Bureau d'économie théorique et appliquée (BETA)
UMR 7522

Documents de travail

« Networks, Irreversibility and Knowledge Creation ».

Auteurs

Patrick Llerena, Muge Ozman

Document de Travail n° 2010 - **10**

Mars 2010

Faculté des sciences économiques et de gestion
Pôle européen de gestion et d'économie (PEGE)
61 avenue de la Forêt Noire
F-67085 Strasbourg Cedex

Secétariat du BETA
Géraldine Manderscheidt
Tél. : (33) 03 68 85 20 69
Fax : (33) 03 68 85 20 70
g.manderscheidt@unistra.fr
http://cournot2.u–strasbg.fr/beta

Nancy-Université
Université Nancy 2
UNIVERSITÉ DE STRASBOURG

Networks, Irreversibility and Knowledge Creation*

Patrick Llerena[a] and Muge Ozman[a,b]
[a] Bureau d'économie théorique et appliquée (BETA), Université de Strasbourg, 61 avenue de la Forêt Noire, 67085 Strasbourg Cedex
[b] Institut Telecom, Telecom Ecole de Management, 9 Rue Charles Fourier, 91011 Évry Cedex
e-mail: Muge.Ozman@it-sudparis.eu

March 30, 2010

Abstract

The aim of this paper is to highlight the effect of irreversibility in partner choice in strategic alliances. In an environment where firms are binded by contractual constraints regarding the duration of partnerships, how does the complexity of products influence the overall knowledge in the industry? Through an agent based simulation model, we compare the knowledge generation in irreversible and reversible systems in two regimes as tacit and codified. The emerging network structures are also analysed. The results reveal that, in tacit regimes irreversible systems generate more knowledge only when product comlexity is at an intermediate level.

*The research leading to this paper has been carried out in the context of the projects AnCoRA, funded by ANR programme "Apprentissages, Connaissances et Société', ANR-06-APPR-003 and the EU FP7 funded programme AEGIS, Grant n°225134. We would like to thank F. Malerba and R. Cowan for helpful discussions.

1 Introduction

The literature on inter firm networks has deepened our understanding of various mechanisms which underlie *formation* of ties between firms, and their *performance* effects. One of the results of this literature is that, increasing levels of complexity and uncertainty augment the motivation for tie construction. Secondly, the duration of a tie has an effect on the innovative performance of firms.

There are a variety of reasons behind interacting with other firms. These include, reduction in the products' introduction time to the market, sharing the costs and risks of R&D (Hamel et al., 1989; Hagedoorn, 1993), organizational learning (Powell et al., 1996) and network effects (Garud and Kumaraswamy, 1993). In addition to these, the interdependence among products and complementarities among them increases the rate of interactions among firms (Hagedoorn, 1993 and Orsenigo et al., 2000). When products are increasingly complex, a single firm is usually not endowed with all the capabilities required for design, manufacturing and innovation processes. In most of the knowledge based industries, firms network with each other not only to complement their capabilities (Mowery et al., 1998), but also to be informed about the technological developments that may have an effect on their business in the future (Kogut, 2000).

In addition to the research on why firms form ties, another field of study is concerned with the performance effects of these ties. In this strand of research, a central debate has been whether taking place in networks rich in social capital, or filling structural holes in a network results in better performance for the firm. Long term relations between firms and embeddedness (Granovetter, 1985) helps to build trust among the parties, facilitates transfer of tacit knowledge since a common language is developed, which increases efficiency in terms of time and costs of negotiation (Uzzi, 1997). It has also been shown that in industries where knowledge is highly tacit, a clustered network structure facilitates the flow of knowledge (Cowan et al., 2004; Audretsch and Feldman, 1996). Most of the studies find a positive effect of embeddedness on various measures of performance (Echols and Tsai, 2005; Andersson et al., 2002; Uzzi and Gillespie, 2002). Some other studies indicate that, tie age contributes positively to the performance benefits from closure (Baum et al., 2007).

On the other hand, some studies cast doubt on the positive effect of embeddedness on innovation. For example, Uzzi (1997), in a study of the New York fashion industry highlights the paradox of embeddedness: "the same processes by which embeddedness creates a requisite fit with the current environment can paradoxically reduce an organization ability to adapt mainly by decreasing diversity, reduction of non-redundant ties and sometimes causing over-embeddedness". Over-embeddedness can also be caused by the inability of the firm to change its network portfolio, which is termed to be network inertia by Kim et al. (2006).

Proponents of structural holes argue that, firms should act as "bridges" connecting otherwise disconnected clusters of firms (Burt, 1992). Short term relations and weak ties are advantageous for accessing novelties from diverse sources, thus beneficial for exploration purposes especially when knowledge is codified (Rowley et al. 2000). In a similar vein, Baum et al (2007) find that, performance effects of bridging ties reduce with tie age. One of the disadvantages of filling structural holes, and short term relations is that, the flow of tacit knowledge is constrained, which can mitigate innovative performance, as observed in the case of chemicals (Ahuja, 2000). Although majority of these studies focus on the social mechanisms between firms in explaining network structure, recently Cowan and Jonard (2007) that reasons of tie formation, which are purely based on knowledge complementarities can also explain certain network structures.

