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Network-independent partner selection and the evolution of innovation networks*

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Abstract

Empirical research on strategic alliances has focused on the idea that alliance partners are selected on the basis of social capital considerations. In this paper we emphasize instead the role of complementary knowledge stocks (broadly defined) in partner selection, arguing not only that knowledge complementarity should not be overlooked, but that it may be the true causal force behind alliance formation. To marshal evidence on this point, we design a simple model of partner selection in which firms ally for the purpose of learning and innovating, and in doing so create an industry network. We abstract completely from network-based structural and strategic motives for partner selection and focus instead on the idea that firms' knowledge bases must "fit" in order for joint leaning and innovation to be possible, and thus for an alliance to be feasible. The striking result is that while containing no social capital considerations, this simple model replicates the firm conduct, network structure, and contingent effects of network position on performance observed and discussed in the empirical literature.

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1 Introduction

In this paper we are interested in innovation networks — networks emerging from firms' decisions to form strategic alliances aimed at learning and producing new knowledge. The widespread use of collaborative arrangements by firms engaged in R&D intensive activities to enhance their productivity can be explained by the dispersion and rapid development of scientific knowledge, skills and resources they need to incorporate in both innovation and production (Powell et al. 2005). Inter-firm cooperation is thus an efficient way for firms to acquire knowledge in the evolving technological space beyond their boundaries. These benefits are not risk-free, however, as collaborative efforts expose firms to the risk of opportunistic and uncooperative partners (Khanna et al. 1998).

Because firms' participation in these networks affects their conduct and performance, understanding how partners are selected is important from both theoretical and practical standpoints. Current explanations for partner selection draw heavily on Granovetter's (1985) notion of structurally embedded exchange, which refers to the ways in which, by lowering search and enforcement costs, a firm's existing pattern of relationships both enables and constrains its future partner selection.

Imperfect information about potential partners' capabilities, reliability and motives creates considerable risk in inter-firm exchange relations (Oxley 1997). To mitigate this risk, firms tend to repeat their past interactions because repetition increases familiarity, that is, the ability to predict the benefits of collaboration with a given partner accurately (Gulati 1995, Gulati and Gargiulo 1999). Familiarity, in turn, leads to trust — the belief that a partner will not act in a harmful manner (Gulati 1995), which mitigates risks of opportunism. A history of exchange thus allows partners to develop clear expectations of each other and of the potential for productive future exchange. Endorsements and referrals from common partners can also reduce uncertainty regarding a potential partner's quality and motives (Burt and Knez 1995). Such common ties also promote good behavior by facilitating information flow that fosters a concern for local reputation (Rowley 1997).

Structural embeddedness thus leads firms to ally more frequently and more intensely with a restricted set of partners as the information value of ties serves as an incentive for firms to renew partnerships with past partners (creating inertia) and form ties with their partners' partners based on referrals (creating transitivity) (Coleman 1988). Consistent with these predictions, empirical studies find few partnerships formed without prior direct or indirect ties (Baum et al. 2005; Li and Rowley 2002), and alliance networks characterized by uneven structures composed of distinct regions in which firms are more or less densely interconnected (Baum et al. 2003; Gulati and Gargiulo 1999; Nohria and Garcia-Pont 1991; Powell et al. 2005; Duysters and Verspagen 2004; Walker et al. 1997).

But alliance networks are not only locally dense, they are also sparse, with each firm having few ties relative to the number of firms in the industry (Baum et al. 2003; Davis, Yoo and Baker 2003; Powell et al. 2005; Kogut and Walker 2001; Uzzi and Spiro 2005). These features are consistent with the notion of a small world (Watts 1999). A small world is a network in which distinct regions of densely interconnected firms are spanned by relationships that act as information conduits between them. As a result of these clique-spanning ties, firms in a small world network are linked with each other through a relatively small number of intermediaries despite their overall sparse connection. The importance of the small world finding stems from the efficiency of such structures in moving information, innovations, and other resources.

While structural embeddedness provides substantial insight into the cliquishness of alliance networks, it does not account for the formation of clique-spanning ties (Baum et al. 2003, 2005). Explanations for such ties rely on a different logic of structural holes (Burt 1992). Clique-spanning ties provide access to diverse information, technologies and markets, openings to broker the flow of information and resources among otherwise disconnected firms, and chances to control projects involving participants from different regions of the network. These vision, brokering, and control advantages provide incentives for firms to create clique-spanning ties (Baum et al. 2003, 2005; Burt 1992, 2005). Because of their greater risk, uncertainty and costs, firms are generally reluctant to form such ties; consequently, despite their potential benefits, they are relatively rare (Baum et al. 2005; Li and Rowley 2002).

Structural embeddedness and structural holes thus emphasize the causal role of learning about partners and network-oriented strategic motives in partner selection and network formation. In the context of innovation networks, however, learning from partners is also causally relevant. Analyses of innovation networks indicate that firms seek R&D partners with complementary knowledge or capabilities (e.g., Mowery et al. 1998). If firms' knowledge and capabilities are too similar, their knowledge overlaps too much leaving little to learn; if they are too dissimilar, they have difficulty understanding each other, making learning difficult. In addition, partners with initially complementary knowledge profiles will tend to become more similar over time, making them less attractive partners as they continue to interact and learn from one another (Mowery et al. 1998; Uzzi 1997).

Unfortunately, empirical studies emphasizing the causal role of network-oriented structural and strategic motives in partner selection either do not consider partner complementarity at all (e.g., Powell et al. 2005), or control for a static measure of complementarity at the time of alliance formation (e.g., Chung et al. 2000; Gulati 1995). In either case, implicit in the empirical model is that collaboration has no effect on complementarity. As a result, we cannot be certain from these studies whether it is partner complementarity or structural embeddedness that is causal. It may be the case that the latter spuriously captures the former. Indeed, supporting such an interpretation, several studies report concave relationships between the number of prior ties and common partners two firms have and the probability that they partner in the future (Chung et al. 2000; Gulati 1995), consistent with the idea that learning from partners makes partners less attractive.

In this paper we design a simple model of partner selection in which firms ally for the purpose of learning and innovating, and in doing so create an industry network. We abstract completely from network-based structural and strategic motives for partner selection and focus instead entirely on firms' short-term innovation concerns. We treat these concerns as network-independent and examine patterns of partner selection and resulting network structure, as well as the relationship between firms' network positions and their performance.

