The small worlds of strategic technology alliances

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Abstract

This paper analyzes the phenomenon of strategic technology alliances. It is proposed that the concept of small worlds, which has been adopted from mathematical graph theory, is a useful model to combine two theoretical streams that have previously analyzed this phenomenon. These are the theory of social capital and the theory of structural holes. We outline a small worlds model, and apply it to data on strategic technology alliances. We find that networks of strategic technology alliances can indeed be characterized as small worlds, and that this has favorable implications for knowledge transfer. There are, however, also important differences between two different technology fields that we consider: chemicals and food, and electricals.

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1. Introduction

In the past decades, strategic alliances have become an important mechanism for (quasi) external acquisition of technological know-how. The strong upheaval in the use of strategic technology alliances has led to the emergence of complex inter-organizational research networks. The growing strategic importance of these networks has been acknowledged in many contributions (see, e.g., Burt, 1992; Gulati, 1998; Duysters and Hagedoorn, 2002). The quest for a better understanding of these networks subsequently led to the use sophisticated network analysis techniques and conceptions arising from graph theory for the analysis of these networks, both from the point of view of policy and strategic management within firms (Vonortas, 1997).

Recently, the theory of ‘small worlds’ has emerged in the field of graph theory (Watts, 2000; Cowan and Jonard, 2000). This paper will attempt to apply this theory to the case of sectoral technology alliance networks. It will be argued that the theory of small worlds can be seen as a model that unites two distinct perspectives found in the strategic management literature. These are the notions of social capital and structural holes (Walker et al., 1997). Using the small-worlds idea in this way, it is argued here that one may use this concept as a way to judge the overall efficiency of a network of technology alliances. This argument is applied to empirical data on two major RTD networks.

The next section of this paper will briefly review the social capital and structural holes theory of network formation as it is found in the strategic management literature. In Sect. 3 we formulate two specific research questions and we outline the theory of small worlds, and argue how it can be applied to the theory discussed in Sect. 2. Section 4 will present the empirical results. The argument will be summarized and concluded in Section 5.

2. Strategic technology alliances and networks

One of the key trends over the past decades has been the remarkable growth in the number of strategic alliances (see Fig. 1). According to many authors, this trend is likely to continue in the near future. Major consultancy organizations such as Booz–Allen Hamilton (2000) predict that within five years from now, the value of alliances will be in the range of $30–$50 trillion.

The rapid proliferation of alliances is in large part due to an increase in the number of strategic technology alliances (Hagedoorn, 1996; Duysters and Hagedoorn, 2002). Whereas, for a long time firms have relied heavily...

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on the internal development of know-how and new technology, firms have come to realize that internal development is no longer sufficient to deal with their continuously changing technological environment. A growing number of firms seems to recognize that the use of strategic technology alliances allows them to increase their flexibility and to tap into other company’s technological resources.

The growth in the number of strategic technology alliances has led to the emergence of complex “technology networks”. The growing importance of these networks induced a shift of focus in the alliance literature, away from a dyadic relationship level towards a network perspective. Firms which are “embedded” in these networks are increasingly affected by the relationships of their partners and the overall structure of the network (Granovetter, 1992). Embeddedness, on the one hand, restrains firms in their behavior and on the other hand creates opportunities for companies to tap into rich resources.

The central notion in the network literature is what Nootseboom (1999) has coined indirect access. Because an alliance partner is also likely to be connected to others, a firm does not only gain access to resources of its immediate partner, but also, to a certain extent, to those with whom the partner collaborates. The issue of partner-seeking then becomes one of picking partners not only on the basis of their own capabilities and resources, but also those of the indirect actors it gives (partial) access to in terms of its network.

This gives rise to the idea of a set of strategic alliances as a network of actors that are directly or indirectly connected to each other. A direct connection results from participation in a specific alliance. Indirect connections result when information or knowledge exchanged in one partnership is also (implicitly) entered in other partnerships. Such networks have been the topic of the mathematical branch of graph theory, and have been studied since the 1950s (Watts, 2000 provides a brief overview of the history of the field). A crucial element in this theory is the structure of the network and the position that actors occupy in them.

The focus on the importance of indirect ties gave rise to two different perspectives on the dynamics governing the formation of networks and their efficiency as information or knowledge transmitters.

