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« The Joint Effect of Technological Distance and Market Distance on Strategic Alliances »

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The Joint Effect of Technological Distance and Market Distance on Strategic Alliances[♦]

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Abstract

The literature on strategic alliances has deepened our understanding of the mechanisms behind their formation. This literature has given a central role to complementarities between firms, whereby complementarities are usually measured by technological overlap. An established result tells us that, there is an inverted-u relationship between technological distance and learning by firms. In this paper, we argue that technological distance is only one aspect of complementarities. Equally important is the market distance, which we define as the extent to which the value generated by the alliance depends on the synergies between firms' products. These synergies may occur because of the complementarities between products, or the possibilities to apply similar knowledge fields in different product domains. Through an agent based simulation study, we show that when firms consider both distances jointly, an alliance strategy which favours being close in at least one dimension yields the highest payoff, rather than being at the intermediate distance in both dimensions.

[♦] I thank Altay Ozaygen for helpful discussions, and for his suggestion of the Rayleigh distribution.

INTRODUCTION

The two central issues addressed in the literature on strategic alliances are, why firms form alliances, and what are the effects of alliances on firms' performance. In addressing these questions, probably the most widely accepted theoretical framework has been the resource based view (Pfeffer and Salancik, 1978) which explains alliances with respect to the complementarities in firm resources, and it has been confirmed empirically as well (Hagedoorn 1993;Walker et al., 1997; Shan et al., 1994; Mowery et al., 1998; Eisenhardt and Schoonhaven, 1996). By accessing complementary resources of others, firms have the chance to exploit their knowledge own bases, and explore distant knowledge lying outside their boundaries. Therefore, external relations are an important source of developing dynamic capabilities (Schoenmakers and Duysters, 2006; Powell et al., 1996; Rothaermel and Deeds, 2004; Oliver, 2001).

A body of empirical work on strategic alliances positions the firms in some notion of space, and measure motivations behind alliances with respect to the distance between firms in the defined space. Some commonly used notions of space has been geographical space (Gomes Casseres et al., 2006), cognitive space (Nooteboom et al. 2007; Schoenmakers and Duysters, 2006), social space (Gulati, 2007) and strategic space (Garcia Pont and Nohria, 2001). Following this approach, in this paper, we analyze both the formation and performance effects of strategic alliances through positioning firms in a two dimensional space defined by knowledge and market. Knowledge distance refers to the overlap between firms in terms of the technical knowledge they embody. Market distance, on the other hand, measures the extent of complementarities between products of firms. The starting point of this paper is that, the knowledge base of a firm is distinct from its product base, and both dimensions should be taken into account when trying to understand the patterns shaping strategic alliances. Therefore, we argue that focusing solely on technological distance, as it is done in most of the studies in this tradition, falls short of explaining a very important phenomena that many of the real world alliances reveal; the cases when there are strong opportunities for synergies between the product bases of firms, independent of their knowledge endowments. In this sense, we take exploration activities to be the firms' search for the application of its knowledge in different product domains, rather than searching for distant partners in technical knowledge sphere, as most studies assume. In a similar manner, we take exploitation as the firms' efforts to improve the way that it applies its knowledge to its current product domain.

We perform an agent based simulation study in which firms are positioned in a two dimensional space defined by a technology address and a market address. Firms have different preferences when they are selecting partners, depending on the distance between them in both spaces. They collaborate, and their coordinates in this space change, as well as their profits. In this way, inter-firm networks form and evolve. We investigate the relation between firms' distance preferences and their final profit levels. We also analyze the networks that form during this process. We carry out four simulation studies. In the first, firms take into account only the simple Cartesian distance between them. In this model, we confirm the inverted-u relationship between cognitive distance and learning, which is an established result in the literature (Mowery et al.,1998; and Duysters, 2006; Gilsing et al. 2008) . In the second model, firms take into account both dimensions separately in selecting partners. Our results show that those firms which prefer close connections in *at least* one dimension are more successful. In other words, an alliance in which either market domain or technology domain is distant proves to yield highest performance. We explain this result by referring to the established theory in creativity research, which underlines the importance of analogous thinking (Gassman and Zeschky, 2008) and recombinant innovation (Hargadon, 2003). Thirdly, we introduce an exogenous innovation in the model. The effect of an exogenous innovation is mostly on the network structure, and diffusion of firms in the market and knowledge space, in accordance with the findings of Baum et al. (2009). Finally, we modify the functional form employed, and test the robustness of the results.

In this first section, the theoretical background is presented. The second section is devoted to the explanation of the model, including the analytical framework, assumptions and technical information on simulations. The third section presents results and modifications of the model. Fourth section includes some discussions and interpretations of the model, as well as some directions for future research.

BACKGROUND

According to the resource based view, firms form alliances to make use of complementarities in their resources (Pfeffer and Salancik, 1978; Wernerfelt, 1984). According to the knowledge based theory of the firm, which recognizes the most valuable resource of the firm to be knowledge (Kogut and Zander, 1992; Grant, 1996) complementarities in knowledge is the key aspect of alliances. Empirical studies in this tradition usually measure firm complementarities through employing the notion of knowledge distance between firms. In this section, we will first make an overview of this literature in relation to organizational learning. Afterwards, in building the theoretical background of the model, we will discuss why the notion of knowledge distance is not sufficient to have a meaningful measure of complementarities between firms.

External Networks, Exploration and Exploitation

Theoretically speaking, technological distance is usually taken as the overlap between the knowledge bases of firms (Mowery et al., 1998). In a dynamic capabilities framework, the knowledge bases of firms change through time, which can be through internal means, as firms carry out R&D activities to increase their absorptive capacity (Cohen and Levinthal, 1991) and through external means, as firms explore and exploit knowledge lying outside their boundaries. While exploration refers to experimentation with new alternatives, exploitation aims at refinement and extension of existing competencies, technologies and paradigms (March, 1991: 85). Traditionally one of the central questions in organizational learning literature has been, whether exploration and exploitation should be considered as the two ends of a spectrum, or whether they are orthogonal to each other (Gupta et al., 2006). While the former view implies a tradeoff between exploration and exploitation, the second view has resulted in the ambidexterity hypothesis, which states that exploration and exploitation are actually complements, and a mix of both types of external linkages are provisioned for firms for increased competitive advantage (Tushman and O'Reilly, 1996; Levinthal and March, 1993; He and Wong, 2004).

