area of collaboration is smaller than Fig. 2 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 lower weight of the minor category. Consequently, as γ_{11} increases, the area of collaboration falls as shown in Fig. 1 in comparison to Fig. 2.

To summarize, the likelihood of single 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. The higher are these production parameters, the less difference among competencies is permitted for collaboration to take place (see Fig. 1).

Proposition 2. *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.*

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.

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 in the case of joint production. In each period, we assume agents re-consider their decision about collaborating, based on the new knowledge levels. The learning function by which knowledge levels are updated is given by Eq. (6), for producer i in knowledge type s.

$$\begin{aligned} k_{is}(t) &= k_{is}(t-1) + \theta_i y(t) g(t), \\ g(t) &= \delta_i(t) \text{if } k_{is}(t-1) > k_{js}(t-1) \\ &= \delta_i(t)\frac{k_{is}(t-1)}{k_{js}(t-1)} \text{ else} \end{aligned} \tag{6}$$

Eq. (6) implies that learning is measured by how much the agent can make use of production $y(t)$ (given by Eq. (3)): According to this function, the amount that the agent learns in a particular knowledge type depends on the following. Firstly, it depends on the amount of production that took place, $y(t)$.The higher is the amount produced, the higher is the amount that the agent can increase his knowledge. Since production embodies knowledge in this model, this learning process can be thought as learning by doing, in which the agent learns from production experience. Obviously, the amount that he can make use of production depends on other factors as explained below.

Secondly, the amount of learning depends on the capability of the agent which is different for all agents, as given by θ_i: This parameter measures the ability of the agent to make use of the production to increase his knowledge. In other words, it measures the extent to which he can use $y(t)$ to accumulate more knowledge.

In the learning function, we also include the term measuring the relative knowledge levels between the partners i and j; as given by the second part of (6), ($g(t)$). This part is based on the intuition that, in a joint production process, the amount by which the agent makes use of the production experience will be limited to the extent that he contributes to production relative to the partner. If his initial knowledge is too little compared to his partner, he cannot learn much, as given by the second part of $g(t)$.[4] On the other hand, if agent i knows more than his/her partner (agent j) before production, there is only an uncertainty in his ability to make use of production and increase his knowledge given by $\delta_i(t)$ for agent i in period t. This is because now there is no other partner from whom he can learn, since he is already the expert in the partnership. This is given in the first part of the function $g(t)$. Overall, in this case, his learning depends on his capability, the production amount and an uncertainty term, $\delta_i(t)$. We include an uncertainty term, which we take to be 1 in the analytical model, but which we change in the simulations. This term is used to capture the *temporal variations* in which an agent can make use of the production to add to his knowledge, which is not the same in all periods because of environmental conditions. Therefore, it is not always fully in the agents control to make use of production, but external conditions are also taken into account which maybe more favourable for adding to the knowledge in some periods than in others which we measure by $\delta_i(t)$.[5]

[4] Here, the agent cannot increase his knowledge too much if he knows much less than his partner, because it is the partner's knowledge which makes the highest contribution to the product. This part also makes sure that there are no big jumps in the learning amounts of the agents. However, if the agent has a very superior capability θ_i, he can still leapfrog the partner.

[5] We interpret this learning function as learning by doing. Indeed, in the Alchian sense this functional form does not rule out a concave learning function. In this function, we take into account the relative knowledge levels between the partner and the agent, so that the amount the agent learns depends on what his partner knows among other factors. For example, if in two consecutive periods, the agent has a partnership in which he/she is the expert, and in the next period he/she has a partnership with another agent who knows more than him/her, his/her learning amount can diminish in this knowledge type. Therefore, the function emphasizes the important role of partners in the learning process.

The knowledge types are updated in all the knowledge types that enter the production function of goods produced by the pair or the agent him/herself.

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.

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 and $\delta_i(t)=1$.

Proposition 3. *If capability levels are the same among producers, and if there was collaboration in the first period, collaboration will continue in the second period if and only if the following conditions are met for producers 1 and 2,*

For producer 1

$$k_{11}^{1-\gamma_{11}-\gamma_{22}}(t-1) > \left(\frac{2k_{12}^{1-\gamma_{11}}(t-1)}{k_{22}^{\gamma_{22}}(t-1)} - k_{22}(t-1)^{1-\gamma_{11}-\gamma_{22}} \right)\psi \tag{7}$$

where

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

For producer 2

$$k_{22}^{1-\gamma_{11}-\gamma_{22}}(t-1) > \left(\frac{2k_{21}^{1-\gamma_{22}}(t-1)}{k_{11}^{\gamma_{11}}(t-1)} - k_{11}(t-1)^{1-\gamma_{11}-\gamma_{22}} \right)\phi \tag{8}$$

and

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

Proof. See Appendix A. □

Proposition 3 is interpreted as follows. Since we assume there is collaboration in the first period, the conditions given by (4) and (5) are already satisfied. The new condition imposed by Proposition 3 is shown by Fig. 3 which is the same as Fig. 1 plus the new constraints shown by dark grey areas.