The first perspective emphasizes the importance of social capital (Bourdieu, 1980; Coleman, 1990). Social capital can be defined as “the sum of the resources, actual or virtual, that accrue to an individual or a group by virtue of possessing a durable network of more or less institutionalized relationships of mutual acquaintance and recognition” (Bourdieu and Wacquant, 1992, as cited by Walker et al., 1997, p. 109). Putting the concept of social capital in a network context, Walker et al. have argued that the density of network relations is a good proxy: “Some firms occupy positions that are embedded in regions filled with relationships, indicating a high level of available social capital, but other positions are located in regions with few relationships, suggesting a low social capital” (Walker et al., 1997, p. 111). In general, one can argue that firms with more social capital will have access to a larger pool of information sources and will be able to attract better partners (Gulati, 1998).

The second perspective on networks stems from the work by Burt (1992), who argued that a firm interested in using networks as a source of information should attempt to fill the structural holes in between the dense areas of a network rather than replicate existing partnerships that are already in place. In other words, in strategically selecting one’s partners for cooperation, one should look for partners that have strong links to other actors with whom oneself does not yet have strategic links, in order to try to bridge holes in one’s own network. From this perspective, the primary strategic aim of forming partnerships becomes the desire to serve as ‘bridges’ between two relatively unconnected parts of a network.

Fig. 1. Number of newly established strategic alliances per year (1985–2000), three-year moving averages. Source: Thomson Financial.
Burt (1992) argues that this strategy will provide access to knowledge or information that has a high yield. The roots of this perspective can be found in social network literature that emphasizes the importance of “weak ties” and the importance of overarching structural holes. McEvily and Zaheer (1999) have argued that bridging ties are characterized by:

- Non-redundancy, operationalized as the degree to which the contacts in a firm’s ego network are not linked to one another.
- Infrequency of interaction with the partners.
- Geographic dispersion — the more distant, the more non-redundant.

Overall, Burt argues that redundant contacts often carry the same information. Therefore, organizations should focus on establishing non-redundant contacts that enable firms to bridge dense areas in the network.

Confronting these two perspectives, one can clearly see two distinct tendencies emerging. Strategies built solely on the idea of enhancing social capital would lead to networks with highly dense local environments. When, on the other hand, in an extreme case, firms mainly try to pursue a strategy of filling structural holes in their own network, a tendency towards less densely connected local environments would result.

3. Research question and theory

3.1. Research question

Intuitively, the ‘social capital strategy’ and the ‘structural holes strategy’ will lead to quite different networks of strategic technology alliances. Firms dominated by a ‘social capital’ view of the world will seek out a limited number of partners with whom they build strong and repeated ties. This will result in an overall network structure in which local environments of a firm are densely populated with alliances, but where path length to other local environments is long. Alternatively, in a world dominated by strategies aimed at bridging ‘structural holes’, local environments will tend to be populated less densely, while paths through the network will tend to be shorter.

This intuitive argument would suggest that there is some degree of trade-off involved between social capital (density of network) and path length, where higher social capital leads to longer paths. We will use a simple model presented by Watts (2000) in order to investigate the nature of this trade-off. The model will show that there is a particular class of networks, which are known in the literature as small worlds, in which relatively high social capital can go hand in hand with relatively short path length. The mechanism involved in shaping the network as a small world will be the existence of so-called short-cuts in the network. We will relate this concept to the notion of bridge-building in Burt’s theory.

Our second research question is how actual networks of strategic technology alliances compare to our hypothetical network structures. In other words, we will investigate whether these actual networks resemble one of our extreme network structures (social capital world, or world dominated by bridges to cover structural holes), or whether they can be classified as a small world. In this way, we will be able to put a value on the relative efficiency of the whole network as a generator of social capital, or as a transmitter of information and knowledge. Our special interest will be in finding differences in this respect between different technology fields, or over time.

3.2. Concepts and definitions

In order to describe our two extreme cases, two central concepts will suffice. These are the concepts of characteristic path length of a network, and that of clustering. An assumption in our treatment of the concepts and the theory hereafter will be that we deal with a network in which all nodes are connected through each other (directly or indirectly), i.e., that there are no parts of the network that are unconnected to other parts. In our empirical applications below, we will construct the network by defining a direct link to be present if two firms participate in at least one alliance together.

