Emergence of Innovation Networks from R&D Cooperation with Endogenous Absorptive Capacity*

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Abstract

This paper extends the existing literature on strategic R&D alliances by presenting a model of innovation networks with endogenous absorptive capacity. The networks emerge as a result of bilateral cooperation over time between firms occupying different locations in the knowledge space. Social capital is ignored, and firms ally purely on the basis of knowledge considerations. Partner selection is driven largely by absorptive capacity which is itself influenced by cognitive distance and investment allocation between inventive and absorptive R&D. Cognitive distance between firms changes as a function of the intensity of cooperation and innovation. Within different knowledge regimes, we examine the structure of networks that emerge and how firms perform within such networks. Our model replicates some stylised empirical results on network structure and the contingent effects of network position on innovative performance. We find networks that exhibit small world properties which are generally robust to changes in the knowledge regime. Second, subject to the extent of knowledge spillovers, certain network strategies such as occupying brokerage positions or maximising accessibility to potential partners pay off. Third and most importantly, absorptive capacity plays an important role in network evolution: firms with different network strategies indeed differ in the build-up of absorptive capacity.

Keywords: *absorptive capacity; agent-based modeling; cognitive distance; dynamics; innovation; knowledge spillovers; networks*

JEL Codes: *C61, C63, D83, D85, L14, O33*

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1 Introduction

The main aim of this paper is to examine the influence of absorptive capacity on the structure and performance effects of innovation networks that emerge from bilateral R&D collaboration. Innovation is, by nature, a highly uncertain process which involves recombination of knowledge (Dosi, 1988). Knowledge recombination is facilitated when it diffuses effectively. Networks are often perceived as an infrastructure for knowledge diffusion (Cowan, 2005). These networks usually arise out of voluntary cooperation either among firms or between firms and other economic agents. A standard result in studies of strategic alliances and networking is that firms benefit through cooperation. The benefits show up in terms of accessing complementary resources, division of labor, risk sharing, reduction of uncertainty and improved chances of innovative success through multiple search efforts (Pittaway et al., 2005; Powell, 1998). Two alternative explanations for the emergence of and benefits derived from networks can be found in literature.

From the social capital perspective, network position is considered to be very crucial, such that more central firms tend to outperform peripheral ones both in terms of successful alliances and innovativeness (Gulati, 1995; Powell et al., 1999). For this reason, alliances are thought to be largely motivated by social capital considerations (Coleman, 1988; Ahuja, 2000; Burt, 2004; Gilsing et al., 2008) and most of the empirically observed properties of innovation networks are explained by the fact that firms are seeking to increase their number of economically valuable connections. In particular, some authors argue that it is strategically important to combine both relational and structural embeddedness in networks (Moran, 2005; Rowley et al., 2000). In this regard, small world structures are thought to be particularly beneficial for innovation and the diffusion of knowledge (Schilling and Phelps, 2007).[1]

From a knowledge perspective, alliances can be heavily motivated by technological fit, that is the extent to which partners potentially learn from each other (Cowan, 2005). On the one hand, what is missing from a firm's stock of knowledge and competences influences its decision to cooperate and its choice of partners. In this sense, multiple partnerships may not be necessary and a firm may stop its partnership search once it locates a technologically fit partner. On the other hand, a firm's suitability is assessed by potential partners on the basis of what is present in its knowledge base. Thus, firms' internal knowledge deficiencies and externally available complementarities play a significant role in the emergence of learning and innovation networks. In this regard, small world structures are important because they preserve the quantity and diversity of knowledge (Baum et al., 2003), thereby affecting the learning and innovation potential of alliances.

The foregoing considerations are central to the models of Cowan et al. (2007) and Baum et al. (2010) in which alliance formation is driven by its probability to succeed in terms of knowledge generation and innovation, as well as the proximity of the potential partner. The studies demonstrate that networks with small world properties and other empirically founded network characteristics such as repeated alliances and transitivity can be observed even when alliances are formed only on the basis of knowledge considerations. However, these studies treat absorptive capacity as an exogenous parameter which is similar for all firms in an industry. This simplification is motivated by the fact that it allows to focus on the nature of the innovation process and its effects on emergent network

[1] With respect to a network of firms, a small world is a network in which distinct regions with dense interconnectedness (or cliques) of firms are linked by relationships (or clique spanning ties) that act as information conduits between them (Watts and Strogatz, 1998).

properties. However, this imposes the neglect of an important source of heterogeneity, that is, differences in firms' learning rates.

In this paper we also approach alliance formation from the knowledge perspective but with endogenous absorptive capacity. Firms form alliances for the purpose of knowledge sharing. Partner selection is entirely network-independent, implying the exclusion of network-based motives. The effectiveness of alliances is influenced by two factors: cognitive distance between partners and their investment allocation. Both factors determine absorptive capacity which is required to effectively deploy externally generated knowledge (Cohen and Levinthal, 1989). While the former has an inverted 'U'-shaped relationship with the learning and innovation potential of the alliance (Wuyts et al., 2005), the latter presents a trade-off in the optimal distribution of total R&D investments between the creation of own knowledge and the improvement of absorptive capacity. The higher the investment in original knowledge creation, the more attractive a firm appears as an innovation partner. At the same time, the lower the investments in the build-up of absorptive capacity, the more difficult it is to exploit external knowledge.