In the model, a firm's performance depends on the knowledge endowments of its partners. Excessively similar or dissimilar firms are less successful in effectively innovating, and thus less likely to partner. Notably, this network-independent assumption implies both repetition and transitivity in firms' partnering decisions. If two firms, i and j, form an alliance, they are likely to partner again, although with decreasing probability as they learn from each other through subsequent interactions and the overlap of their knowledge portfolios increases. Moreover, if i and j are partners, and so are i and k, then the likelihood of j and k also being neither too similar nor too dissimilar is larger than for a random (j, k) pair. So complementarity in the knowledge space translates into both repeated ties and transitivity, resulting in cliquish networks. Additionally, discontinuities in knowledge endowments resulting from major innovations, will translate into randomness in the network, resulting in cross-clique ties that shorten network distances.

Could, then, the empirical properties of networks have a simpler origin than is generally expressed, based on properties of the underlying knowledge space? We examine how such a hypothesis performs when we vary the disruptiveness of innovation, to contrast disruptively innovative industries, and industries in which technological change is incremental. We find that when firms select partners solely on the basis of knowledge complementarity the emergent network displays all the conduct (repeated ties and transitivity) and properties (clustering and short distances) characteristic of observed alliance networks, particularly when innovations are moderately disruptive. Additionally, consistent with recent theory on the contingent benefits of network positions (Rowley, Behrens and Krackhardt 2000), we find that firms benefit more from structural embeddedness in dense cliques when innovation is incremental, and more from spanning such cliques when innovation is disruptive. And, all this is the case despite the fact that in the model, firms pursue goals that are network-independent, and pay no attention to issues of social capital while making alliance decisions.

2 The model

The industry consists of a fixed population of firms which perform R&D activities, seeking both to learn from each other by absorbing existing knowledge, and to produce new knowledge through innovation. These R&D activities take place within bilateral strategic alliances, the set of which constitutes the larger industry network. For any potential partnership, learning and innovation possibilities depend on the extent to which the two participating firms' endowments both resemble and complement each other.

We use a simple representation of firms located in an abstract, 2-dimensional metric space to capture proximity. While a firm's position in the underlying knowledge space has no particular meaning, the distance between firms in that space determines their partnering possibilities. Empirical results (see Mowery et al. 1998 and 1996; Ahuja and Katila 2001 and Schoenmakers and Duysters 2006) on technological distance and alliance formation translate in the model into the simple assumption that partnering is worthwhile (in expected terms) if and only if the two firms are neither too close to nor too far from each other. Thus positions in the knowledge space translate directly into a network of strategic alliances.

Innovation can be seen as having both economic and technological effects on an industry, and in this paper we address both. Economically, when a firm innovates, relative to others in the industry its profits increase. Small, incremental innovations have small effects on relative profits; large, disruptive innovations have large effects. Technologically, an innovation disrupts the knowledge space, as it changes which types of knowledge or technology are immediately valuable, and also which can be combined effectively to generate future valuable knowledge. Again, small, incremental innovations will have small effects, and they will tend to be localized to firms nearby the innovating firm. Large, disruptive innovations will have bigger, and wider spread implications. Generally, though, because an innovation changes the value and possibly the relevance of different types of knowledge, it will change how well different firms' knowledge fits together, and thus will change the partnering opportunities of firms. We compress both aspects into one representation by assuming that innovation disrupts the knowledge landscape so that firms are relocated within it, and imposes a relocation cost to all (but the innovating) firms which is proportional to the relocation imposed in knowledge space.

Two forces shape the properties of the larger network of all alliances. The first is the process of strategic alliance formation. The need to have both common and distinct features for successful joint innovation implies that partners will be neither too close nor too far apart in knowledge space. Because the knowledge space is a metric space, this need for proximity will induce some amount of local correlation in the decisions to ally, yielding clustering, or cliques, at the local level.

The second force is innovation. When a firm innovates other firms are dislocated in the knowledge space. The size of this dislocation, and its attendant costs depend on the distance to the innovators. This maintains a heterogenous population of firms, scattered over the knowledge space. And this intermittent scattering generates clique-spanning ties, lowering average distances between agents. This combination of a random evolution of firms' knowledge attributes (their locations in knowledge space) and the strategic decisions of firms to ally only with profitable partners, may produce networks that exhibit elements of both structure and randomness.

We are interested in several aspects of firms' behaviour. First looking at the network of alliances, we ask whether it displays small world features. We examine how these respond to the disruptiveness of innovation, to see whether the properties of the technological environment affects how the industry network self-organizes. We then move to individual behaviour, analyzing the relation between firms' performance and firms' network positions.

2.1 Strategic alliances

We assume firms are located in a 2-dimensional aperiodic structure $k = [0,1] \times [0,1]$, the knowledge space. As learning and innovation will modify firms' location in k, firms partnering possibilities, and thus their profit opportunities will also be modified.

The address of firm i in the knowledge space k at any point in time is a pair (x_i, y_i), $0 \leq x_i, y_i \leq 1$. Defining $d^k_{i,j}$ as the standard Euclidean distance between i and j in knowledge space k, $d^k_{i,j} = ((x_i - x_j)^2 - (y_i - y_j)^2)^{1/2}$, the demand that alliance partners be similar and complementary implies simply that they are close but not too close in knowledge space: a partnership is profitable if and only if

$$\delta_1 \leq d^k_{i,j} \leq \delta. \tag{1}$$

Formally, the strategic alliance game is a simultaneous link formation game. Because distance in k is symmetric, firms incentives to form (or not to form) a partnership are symmetric, and so from Eq. (1) we can immediately see that in each period there is a unique equilibrium network, in which all firm-pairs with technological distance between δ_1 and δ form an alliance, i.e. $g = \{ij : \delta_1 \leq d^k_{i,j} \leq \delta\}$.

2.2 Knowledge dynamics

Firms engage in joint R&D activities both in order to absorb existing knowledge and to produce new knowledge. We examine them in turn.

2.2.1 Learning

Two partnering firms i and j learn from each other, increasing the overlap of their technological portfolios and thus moving closer to each other in knowledge space. This is implemented as a simple partial linear adjustment according to

$$\begin{cases} x_i^{t+1} = \alpha x_j^t + (1-\alpha)\, x_i^t, \\ y_i^{t+1} = \alpha y_j^t + (1-\alpha)\, y_i^t, \end{cases} \tag{2}$$

with $0 < \alpha < 1/2$ measuring the absorptive capacity in the industry.

2.2.2 Innovation and its implications

With low probability a partnership makes an innovation, affecting other firms in the industry to an extent that depends on the distance to the innovators in the knowledge space k.