For any pair of actors in the networks, define the path length between them as the minimum number of intermediaries necessary to connect them, plus one. It follows from this definition that actors that are directly connected have a path of length of one between them. Two actors that are not directly connected, but share a third firm as a direct connection, have path length equal to two, etc.

The particular indicator that has been used in much theoretical work in order to arrive at a single measure of path length for the network as a whole is called characteristic path length. This is defined as the median of average path length of all actors in the network. Average path length of an actor is defined as the average of path length to all other actors in the network.

Characteristic path length of the network is interesting because it gives an indication of the relative (potential) efficiency of the network. The shorter path length in a network, the easier and quicker knowledge or information may diffuse through the network. Form the point of view of a single actor in the network, shorter path length implies easier access to the knowledge of other actors in the network.

Characteristic path length will depend on a number

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1 The exposition here draws heavily on Watts (2000).
of network characteristics. The number of actors in the network is one prime determinant, as is the average number of direct connections that each actor has (the latter is called average degree of the network). In addition to these quantities, which can be easily measured for any network, it is the network topology that determines characteristic path length. A prime factor of interest with regard to network topology is the way in which the edges are distributed over the network as a whole.

The concept of network clustering can be used to quantify some interesting factors in network topology. In order to define network clustering, one must first define the neighborhood of actor \( i \). The term will be used to describe the subset of actors that have a direct connection to actor \( i \) (this is also called ego network of actor \( i \)). Obviously, the number of actors in the neighborhood of actor \( i \) is identical to the degree of actor \( i \) (\( i \) is defined not to be a member of its own neighborhood). Now define clustering of the neighborhood of \( i \) as the number of edges in the neighborhood \( i \) as a fraction of the maximum possible edges in that neighborhood. The latter is simply the number of combinations of two distinct actors one can draw from a subset of \( k \) actors, where \( k \) is the degree. Clustering at the level of the network as a whole is then defined as the average of clustering of all neighborhoods \( i \). Obviously, clustering is a direct indicator for social capital, where high clustering indicates high social capital.

A final concept that will be necessary to set out the theory of small worlds is that of a shortcut. Shortcuts are edges that complete triads, or, alternatively, shortcuts are edges that connect two vertices that would otherwise be (widely) separated. We will use the parameter \( \phi \) to denote the fraction of edges in a graph that are shortcuts. Clearly then, shortcuts are exactly the ‘bridges’ that fill in structural holes in a network member’s environment. The fraction \( \phi \) of such shortcuts or bridges in the total of all connections can thus be seen as a degree of presence of the structural holes strategy in overall network formation.

### 3.3. The theory of small worlds

We have already introduced the intuition that high clustering goes hand in hand with long characteristic path length, and vice versa. Mathematical work in network theory (e.g., Watts, 2000) tends to support this intuition. In fact, two specific network typologies have attracted much attention, each representing one extreme of the average clustering–characteristic path length relation.

The first typology is the so-called ‘connected caveman world’. Such a world consists of a number of distinct ‘caves’ that are connected to each other by a single edge. A cave is a subset of actors that is fully connected. Each cave is connected to exactly two other caves by two distinct members, each of whom are connected to one other actor in a different cave. In such a network, which is depicted in Fig. 2, all paths to actors in the same cave have the minimum length of 1, but paths to actors outside the cave are much longer because they depend on only a few actors that can act as intermediaries. Since the cave is almost fully connected internally, the degree of clustering of this neighborhood is close to one. This high clustering leads to a relatively high value for characteristic path length (we will present values for these two variables below).

The connected cavemen world is one that can be interpreted as emerging from pure social capital strategies. The individual caveman obviously has a high amount of social capital, because (s)he is a member of a densely populated environment. However, the world is larger than a single local environment (cave), and the high resulting characteristic path length implies that the high social capital comes hand in hand with a large average distance to other parts of the world. This implies that it would take a long time for information emerging in one cave to spread through the world as a whole.

The other extreme network typology of interest is that of the Moore Graph. This is a network in which every vertex is adjacent to exactly \( k \) other vertices, and none of these other vertices are connected to each other. The Moore Graph is a purely theoretical construction, and cannot even be obtained for many combinations of \( n \) and \( k \). This is why Fig. 2 only displays a local view around a single vertex for the Moore Graph. It can easily be verified that in the Moore Graph, clustering is zero, and one may conclude that social capital strategies played no role in network formation. On the other hand, there is always a relatively efficient path to other members of the network, because every node is in fact operating as a bridge.