Figs. 3 and 4 are based on Eqs. (7) and (8), where 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 Fig. 1). The second period constraints are revealed by the addition of the dark grey areas. 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

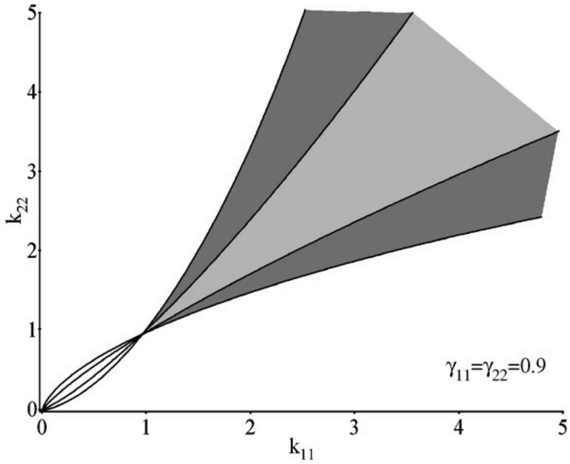

Fig. 3. Second period collaboration conditions ($\gamma_{11}=\gamma_{22}=0.9$).

second period too, since the light grey area is covered by the total shaded area (light grey and dark grey).[6]

Another question of interest is, what happens in the second period if there is no collaboration in the first period? From Figs. 1 and 2, it is known that if the major knowledge levels of the two producers are not within the shaded regions, than there is no collaboration in the first period. Nevertheless, if their initial major knowledge levels fall within the dark shaded regions in Figs. 3 and 4, then collaboration will begin in the second period, although there was no collaboration in the initial period. The intuition behind this is as follows. No collaboration in the first period means that the agents are too far apart from each other in terms of their expertise levels (see Proposition 1) initially. Nevertheless, for the same capability levels, the distance between their knowledge levels after learning takes place can bring them closer to each other in the second period. There is a certain range of initial knowledge levels which will permit this to take place in the second period. These initial knowledge levels are given by dark shaded regions in Figs. 3 and 4. Therefore, if the initial knowledge levels are within this range, collaboration will begin in the second period.

In this section, 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.

Although this model gives a basic idea on the logic of knowledge integration and production, 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 singly 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

[6] In Figs. 3 and 4, we take into account the cases where the capability levels of the two producers are the same. Nevertheless, if the capability of an agent is different from the other, the higher capability agent learns faster and thus increases his/her knowledge faster. In this case, the conditions for collaboration in the following periods become stricter.

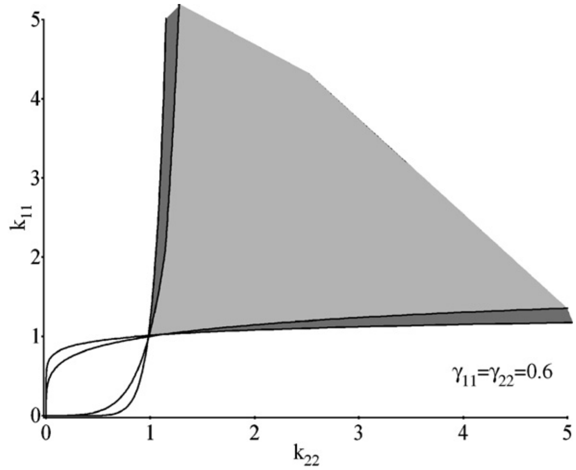

Fig. 4. Second period collaboration conditions ($\gamma_{11}=\gamma_{22}=0.6$).

following period. Also in this section, 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 with a higher number of goods, producers and knowledge types.

3. Simulations

3.1. General

In this section, 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.