Empirical studies show that the choice between exploring and exploiting depends on the external conditions, like the stage in the industry life cycle (Rothaermel and Deeds, 2004), the growth phase of the firm (Oliver, 2001) and uncertainty (Beckman et al., 2004). During the beginnings of industry life cycles when there is technological turbulence, firms are more vulnerable with respect to an uncertain future. Evidence shows that exploration activities, through accessing distant knowledge, can be a source of competitive advantage (Rowley et al., 2000). In this way, firms increase their chances to gain competence in different fields which maybe critical in future technologies and products.

While distant knowledge sources can be a source of competitive advantage in some cases, in more stable environments, having similar knowledge with alliance partners can be beneficial for competitive advantage. One of the cases which drive firms to proximate firms in the knowledge space is, when firms prefer to deepen their existing competences. Scholars have long argued that such exploitation activities take place in dense networks, characterized by embedded relations (Coleman, 1988; Granovetter, 1985) in which interactions are accompanied with thick knowledge exchange, face to face, and they help to build trust among the parties.

The Optimal Technological Distance

With regards to the relationship between distance and alliances, a major finding in the literature is an inverted-u relationship between technological distance between firms and learning (Mowery, 1998; Gilsing et al, 2008, Schoenmakers and Duysters, 2006; Nooteboom et al., 2007). Moreover this distance diminishes as firms interact with each other (Mowery et al., 1998). The underlying logic in this construct is simple; when firms are too close in the knowledge space, they have few to add to each others knowledge, when they are too far, they cannot access each others knowledge base, and learning is limited. This construct has become an attractive one for researchers in the theoretical and empirical spheres.

According to the optimal distance hypothesis, there is a tradeoff between establishing links with close firms and distant firms. An implicit assumption in this tradeoff is that, exploration and exploitation alliances are the two ends of a spectrum; therefore it suggests that learning will be maximized if firms find partners who are at the optimal distance. However, we argue that there are few problems with the linear perception assumed in the optimal distance formulation. Firstly, it implicitly assumes that exploration and exploitation activities are substitutes with each other. To cope with this issue, researchers have sometimes assumed distinct exploration and exploitation regimes and looked at the optimal distance within two different frameworks (Nooteboom et al. 2007; Katila and Ahuja, 2002). Nevertheless assuming distinct exploration and exploitation regimes does not given an insight into how firms decide between exploration and exploitation at first hand.

In addition, assuming a unique optimal distance between firms reduces the parameters involved in the complex search process to a single dimension, which is knowledge. In most of the cases, this functional relationship is detected through the analysis of patents (Mowery et al., 1998; Schoenmakers and Duysters, 2006; Katila and Ahuja, 2002), by looking at the overlap of patent fields, and/or citations between firms' patents. While patent analysis is a useful one in many aspects, one should be careful in interpreting the results obtained through patent analysis. Notwithstanding the usual doubts concerned with patent analysis (Griliches, 1989), patents usually measure the codified knowledge of firms, and do not measure the knowledge embedded in a tacit manner. Another problem is that, which subject matters will be included in a patent document sometimes depend on the patent strategy of the firm, and usually this decision is given by the people who are not themselves the inventors in the firm.[1]

Finally, the most important problem associated with patent measures for the purposes of this paper is that, it is difficult to draw a distinction between the knowledge base and product base of firms, by looking solely at patents. Do patents measure what firms know or what firms make? One of the most important weaknesses about patents when measuring complementarities is that, they do not capture the complementarities between firms' *products*, which seem to be an

[1] This fact was pointed out to the author by one of the inventors in a large telecommunications firm.

important driver of alliances. In the formation of alliances, it is not the knowledge of the partner that matters most, but rather, the possibilities the partner offers to the firm concerning the application of its knowledge in connection to designing different products. The main premise of this paper is that, exploration activities are in essence concerned with the search for different products in which firms existing competences can be applied in. At the same time, exploitation involves, improving upon the way the firms' knowledge is applied in a particular product domain.

Complementarities between products of firms can be quite unrelated with their patent domains. To demonstrate the significance of the difference between knowledge and product domains, let us consider the alliance between Nike Inc. and Apple Inc., which took place in 2005 to develop "smart shoes", which permits various performance measures to be recorded digitally. Figure 1 shows the patent overlap between the two companies for their granted patents in 2002. There is little overlap between the two firms in terms of the subject matters of their patents; yet, the alliance was a success in terms of its innovative potential. Although the knowledge bases of these two firms are quite distant, their products had a high potential of complementarity. In this way, both firms explored successfully the possibilities of applying their competence in different market domains.

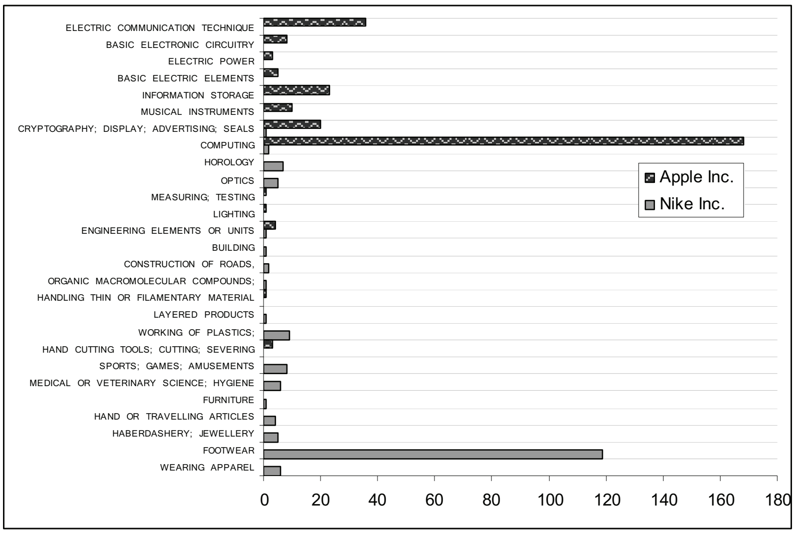

Figure 1. The patent domains of Nike Inc. and Apple Inc.

At this point, the difference between *cognitive distance* and *technological distance* seems critical. It has been argued that, cognitive distance is broader than knowledge distance (Wuyts et al. 2008), which incorporates engineering and marketing domains. However, because patent data is widely used, most of the studies are confined to the technology distance, ignoring the impact of synergies among the products.