A disruptive innovation causes a major reorganization of the knowledge space, and partnering possibilities. We model this as a dislocation of firms in the space. But the size of the relocation for any firm is determined not only by the disruptiveness of the innovation but also by the distance (in knowledge-space) of the firm from the innovators. Defining the distance to a partnership ij to be $d_{ij,l}^k = (d_{i,l}^k + d_{j,l}^k)/2$, the size of the dislocation is, in expectation, decreasing in distance. Specifically, for any $l \neq i, j$, the dislocation is written as

$$\begin{aligned} \Delta x_l &= \epsilon_l^x \exp(-d_{ij,l}^k/\theta), \\ \Delta y_l &= \epsilon_l^y \exp(-d_{ij,l}^k/\theta), \end{aligned} \tag{3}$$

where ϵ_l^x and ϵ_l^y are independent random variables uniformly distributed over the interval $[-1/2, 1/2]$. Thus each dislocation is random, but the range of possible values falls with the distance from the innovators and increases with the disruptiveness of the innovation. In Figure 1 we display the scope of possible dislocations as a function of distance, for 2 values of θ.

Innovation also affects profits. In the post-innovation state, assuming alliance ij has innovated, the innovators' profits increase, and other firms incur losses. The size of the loss incurred by a particular firm depends on the relocation imposed on it by the innovation. A disruptive innovation forces a major relocation (reorganisation of the knowledge basis and routines) and a large cost whereas a minor one would only impose a minor relocation and thus a minor cost. We simply assume that the cost of dislocation is equal to the size of the dislocation. Thus the relative performance of the innovators i and j can be measured by the sum of the dislocation costs imposed on other firms.

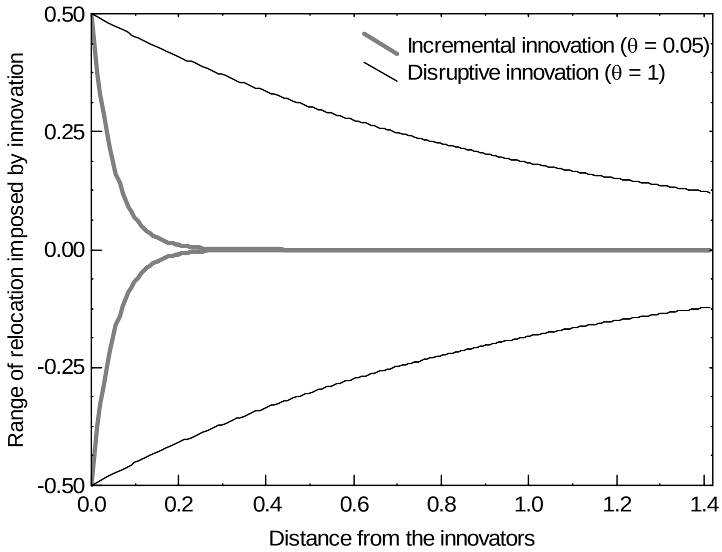


Figure 1: The relationship between dislocation and distance to the innovators for 2 values of θ.

2.3 Numerical experiment

Although the model is very simple, the dynamics at work give rise to a complex network whose properties we analyze through extensive numerical simulation.

At each time step all firms form all possible alliances with partners satisfying the knowledge constraint (1). Firms learn from, and move towards their neighbours according a partial linear adjustment (2). At fixed intervals one innovation occurs. The innovation imposes a relocation in knowledge space on all firms in the industry, the magnitude of which is dependent on the disruptiveness of innovation (3). The process then simply iterates.

We use $n = 75$ firms, $\delta = 0.2$, $\delta_1 = \delta/\sqrt{10}$ (implying that the area in which 2 firms are too close to ally is 10% of the area in which they are close enough to ally), absorptive capacity is set to $\alpha = 0.01$, history length is $T = 1,400$ (we run the system for 1,500 periods but discard the first 100), the parameter governing disruptiveness, θ, varies from 1/20 to 1, with 25 constant increments on a log-scale, and for each θ value we do 25 replications. Every 5 periods innovation occurs. The majority of innovations take place in alliances, but with small probability the innovation takes place in a single firm.[1] With probability 0.95 one randomly selected alliance innovates; with probability $1-0.95 = 0.05$ one randomly selected individual

[1]This eliminates the possibility that firms get stuck, surrounded by firms that are too close in knowledge space, and thus never innovate, and never again form an alliance.

firm innovates.[2]

3 Results

We are interested in two aspects of the model: the aggregate properties of the emergent networks, and the relationships between ego-network position and innovative performance. We record two types of output. First are aggregate statistics describing the emergent networks. For these we cumulate the final 1,400 periods (implying 140 innovations) into a single weighted network, and report the standard network statistics on this network. The second are correlations between ego-network statistics and innovation performance.

We use several standard network measures, all of which are defined formally in the appendix. Average *degree*, the number of distinct partners the average firm has, is a standard measure of sparseness. *Clustering* measures local density: to what extent are the neighbours of i also neighbours of each other. Contrasting with clustering, which is a local measure (of redundancy), a measure of global structure is provided by the distribution of pairwise distances between nodes, indicated by *average distance*. *Betweenness* is a measure of the centrality of a node, defined as the number of times it appears on the shortest paths between all pairs of nodes. It is a measure of information control: a higher betweenness centrality for a firm suggests a stronger position in terms of brokerage, i.e. more control (and thus power) over knowledge flows across the network. *Network constraint* is another measure of brokerage. Burt (2004) argues that constraint encapsulates 3 dimensions of the local network of a firm: degree, redundancy as measured by clustering, and hierarchy.

All these statistics are defined for binary networks, but can be generalized to weighted networks. This will be useful when we study the cumulative matrix of firms' past interactions (by recording the number of times each potential partnership has been active over the history of the industry). In particular, *strength* is the weighted equivalent of degree, counting not the number of distinct partners, but rather the number of alliances of the firm (regardless of whether they are repeats with old partners). The *weighted clustering coefficient* is simply a generalization of clustering, taking into account the fact that some edges are more active than others, which would indicate closer connections between the nodes involved. Finally, the weight of an edge indicates how many times it has been activated. One can treat this as related to a virtual cost: "more active edges are lower cost edges". By transforming weights into costs (taking the reciprocal) we can calculate least-cost

[2] An obvious expansion of the model would be to endogenize the timing of innovations, perhaps by making the probability of any alliance innovating each period a function of how close the partners are to some optimal distance from each other in knowledge space.

(in contrast to shortest-distance) paths between pairs of nodes.