There are 5 goods, 5 knowledge types, and 50 agents in the economy. Each agent i is endowed with a knowledge vector, $\mathbf{k}^i$ assigned randomly (drawn from a uniform distribution, $\mathbf{k}^i \in [0, 10]$) at period $t=0$; k_{is} shows the level of agent i's knowledge in type s. There exist a knowledge type s for all i such that $k_{is}>k_{it}$ $\forall t \neq$ s.[7] Given his/her knowledge vector, each agent in each period produces a good. But an agent can produce singly, 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 a is equal to the weight of his expertise type s required by the good.[8] We adopt the term a-type agent if the agent produces good a. The amount that he/she produces singly is given by y_a^i as given by Eq. (1).

[7] The knowledge setting used here is first introduced by Cowan et al. [20]. Specifically, $k_{is}=k_{js}$ means that agents i and j have exactly the same knowledge in type s. If $k_{is}>k_{js}$ agent i knows everything that agent j knows in type s, and has some knowledge in addition.

[8] If an agent is expert in type s, and if one of the goods require 90% of s and the other good requires 20% of s, with 0.9 probability he will produce good 1 and with 0.2 probability he will produce good 2. The intuition behind this is as follows. We try to model an economy in which optimization in terms of the efficiency of knowledge distribution may not be the case all the time, by making knowledge distribution stochastic. Any agent who has an expertise does not necessarily work on a field that uses his expertise intensively. Nevertheless, the more a certain field requires his competence, the more likely that he will use his competence in this area.

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 agents. When an a-type agent and a b-type agent form a pair, we assume they produce both goods a and b. It is assumed that if two agents i and j collaborate (a-type and b-type, respectively), their joint knowledge in category s is given by Eq. (2) which enters the production function of both goods according to Eq. (1) and shared among them according to Eq. (3). Therefore, agent i compares his/her single output y_a^i with $y_{a,b}^{\text{pair}}$ 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 roommate problem, where pairs are formed within a single population [19]. Within a similar framework as this paper, Cowan et al. [20] utilize this matching algorithm for analysing the network dynamics resulting from joint innovation by interaction and knowledge integration of agents. After production, learning takes place according to Eq. (6), pairs dissolve and next period expertise areas are updated, and new pairs form.

3.2. Relatedness

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 between two goods by the cosine of the angle between them. More specifically, the cosine index between two products a and b is given by;

$$\cos_{mn} = \frac{\sum_{s=1}^{K} \gamma_{as}\gamma_{bs}}{\sqrt{\sum_{s=1}^{K} \gamma_{as}^2}\sqrt{\sum_{s=1}^{K} \gamma_{bs}^2}}. \tag{9}$$

Obviously, in the extreme cases $\cos_{aa}=1$, and if there is no common knowledge between the goods, $\cos_{ab}=0$. 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 $\cos_{ab}$ gives the cosine between products a and b.

The model consists of a setting in which all goods have an equal number of knowledge inputs. In other words, all goods have 3 knowledge inputs. 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 knowledge types.

As a demonstration, the production parameters are given by Table 1 where the rows and columns represent goods and knowledge types, respectively, and γ_{as} gives the weight of knowledge s in good a.[9]

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

[9] In Table 1, we do not use double subscripts for purposes of clarity, since the elements of the matrix represent the same numerical values.

Table 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

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,

$$\gamma_1 = 1$$

$$\gamma_2 = \gamma_3 = 0. \tag{10}$$

Corresponding to this case, the COS matrix is given by Table 2.

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

$$\gamma_1 = \gamma_2 = \gamma_3 = 1/3. \tag{11}$$

The corresponding COS matrix is given by Table 3.

The main parameter that is varied in different simulations is the production parameters that are inputs in the production function (given by Eq. (1) and Table 1). From the production parameters, we derive measures of relatedness using Eq. (9) 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.

3.3. Simulations and network definition

We carry out 40 simulation runs. In each of these runs, a different set of input coefficients is used for the 5 goods. On one extreme, we have the case given by Eq. (10) and on the other extreme we have the case given by Eq. (11). In between cases consist of parameters which yield intermediate levels of relatedness among the products. We present the results with respect to the relatedness measures, which

Table 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

Table 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

are derived by taking the average of the cosine matrices that correspond to each set of input coefficients in different runs.[10]

In each of the runs there are 10,000 periods. In each period, matching takes place, pairs form and produce according to Eq. (1) and agents update their knowledge according to Eq. (6). In each period who forms a pair with who is recorded as an adjacency matrix. We take into account only bilateral link formation in a single period, but when sufficient time periods elapse, these bilateral links form a network, and a certain network structure emerges. We consider the results when the network stops changing, i.e. when the stability in the network is achieved. The results presented below are based on the frequency matrices of the last 500 ± 10 periods. Therefore, in the final networks, a link between two agents exist when they have formed a collaboration at least once in the last 500 periods.[11]