The Necessity to Include Market Distance in Measuring Complementarities

In certain cases, firms ally with other firms because of the complementarities in the respective market domains. This is particularly marked in industries where there are strong network effects, where firms ally with each other to access each others' installed base, and to strengthen a certain standard in the economy (Hill, 1997). ICT industry is an interesting one in this sense. Many of the products have a complementary aspect, where the value generated depends on the number of users who adopts a technology system and also on the number of complementary technologies available. Here, not only knowledge overlap between firms, but the extent to which consumers can derive additional value from using two technologies together is of prior concern for firms. For example during the 1980s, Intel's product development strategy favoured the design of a modular PCI (peripheral component interface) to support the speed of its future microprocessors (Gawer and Cusumano, 2002). The development of the PCI shaped the architecture of the dominant computer design. Chesbrough (2003) explains how Intel was allying with young and dynamic firms who could strengthen its own microprocessor market by providing complementary systems. The complementarities in knowledge was not the prior concern of Intel; rather, it aimed at establishing the PCI as a standard through its alliances, in which significant knowledge transfer between firms was taking place as well. Complementarities between these firms existed not only in the knowledge sphere, but also because of the synergy between firms spreading the PCI standard.

Assuming a single type of distance between firms in measuring complementarities runs the risk of ignoring the distinction between market domain and knowledge domain of firms. Two firms, which are close in market space can be very far in knowledge space, and two firms which are close in knowledge space, can be too far in market space. These two distances jointly determine the value that firms expect from their alliances.

To summarize our discussions, in Figure 2, we demonstrate the strategic alliance formation motives with respect to two dimensions, as technological distance and market distance. Technological distance refers to the extent to which firms have common technical knowledge. Market distance refers to the extent to which consumers can increase the utility from utilizing the two firms' products together.

Market Distance

Technological Distance	Close	Distant
Close	***I*** ***Competitive pressure:*** *high* ***Alliances:*** *limited learning*	***II*** ***Competitive pressure:*** *low* ***Alliances:*** *application of common knowledge to different market contexts*
Distant	***III*** ***Competitive pressure****: low* ***Alliances:*** *application of distant knowledge to products who have complementary potential*	***IV*** ***Competitive pressure:*** *low* ***Alliances****: limited possibilities for complementarities, chances of rare radical innovations*

Figure 2. Strategic Alliance motives in two dimensions: market distance and knowledge distance

Box 1 shows the case in which two hypothetical firms have a high degree of technological overlap and market overlap. This usually corresponds to the case where firms are facing high competitive pressure from each other. Alliances can be formed with the objective of combining two complementary standards (Hill, 1997; Schilling and Hill, 1998). The alliance between Sony and Philips in 1989, for the common Compact Disc (CD) standard is a good example in this sense. Similarly, alliances can be in the form of "good will relations", like Microsoft with compatible software providers for the Windows platform, or Sony's relations with game developers for the Playstation platform (Schilling, 2002). In these relations, variety has a key role. These firms are close in their knowledge space, but through alliances, they have access to the variety offered by specialized firms, and hence they have the chance to strengthen their installed base.

Box II refers to the case in which firms have similar technical knowledge bases, but in which they operate in different markets. The fact that a certain piece of knowledge can be reused in different contexts gives firms the opportunity to apply knowledge in different market domains. The history of computer industry is very remarkable in this sense. Continuous collaborations and complex relations among people and firms in the beginning of the industry life cycle resulted in one piece of knowledge being applied in very different contexts (Moggridge, 2007; Campbell Kelly and Aspray, 2004). Another example is, when government funded research finds applications in civilian industries; the defense sector being the most prominent case. Again, firms' technical knowledge is similar, yet, the same knowledge finds different applications in different domains through alliances.

The Box III involves firms who are distant in their knowledge space, but whose products have strong complementary potential. In this case, competitive pressure is not high and there are also strong incentives to form collaborations. Apart from Nike and Apple example, here one can include the recent alliances between publication companies and software companies, in developing electronic versions of traditionally published media. [2] In 1922, an alliance between the automobile manufacturer Ford Motor Company and Pilkington Brothers glass resulted in a process innovation for the continuous production of large pieces of sheet glass (Utterback, 1994). Two companies were far in their knowledge space, yet, their products had high complementary potential.

It is possible to argue that there is a high potential for breakthrough innovations in the 1st and 3rd boxes. Innovation scholars have used terms like analogous thinking (Gassman and Zeschky, 2008) or recombinant innovation (Hargadon and Sutton, 1996; Hargadon, 2003) for these cases, and in this paper we incorporate this perception of innovations into the strategic alliance framework. In these views, radical product innovations are seen as application of knowledge in one domain, to another domain. This can happen between firms who share similar knowledge, but are involved in different applications, or among firms who satisfy related needs based on completely different knowledge domains. In both cases, there is scope for increased creativity, and successful new product development. Yet, we do

[2] The recent alliance between the Conde Nast and Adobe systems is an example.

not have sufficient evidence that these aspects of complementarities between firms are adequately captured by patent data.

Such a conceptualization of firm’s technological distance and market distance can be analyzed through an agent based simulation of strategic alliance formation of firms. In this paper, we construct a theoretical model to analyze the performance effects of strategic alliances based on the motives presented herein. In particular, our objectives are as follows. With this theoretical model, first we aim to confirm the optimal distance hypothesis, when firms consider only a single distance between them. Second, we aim to show the performance outcome when firms give their decisions under a two dimensional space. When firms make decisions under two dimensions, does the optimal distance hypothesis still hold? In other words, do firms form alliances in intermediate distance under two dimensions? We also aim to look at the evolution of networks between firms, as they interact with each other under the two dimensional space. Finally we investigate these issues, when there is an exogenous innovation in the system.

THE MODEL

A Brief Description of the Model

In the model, there is a randomly located population of firms on the two dimensional Cartesian space (Baum et al., 2009). Theoretically speaking, the distance between firms can be interpreted in any context, and the idea behind the model is that, firms search for partners in this space considering the distance between them. First, we consider the case when firms give decisions taking into account the simple Cartesian distance. Second, we look at the case when firms search for complementarities in two *different* dimensions, rather than a single dimension as is usually taken in the literature.

The firms are idiosyncratic in their choices; some of them may prefer close firms in the two dimensions, and some of them may prefer distant connections in the two, and others may fall in between. Through a matching process described below, firms form alliances by forming pairs. The effect of a performing an alliance is twofold, first firms earn profits, and second their location in the Cartesian space changes; they become closer to their partners (Baum et al., 2009). The fact that after collaboration they become closer in space restricts the possible interpretations we might make about these dimensions. For example, we cannot interpret it as physical distance, since it would imply that firms change their geographical space after alliance, which is more unlikely. In this context, market complementarity and knowledge complementarity fit reasonably within the model.