The Moore Graph is of interest here because it puts a lower limit on characteristic path length. An approximate expression for characteristic path length of the Moore Graph with given \( n \) and \( k \) can be obtained, and it can be shown (Watts, 2000, Sect. 4.1.2 and the references there) that it is impossible to obtain shorter charac-

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**Fig. 2.** The Connected Caveman World (left) and a local view of the Moore Graph (right).
teristic length for any graph with identical $n$ and $k$ provided that the degree of the individual vertices does not differ too widely. Hence, the Moore Graph has much lower characteristic path length than the Connected Caveman World.

In practice, one can only approximate the perfect Moore Graph by means of a graph in which the links are distributed randomly. This will yield values for the clustering coefficient that are in fact positive, but very close to zero. By drawing random graphs in which the probability of shortcuts is varied, it is possible to construct graphs that provide a more or less smooth transition between the highly clustered and long connected caveman world and the short and not very highly clustered Moore Graph. This will be shown below.

Summarizing, two main typologies of graphs have been introduced: one for which the characteristic path length is high, and hence information takes a long time to travel from one (average) network member to another; and one for which the characteristic path length is much lower, and hence information travels much more rapidly. The ‘long’ network is characterized by high clustering, the short one by low clustering. The extreme case of high clustering and long path length can be seen as a representation of the pure social capital perspective on network formation. The other extreme (short path length and low clustering) can be seen as an extreme network structure associated with the structural holes perspective. Is the negative relationship between clustering and path length that results from comparing these two stereotypes a general phenomenon?

It can be shown that high clustering and long characteristic path length need not always go together. A special class of networks can be identified in which clustering is relatively high, but characteristic path length is relatively short. This type of networks has been called ‘small worlds’ (Watts, 2000). This term has been derived from the hypothesis that although most people in the world mainly know other people that belong to a fairly clustered set of friends, there are five to six intermediaries necessary to connect the largest part of the population of the globe. In other words, even though a person knows mainly people in her own environment, she will know indirectly most other people in the world through only a small number of indirect steps.

Specifically, a small world has been defined as a network with $n$ actors and average degree $k$ that displays characteristic path length approximately equal to a Moore Graph with the same $n$ and $k$, but has much larger clustering than such a graph. The relevance of the idea of small worlds becomes immediately obvious in the context of the comparison of the structural holes perspective and the social capital perspective. Suppose one would start from a situation of the connected cavemen world, i.e., a world in which social capital dominates the formation of networks completely. Then imagine that in a controlled experiment, network members are allowed to fill in structural holes in their personal network, by engaging in partnerships with firms in other parts of the network. How would this affect the characteristic path length of the network, and hence the efficiency of knowledge transfer? How ‘many’ structural holes would have to be filled before a certain degree of network efficiency would be reached? It turns out the theory of small worlds provides a very clear-cut answer to these questions.

In order to see how the small world is located in between the Connected Caveman World and the Moore Graph, Watts (2000) has proposed a number of formal models describing the construction of (random) graphs. The exact construction of these graphs need not concern the reader here. What is interesting, however, is that these networks can be tuned by the single parameter $\phi$ to either side of the Connected Caveman World or the Moore Graph. Moreover, this parameter has a clear interpretation in terms of the structural holes perspective: it measures the tendency for network connections to fill in structural holes. Fig. 3 illustrates the model.

The horizontal axis of Fig. 3 displays the parameter $\phi$, which tunes the graph, and which has an obvious interpretation as the degree to which strategies aimed at bridging structural holes play a role in partner seeking.2

![Fig. 3. Length and clustering as a function of the graph tuning parameter $\phi$.](image)

2 Instead of using $\phi$, one may also use a slightly different parameter denoted $\Psi$. This parameter measures the fraction of all pairs of edges in the network that are not connected and have one and only one common neighbor. Such pairs of edges are called contractions, and can be seen as an alternative conceptualization of the idea of bridges filling in structural holes. Watts (2000, p. 73) argues that “$\Psi$ is an analogous parameter to $\phi$, although it is more general, as most shortcuts result in contractions, but not the reverse”. In the networks depicted in Fig. 2, there is an exact quadratic relationship between $\phi$ and $\Psi$, which is...
The figure shows that for a low fraction of shortcuts in the set of the network’s edges, one observes a high value for characteristic length of the network, and also a high value for the clustering coefficient of the network. This, in other words, corresponds to the connected caveman world network, or, alternatively, to a world in which social capital completely dominates network formation. At the other extreme, where the large majority of all edges are shortcuts and the bridging of structural holes is very important in strategy, one observes low values for clustering and characteristic length. This corresponds to the Moore Graph. Thus, we clearly find support for the intuition that a social-capital-dominated strategy increases path length, while strategies aimed at bridging structural holes decrease overall network length.