One other option in the construction of the network is to take into account weighted links. We tried the simulations in this way also, but the major pattern in the results did not change. The reason is that, since the networks after stability is taken and after sufficient time periods have elapsed, either the same agents collaborate all the time, or different agents collaborate and form certain cliques or clusters. Therefore, there is no case in which the collaboration between two agents is once and for all. This observation gives us confidence about the robustness of the results with respect to the use of weighted or non-weighted links. The uncertainty parameter $\delta_i(t) \in [0.95, 1.05]$ and capabilities are $\theta_i \in [0.8, 1.2]$.[12]

4. Results

4.1. Network density

Firstly, we looked at the density of the final networks.[13] It is given by:

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

[10] As 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% of a particular knowledge type is shared between them.

[11] In general, it is difficult to construct an exact correspondence between real time and simulation time. Nevertheless, a very rough measure can be obtained by analysing the average density in the simulations and the number of partnerships constructed by firms per year in real time. If on the average in a certain industry n partnerships are formed per year per firm, and if m is the density of the network in the simulations corresponding to the last 500 periods for a population of p firms than $m * p/n$ will give a rough measure of how many years 500 periods of simulation correspond to.

[12] Different parameter ranges were tried to test for the robustness of the results. The results do not change significantly, except that higher values of uncertainty parameter has the effect of increasing the absolute levels of network density.

[13] In the rest of the paper, software UCINET is used for given network measures (Borgatti et al. [21]).

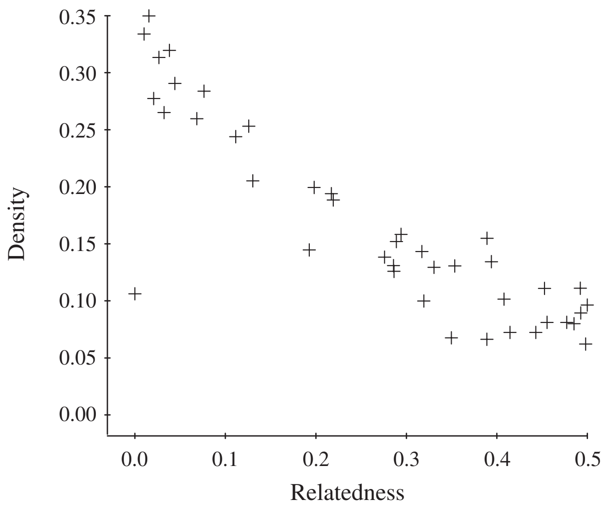

Fig. 5. Network density.

where $x_{ij}=1$ if there is an edge between agents i and j and 0 otherwise and N is the total number of nodes.[14] The denominator measures total number of available links in the network, and numerator measures the number of existing links.

Fig. 5 depicts two results. Firstly, there is a clear negative relationship between relatedness and network density. As the relatedness among the products' increases, the density of the network falls (lowest density occurring for the case of Eq. (11) 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 little relatedness among the products (which means that agents change their partners frequently).

The second result that can be deduced from Fig. 5 is the discontinuity observed when the products are totally unrelated, that is the leftmost point (corresponding to the case Eq. (10) 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 single production (which will reduce network density), or the same agents tend to form pairs all the time so that there is no variety in the network.[15] 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.[16] This discontinuity is also observed in the remaining parts of the results below.

[14] The matrices upon which density is calculated are 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 past 500 ± 10 periods. We use the frequency values in the analysis below.

[15] In this case, producing singly is higher than other cases.

[16] Integrating 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.

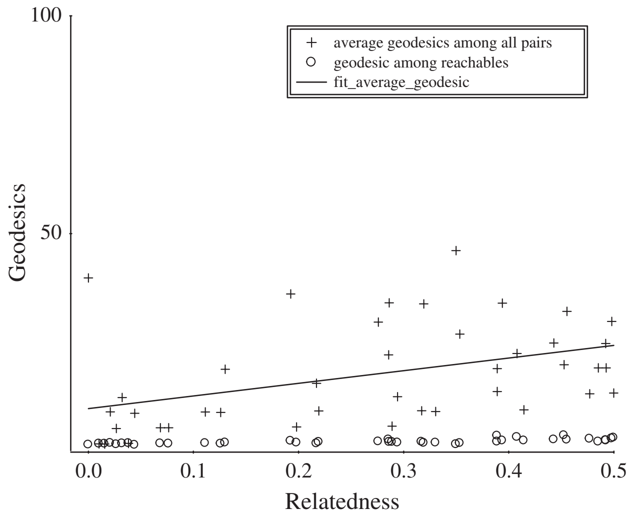

Fig. 6. Geodesics and relatedness.