With the updated levels of profits and their new location, the above procedures are repeated. We look at the structure of networks that emerge, and analyze the relationship between firm preferences and final profit levels. In short, can we identify a relationship between the strategy of the firm and its realized profits? What type of partner selection strategy brings highest gains?

Before collaboration: Partner Preferences

Each firm has a location in the Cartesian space given by m_i and k_i showing its market address and knowledge address respectively. The profits that firm i expects from its collaboration with firm j, $\pi_{ij}(d_{ij})$, depends on the distance between them. Distance is simple Cartesian distance, given by $d_{ij} = \sqrt{(m_i - m_j)^2 + (k_i - k_j)^2}$.

Profit Function

The profit function that we use needs to have the following properties in line with our assumptions. First, we assume that each firm has a different strategy concerning how it selects partners. The strategy of firms are shaped by their profit expectations. Some firms expect to gain highest profits through connecting to close firms, and some firms prefer distant connections. Nevertheless, deviations from its perceived optimal distance does not imply that it will not ally with other firms. In this sense, we assume an inverted-u relationship between expected profits and distance. Deviations from the optimal distance will reduce the expected profits of the firm. Second, we assume that distant connections are more costly, because of increased costs of communication and higher risks of partnership. Moreover, expected profits from distant connections are more uncertain, which makes it difficult to judge among firms who are in more or less the same distance from the focal firm. Finally, these properties should be captured via a simple function to make the simulation easy to control. These properties are satisfied with the Rayleigh probability distribution function, which is given in Figure 3.

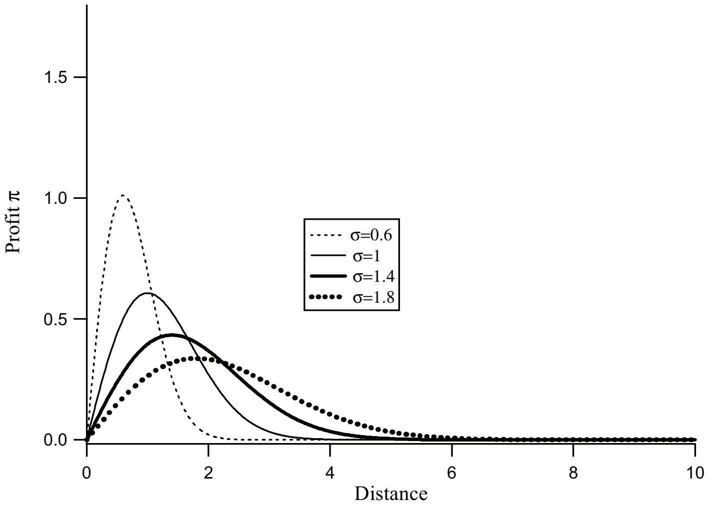

Figure 3. The Rayleigh Distribution

In Figure 3, profits are given as a function of distance between firms. For a fixed σ, there is an optimal distance between two firms, which maximizes profits. But changing the value of σ permits us to model the different preferences of firms in terms of distance. As σ increases, two things happen: First, the peak of the function reduces, which means that the maximum profits expected by high-σ firms are less then the maximum profits expected by low-σ firms. But at the same time, the set of firms among which firms chose expands as σ grows. [3] Moreover, as we explain in the next section, when firms connect to distant partners, their post alliance movement is higher in the Cartesian space. In accordance with this function, the profits that firm *i* expects from its collaboration with firm j is given by:

$$\pi_{ij}^{e} = \frac{d_{ij}}{\sigma_i^2} e^{-d_{ij}^2/2\sigma_i^2} \tag{1}$$

Where, d_{ij} is the distance between them, and σ_i is the distance preference parameter for firm *i*, which is fixed and different for each firm.

After Collaboration

[3] Because the function is a probability distribution function, the total area under the curves are the same, which means that expected total profits are the same for all firms regardless of their σ. We release this assumption in the last section.

We assume that, firms come closer to each other in the industry space after a partnership (Baum et al, 2009). In forming their profit expectations before collaboration, they foresee their change of location, and include a loss term in their expectation function, depending on the crowdedness of their new position. If the final point that they arrive is occupied by a number of other firms in the close vicinity, competitive pressure would increase, which we assume has a negative effect on expected profits. Hence, the $L^e{}_{ij}$ attempts to capture this effect by taking into account where the firm expects to find itself if the partnership is materialized. Then we modify the profit function as follows:

$$\pi_{ij}^e = \frac{d_{ij}}{\sigma_i^2} e^{-d_{ij}^2/2\sigma_i^2} - L_{ij}^e \tag{2}$$

The new locations of firm *i*, after its collaboration with firm *j* is given by:

$$m_{it} = m_{it-1} + \alpha(m_i - m_j) \tag{3}$$

$$k_{it} = k_{it-1} + \alpha(k_i - k_j)$$

And the *realized* profits, if firms *i* and *j* match with each other is:

$$\pi_{ij} = \frac{d_{ij}}{\sigma_i^2} e^{-d_{ij}^2/2\sigma_i^2} - L_{ij} \tag{4}$$

It is important to mention that, firm *i* cannot predict precisely its profits in advance because the realized profits depend on the partnerships formed by other firms. If many firms move to a similar location, the realized losses can be more than expected.

Matching

Based on Eq. (2), each firm calculates its expected profits from collaboration with each of the other firms. The matching process that we use is based on the Gale and Shapley (1962), and have been previously used in agent based simulations (Cowan et al., 2007; Ozman, 2010). Two firms form a partnership, if and only if their mutual profit expectations are higher than the rest of the available partners, and their mutual expectations do not differ by more than a certain percentage. [4] After matching takes

[4] In this model, the mutual profit expectations are not the same (what firm i expects from its collaboration with j, and what j expects from i), because their distance preferences might be different.

place, the coordinates of firm *i* changes according to Eq. (3) and realized profits are calculated according to Eq. (4).

Assumptions

It is important to clarify our main assumptions. Firstly, we assume a heterogeneous population of firms where they have different criteria in selecting partners. In an implicit way, we exclude environmental conditions which may lead firms to behave in similar ways. Nevertheless, this is also the strength of this model, since it permits us to include inter-industry alliances. In addition, because firms' distance preference parameters are set randomly, some firms are similar to each other. So there are group of firms who find it more beneficial to be close in both dimensions, etc.