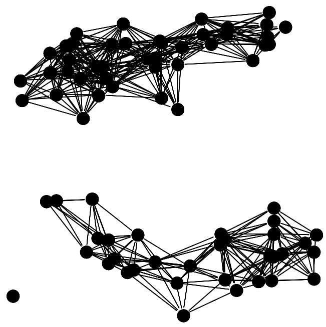
Finally, a common observation is that alliance networks are small worlds, and we are therefore interested in whether they emerge in our model. A small world is defined as a sparse network in which the average distance between pairs of nodes is relatively short, but at the same time the networks are locally dense, displaying significant amounts of clustering. This issue can be addressed using degree (strength), average shortest paths (average least cost paths), and (weighted) clustering. All of these measures, however, respond mechanically to degree. Thus a more relevant issue is whether the emergent networks are more "small-world-ish" than some comparable benchmark. The standard benchmark is an equivalent random network, namely a random network having the same number of nodes and the same density (typically a random graph à la Erdös and Rényi 1960 with edges allocated randomly between pairs of vertices). With weighted networks this definition of equivalent is ambiguous, due to the weights on the links. So for this normalization we have defined an equivalent network as one which has the same number of nodes, the same number of links, and the same strength distribution. Thus to normalize we create an equivalent network by first creating an Erdös-Rényi random network having the same number of nodes and the same number of links. Then we use the observed distribution of weights across links from the network under scrutiny as the probability distribution of link weights. Using this distribution we assign probabilistically weights to the links in the E-R network. We replicate this procedure 10 times, calculating the clustering coefficient and characteristic path length each time, then use the averages of those statistics to normalize.

3.1 The network

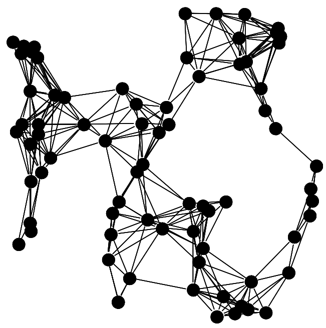
We start by providing a first visual impression of the results. In Figure 2 we display three networks which are "representative" of the behaviour of the model in three different contexts: incremental, moderately disruptive and highly disruptive innovation. These are one period snapshots of the network, as they were observed at time period 500, and thus each link represents a single partnership in one period. Firms' locations in the panels correspond to their locations in knowledge space, so here knowledge space is represented as the (two-dimensional) unit square.[3] To the right of each network are the values for that network of the statistics discussed earlier.

The top panel depicts a context of incremental innovation ($\theta = 0.05$). The network consists of 3 components: one isolated firm and 2 large, dense components.

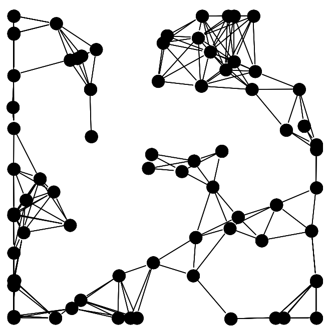
[3]Note here that the graphical layout of the network, that is the position of the nodes on the 2-D plane, is not determined by which links are formed (as is the case in typical network layout algorithms) but rather is determined by independent attributes of the nodes, namely their locations in knowledge space.



$\theta = 0.05$	
Component size(s)	1, 32, 42
Average degree	12.7
Density	0.17
Clustering	0.56
Rescaled clustering	3.25
Average pairwise distance	2.01
Rescaled distance	1.02



$\theta = 0.1$	
Component size(s)	75
Average degree	7.01
Density	0.095
Clustering	0.52
Rescaled clustering	5.45
Average pairwise distance	4.05
Rescaled distance	1.67



$\theta = 1$	
Component size(s)	75
Average degree	5.01
Density	0.067
Clustering	0.40
Rescaled clustering	5.92
Average pairwise distance	7.80
Rescaled distance	2.76

Figure 2: Three representative networks for low, intermediate and large values of θ.

The average neighbourhood size is slightly less than 13, and the average proportion of a firm's partners who are partners of each other is 56%, which is relatively large.

Finally the rescaled values for clustering and distances suggests a structure which is more clustered than a random graph, though with comparable pairwise distances. As we move to a moderately disruptive environment ($\theta = 0.1$), density and average degree fall. Clustering decreases slightly, but once rescaled to take into account the effect of the decline in degree, it actually points at a strongly clustered network, with rescaled distances only slightly larger than in an equivalent random graph. Finally a disruptive environment ($\theta = 1$) produces an even sparser network, characterized by less clustering and longer distances between pairs of firms. Rescaled clustering remains very high, but rescaled distance has grown to 2.76. Whether or not this constitutes a small world depends on definitions, for which as yet there is no consensus. We do observe though that some firms achieve very high levels of betweenness as they span structural holes. A few partnerships are even critical, in the sense that their removal would disconnect the network.

3.2 Network evolution over time

In this section we observe the system over time. As innovation will endlessly reshuffle firms' locations, network statistics will never settle down to an absorbing value, but rather will fluctuate for ever. In this section we consider the same 3 values of θ as in the previous section, and display the time series of average degree, average clustering and average pairwise distance of the lifetime of the industry. We display 20-periods moving averages to smooth the fluctuations.

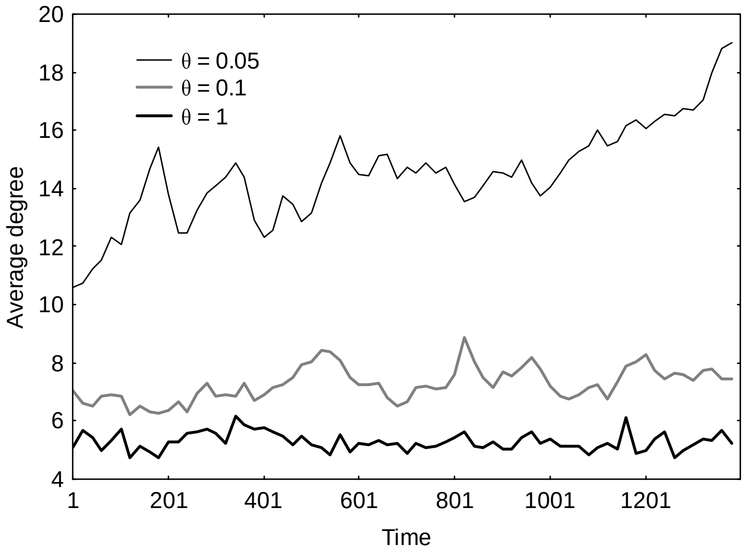


Figure 3: The evolution of average degree over time.

Figure 3 shows that over time average degree displays continued fluctuations, suggesting that the industry travels through a variety of states, marked with outbursts and collapses in network activity. Learning brings firms together, and if they get too close reduces degree, but innovation scatters them over the knowledge space again, giving opportunity for new partners. The resulting behaviour of average degree will depend on the relative importance of these two effects. We observe the same general tendency (degree falling with θ) observed in the previous section.