4.2. Geodesics

The distance between two agents is the number of the edges in the shortest path connecting them.[17] Based on this definition, for all final networks, a geodesic matrix was constructed, where g_{ij} shows the length of the shortest path between i and j. We took the averages of these matrices over all pairs. Fig. 6 shows these measures, firstly when only the nodes that are reachable to each other is taken, and secondly when all of the nodes in the networks are taken. The figure confirms the reduced interaction among agents as goods become more related. It is also interesting to note that, as relatedness rises, not only the geodesic between all pairs increases, but also the average geodesic between only reachable pairs rises. As it is shown further below, this implies that clustering increases (the case of totally isolated pairs being the extreme case) as goods become more related.

4.3. Clustering coefficient

Fig. 7 shows the mean clustering coefficient of the network with respect to relatedness. Clustering coefficient of an agent measures the density of his/her open neighbourhood, and the mean clustering coefficient of the network is the average clustering coefficient taken over all agents weighed with respect to the individual degree of an agent.[18] Fig. 7 shows that the clustering in the network increases slightly as relatedness increases. This is largely because when there is a high degree of relatedness among the goods, the same agents interact, or agents produce singly. This reduces both the density of the network, and also increases the extent of isolated pairs who collaborate consistently or single producers.

[17] If two agents have no path between each other, it means that there are no intermediate agents through which the two agents are connected. In this case, the distance is taken to be zero. As mentioned above, these values are based on the last 500 ± 10 periods of the simulations, from which we derived the frequency matrices. Basically, these matrices show how many times during the last 500 ± 10 periods two agents have formed a pair.

[18] Degree of an agent is the number of links that the agent has in the network.

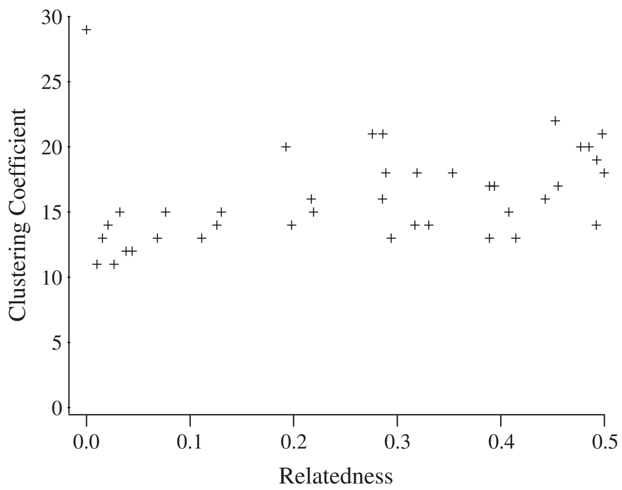

Fig. 7. Clustering coefficient and relatedness.

4.4. Knowledge dynamics

In Fig. 8, we present the average knowledge levels over all agents with respect to relatedness. There is a very high variance in the level of average knowledge levels, which makes it difficult to detect a certain trend. Nevertheless, relatedness seems to influence expertise levels significantly as Fig. 9 shows.

We measured expertise by the Blau index [22] in the final periods for each run. The weight of knowledge s in the total amount of knowledge for agent i in all types of knowledge is given by;

$$w_s^i = \frac{k_s^i}{\sum_{s=1}^{K} k_s^i}$$

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;

$$\mathrm{Exp}_i = \frac{1}{1 - \left(\sum_{s=1}^{K} \left(w_s^i\right)^2\right).}$$

As Fig. 9 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. (10) above).[19] 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 as shown in Fig. 5. 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, and one of the reasons of variety in pairs is that expertise types also change more frequently in the population (agents shift their expertise). The average change of expertise is demonstrated in Fig. 10. Whereas when relatedness is high, same agents join for production so that

[19] Because the expertise index is extremely large in this case, it is not shown in Fig. 9.