Second we assume that losses are incurred because of the crowdedness of the area in which the firm finds itself in, after the alliance. Especially in rapidly changing environments, after the alliance the firm may find itself in a position in which it did not foresee before, and receive more, or less profits than what it expected initially.

Thirdly we assume that the profits fall as distance increases. This assumption is based on the fact that, distant connections are more costly in terms of communication, and uncertainty, but the firms have more alternative partners to select among. At the same time, distant connections make firms move more in the space, the distance between their initial location and post alliance location is bigger.

RESULTS AND MODIFICATIONS

Simulations and Parameters

The population consists of N=100 firms. The coordinates of firm i in period t=0 is drawn from a uniform distribution such that $(m_i, k_i) \in$ [0,10]. The distance preference parameter is given as $\sigma_i \in [0.1,4]$ and for 100 firms, we increase it

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When firms have the same expectations, a commonly employed matching process can be seen in Cowan et al. (2007). Here, we slightly modify this algorithm, such that if the ratio of their profit expectations differ by less than 0.9, they do not form a partnership. We impose this constraint so as to make sure that a firm which prefers a distant partner is not likely to collaborate with a firm who prefers a close partner during matching.

incrementally in the first set of simulations.[5] The parameter measuring the amount of distance travelled after the collaboration is α=0.05. The amount of loss is given by, $L_{ij} = \{\# j \in N \setminus \{\mathrm{i}\} : d_{ij} < 1\}$ which states that loss incurred is the number of firms which are within a unit of distance from firm *i*. We run 10 simulations. In each simulation, we keep the distance preference parameter (σ) of firm *i* fixed, but assign a different beginning coordinate for the firm. In this way we have the chance to confirm that the results do not depend on the initial position of firms in the space, and we can isolate the effect of preference parameter on profits. There are 1000 periods in one simulation run. The results presented are the average profit levels of firms for the 10 different runs. In the model, there are only bilateral links in a single period, but after 1000 periods, we obtain a network (Cowan et al., 2007) through the accumulation of relations. The network measures shown in the Appendix are based on the final networks.[6]

In Figure 4, we show the distance preference paramater (σ) with respect to the final profits. It reveals that, the highest profits belong to the firms who prefer partners at an intermediate distance. This result confirms the optimal distance hypothesis which detects an inverted-u relationship between learning and knowledge distance. Why is this result obtained from this model? The analytical interpretation is as follows. Due to the fact that firms move towards each other after collaboration, firms who prefer close partners can move only little, and their set of available partners do not change significantly as periods elapse. Firms who prefer very distant partners move a lot, but distant connections are more costly by our initial assumptions. This is why it is possible to confirm the optimal cognitive distance hypothesis. Nevertheless, our main question in this paper is concerned with what happens when firms consider two distances separately and give different weight to market closeness and knowledge closeness when forming their decisions? In the next section we release the assumption of a unique σ for firm *i*.

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[5] This means that the firm who prefers closest connections has a σ=0.1 and the firm which prefers most distant connection has a σ=4.

[6] We wrote the code of the simulation in C++ language; the code is available upon request.

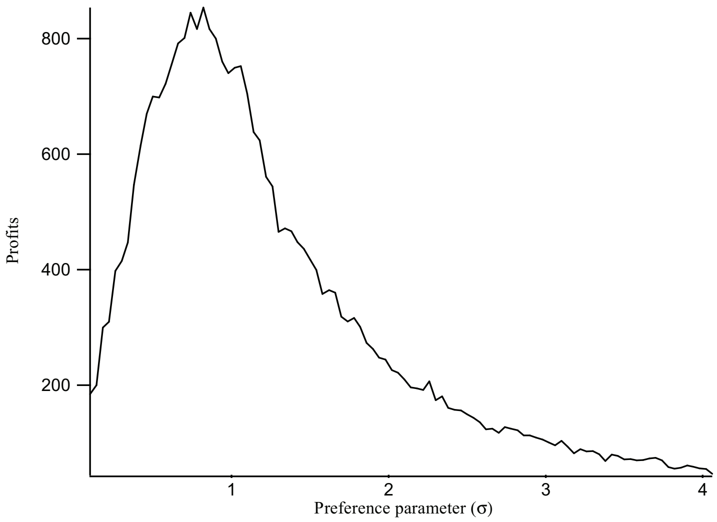


Figure 4: Profits and distance preference parameter

Modification 1: Distinguishing between Market and Knowledge Dimensions

In this section we modify the model, so that, the profits that firm *i* expects from its partnership with firm *j* has the following form:

$$\pi_{ij}^{e} = \frac{d_{ij}^{m}}{\sigma_i^{m2}} e^{-(d_{ij}^{m})^2/2\sigma_i^{m2}} + \frac{d_{ij}^{k}}{\sigma_i^{k2}} e^{-(d_{ij}^{k})^2/2\sigma_i^{k2}} - L_{ij}^{e} \qquad (5)$$

Eq. (5) is a simple modification of Eq. (2) where distance is decomposed into its two constituents. According to Eq. (5), expected profits from collaboration with firm *j* has three components. First, profits expected due to market complementarity, $\pi_{ij}^{m}(d_{ij}^{m})$; second, profits expected from knowledge complementarity $\pi_{ij}^{k}(d_{ij}^{k})$, and third, the losses expected due to the change in the location of the firm, which depends on the crowdedness of the new location. In Eq. (5), σ_i^m and σ_i^k are firm *i*'s distance preference parameter in market and knowledge domains respectively. The distance between firms in the market and knowledge dimensions are given by d_{ij}^{m} and d_{ij}^{k} and they are simple Cartesian distances taken separately in both dimensions:

$$d_{ij}^{m} = m_i - m_j \qquad (6)$$

$$d_{ij}^{k} = k_i - k_j$$

Therefore each firm i is characterized by two features. First its location in the Cartesian space (m_i, k_i). This location determines its distance with firm j (d_{ij}^m, d_{ij}^k) in both dimensions as given by Eq. (6). Second, its preference for connections in both spaces (σ_i^m, σ_i^k). For example, a firm who prefers distant market connections, and close knowledge connections will have $\sigma_i^m > \sigma_i^k$. These two features are assigned randomly to firms in the beginning period. We hold all the parameters of the simulations same, as given above. The distance preference parameter is given as $(\sigma_i^m, \sigma_i^k) \in [0.1,4]$ and for 100 firms, we determine them randomly drawn from a uniform distribution. In the same way, we run 10 simulations. In each simulation, we keep the (σ_i^m, σ_i^k) of firm i the same, but assign a different beginning coordinate for the firms. The results presented are the average profit levels of firms for the 10 runs.