Although a rich strand of literature addresses the performance effects of different types of ties and network position (according to age, strength, social capital, structural holes etc.), there are certain weaknesses of the existing literature. Firstly, it is important to underline whether duration of ties can be freely determined by partnering firms. The current literature on tie duration considers this process as the result of voluntary choices of firms. In other words, in some circumstances firms might find it more beneficial to be engaged in repeated ties. In real world, however, cooperative firm strategies are shaped by commitments, in which once a tie is constructed, firms are bounded by contractual constraints which may set a lower limit to the tie duration. These commitments are usually shaped by transaction costs associated with frequently changing partners, like reputation effects, or, the sunk costs incurred once a partnership agreement is made. As a result, even if firms might find it beneficial to change partners, they might not be able to do so in the short term. Moreover, one of the factors which contribute strongly to these sunk costs are complexity of the projects which are the subjects of partnerships. As projects get more and more complex, firms may lose their flexibility in changing their partners, augmenting the existing contractual constraints. Secondly, most of the studies are empirical in this literature. Because empirical studies are usually constrained by certain contexts, in terms of time period and industries, theoretical studies are valuable to be able to highlight more general patterns in networks that emerge, and their performance implications. Thirdly, our knowledge about how the *complexity of products* contribute to these processes remains limited. One of the reasons of this limitation is that it is difficult to define a common measure of complexity applicable to a variety of product systems.

In this paper, we aim to fill these gaps by analysing how irreversibility in tie formation influence overall learning in a range of industries with different levels of product complexity. The measure employed to define product complexity is the range of different knowledge types that goes into the product during the process of manufacturing. We show that the effect of irreversibility on overall innovative potential in an industry depends on the relatedness between the knowledge content of products, and the extent to which knowledge can be transferred. One of the results of the paper is that, when there is a certain degree of relatedness among products so that they are neither the same nor completely different in terms of their knowledge that enters their production, irreversibility in ties yield higher average knowledge levels in tacit knowledge base regimes.

In an agent based simulation study we investigate the overall effect on knowledge and networks of two cases: in the first case, firms can freely change their partners whenever they wish (although they may not prefer to do so), and there are no costs and negative reputation effects from doing so. In the second case, ties are irreversible and once a partnership is formed the partners commit their resources for a certain period of time. In the simulation study firms form voluntary partnerships to combine their competencies with other firms and to produce together, and the way they select partners is through maximising their own gains. Firms learn from their partnerships and their competencies change through time, which influences their future choice of partners. In such a system, we compare irreversible and reversible systems in terms of overall knowledge levels and networks.

In the first section, we explain the model. Second section is allocated to simulation results. Third section includes discussions.

2 The Model

2.1 A Description of the Model

There are M goods, K knowledge types, and N firms in the economy. Each firm i is endowed with a knowledge vector, $\mathbf{k}^i$ assigned randomly (drawn from a uniform distribution) at period $t = 0$; k^i_j shows the level of firm i's knowledge in type j. We define expertise of a firm to be that subject in which it has the highest knowledge. There exist a knowledge type j for all i such that $k^i_j > k^i_m$

$\forall m \neq j$.[1] Given its knowledge vector, each firm in each period produces a good. But a firm can produce by itself, or integrate its knowledge with another firm and produce together.

If a firm i performs in-house research, the type of product it produces depends on its expertise type (j) and the weight of this expertise in different goods. In other words, the probability that it will produce good type n is proportional to the weight of its expertise type (j) required by the good.[2] We adopt the term $n - type$ firm if the firm produces good n. The amount it produces as singleton is given by $y_n(\mathbf{k}^i)$.

2.2 Matching

Each firm selects between producing alone or producing jointly with another firm. In making this decision, the firm's criteria is to maximize its output. Therefore, it makes a comparison between its joint output with other firms in the economy. Joint production happens through the integration of knowledge of the two firms. When an $n - type$ firm and a $m - type$ firm form a pair, we assume that they produce both goods n and m. The quantities are found as follows. It is assumed that if two firms i and l collaborate ($n - type$ and $m - type$ respectively), their joint knowledge in category j is given by

$$k_j^{pair} = \max(k_j^i, k_j^l) \ \forall j = 1....K \tag{1}$$

When an *n-type* firm i forms a pair with a *m-type* firm l, the joint knowledge vector, as given by Eq.(1) enters the production function, of both goods n and m. If we denote the joint knowledge vector by $\mathbf{k}^{pair}$ the output is shared equally

[1] The knowledge setting used here is first introduced by Cowan and Jonard (2003). Specifically, $k_{j,t}^i = k_{j,t}^h$ means that agents i and h have exactly the same knowledge in type j. If $k_{j,t}^i > k_{j,t}^h$, agent i knows everything that agent h knows in type j, and has some knowledge in addition.