What is interesting, however, is that the path from high to low values of \( \phi \), i.e., the path from a pure social capital perspective to a pure structural holes perspective, is quite different for the two variables in the graph. The clustering coefficient does not descend very much in the beginning, but shows rapid decline towards the end. Characteristic path length shows more or less the opposite path: it declines rapidly at first and reaches very low levels already at relatively low levels of \( \Phi \). Small worlds are defined as networks in the limited range (say between 0.01 and 0.1) for which characteristic path length is already at levels comparable with the Moore Graph (right extreme), but the clustering coefficient is still relatively high. This world thus combines high social capital with an efficient flow of information and knowledge.

Note that the curves in Fig. 3 are drawn for some specific values of other networks parameters. These are the size of the network (number of vertices) and the average number of direct connections that each of them has (average degree). Also, the underlying model assumes that the vertices do not differ too widely in their actual degree (see Watts, 2000, Chaps. 3 and 4 for more details). When applying the theory to a specific real-world case, as will be done in the next section, violation of this assumption may lead to observed values of \( \Phi \), length and clustering that are off the curves.

Also, the model applied to draw Fig. 3 does not contain any behavioral foundation. It is just a mathematical construct useful to provide some benchmark against which we can compare values of \( \phi \), length and clustering observed in actual practice. The benchmark enables us to assess how important the two network strategies (structural holes and social capital) are in a real-world case, and whether we find values of path length and clustering that are in broad accordance with these strategies.

Coming back to our research questions, the model shows that very dense networks in which social capital dominates network formation indeed lead to inefficient networks in terms of the overall speed of transmission of knowledge flows through the network. Compared to this extreme case, the application by network members of a strategy of trying to fill structural holes will generally decrease characteristic path length, and hence facilitate knowledge flows in the network as whole. The theory also shows how frequently the structural holes strategy needs to be applied in order to approach the theoretical lower boundary on characteristic path length. Specifically, the model suggests that the small worlds range of the parameter \( \phi \) is relatively efficient. Forming shortcuts beyond the upper limit of the small worlds range does not lead to a noticeable further decrease of characteristic path length, but it does decrease social capital.

Note that this line of reasoning refers to overall network path length and clustering. In any real-world network there will be some firms with shorter (or longer) path length. In other words, even in the small worlds range, there will be an incentive for some firms to invest further in alliances that fill in structural holes in their own local environment.

The analysis will now proceed by investigating how the real-world networks of strategic technology alliances compare against the benchmark theory.

4. Empirical results

We use the CATI database as our source of information on strategic technology alliances. The data covers alliances from the period 1980–1996. In constructing our networks, we defined two firms to be connected when they are present in at least one joint alliance. A moving window in time was used to date the networks, so that the network at time \( t \) covers alliances in the period \( t-l \) to \( t \), where \( l+1 \) is the window length. We experimented with \( l=4 \), \( l=2 \) and \( l=17 \) (the latter means we include the whole period for which we have alliances data). The results are largely invariant to the value for \( l \). The alliances were also assigned to a technology field, and we made calculations for all technology fields together, as well as two separate fields. In order to have sufficient observations, we defined the two technology fields for which separate calculations were done relatively broadly. The two fields were chemicals and food, and electricals (including electronics and ICT). When we consider a network, we concentrate on the portion of the network that is connected. In all cases, this involves by far the largest proportion of firms that is present in the database. The parts of the network that are not connected

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governed by only one additional parameter. This is the so-called bundle size, which is roughly equivalent to the number of parties involved in a single partnership or alliance. However, because the quadratic term in this relationship adds little for the values of \( n \) and \( k \) that characterize the networks of interest in this paper, using \( \phi \) or \( \Psi \) is more or less equivalent from a theoretical point of view.
usually consist of a fairly high number of pairs of firms that have only one alliance. Details on this are available from the authors on request.