Figure 5 shows the distribution of firms in the two dimensional space defined by (σ_i^m, σ_i^k). The size of the bubbles show the final profit levels achieved after 1000 periods elapse. The results reveal that, firms who prefer partners who are close in at least one dimension have higher profits than others. [7]

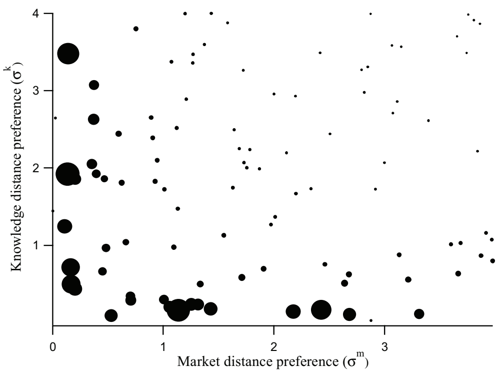
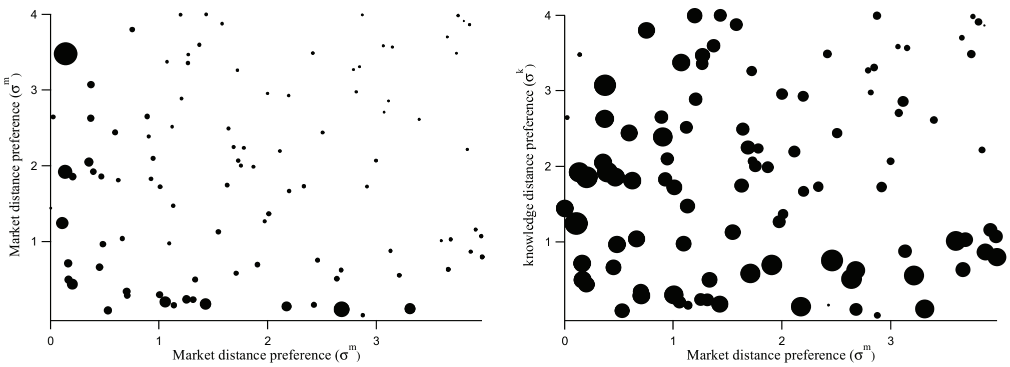


Figure 5 Profits and Distance Preference Parameters: spread of firms

One of the questions of interest is the relation between the number of partners of the firm, its strength of connections and its final profit levels. Here, connection strength refers to the average number of times two firms interact with each other. The firm's degrees refer to the number of different partners of the firm. Our results reveal

[7] Note that, the highest profits in the optimal intermediate distance in both dimensions would have been revealed by biggest bubbles in the middle of the graph.

that, agents in the range of maximum profits also have high connection strength as given in Figure 6.

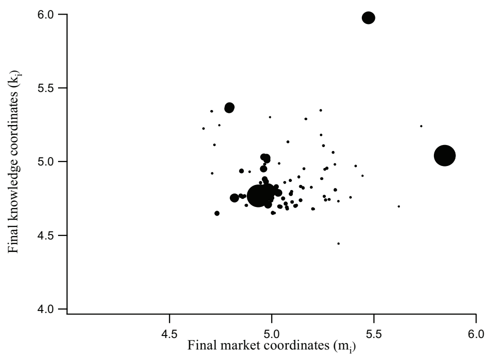


(a) (b)

Figure 6 Strength of Ties (a), degrees (b) and Distance preference parameter

Comparison of Figure 5 and 6a and 6b reveal that, there is a positive relation between strength of relations and profits, and only a weak relation between the degrees and profits. In other words, firms with high profits are also the ones who repeat their ties with their partners. Some further selected network measures are shown in the Appendix.

Figure 7 shows the physical location of firms at the end of the simulation runs.[8] Absent new entries, firms converge to each other in the Cartesian space, therefore after a while, their losses exceed their profits and they can no longer find partners sufficiently profitable and/or, who is equally willing to form partnership with them. In other words, firms become so similar to each other in the market and knowledge space, that losses because of competitive pressure is higher than the gains from collaborating.



[8] Because initial coordinates are different for each of the 10 simulations, the final coordinates are also different. Therefore we show only one of the simulations here, as an example of convergence.

Figure 7 Final coordinates of the firms (scale between 4 and 6)

Modification 2: External Innovation

In the third set of simulations, we introduce an external innovation, in which each firms in each period has a 0.1% probability of a random change in its location. Figure 8 shows the final profits in the space defined by distance preference parameters of the firms.

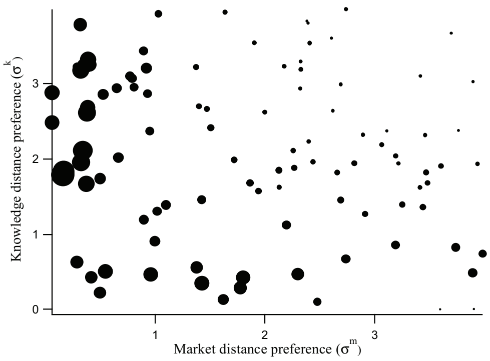


Figure 8 Profits and Distance Preference Parameters: spread of firms when there is an external innovation

While the structure of the relation between market and knowledge preference and profits do not change, as revealed by the comparison of Figures 5 and 8, the introduction of an external innovation reduces convergence in physical locations. There are opportunities for the formation of new partnerships continuously. As expected, firms are more spread in the market and knowledge space, and convergence is much less when there is external innovation. Figure 9 shows the new coordinates of firms in the market and knowledge space.