[2] If product n uses 90% of knowledge type j, then there is 0.9 probability that agent i produces good n. With 10% probability it produces one of the other goods, depending on their requirements of knowledge type j.

among firms so that individual output shares are given by

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

Therefore, firm i compares its singleton output $y_n(\mathbf{k}^i)$ with $y_{n,m}(\mathbf{k}^{pair})$. Every firm has a preference listing (other firms ranked according to the maximum output they can produce with it). In practice, pairing in the population is made in such a way that no two firms prefer each other to their current partners. In practice, when firms rank other according to maximum joint output, a listing of pairs can be made with respect to falling joint output. The algorithm used involves picking the highest producing pairs one by one. Finally, some firms are left as singleton in this process. This algorithm ensures that there are no two firms in the whole population who would both have preferred to be with each other, rather than their current partners (Cowan et al., 2001) 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).

2.3 Production

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

$$y_n(\mathbf{k}) = \alpha \prod_j k_j^{\gamma_{nj}} \text{ where } \sum_j \gamma_{nj} = 1 \; \forall \; n = 1, 2, ..., M. \tag{3}$$

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

[3] The use of the term "knowledge" can be thought of as human capital or competence, so that it accumulates as a result of learning.

by an $M \times K$ matrix which shows the respective parameters of the production function. We assume that there are no competing uses for knowledge, so that its opportunity cost is zero, and firms use all their knowledge in production. We also assume that demand is perfectly elastic so that profits increase monotonically with quantity.

2.4 Relatedness among Products

The production parameters permits to construct a measure of breadth of knowledge base, as well as the relatedness among products. Let us assume a hypothetical matrix showing production paramaters in an industry with 5 goods and 10 knowledge types. Figure 1 shows three matrices of production parameters as an example. In the first diagram, products have narrow knowledge bases, because only two knowledge types are included in their production. Consequently, many products have no knowledge in common. The diagram in the middle shows the case where the products take as input five knowledge types. Relatedness among products is consequently higher than the first case. Finally, the bottom diagram shows the case where products are completely similar in terms of the intensity of the knowledge types they contain. These figures show the extreme cases. In the simulations randomly constructed matrices are taken exogeneously including intermediate cases as well.

In the model presented, the goods in the economy require various proportions of different knowledge types in their production and firms integrate their knowledge to produce these goods. The ultimate motivation underlying these interactions is production of goods. Moreover, a significant amount of *new* knowledge, which builds upon existing knowledge, is created during this process. Therefore the model stresses the cumulative nature of knowledge and learning.

	K1	K2	K3	K4	K5	K6	K7	K8	K9	K10
P1	0	0	0	0	0	0	0	0	0,5	0,5
P2	0,5	0	0	0,5	0	0	0	0	0	0
P3	0	0	0	0	0,5	0	0	0,5	0	0
P4	0	0	0,5	0	0	0	0,5	0	0	0
P5	0	0,5	0	0	0	0,5	0	0	0	0

Low breadth, low relatedness among products

	K1	K2	K3	K4	K5	K6	K7	K8	K9	K10
P1	0	0,2	0	0,2	0,2	0	0,2	0	0	0,2
P2	0	0	0	0,2	0,2	0,2	0,2	0	0,2	0
P3	0,2	0	0,2	0	0	0,2	0	0,2	0	0,2
P4	0,2	0	0,2	0,2	0,2	0	0	0	0	0,2
P5	0,2	0,2	0,2	0,2	0	0,2	0	0	0	0

Medium breadth, medium relatedness among products

	K1	K2	K3	K4	K5	K6	K7	K8	K9	K10
P1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1
P2	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1
P3	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1
P4	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1
P5	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1

High breadth, full relatedness among products

Figure 1: Product Complexity

2.5 Learning

In this model, the knowledge levels of firms are updated in every period. The learning process is learning-by-doing, and is the result of the experience in production. We assume that agents are myopic, so that they do not consider long term effects of learning from the partners that they select. [4] Learning takes place as production proceeds. In the simulations we take into account two different learning functions. In the first case, relative knowledge levels between the two firms determine the extent of learning. In the second case, learning is independent of relative knowledge levels. We explain these learning functions below.

2.5.1 Tacit Knowledge

When knowledge is tacit, transferring it from one party to the other is more difficult. In this case we assume that the relative knowledge levels between two firms determine the extent of their learning. In particular, the less one firm knows relative to the other, the less it can learn. One of the reasons behind this is the lack of a codified knowledge base that firms can draw upon. Learning happens mainly through interactions, and hence the closer is the knowledge levels of two firms, the more they can communicate. As knowledge becomes more codified, relative knowledge levels has less role since there is already a knowledge base that is explicitly available to all firms in the industry. This will be the case in the next section.

We also include an uncertainty term in this learning process, as the details are given in the Equation 4.

The following function is used to update firm $i's$ stock of knowledge type j:

[4] We assume a complex environment in which agents consider only the short term joint production amounts, and that they cannot predict the amount of learning that will take place in the long run because of uncertainty. Although this assumption might seem too strong at first glance, the results obtained reveal that, if the firms do consider the long term effects of learning, this would strengthen the results obtained further, rather than invalidating them.

$$k^i_j(t) = k^i_j(t-1) + \theta_i y(t) g(t) \tag{4}$$

$$\begin{aligned} g(t) &= \delta_i(t) \quad \text{if } k^i_j(t-1) > k^l_j(t-1) \\ & \quad \delta_i(t)\frac{k^i_j(t-1)}{k^l_j(t-1)} \quad \text{else} \end{aligned}$$

where θ_i measures the combinative capability of the firm, and $\delta_i(t)$ is an uncertainty effect. Eq. (4) implies that learning is measured by how much the firm can make use of production $y(t)$. This is firstly a function of capability of the firm, as given by θ_i. Second, it is a function of the relative knowledge levels between the partner firms.