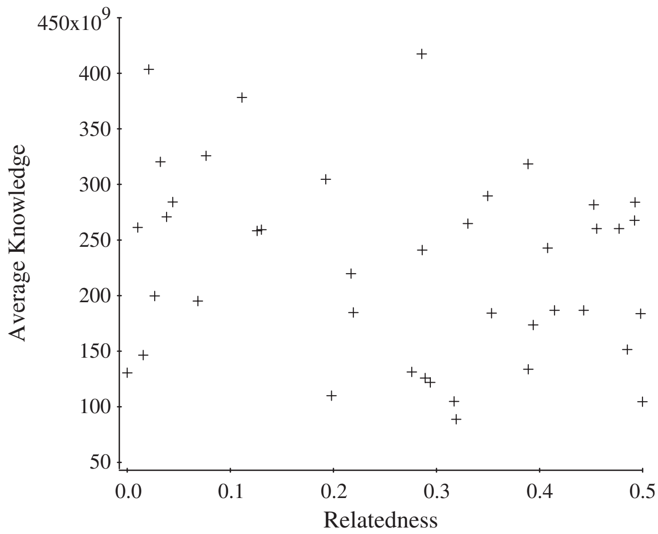

Fig. 8. Average knowledge and relatedness.

the density is low. This implies that they learn in a limited number of knowledge types. This increases expertise levels in the population.

5. Empirical implications

Above we modeled the goods in an economy which are taking knowledge as competencies and we looked at the dynamics of networks in a highly abstract simulation model. One of the premises of this

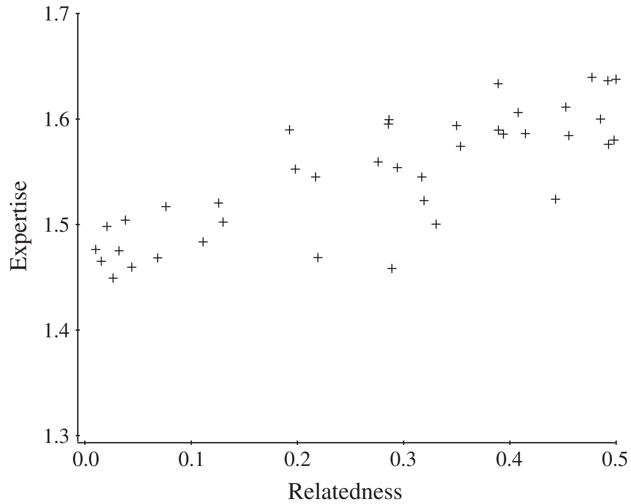

Fig. 9. Expertise and relatedness.

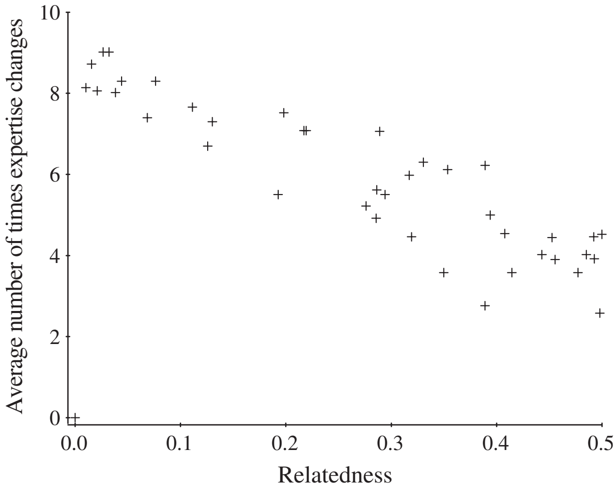

Fig. 10. Frequency of change in expertise and relatedness.

model is that industries exhibit differences in terms of the composition of knowledge types that are utilized in production. Although empirical research in this field is limited, there exist some studies which aim at demonstrating the knowledge-based regime of an industry. 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 [23], 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. These measures are provided in Table 4.

In a recent study [24], the concept of depth has been developed to measure the extent of specialization of a good. In this study, the patents are taken to be goods, and the depth of patents in various technology fields are measured. Fig. 11 shows these measures and their evolution through time.

Table 4
Percentage of principal product group's patents in technology field

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
Computers	5.2	16.3	77.3	0.2	1
Aircraft	8.1	48.5	31.2	8.3	3.9

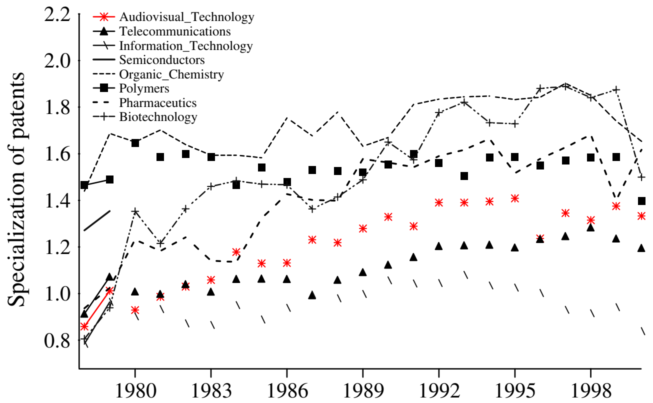

Fig. 11. Depth of patents in selected technology fields (source: Ozman [24]).