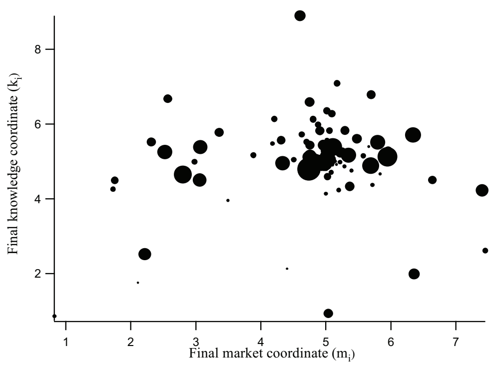


Figure 9 Final market and knowledge locations of firms (scale between 1 and 8)

Modification 3: Profit Function

One of the assumptions we made above was that distant connections are more costly, so that the maximum expected profits are less, as distance grows (Eq. 1 and Figure 2). In this section, we release this assumption, and assume the following functional form for the expected profits, as also shown in Figure 10:

$$\pi_{ij}^{e} = \frac{d_{ij}^{m}}{\sigma_i^m} e^{-d_{ij}^{m}/2\sigma_i^{m^2}} + \frac{d_{ij}^{k}}{\sigma_i^k} e^{-d_{ij}^{k}/2\sigma_i^{k^2}} - L^{e}{}_{ij}$$

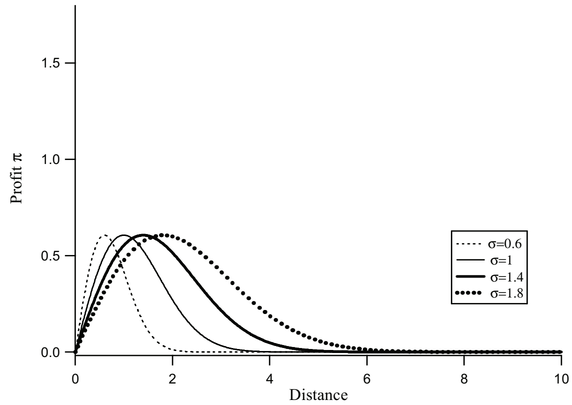
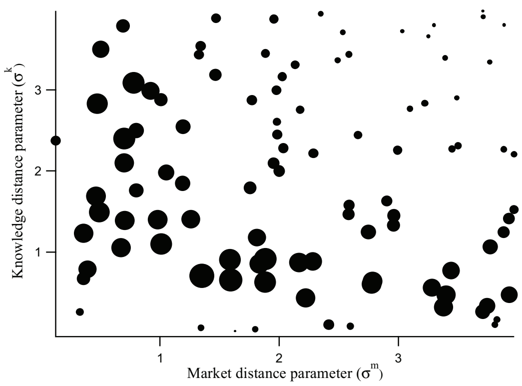


Figure 10 Modified Profit Function

Figure 11 shows the profit levels in the distance preference space. Firms who prefer distant partners in both dimensions are not profitable. Firms who prefer too close connections in only one dimension are also not profitable. In this case, the highest payoffs belong to firms who are at a more or less intermediate location in at least one dimensions.



DISCUSSION AND CONCLUSION

The beginning point of this paper is the need to incorporate the concept of market distance into the analysis of strategic alliances. In the literature, complementarities between firms are usually measured by considering a single dimension as technological distance. Studies show that there is an optimal distance between firms which maximizes learning. Being too close in knowledge space is not useful, since firms cannot add anything new to their existing knowledge. Being too far is also not useful, because firms have difficulty in understanding each other. While this result has proven to be very useful in understanding alliances, it falls short of explaining those in which firms who are very distant in their knowledge domains can explore opportunities to apply their knowledge in different market domains. In other words, focusing only on knowledge distance reduces the complex search process into a single dimension. In explaining the generation of novelties from distant connections this issue has been recognised by most scholars, however, it has not been tackled adequately in models incorporating only technological distance. Moreover, the detection of an inverted-u relationship between distance and learning has mostly been done through analysis of patents. How well patent data captures complementarities between firms in the market domain is questionable, and should be subject to more rigorous research in the future. Explaining alliances can be better done by taking into account not only the cognitive distance between firms, but also the extent to which their products can be consumed jointly. We define the latter as market distance in this paper. Our results show that there is a complementarity between both dimensions, firms need to be close in at least one dimension for higher profitability, rather than being in the intermediate distance in the two dimensions.

In this paper, we perform an agent based simulation, to reveal the complex dynamics involved in the partner selection process. The abstract notion of the two dimensions that we use can be replaced by other notions of distance, in which firms come closer to each other after collaboration. Other studies show that as firms learn from each other through alliances, the overlap between their capabilities increase (Mowery et al., 1998; Baum et al., 2009). We prefer to focus on knowledge and market proximity, because they fit nicely in the model as firms come closer to each other after collaboration, and as firms converge finally in the market and technology domains. Secondly, we prefer to choose market distance, since we are convinced that market distance has not received sufficient attention in explaining alliances, while many of the real world alliances seem to be motivated by complementarities between the products of firms.

Market and knowledge dimensions have been explored in different ways in previous literature. For example, Cotterman et al.(2009) find that, in firms where there is a high communication between market and knowledge aspects perform better (Cotterman et al., 2009). The inability of large R&D labs to commercialize their highly sophisticated scientific knowledge is also an issue covered in the strategic management literature. Some scholars stress the need to open the innovation process to make use of external knowledge lying outside firm boundaries, to be able to commercialize their dormant technical knowledge (Chesbrough, 2003).

Through a simple analytical model, we show that when firms consider only a single distance between them, there exists an optimal intermediate distance, which maximizes profits. Introducing a second decision parameter, however, changes the results. When firms consider two dimensions in selecting partners, we show that the firms who prefer close partners in *at least one dimension* have higher payoffs. This result seems to be quite robust. When we change the functional form employed, the only change was that, firms who prefer intermediate connections in at least one dimension had higher payoffs.

We interpret our results by considering industries where complementarity between products is an important feature of competitive advantage. Real world examples in new product development alliances demonstrate the importance of market overlap between firms, as a driver of alliances, and their performance effects. Our results seem to fit very well into the literature on the role of analogical thinking (Gassman and Zeschky, 2008) and recombinant innovation (Hargadon, 2003) in new product development literature. Gassman and Zeschky (2008) provide a case study explaining how four companies used analogous thinking to solve problems, and they emphasize the importance of search process in external relations. History of technological change is full of examples in which knowledge developed in one context is applied in other contexts to solve problems (Arthur, 2009; Bassala, 1988). For example, as early as 1922, when the enclosed automobile was becoming fashionable, an alliance between Ford Motor Company and Pilkington Brother's glass, an established UK glass firm, resulted in the continuous glass production process, which combined casting and annealing in a single production chain. The two companies were largely disconnected as far as their competences were concerned; nevertheless, the fact that the mass production of the automobile required large supply of high quality glass brought them closer in the market space. The production time of a sheet of polished glass was reduced from 10 days to three days thought the Ford Pilkington glass process (Utterback, 1994).