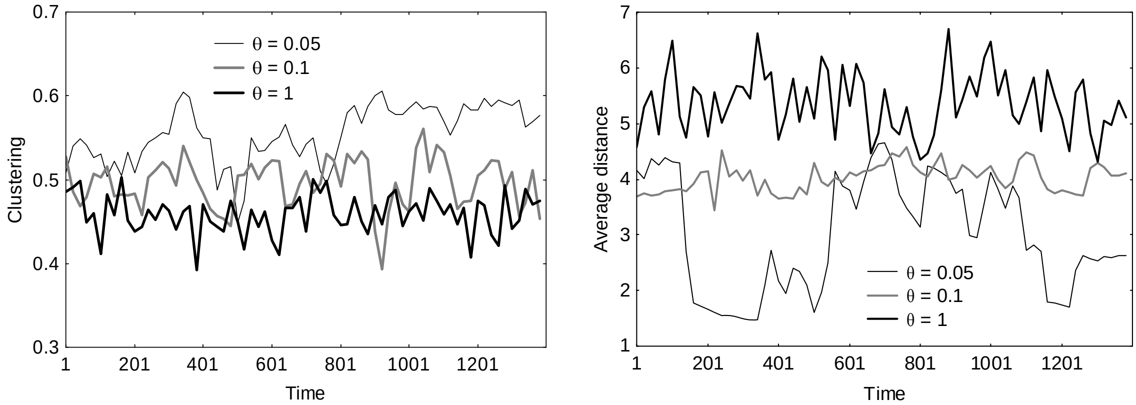


Figure 4: Time evolution of clustering and average distance.

In the left panel of Figure 4, the clustering coefficient shows strong oscillations between 0.4 and 6, with larger values of clustering being more prevalent for smaller θ. In the right panel, average distance fluctuates between 2 and 7, longer distances being associated with larger θ. This is in line with the properties of the representative networks displayed in Figure 2.

3.3 Aggregate network statistics

We suggested above that since the network emerges from alliance decisions, network structures should respond to the disruptiveness of innovation. The idea here is that in different stages of the life cycle of an industry or technology, innovations will have a tendency to be more or less disruptive, and this will change partnering patterns of firms. In order to permit a clear view of how the regime will affect network structures, we have made the strong assumption that in a given regime (represented by parameter θ) all innovations are equally disruptive.

In general, in a regime of disruptive innovation (or an industry in the disruptive phase of its life cycle), we would expect that an innovation will have dramatic effects on the knowledge base on which firms draw. Innovation renders obsolete large portions of the existing knowledge base, creates significant relocations in knowledge space, and this, for the average firm, changes partnering possibilities dramatically. This would imply a large number of distinct partners, but a relatively small amount of repeat partnering in a disruptive regime.

We show in the figures below the relationship between several network measures and the degree of disruptiveness of the innovation regime.[4] We use whiskers to represent the range of the data over the set of replications, and the median as the measure of central tendency.

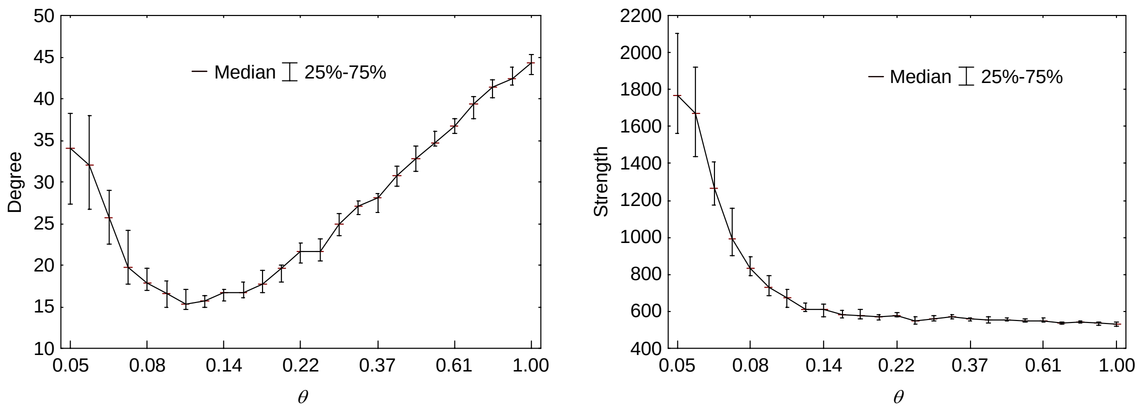


Figure 5: Average degree and strength for the aggregated network, as a function of the disruptiveness of innovation.

A firm's strength is its interaction count, that is, the number of alliances it has participated in over the history of the economy (which is bounded above by $T(n-1)$). Strength does not distinguish, however, whether a firm has been going back to the same partners all the time, or whether it has formed alliances with different partners each period. We thus also use degree, defined simply as the number of distinct partners a firm has had. Figure 5 shows the averages over the population of firms, of strength and degree.

Consider first the values of $\theta > 0.1$. Here, as innovations become more disruptive, degree increases but strength falls. Innovations cause major dislocations in knowledge space; previous partners become impractical, and new partners emerge. These patterns combined imply a decrease in repeat partnering. For incremental innovations, in the range $0.05 < \theta < 0.1$, a different pattern is present. Here strength falls with θ as before, and for the same reason. When disruptions are small, old partners remain good partners from the knowledge point of view; distances between partners do not change much as a result of innovation. In this range, though, degree is falling with θ. So for very incremental innovations, degree is high. This is driven

[4]These statistics are only somewhat comparable to those shown in Section 3.1 since those were snapshots of one period's alliances and these represent all alliances accumulated over 900 periods.

by the learning effect. When innovations are very incremental the learning process is what dominates movement in the knowledge space. Learning draws firms closer together, and will create clusters of firms in knowledge space, who are, for a time at least, well connected. This creates high degree. As θ increases, the extent to which this process is interrupted by innovation increases, and so degree falls: clusters are blown apart before they can get very big.

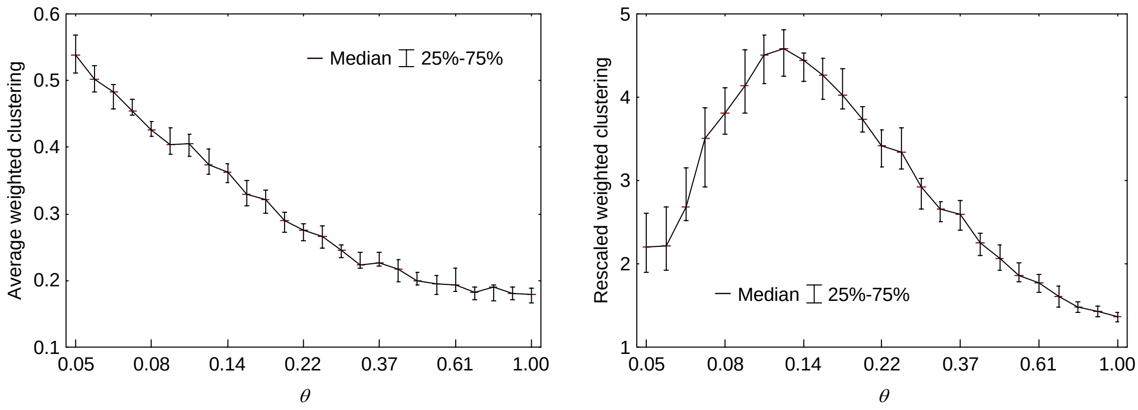


Figure 6: Weighted clustering and rescaled weighted clustering, as a function of the disruptiveness of innovation.