Table 1 gives an overview of the main results. All five cases show a similar pattern: characteristic network length (L) has the order of magnitude corresponding to a Moore Graph, while the clustering parameter (γ) has an order of magnitude that is quite a lot higher than that of a Moore Graph, although also somewhat lower than that corresponding to the connected caveman world (CCW). On the basis of these results, we can classify the network of strategic alliances that we investigated as small worlds.

The first three lines consider the total network, i.e., no split-up has been made with regard to technology field. Here we see that the general tendency of a low value for L and a fairly high value for γ is surprisingly invariant to the value for t, although obviously the size of the network depends on this. At the level of the two separate technology fields, larger differences arise, as is obvious from the two last lines in the table. Here we see that the electricals field is characterized by a relatively low value for L, as compared to chemicals and food, as well as the total network, although the value for γ is quite similar for the two fields.

Fig. 4a–c show how, for the networks in Table 1 with t=4, the network structure compares to the benchmark of a random network with varying φ, as in Fig. 3 above. The figure gives both the theoretical network structure (indicated by the lines) for n and K given for the specific case in Table 1, and the observed values of L and γ (dots). Hence the distance between the dots and the lines is an indication of how much the observed network structure differs from the theoretical one. Note that we have no reason to expect that the observed values will match the theoretical case, since the model used to construct the latter is a random model without behavioral basis. Thus, the theoretical lines cannot be seen as predictions, but rather as benchmarks corresponding to ‘random partner seeking’. The deviations from these benchmarks are then indications of strategic networking behavior leading to a specific tendency for higher or lower L and/or γ.

For the network for all technology fields, we observe that the value for L is almost on the rightmost flat part of the benchmark line. Hence we conclude that somehow, network length has been minimized, and the fraction of shortcuts in the network (φ) is a good predictor for this. Clustering is somewhat higher than the benchmark value, indicating a tendency for the building-up of social capital.

The figure for electricals shows a somewhat similar situation, although here the observed value for L is a bit more below the benchmark. The value for clustering (γ) on the other hand is somewhat closer to the benchmark, although still above. This again indicates a tendency for strong social capital. For chemicals and food, the deviation from the benchmark is most extreme. This is the field where the value for φ (shortcuts) is very high. The benchmark would predict low clustering (low social capital) on the basis of this, but the contrary is the case. In this technology field, clustering is almost as high as the maximum value in the benchmark (for low φ).

How can this be interpreted? The relatively high values for clustering (γ) can be taken as an indication of the importance of social capital. On the other hand, the relatively high values of φ and (partly as a result) low value of L is an indication of strategic partner seeking in line with a structural holes perspective on alliance formation. In other words, the networks under consideration seem to combine features of both theoretical perspectives that we have outlined above. The result of this combination of perspectives is a network structure similar to a small world, in which information flow is relatively efficient (low L), but social capital (γ) still high.

How exactly these two strategies are combined in terms of alliance formation is an issue that is open to future research, which could possibly lead to a more adequate (mathematical) model of network development. Our results indicate that in such a theory, there would certainly have to be a role for factors that are specific to technology fields or industrial sectors. This is clear from the large differences in networks in the two technology fields in Table 1, as well as from the observed values for φ in these two fields. The electricals field displays a value for φ that is broadly comparable to the total network. The chemicals and food field, on the other

Table 1
Basic network statistics, networks of strategic alliances from CATI

<table>
<thead>
<tr>
<th></th>
<th>φ</th>
<th>n</th>
<th>K</th>
<th>Actual</th>
<th>CCW</th>
<th>Moore</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>L</td>
<td>γ</td>
<td></td>
<td>L</td>
<td>γ</td>
<td></td>
</tr>
<tr>
<td>Total, t=4, n=1996</td>
<td>0.406</td>
<td>1886</td>
<td>5.02</td>
<td>0.33</td>
<td>185.2</td>
<td>0.95</td>
</tr>
<tr>
<td>Total, t=2, n=1996</td>
<td>0.422</td>
<td>1300</td>
<td>5.34</td>
<td>0.30</td>
<td>134.5</td>
<td>0.94</td>
</tr>
<tr>
<td>Total, t=17, n=1996</td>
<td>0.330</td>
<td>5504</td>
<td>5.29</td>
<td>0.34</td>
<td>437.1</td>
<td>0.97</td>
</tr>
<tr>
<td>Electricals, t=4, n=1996</td>
<td>0.295</td>
<td>837</td>
<td>4.75</td>
<td>0.28</td>
<td>72.37</td>
<td>0.97</td>
</tr>
<tr>
<td>Chemicals and food, t=4, n=1996</td>
<td>0.760</td>
<td>639</td>
<td>2.79</td>
<td>0.31</td>
<td>83.94</td>
<td>0.88</td>
</tr>
</tbody>
</table>
hand, displays a much higher value for $\phi$ in combination with a low degree of centrality.