Firstly, if firm i knows less than its partner, the amount of its learning is limited by their relative knowledge levels and its own capabilities. For example, if its learning capability is too high relative to partner, it can even leapfrog the partner.

Secondly, if firm i knows more than his/her partner (firm l) before production, there is only an uncertainty in its ability to make use of production and increase its knowledge. This is because, there is no other partner from whom it can learn from, since it is already the expert. This is given in the first part of the function $g(t)$. In this case, learning can be considered as the result of its own R&D. Here, uncertainty is given by the parameter $\delta_i(t)$ which is different for all firms in each period (the values of parameters are given below in simulations). In this case, the extent to which the firm can add to its knowledge depends on its capability to innovate captured by the parameter θ_i, as well as on the extent of uncertainty, captured by $\delta_i(t)$.

2.5.2 Codified Knowledge

In this case, we assume that the relative knowledge of agents has no impact on the extent of learning. This is because there is a pool of explicit knowledge available to all firms in the industry. Therefore whether the firm knows relatively less than his partner has no influence on the extent to which he will learn from her. In this case, Equation 4 is updated as:

$$k_j^i(t) = k_j^i(t-1) + \theta_i y(t) g(t) \tag{5}$$

$$g(t) = \delta_i(t)$$

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

2.5.3 Irreversibility and Selectivity

Irreversibility and selectivity shape the process of partner selection. In the reversible case, the matching process explained above is made *in each period* by each agent. In the irreversible case, once a partnership is formed it cannot be ended for a certain period of time. The period of contracts is different for each pair of firms. Consequently, because firms are aware that they will commit themselves for a fixed period, they are more selective in choosing partners. Selectivity refers to the threshold level of rank above which a firm will not accept a partnership in its preference listing. Instead it prefers to produce by itself, and wait for the next period to repeat the selection process. For example, when selectivity parameter is 5, the firms accept to form a partnership with only the first 5 firms in their preference list. However, if none of these 5 firms accept to form a link with the firm, then for that period the firm produces by itself, until the next period when he makes an evaluation again. One of the implications of high selectivity in the model is that, firms will form partnerships with other firms who are similar to themselves in terms of level of knowledge. For example, high-knowledge firms will form partnerships with other high-knowledge firms and so on.

3 Simulations

The simulation model consists of a population of firms endowed with different types of knowledge. In each period firms form pairs, by selecting their partner according to their calculated joint production. Paired firms pool their knowledge according to Equation 1. They produce together according to Equation 3 and share total output according to Equation 2. In the second period, they update their knowledge levels according to Equation 4. Depending on the extent of irreversibility, those firms who can match with their preferred partners commit their resources for a certain period of time. Other firms produce single, until the next period where they search for new partners again. Pairs are dissolved, and new pairs are formed with the updated knowledge levels.[5]

There are $M = 5$ goods and $K = 10$ knowledge types. The choice of these numbers are based on experimentation. Increasing the number of goods by one unit increases the simulation time significantly. Reducing the number of goods run the risk of loss of precision. With a few initial simulations, we confirmed that changing these figures do not change the final patterns observed, rather, they effect the absolute values of the results.

Each of the goods is characterized by a vector of knowledge input coefficients, and consequent breadth measures (as shown in Figure 1). For any good, the breadth of the knowledge base is the range of different knowledge types that its production requires. We measure this by the number of coefficients in the production function that are greater than zero. Goods with minimum breadth use only two types of knowledge inputs, and goods with maximum breadth use all of the knowledge types. Intermediate level of breadth corresponds to the case

[5] We take into account only bilateral link formation in a single period, but when sufficient time elapses, these bilateral links form a network.

where the goods are neither the same nor completely different in terms of their knowledge content. This means that they have some knowledge in common, but not all.

We take into account 8 unique knowledge - good configurations, ranging from minimum breadth to maximum, because we think that it provides a sufficient degree of balance between excessive detail and too broad results which make generalization difficult. In the Appendix, an example set of goods is provided for such a set knowledge - good configuration.[6]

Firstly the simulations are run for the reversible case. In a single run, a certain knowledge-good configuration is taken exogenously, resulting in 8 runs for all knowledge good configurations. In each of these runs there are 1000 periods. Each of these 8 runs correspond to a unique exogenous knowledge - good configuration. In each of the runs, the same population is used (same initial knowledge stocks and capabilities). We repeat this procedure (8 runs) 10 times. In each of these 10 repetitions, we use a different population. Therefore, there are 80 runs with different combinations of population and knowledge good configuration. The results presented below are the averages taken over the 10 repetitions with different populations.

Secondly, this procedure is repeated for irreversible case with different selectivity levels. We take into account 4 cases of selectivity, as 1, 5, 15, 30 which refer to the critical rank of the partner in the preference listing of the firm, above which firms do not enter into a relationship. Consequently, we run a total of 80 runs for the reversible case, and 80 * 4= 320 runs for the irreversible case.