Figure 6 shows the averages over the population of firms, of weighted clustering and weighted clustering re-scaled by an equivalent random graph. We display only weighted clustering. The traditional (unweighted) clustering coefficient would be calculated from the same adjacency matrix as degree in Figure 5, that is, links are, to some extent, "over-estimated", and information is lost. By contrast, weighted clustering uses the "strength" adjacency matrix and the information is retained. It thus gives a more faithful picture of the intensity of the interactions between a firm's neighbours.

Weighted clustering is initially large, but decreasing as innovations become more disruptive. This is driven by learning. Learning draws firms closer to their partners in knowledge space. In general, that implies also firms being drawn closer to their partners' partners, producing clusters in knowledge space.[5] Thus over time, if the dislocating effects of innovation are weak, clustering is a strong force, and the clusters in knowledge space form and translate directly into clusters in network space. When innovations are disruptive, the clustering process is interrupted when an innovation takes place and firms are scattered. Thus while this effect is present regardless of how unsettling innovation is, a smaller θ means less disruption from

[5]This is a general, average tendency. A firm whose initial partners migrate into different clusters will obviously lose some partners, and can only be drawn towards the partners of some of its partners. The dominant tendency is one of clustering however.

innovations, thus preserved neighbourhoods and so a persistently larger clustering. This is what we see in the figures, both for clustering and rescaled clustering, the latter indicating that the result is not a mere consequence of the behaviour of degree (or strength). Re-scaled clustering is everywhere significantly greater than one, indicating excess clustering (which is one condition for the presence of small worlds) but rising and then falling with θ, showing that excess clustering is strongest when the disruptiveness of innovation is at an intermediate level.

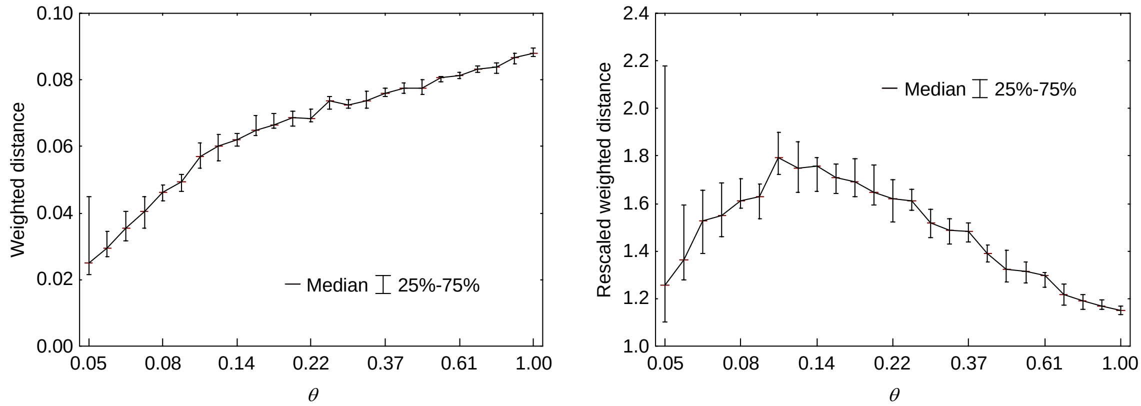


Figure 7: Weighted distance and rescaled weighted distance for the aggregate network, as a function of the disruptiveness of innovation.

Weighted distances as they appear in Figure 7 represent "least costs" between pairs of vertices (obtained as the inverse of the interaction count). So a lower value for average weighted distances indicates that, within the network, information is on average easier (less costly) to transmit from one firm to another. Weighted distance increases monotonically with disruptiveness. This reflects the fact that as disruptiveness increases, network activity falls, which is reflected then in the average pairwise "least cost". Rescaled weighted distance is always larger than but close to one, rising and then falling as innovations become more disruptive, suggesting that the distribution of distances in the industry network displays random graph features.

High clustering and low characteristic path length are the defining features of small worlds. The results so far suggest that small worlds arise in the model proposed, without any sophisticated attempts from firms to strategically manipulate their network, but rather from the conjunction of randomness in the innovative process and the quest for suitable partners.

3.4 Innovation performance and ego-networks

In this section we show the relationship between a firm's ego-network structure and its innovative performance. To recall, the value of an innovation to a firm can be thought of as the "dislocation costs" it imposes on the other firms in the industry. We show here instantaneous correlations, treating the network created each period individually. So here the observations are, for each innovation, the two innovators' performance and their network characteristics at the time they innovated.

Each time an innovation takes place, the innovators occupy a particular network position and achieve a certain level of relative performance. We simply compute correlation coefficients between network position and performance at the time of all innovations in the industry. (Since we are observing one-period networks, they are by definition unweighted.)