Thus, the chemicals and food technology field is one in which a rather peculiar networking strategy is found. Strategic partnering ($\phi$) is rather strong, and although, according to our benchmark, this induces a smaller role for social capital (low $\gamma$), we find exactly the opposite: a high value for social capital ($\gamma$). As a preliminary explanation of this finding, one may point to the nature of the knowledge base underlying this technology field. Especially in pharmaceuticals and biotechnology, the close relations to science have induced an industry structure of many small firms, which are highly specialized in research. Each of these firms covers a rather small field in a very in-depth way. Large companies tend to focus their research on specific major diseases and have adopted a strategy of tapping into this knowledge base by means of many partnerships with these small specialized firms. Further research specifically on the comparison between partnering strategies in different industries may obviously enlighten this issue more.

5. Conclusions

This paper has argued that the recent theory of small worlds provides a natural way of unifying two perspectives found in the strategic management literature on networks and strategic alliances. One perspective, that of the theory of social capital, leads to a view in which networks consist of densely connected local environments, corresponding to high values of social capital. Firms are considered to seek such dense local environments in building their strategic alliances. The theory of small worlds shows that in the extreme case of very dense local environments, the ‘average’ path length for knowledge flows between two actors in the network becomes very large. This can be considered as an impediment to the efficient spread of knowledge and information within the network, and thus an undesirable property both from the point of view of the networking firm, and the policy point of view.

The other perspective found in the strategic management literature is the one of structural holes. This theory argues that firms will seek partnerships that form bridges between their ‘own’ part of the network (local environment which may be densely connected) and other interesting parts of the network. Rather then extending their network based on an argument of enhancing social capital (i.e., dense local relations), firms are expected to pick and choose partnerships based on the strategic position of potential partners in the network. From a structural holes perspective one might argue that firms should be engaged in a strategy of bridging structural holes. This will lead to short average path length in the network, and hence to efficient information flows.
The theory of small worlds provides a useful way of representing the tendency for this ‘bridging behavior’ in terms of a single parameter. This parameter measures the number of ‘shortcuts’ (links that complete a triad) as a fraction of all links in the network. The theory then shows how the characteristics of the network in terms of clustering (defined as density of local environments) and average path length of the network develop as a function of this tendency. For very dense local environments (i.e., a world dominated by network ties resulting from a social capital view of the world), average path length is very long, while for extreme levels of ‘bridging’ (a ‘structural holes world’) path length approaches a lower limit. In between these two extreme cases one finds a small range of the bridging parameter for which clustering is still relatively high, but average path length is already close to the lower limit implied by the extreme structural holes world. This is the range of ‘small worlds’ as it has been defined by Watts (2000). It is argued here that these small worlds can be characterized as relatively efficient networks in terms of knowledge transfer. In contrast to a pure structural holes or social capital perspective, the small-worlds perspective is able to assess the optimal configuration of ties within cohesive sub-groups and bridging ties.

The theory of small worlds thus enables us to compare the efficiency of empirically observed networks to a theoretical optimal configuration of these networks. In such an empirical application, the analysis has shown that networks of strategic technology alliances between large multinational firms indeed show small-worlds properties. It can thus be concluded that these technology networks are relatively efficient means of knowledge transfer. When splitting our total network between two distinct technology fields (chemicals and food, and electricals, the latter including electronics and ICT), it was found that especially the chemicals and food field shows ‘extreme’ properties of networking structure. Here the fraction of shortcuts (i.e., bridge building) is very high, while this still does not lead to a significant decline in social capital building.

As a suggestion for further work, we propose more research into the relative role of social capital and bridge building in network-partner seeking. The results summarized above suggest that especially the chemicals and food sector would be an important field for this research.

References

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