The simulation model presented above 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 more specialized. Ozman [24] tests the effect of both specialization levels, and also the breadth of different knowledge types embodied in patents on networks formed by inventors in a regression analysis covering the largest 50 firms in biotechnology and telecommunications. According to the results, both depth of a patent and also the breadth has a significant effect on network density. The more specialized are the patents, the higher is the density of the networks formed by inventors. These results point to the importance of complementarities in the knowledge embodiment of patents. The more specialization brings about less relatedness, but at the same time, increased gains from knowledge integration among the agents.

6. Discussion and conclusion

According to our results, the knowledge regime in the industry has a significant effect on the structure and intensity of interactions. One of the results that both our simulations and analytical model reveal is that collaboration takes place when there are gains from knowledge integration, which depends on the structure of goods. In a two-producer, two-good economy, the more specialized are the products (and thus the less related they are), the more important it becomes to have similar expertise levels for each party to benefit from collaboration, so that there are less possibilities for collaboration when agents are too far apart in terms of their endowments. Contrarily, when there are many producers, specialization of the goods results in intensive interactions among various pairs since there are many partners to select from so that different agents form pairs mostly (which increases the density of the network). Therefore, the restrictions of the two-producer economy is not valid. Also in this case, variety in the pairs results in agents who learn in a diverse range of fields, which reduces expertise and results in a population in which knowledge is more distributed. When this is the case, the fields that agents know most about also change frequently, which increases the density of the network. Although weakly, we can also infer that knowledge levels tend to fall as relatedness increases which might be because of lower density in the network. This lower density also implies that clustering in the network increases, which is to say that the same agents form pairs consistently, or single production prevails.

These results point to the importance of complementarities among products, and their implications for collaboration patterns. According to Mowery et al. [11] 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 paper, 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 when the goods are too similar, there is hardly any benefits from collaboration. When they are not related at all, there is also no benefit from collaborating. Only when there is a low degree of relatedness, so that a major input in one good is only minor in the others, do we see high benefits from integration of knowledge and high network density.

These results have direct bearing on the innovation policies. Innovation policies directed towards deepening of the knowledge base (so that the products become more specialized in their composition of certain inputs) increases the intensity of interactions, the average knowledge levels, and also it results in a more distributed knowledge among producers.

Obviously, there are many factors other than the knowledge base that influence networks as a growing literature reveals, ranging from institutional factors, stage in the industry life cycle, demand side effects, cost considerations, firm strategies and many more. Nevertheless, 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.

Acknowledgements

I thank Robin Cowan for many helpful suggestions.

Appendix A

Proof of Proposition 1. 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

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

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

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

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 Eq. (12) is greater then the LHS, producer will prefer singleton. Therefore, the condition for collaboration is given by

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

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

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

□

Proof of Proposition 3. In this case, the new knowledge levels are

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

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

$$k_{12}(t) = k_{12}(t-1)\left[1 + \theta/2\left(\frac{k_{11}^{\gamma_{11}}(t-1)}{k_{22}^{\gamma_{11}}(t-1)} + \frac{k_{11}^{\gamma_{21}}(t-1)}{k_{22}^{\gamma_{21}}(t-1)}\right)\right] \tag{13}$$

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

$$k_{11}^{1-\gamma_{11}-\gamma_{12}}(1+\Delta m)^{1-\gamma_{11}-\gamma_{12}} > \left(\frac{2k_{12}^{1-\gamma_{11}}(1+\Delta n)^{1-\gamma_{11}}}{k_{22}^{\gamma_{22}}(1+\Delta n)^{\gamma_{22}}} - k_{22}^{1-\gamma_{11}-\gamma_{22}}\right)(1+\Delta n)^{1-\gamma_{11}-\gamma_{12}} \tag{14}$$

and

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

yields

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

where

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

□

References

[1] C. Jones, W.S. Hesterly, S.P. Borgatti, A general theory of network governance: exchange conditions and social mechanisms, Academy of Management Journal 22 (1997) 911–945.