The irreversibility parameter is in the range $[150, 250]$ periods. The population consists of $N = 30$ firms. The uncertainty parameter $\delta_k(t) \in [0.95, 1.05]$, and a different value is used for each agent in each period (Eqs. 4 and 5) and the capabilities are $\theta_k \in [1.3, 1.7]$. A single run consists of $T = 1000$ periods.

[6] Each of these matrices is an input to a single run (5 goods, 10 knowledge types).

The simulation parameters were selected based on mathematical feasibility.

3.1 Results

Analysis of our results covers both knowledge and network dimensions. In other words, we analyse the average knowledge levels in three dimensions as selectivity, irreversibility, and breadth of knowledge base. Second we analyse the network densities in the same space. Finally we analyse the joint implications of network and knowledge dynamics.

3.1.1 Knowledge Dynamics

Our results reveal that various factors interact in interesting ways in determining the average knowledge level in the industry. The average knowledge level is measured by considering the final average knowledge level among all agents at the end of a simulation run. And then, the averages are taken over the 10 repetitions (see section Simulations). It is given by;

$$K_T = \frac{\sum_{j=1}^{N} k_j}{N}$$

$$K_A = \frac{K_T}{10}$$

where K_T is the average knowledge in a single run, and K_A is the average knowledge obtained from the 10 repetitions. In particular, the selectivity of firms, the breadth of the knowledge base and the learning function all have an influence on whether long term contracts or short term contracts are better for average knowledge creation. We explore each of these factors and their effect on knowledge below. We use average knowledge as a measure of performance, since it reveals the extent of total learning from partnerships in different regimes.

Our first result is that when firms are the least selective, the average knowledge levels are higher in nearly all cases. Least selectivity of firms happen when firms form partnerships with whoever they match with, instead of insisting on the highly ranked ones in their preference listing. Figures 2 and 3 respectively show average knowledge in tacit and codified learning cases respectively. It can be seen in the figures that lowest selectivity (30 referring to the case where all firms can form partnerships with all other firms) yields the highest knowledge growth in all the cases. In short, the more diverse partnerships are formed between firms of different levels of competence, the better it is for overall knowledge levels.

Our second result is that, whether irreversible or reversible contracts are better depends on the learning function employed. When the relative knowledge levels determine the extent of learning (as given in Equation 4 which refers to tacit knowledge regime) long term contracts (irreversibility) are significantly better in terms of average knowledge generation. This is given in Figure 2 where it can be seen that irreversibility is significantly better than short term relations, except when firms are highly selective. In different ways, this result has been shown in the literature, as we reviewed in the first section.

On the other hand, when relative knowledge levels are not taken into account (Equation 5) which is given in Figure 3 reversible systems characterized by short term contracts yield more knowledge. However, the *strength* of the difference between irreversible and reversible cases depend on the breadth of the knowledge base.

Our third result concerns the effect of the breadth of the knowledge base which turns out to be the most critical parameter determining the outcome in terms of knowledge. In particular, our results highlight a critical region where breadth is intermediate given by Figures 2 and 3. This is the area where products are neither the same, nor too different in terms of their knowledge requirements. In this area, the discrepancy between the performance of tacit and codified regimes in reversible and irreversible systems is the most pronounced. This is

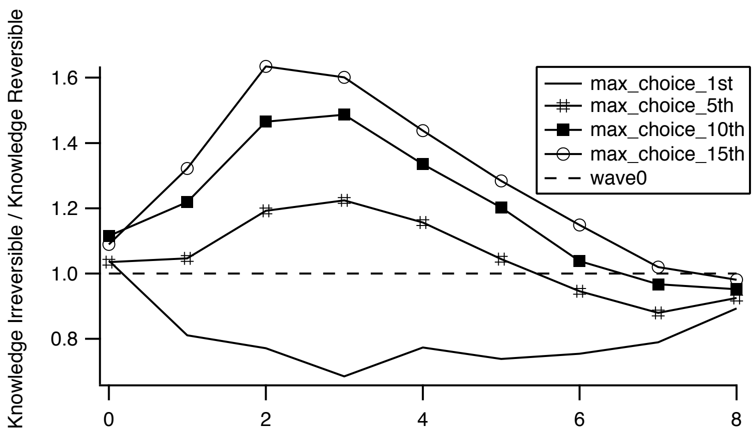

Figure 2: Average Knowledge and Breadth, Tacit Knowledge

to say that, when breadth is intermediate, tacit industries perform significantly better with irreversible ties. On the other hand, codified industries perform significantly better in short term relations. In other areas where breadth is either too high or too low, knowledge levels in irreversible and reversible systems seem to be close to each other in both tacit and explicit industries. An exception to this pattern is where firms are highly selective as given in Figure 2. Here, even if the knowledge is tacit, short term contracts are better[7]. This happens because only a few firms are lucky enough to form partnerships with their first choices. So mostly, firms remain alone, rather than forming partnerships.