IBM's leader position in the computer industry was very effective in the shift from 150 mm to 200 mm wafers, used in the fabrication of integrated circuits. IBM was collaborating with major equipment suppliers and invested heavily in research to this end. Having early access to a critical equipment resulted in an active role in setting standards, which was the source of competitive advantage in the market (Chesbrough, 2003). The collaboration of IBM with suppliers was not because these firms were at an intermediate distance in terms of their technical knowledge, rather it was because, these firms were critical in the establishment of PC standard with the complementary technologies they were specialized at producing. Another example can be given from medical equipment industry. Schilling (2008) explains that the collaboration between a variety of actors from distinct areas, one of them being from the defence industry, resulted in the introduction of the first swallowable camera pills to the market in April 2000. The spillovers between military technologies and civilian industries is an important case in which actors from distinct industries join their knowledge to find applications of knowledge in a variety of market needs. Even in the early phases of the computer industry, the necessity to process large amounts of data in short time period in US Census Bureau initiated the development of punch cards, which later lay the basis of computers for civilian use (Campbell Kelly and Aspray, 1996). Perhaps the computer industry is one of the cases in which the joint effect of knowledge and markets is the most striking. Looking at the history of the industry, actors knowledgeable in one context were finding applications of their knowledge to meet different market needs (Moggridge, 2007; Steinmuller, 2007).

Davis et al. (2007) provide an excellent analysis of the contexts in which simulation models can be used safely in management research in developing theories. They state that simulations permit testing simple theories, especially when complex dynamics are involved. In this sense, our model is no exception. This simple model incorporates complex dynamics involved in firm networks. Intuitively, and based on examples from the real world, our results seem to fit very well into most of firm alliances especially in new product development. Nevertheless, we believe that more formal empirical research is complementary to simulation models, and this paper opens up direction for future research in which not only knowledge overlap but also market overlap is considered in understanding complementarities between firms.

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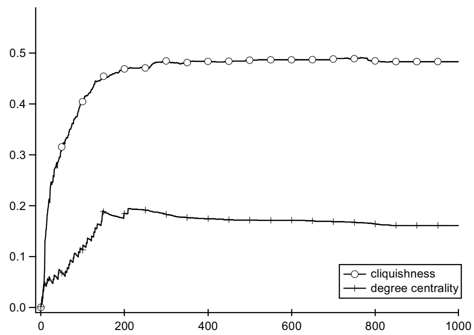
APPENDIX

Selected Network Measures

Figures A1 and A2 show the evolution of selected network measures in the model described in Modifications 2. First, we show the cliquishness of the networks, which shows the extent to which partners of a firm are also partners with each other. Secondly, we show the average degree centrality of networks and the average shortest path length between any two firms in the network.



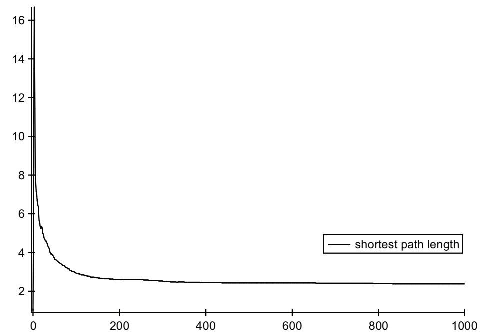


Figure A1 Cliquishness, Degree Centrality and Shortest Path Length

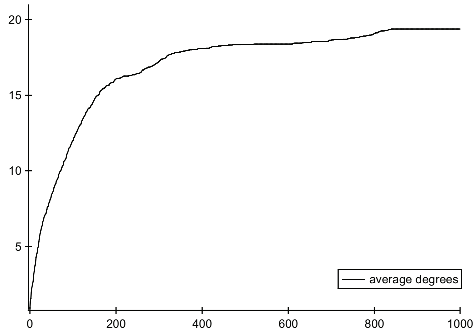
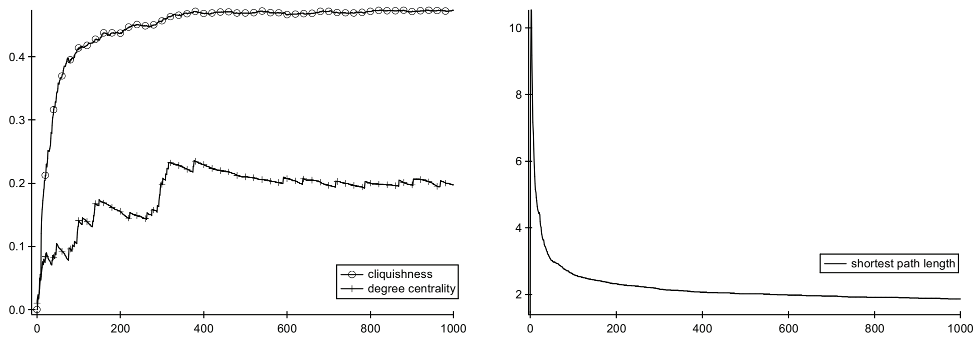


Figure A2 Average Degrees of a Firm

In the final networks on the average 50% of neighbors of a firm are connected with each other (Figure A1), and on the average 2.21 intermediate firms are needed to link any two firms in the space (Figure A1). The average degrees are shown in Figure A2, and it means that, each firm connects to 20% of other firms in the market knowledge space.

Figure A3 shows the cliquishness, degree centrality and average shortest path length when there is an external innovation, given in Modification 3. Cliquishness and degree centrality are slightly higher than the case with no innovation. The shortest path length after 1000 periods, which is given in Figure A3 is 1.95 which is lower than the case with no innovation. Figure A4 shows the average degrees of firms, which reveals that after 1000 periods, each firm, on the average has connected to 35% of the remaining firms.



(a) (b)

Figure A3 Cliquishness, Degree Centrality and shortest path length with External Innovation

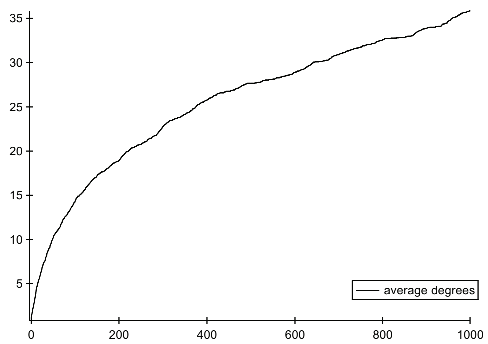


Figure A4 Average degrees per firm with external innovation

Comparison of the networks in both cases reveal that, when there is an external innovation, the network approaches a complete one, where all firms are connected to all other firms. Nevertheless this is not shown in the model, since it requires more than 1000 periods. This is an expected result, since when there is an external innovation, random dislocation of firms result in the fact that they do not converge (see Figure 9 in the main text), and can always find profitable partners to collaborate with.

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