[2] J. Hagedoorn, Understanding the rationale of strategic technology partnering: interorganizational modes of cooperation and sectoral differences, Strategic Management Journal 14 (1993) 371–385.

[3] R. Allen, Collective invention, Journal of Economic Behavior and Organization 4 (1983) 1–24.

[4] E. Von Hippel, Cooperation between rivals: informal know-how trading, in: B. Carlsson (Ed.), Industrial Dynamics, Technological Organizational and Structural Changes in Industries and Firms, Kluwer, Boston, 1989, pp. 157–176.

[5] B. Uzzi, Social structure and competition in interfirm networks: the paradox of embeddedness, Administrative Science Quarterly 42 (1) (1997) 35–67.

[6] R. Gulati, Network location and learning: the influence of network resources and firm capabilities on alliance formation, Strategic Management Journal 20 (1999) 397–420.

[7] T. Rowley, D. Behrens, D. Krackhardt, Redundant governance structures: an analysis of structural ad relational embeddedness in the steel and, semiconductor industries, Strategic Management Journal 21 (2000) 369–386.

[8] J. Hite, W.S. Hesterly, The evolution of firm networks: from emergence to early growth of the firm, Strategic Management Journal 22 (2001) 275–286.

[9] L. Rosenkopf, M.L. Tushman, The coevolution of community networks and technology: lessons from the flight simulation industry, Industrial and Corporate Change 7 (1998) 311–346.

[10] R. Madhavan, B. Koka, E. Prescott, Networks in transition: how industry events (Re)shape interfirm relationships, Strategic Management Journal 19 (1998) 439–459.

[11] D.C. Mowery, J.E. Oxley, B.S. Silverman, Technological overlap and interfirm cooperation: implications for the resource based view of the firm, Research Policy 27 (1998) 507–523.

[12] T.E. Stuart, J.M. Podolny, Local search and the evolution of technological capabilities, Strategic Management Journal 17 (1996) 21–38 (Special Issue: Evolutionary Perspectives on Strategy).

[13] T.E. Stuart, T.E., Network positions and propensities to collaborate: an investigation of strategic alliance formation in a high technology industry, Administrative Science Quarterly 43 (1998) 668–698.

[14] L. Nesta, V. Mangematin, Industry life cycle, knowledge generation and technological networks, in: J. De la Mothe, A.N. Link (Eds.), Networks, Alliances and Partnerships in the Innovation Process, Kluwer Academic, Dordrecht, 2002.

[15] K. Frenken, A complexity approach to innovation networks: the case of the aircraft industry, Research Policy 29 (2000) 257–272.

[16] J. Birkinshaw, R. Nobel, J. Ridderstrale, Knowledge as a contingency variable: do the characteristics of knowledge predict organization structure? Organization Science 13 (3) (2001) 274–289.

[17] L. Orsenigo, F. Pammoli, M. Riccaboni, A. Bonaccorsi, G. Turchetti, The evolution of knowledge the dynamics of an industry network, Journal of Management and Governance 1 (1998) 147–175.

[18] R. Cowan, N. Jonard, M. Ozman, Knowledge dynamics in a network industry, Technological Forecasting & Social Change 71 (5) (2004) 469–484.

[19] D. Gale, L. Shapley, College admissions and the stability of marriage, American Mathematical Monthly 69 (1967) 9–15.

[20] R. Cowan, N. Jonard, J. Zimmermann, The joint dynamics of networks and knowledge, in: D. Gallegati, M. Marsili (Eds.), Lecture Notes in Economics and Mathematical Systems, vol. 521, Springer, 2002, pp. 155–174.

[21] S.P. Borgatti, M.G. Everett, L.C. Freeman, UCINET for Windows: Software for Social Network Analysis, Analytic Technologies, Harvard, 2002.

[22] P. Blau, Heterogeneity and Inequality, Free Press, New York, 1977.
[23] P. Patel, K. Pavitt, The technological competencies of the worlds largest firms: complex and path dependent but not much variety, Research Policy 26 (1997) 141–156.
[24] M. Ozman, Networks, Organizations and Knowledge, unpublished PhD thesis, Maastricht University, 2005.

Muge Ozman finished her PhD in Maastricht Economic Research Institute on Innovation and Technology (MERIT), Maastricht University. Currently she is a post-doctoral researcher at Bureau d'Economie Théorique et Appliquée (BETA), Strasbourg, France.