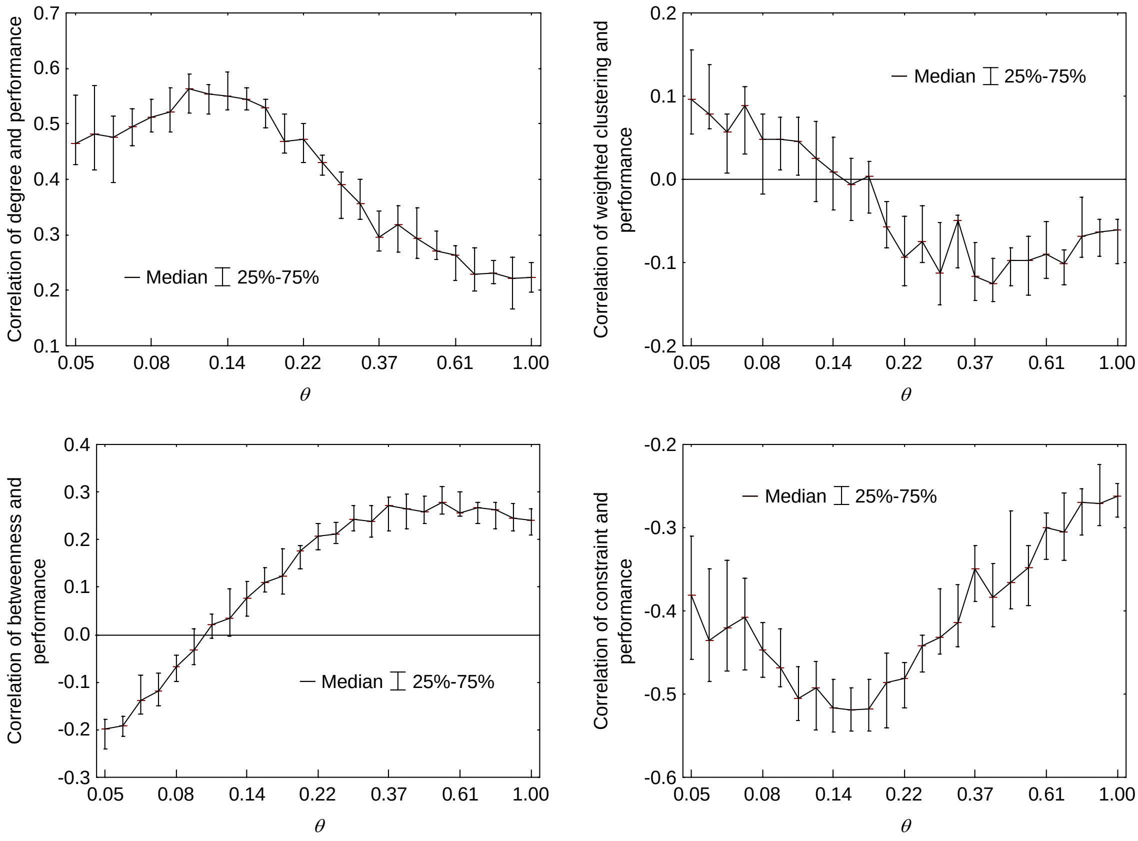


Figure 8: Correlations of network position and performance.

The first result (upper left panel) is that the association between performance and the degree of innovating firms is always positive. This is to be expected for two reasons. First, as innovation takes place in a partnership selected uniformly at random, a higher degree firm has more partnerships and thus a larger probability of being selected. Second, a higher degree firm tends to have more partners close by, and thus innovation will impose larger dislocations to more firms. The strength of the association varies with θ, though. We can observe that the relationship weakens as innovations become more disruptive. This is largely a statistical phenomenon having to do with the standard deviation of degree over agents (a statistic not shown) being small in very disruptive environments.

An issue that often arises in network discussions is "brokerage", and whether this affects innovation performance. We can address this with three statistics: a firm's clustering, its betweenness and its constraint. We find that the three measures yield consistent results.

When innovation is incremental the association between a firm's neighbourhood clustering and its relative performance is positive (upper right panel). Firms embedded in clustered ego networks outperform those whose neighbourhoods have more holes, suggesting that clustering is a source of competitive advantage when competitive advantage is not frequently upset by relocations in knowledge space. Things are reversed in disruptive environments. There, superior performance is achieved by firms whose ego-networks are not redundant.

Examination of betweenness centrality confirms this result (lower left panel). In incremental environments firms occupying peripheral positions (as measured in terms of betweenness) have a performance superior to those who are more central. In disruptive contexts of innovation, the logic is reversed: firms acting as gate keepers and spanning more structural holes are better off, their structural advantage translating into superior relative performance.

Constraint also shows the value of brokerage in fast-changing environments. Constraint is always negatively associated with performance. The association is weakest when innovation is incremental (θ small) or disruptive (θ large), and strongest when disruptiveness is intermediate, a pattern which echoes that of the correlation of degree and performance.

These findings are similar to those reported by Rowley et al. (2000) in their comparison of the steel (incremental innovation) and semi-conductor (more disruptive innovation) industries. But the logic in our model is that these relationships between network position and innovative performance originate in the properties of knowledge recombination. There is no explicit concern of firms to span holes in order to be insured against innovations taking place in distant parts of the industry network. There are also no considerations of social capital such as partner referrals or returning to known partners. In the simple model discussed here, firms perform no sophisticated calculation in order to optimize their network position, nor do they use their own or their neighbours' partnering experience in choosing partners. Instead, firms simply form alliances with partners at the right distance, and have their partnering possibilities refreshed to an extent that depends on how disruptive innovation is. No specific social capital value is attached to any particular position — both partner selection and innovative success are based solely on knowledge attributes — and yet the relationships between network positions and performance are consistent with empirical findings and their interpretations in terms of social capital.

4 Conclusion

Discussions of strategic alliances have emphasized that connections with outside partners are often driven by a firm's search for technology or knowledge which it needs but does not have in-house. Alliances are formed between firms whose knowledge stocks (broadly defined) complement each other. Empirical research on strategic alliances, however, seems to have focused more heavily on the idea that alliance partners are selected on the basis of social capital considerations. In this paper we argue that the former reasoning should not only not be overlooked but may in fact be the true causal force behind alliance formation. To make this point we developed a simulation model in which alliance decisions are based on knowledge. We focus exclusively on the fact that firms' technologies or knowledge bases must "fit" in order for joint innovation to be possible, and thus for an alliance to be feasible. The striking result is that while containing no social capital considerations, this simple model replicates the firm conduct, contingent performance effects, and network structures observed and discussed in the empirical literature.

Social capital arguments emphasize the causal role of learning about partners and network-oriented strategic motives in partner selection and network formation. Structural embeddedness leads firms to ally more frequently and more intensely with a restricted set of partners as the information value of ties serves as an incentive for firms to renew partnerships with past partners and form new ties with their partners' partners based on referrals. Structural holes motivate firms to link disconnected regions of the network to secure the vision, brokering, and control benefits of such ties afford. Our simulation replicates these behaviours in the absence of any social capital motives and concerns. Complementarity in the knowledge space, combined with learning, generates inertia and transitivity in firms' partnering decisions; discontinuities in knowledge endowments resulting from innovations generate ties spanning cliques in disconnected regions of the network.

In the literature there has been a debate about the relative value of structural holes and redundant ties: on the one hand firms with structural holes in their networks are thought to be well-positioned to access distant knowledge and broker the flow of information and resources; but on the other hand firms with redundant ties can obtain the benefits of clique membership. Rowley et al. (2000) propose a solution to this tension, arguing that the benefit of structural holes and cliques are contingent on industry life-cycles and the extent to which innovation is disruptive. The results of our model are consistent with this solution: As the innovation regime becomes more disruptive, the correlation between measures of a firm's structural holes and its performance increases. This is a strong result in the sense that firms are not taking this effect into account when forming partnerships. They are not trying to create either structural holes or cliques, nor are they trying to ensure access to distant information or trustworthy partners. It comes about simply from the joint effects of learning and innovation.