These results can be understood in a better way if one analyses the structure of networks that accompany them. In the next section, we compare the network densities corresponding to different levels of selectivity and breadth in the irreversible and reversible cases.

3.1.2 Networks

The density of the network is given by:

[7] This is to say that firms can revert to other partners easily.

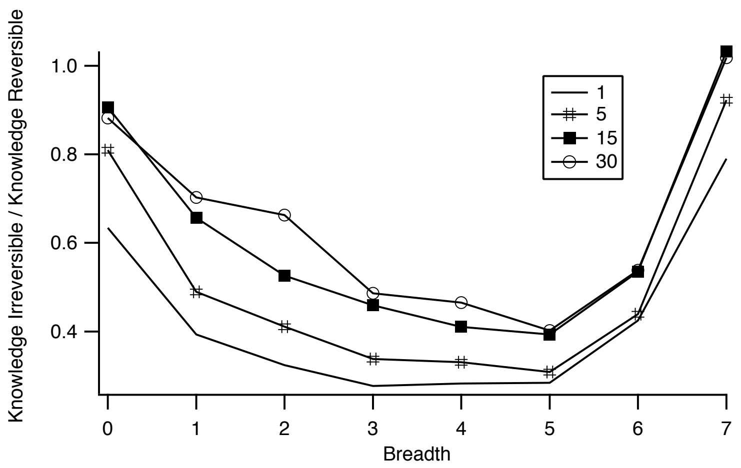

Figure 3: Average Knowledge and Breadth, Codified Knowledge

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

where $x_{ij} = 1$ if there is an edge between i and j and is 0 otherwise and N is the total number of nodes. We take into account network density because it is the most common measure used to understand the *intensity* of connections in a network. In all the simulation runs, we recorded the final density of networks.

The analysis of networks among firms helps to explain why irreversible case yields more knowledge when breadth of the knowledge base is intermediate. Figure 4 gives the network density for a tacit knowledge base regime, and Figure 5 gives the network density in the codified network base regime.

In all the cases, network density in the irreversible case is smaller than the network density in the reversible case. This is expected, since long term relations limit the potential to network with different firms. However, an interesting result is concerned with the tacit knowledge base regime (Figures 2 and 4). Contrary to the conventional expectations that high network density yields more knowledge, here we see that although network density is significantly lower (Figure 4) the knowledge levels are higher (Figure 2). In other words, when products are only

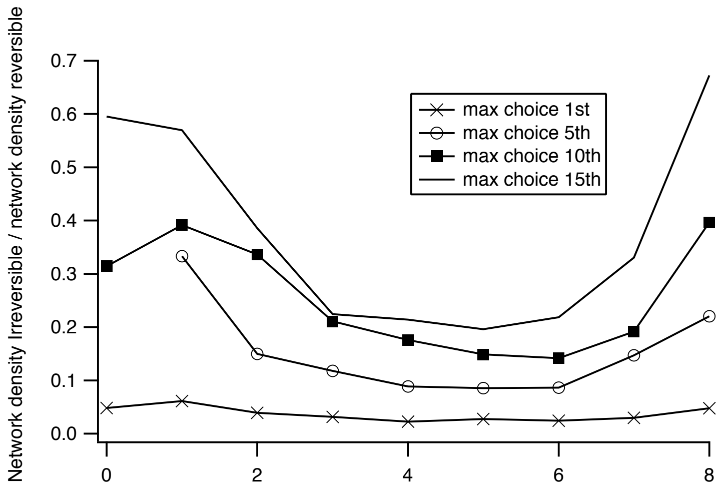

Figure 4: Network Density and Breadth, Tacit Knowledge

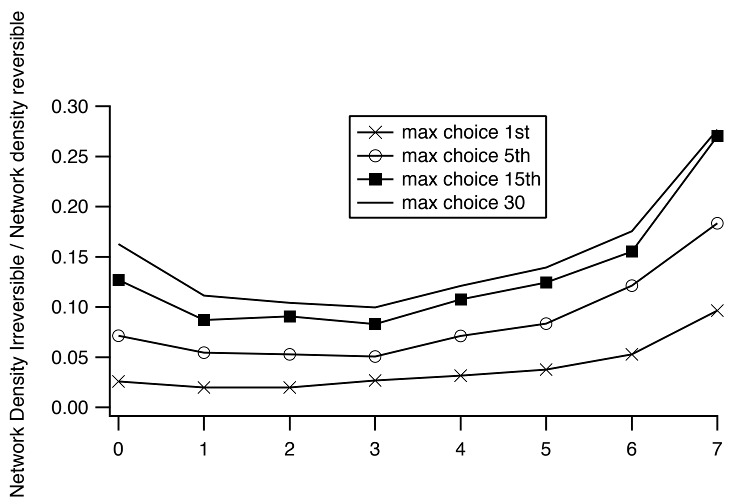

Figure 5: Network Density and Breadth, Codified Knowledge

partially related, long term relations yield the highest knowledge levels. Below we explain why this result is observed in the simulations.

One of the reasons that leads to this result is the fact that relative knowledge levels play an important role in learning in the tacit knowledge regime (Eq 4). As the knowledge gap reduces, learning is higher. The total learning here is higher than would be the case when relations are reversible, because in the latter firms do not have the chance to have long term relations, in which eventually the knowledge gap is closed. This is what happens in real world, the first time we meet an expert, it might be difficult to learn from him/her, but the more we interact, the more our knowledge increases relative to his/hers. When our knowledge levels are close enough, total learning is higher, because now both sides can learn from each other.

An important result of the simulation study is the significance of the intermediate level of product complexity. Our results are augmented for the case of mid levels of complexity. Why is this pattern observed?

To explain, it is useful to compare the network densities in the tacit regime. As Figure 4 shows, density in irreversible case is much lower than the density in the reversible case in intermediate levels of product breadth. This is because network density in the *reversible case* in the intermediate range is very high. On the other hand, extreme breadth levels yield less dense networks. Low density can be interpreted in two ways: first, firms prefer to produce alone, or second, they prefer to have long term relations by themselves, in the absence of contractual constraints. In the latter, they are free to dissolve partnerships, but they don't. The results reveal that, when goods have minimum-breadth, firms prefer the first case: to produce alone. Little amount of partnerships are formed, because there is no common knowledge in the goods, so that firms cannot complement each other. In the maximum-breadth case, on the other hand, once a partnership is formed it is long term, because firms knowledge in different types do not change. This means that, they do not acquire new competences during their interactions. All firms learn consistently, in all knowledge types. Because there is no change in expertise patterns, there is also no reason to change partners.

These explain why there is a significant difference in network densities in the intermediate region. Here, expertise levels and subjects are continuously changing, because goods have some knowledge in common, which provides motivation for firms to come together. Yet, when two firms come together they can also learn in different types of knowledge, since goods are not completely the same. In this way, rapid change in expertise levels result in an environment, in which firms are repeatedly changing partners. However, we can also see that, overall knowledge levels are higher when relations are long term (Figure 3). Based on our analysis, when firms change partners frequently in a tacit regime, they do not have sufficient time to make use of long term gains from repeated ties. This is why, in this region irreversibility is much better for overall learning levels.

These results imply that, when firms have no contractual constraints and when they are flexible in changing partners, they would do so in a certain parameter range (namely when products have an intermediate level of complexity, and when knowledge is tacit). However, this does not yield high levels of learning, on the contrary, in these cases, although firms lose their flexibility, contractual constraints are much better to increase the learning potential of partnerships. At the same time, when products are too complex, or too simple in terms of their knowledge base, firms themselves prefer not to change partners, and their relations are long term. Therefore, we do not see big differences in the average knowledge levels in these two extreme cases.

4 Discussions of the results

In this paper, we find that the effect of tie duration on overall learning by the producers in a product system depends on tacitness of knowledge and product systems complexity. A few remarks on how our results link to previous research maybe helpful to clarify the positioning of this paper in the literature. One of the established results in the inter-firm network literature is that, when knowledge is difficult to transfer, long term ties with partners are better for the overall performance. Our results confirm this finding in general. Nevertheless, we find that the extent of benefits from long term relations also depend on the knowledge content of products. In particular, we find that in two cases irreversibility in tie formation matters very little: first when products are too different in terms of their knowledge content, and second when they are too similar.

Few remarks seem necessary concerning the results and assumptions of this paper. It is important to mention that, as different from other studies in the field, we do not look at the performance of individual firms. Rather, we measure performance by the overall degree of learning in the economy. This is important when interpreting the results of this study, and in comparing it with other studies. Secondly, in this paper we take into account a means by which one can distinguish between different industries. More particularly, complexity of products can be important in influencing the effects and mechanisms which work in interfirm networks. We would like to draw attention to the fact that, effect of complexity, although mentioned by many scholars, have not yet been tackled in a systematic way in network studies. Finally, in this paper we distinguish explicitly between network relations that are reversible, and those that are not reversible. In the real world, once firms enter into an agreement, it is usually costly to break the link, both in terms of reputation, and time and effort of negotiation. Therefore, usually transaction costs are high. We show that, such long term relations in which firms commit their resources, can have positive effects on overall learning in the economy. However, one should always take into account the nature of the product system to understand such effects.

One of the contributions of this paper is to introduce product complexity and irreversibility explicitly into the analysis of the effect of networks. A well grounded result in network analysis is that, long term relations are better for the transfer of tacit knowledge. The specific mechanism underlying this process is usually referred to be the development of trust between parties. In this paper, we do not refer to this mechanism (which is not in the model). Still, we find that long term relations are better in tacit knowledge cases, only when there is an intermediate level of relatedness in products.

5 References

References

[1] Ahuja, G. (2000) "Collaboration Networks, Structural Holes and Innovation: A longitudinal Study", Administrative Science Quarterly, 45(3): 425-53.

[2] Anderson, U., Forsgren, M. and Holm, U. (2002) The Strategic Impact of External Networks: Subsidiary Performance and Competence Development in Multinational Corporation. Strategic Management Journal, 23: 979-996.

[3] Audretsch, D. B. and M. P. Feldman. (1996). "Innovative Clusters and the Industry Life-cycle." The Review of Industrial Organization, 11: 253-273.