The networks that emerge from the simulation are characterized by high clustering and small path length, defining features of small world networks. This results from the inertia and transitivity in partnering producing cliques, and randomness in the innovative process leading to clique-spanning ties that shorten distances. The small world pattern is most pronounced in moderately disruptive regimes ($\theta \sim [0.10, 0.15]$), where the ratio of rescaled clustering to rescaled path length, or 'small world quotient' (Watts 1999), is largest (see Figures 6 and 7). Notably, in such moderately disruptive regimes, the correlation of performance with both clustering and betweenness is zero. Thus, while cliques enhance performance when innovation is incremental and structural holes enhance performance when innovation is highly disruptive, performance is agnostic to network position when innovation is moderately disruptive and the network's small world characteristics are most pronounced. This finding is consistent with the small-world view of cliques and structural holes as complementary network properties that jointly enhance network efficiency in moving information, ideas, and other resources (Watts 1999).

We conclude with two comments about the model and its processes. First, earlier papers making similar arguments (for example Cowan and Jonard 2008 or 2009) have assumed that firms have complete information about the knowledge portfolios of all other firms. By contrast, our model makes relatively weak assumptions about firms' knowledge: they need not have complete understanding of each other's capabilities; we require only that firms can detect whether or not they are within some range of each other in the knowledge space.

Second, Sorenson and Waguespack (2006) point to a self-fulfilling logic that explains apparent superior performance of cliques: a well-known clique will receive more (typically unobserved) effort to improve its performance, simply because it has done well in the past and is expected to do so in the future. In a sense their result casts some doubt on the notion that cliques provide inherently superior (in some conditions) performance for their members. Our results cast a similar doubt but using a different logic. Here to the extent that there is superior performance of cliques, it derives not from any aspect of social capital or social control, or expectations of future performance, but rather from the simple fact that there is a correlation between degree and clustering: Higher degree firms are more likely to innovate, and when they do, firms in cliques disrupt a larger number of firms than do more isolated innovating firms, and this improves their relative performance.

Our model points to the possibility that the observed empirical properties of alliance networks may have their origin in the underlying knowledge space and disruptiveness of innovation, rather than social capital considerations. We hope our findings spark empirical work that takes this possibility seriously by, for example, incorporating time-varying measures of partner complementarity. Such research is critical to advancing our understanding of alliance network dynamics in general and the causal role of social capital in particular.

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A Formal definitions

A.1 Networks

The industry consists of a finite population $N = \{1, \ldots, n\}$ of firms. A *network* is a set g of ties (links) between unordered pairs of firms in N. Writing ij to represent the tie between firms i and j, $ij \in g$ indicates that i and j are linked in the network g.

The *neighbourhood* of firm i consists of the set of firms to whom i is directly connected in g, $N_i^g = \{j \neq i : ij \in g\}$. The size of the neighbourhood of i is the number of ties held by firm i, also called its *degree*, and is denoted $n_i^g = \#N_i^g$.

A.2 Unweighted measures

Density is written as

$$\frac{\#g}{n\,(n-1)\,/2} = \frac{\sum_i n_i^g}{n\,(n-1)},$$

and the average degree is $n^g = \sum_i n_i^g / n$.

The neighbourhood *clustering* of firm i is the proportion of neighbours of i who are neighbours of each other. It is written

$$c_i^g = \frac{\#\{jk \in g : j,k \in N_i^g\}}{n_i^g(n_i^g - 1)/2}$$

The *clustering coefficient* $c^g = \sum_i c_i^g / n$ is the average taken over all the firms.

Path length is a measure of global structure is provided by the distribution of pairwise distances between nodes. A path of length $\ell + 1$ in g connecting i and j is a set of ℓ distinct nodes $\{i_1, \ldots, i_\ell\}$ such that $ii_1, i_1i_2, \ldots, i_\ell j \in g$. The *distance* $d_{i,j}^g$ separating i from j in g is the length of the shortest path in g between i and j. If no path exists between i and j, then by convention $d_{i,j}^g = \infty$. Averaging all finite pairwise distances yields the *characteristic path length* d^g. To cope with the issue of disconnected networks (which would introduce at least one infinite distance in the calculation) we restrict attention to distances between "reachable pairs".

Betweenness centrality of node i, b_i^g, is the sum, over all possible pairs $k, l \in N - \{i\}$, of the proportion $p_{k,i,l}^g$ of shortest paths between k and l that run through

i, i.e.

$$b_i^g = \sum_{k,l \neq i} p_{k,i,l}^g.$$

Network constraint of firm i is computed as

$$\gamma_i = \sum_j (p_{i,j} + \sum_{l \neq i,j} p_{i,l} p_{l,j})^2,$$

where $p_{i,j} = w_{i,j} / \sum_j w_{i,j}$. The term $p_{i,j} + \sum_{l \neq i,j} p_{i,l} p_{l,j}$ is the proportion of i's interactions that are invested directly or indirectly with j. In the case of an un-weighted graph, $p_{i,j} = 1/n_i^g$ if $j \in N_i^g$, and 0 otherwise. So constraint is rewritten $\gamma_i = \sum_{j \in N_i^g} (1/n_i^g)^2 \cdot (1 + \sum_{l \in N_i^g \cap N_j^g} 1/n_l^g)^2$, which decreases when the degree of i increases, when the degrees of i's neighbours increase, and when i's neighbours share fewer common neighbours (being a star or being connected to stars will thus lower my constraint a lot). There are fewer structural holes in more constrained networks.

A.3 Weighted measures

Construct a cumulative matrix of firms' past interactions by recording the number of times each partnership has been active over a history of length h. Denote W this matrix, with $0 \leq w_{i,j} \leq h$.

The *weighted clustering coefficient* is computed using the definition in Holme et al. (2006), taking the individual neighbourhood clustering to be

$$c_i^w = \frac{1}{\max_{i,j} w_{i,j}} \frac{\sum_j \sum_{k>j} w_{i,j} w_{i,k} w_{k,j}}{\sum_j \sum_{k>j} w_{i,j} w_{i,k}}.$$

Due to the normalization, c_i^w belongs to $[0, 1]$. In addition, if $w_{i,j} \in \{0, 1\}$ for all i, j then $c_i^w = c_i^g$, that is, the standard (un-weighted) neighbourhood clustering is recovered. Finally the contribution of a triad to the neighbourhood clustering of i is proportional to the weight of each edge of the triad.

For *weighted distances* we use Dijkstra's algorithm for finding least cost paths. As the weights in our network are equal to interaction counts, we transform them into "costs" by taking the inverse weight of each link, $w'_{i,j} = 1/w_{i,j}$, for all i, j, so that a more frequently activated connection has a lower cost.