[4] Baum, Joel A. C., McEvily, Bill and Rowley, Tim, (2007) Better With Age? Tie Longevity and the Performance Implications of Bridging and Closure Rotman School of Management Working Paper No. 1032282. Available at SSRN: http://ssrn.com/abstract=1032282

[5] Burt, R.S. (1992) Structural Holes: The Structure of Competition, New York: Academic Press.

[6] Cowan, R., N. Jonard and M. Ozman (2003) "Knowledge Dynamics in a Network Industry", Technological Forecasting and Social Change, 71(5): 469-84.

[7] Cowan, R. and N. Jonard (2001) "Knowledge Creation, Knowledge Diffusion and Network Structure" in: A. Kirman and J-B. Zimmermann (eds.) Economies with Heterogenous Interacting Agents, Springer.

[8] Cowan, R. and Jonard, N (2009) "Knowledge Portfolios and the Evolution of Innovation Networks", Academy of Management Review, 34(2): 320-342.

[9] Echols, A. and Tsai, W. (2005) Niche and Performance: The Moderating Role of Network Embeddedness. Strategic Management Journal, 26: 219-238.

[10] Gale, D. and Shapley, L. (1962) "College Admissions and the Stability of marriage", American Mathematical Monthly, 69: 9-15.

[11] Garud, R. and Kumaraswamy, A. (1993) .Changing competitive dynamics in network industries: An exploration of Sun Microsystems' open systems strategy. *Strategic Management Journal* , 14: 351-369.

[12] Granovetter, M.S. (1973) "The Strength of Weak Ties", American Journal of Sociology, 78(6): 1360-80.

[13] Hagedoorn, J. (1993) "Understanding the Rationale of Strategic Technology Partnering: Interorganizational Modes of Cooperation and Sectoral Differences", Strategic Management Journal, 14: 371-85.

[14] Kim, T.Y., Oh, H. and Swaminathan, A. (2006) Framing Interorganizational Network Change: A Network Inertia Perspective. The Academy of Management Review, 31(3): 704-720.

[15] Kogut (2000) "The Network As Knowledge: Generative Rules and the Emergence of Structure", Strategic Management Journal, 21: 405-425.

[16] Mowery D.C., Oxley, J.E. and Silverman, B.S.(1998) "Technological Overlap and Interfirm Cooperation: Implications for the Resource Based View of the Firm", Research Policy, 27: 507-23.

[17] Orsenigo, Luigi., Fabio Pammoli, Massimo Riccaboni, Andrea Bonaccorsi and Giuseppe Turchetti, 1998 "The Evolution of Knowledge and the Dynamics of an Industry Network" Journal of Management and Governance, 1:147-175..

[18] Powell, W.W., Koput, K.W. and Smith-Doerr, L. (1996) "Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology", Administrative Science Quarterly, 41:116-145.

[19] Rowley, T., Behrens, D. and Krackhardt, D. (2000) "Redundant Governance Structures: An Analysis of Structural ad Relational Embeddedness in the Steel and Semiconductor Industries", Strategic Management Journal, 21: 369-86.

[20] Uzzi, B. (1997)"Social Structure and Competition in Interfirm Networks: The Paradox of Embeddedness", Administrative Science Quarterly, 42(1): 35-67.

[21] Uzzi, B. and Gillespie, J.J. (2002) Knowledge Spillover in Corporate Financing Networks: Embeddedness and the Firm's Debt Performance. Strategic Management Journal, 23: 595-618.

Documents de travail du BETA

2010–**01** *The Aggregation of Individual Distributive Preferences through the Distributive Liberal Social Contract : Normative Analysis*
Jean MERCIER-YTHIER, janvier 2010.

2010–**02** *Monnaie et Crise Bancaire dans une Petite Economie Ouverte*
Jin CHENG, janvier 2010.

2010–**03** *A Structural nonparametric reappraisal of the CO_2 emissions-income relationships*
Theophile AZOMAHOU, Micheline GOEDHUYS, Phu NGUYEN-VAN, janvier 2010.

2010–**04** *The signaling role of policy action*
Romain BAERISWYL, Camille CORNAND, février 2010.

2010–**05** *Pro-development growth and international income mobility: evidence world-wide*
Jalal EL OUARDIGHI, mars 2010.

2010–**06** *The determinants of scientific research agenda: Why do academic inventors choose to perform patentable versus non-patentable research?*
Caroline HUSSLER, Julien PENIN, mars 2010.

2010–**07** *Adverse Selection, Emission Permits and Optimal Price Differentiation*
Mourad AFIF, Sandrine SPAETER, mars 2010.

2010–**08** *The impact of ambiguity on health prevention and insurance*
Johanna ETNER, Sandrine SPAETER, mars 2010.

2010–**09** *Equité du plaider coupable : une analyse économétrique dans trois tribunaux de grande instance français.*
Lydie ANCELOT, mars 2010.

2010–**10** *Networks, Irreversibility and Knowledge Creation.*
Patrick LLERENA , Muge OZMAN, mars 2010.

La présente liste ne comprend que les Documents de Travail publiés à partir du 1er janvier 2010. La liste complète peut être donnée sur demande.
This list contains the Working Paper writen after January 2010, 1rst. The complet list is available upon request.