Taken together, the foregoing hold important implications for cooperation and partner selection. On the one hand, a firm needs to carefully balance between R&D investments made to generate inventions and to develop absorptive capacity. On the other hand, the firm needs to select partners that are neither too close to it in the knowledge space (to facilitate novelty) nor too far away (to facilitate understandability). An additional consideration is the distinction that can be made between voluntary spillovers which exist in the context of cooperation and involuntary ones that exist elsewhere. In particular, voluntary spillovers are reciprocal, thereby constituting both a benefit and a potential risk. In this regard, firms will pay attention not only to the amount of knowledge they can get from their potential partner but also to the partner's absorptive capacity. These elements were combined in our earlier model of absorptive capacity and inter-firm cooperation (Egbetokun and Savin, 2012). In that static model, the cognitive distance between cooperating partners was set exogenously. This simplification permitted a focus on the relationship between performance and cooperation strategy for a representative firm.

Building on research on alliance formation, we focus on dynamic aspects of cooperation wherein the cognitive overlap between partners increases with intensity of cooperation, either in terms of duration or frequency (Cantner and Meder, 2007). For instance, Wuyts et al. (2005) argue that the cognitive distance between cooperating firms is a negative function of their frequency of interaction. In other words, their knowledge bases become more similar as they cooperate more frequently. A similar argument was made by Mowery et al. (1998) for the duration of cooperation. *Ex post*, the knowledge overlap may be greater than its pre-cooperation level because of the mutual knowledge exchange over time. Cooperating firms may then become so close that the knowledge potential of their partnership becomes too low to permit recombinant novelty (Antonelli et al., 2010, p. 53). At this point, investments in absorptive capacity become less productive as far as the particular partnership is concerned. This may motivate the firms to invest more in own knowledge generation (inventive R&D) while reducing the absorptive R&D. In addition, when this stage is reached, the firms might reconsider their cooperation decisions and the partnership may dissolve.[2] Heterogeneity between the firms increases again

[2]This situation arises even between asymmetric firms, that is, a technological leader and a follower, because, as long as they operate within the same technological trajectory, the leading firm has little reciprocal incentive to continue the relationship except that of opportunism or expropriation, which constitute disincentives for the follower. As noted by Nooteboom (1999, p. 802), "A problem in collabo-

if they subsequently generate new knowledge either alone or in cooperation with other partners. The two firms may then be incentivised to re-establish partnership.

This paper analyses a dynamic model[3] in which networks emerge as a result of bilateral cooperation between firms occupying different locations in the knowledge space. The hypothesis that we examine is straightforward: could the empirically observed properties of networks be reproduced by abstracting from social capital and focusing exclusively on knowledge considerations with endogenous absorptive capacity?[4]

An important contribution of this paper is that, in contrast to Cowan et al. (2007) and Baum et al. (2010), we account for differences in firms' absorptive capacity and how this affects their dynamics in the knowledge space. Absorptive capacity is endogenously defined by two factors: (i) a firm's distance both to a potential partner and to aggregate external knowledge, and (ii) its decision on the investment trade-off between inventive and absorptive R&D potentially compensating for a larger distance to a partner. This way, absorptive capacity combines elements of searching for, valuing, identifying and assimilating new knowledge (Zahra and George, 2002).

Furthermore, distinguishing between voluntary and involuntary spillovers allows us to examine our hypothesis with respect to different knowledge regimes. The intuition here is that at different times in the history of an industry, different extents of voluntary and involuntary spillovers will be observed due to varying levels of inter-firm cooperation. For instance, industries tend to cluster in the early stages when knowledge is more tacit and its diffusion require face-to-face interactions (von Hippel, 1989; Audretsch and Feldman, 1996). At such times, a higher proportion of inter-firm collaborations characterised by high levels of voluntary spillovers is likely to be observed. However, in later stages, the effects of localised spillovers have been reported to diminish significantly (Potter and Watts, 2011) partly due to congestion, obsolescence of local knowledge and, in particular, a high amount of codifiable intra-industry spillovers.

Our results do indeed replicate important empirical facts and generate some new insight. We observe networks with small world properties at all levels of spillovers that we examine. The effects of network structure on firm performance varies with changes in the knowledge regime. Aggregate profit in the networks increases with increasing involuntary spillovers but an inverted 'U'-shaped relationship is observed with increasing voluntary spillovers. Moreover, when involuntary spillovers are small, networks with high average path length - implying low accessibility and inefficient information flow within the network - are especially detrimental for innovation. High betweenness - that is, occupying some kind of brokerage positions - turns out to be a very profitable network strategy at low levels of involuntary spillovers. A particularly striking result is that firms which employ different network strategies do indeed differ in their absorptive capacities.

The rest of the paper is organized as follows. Section 2 presents the basic model. In Section 3 we address the parameter calibration issues of the present ABM. Section 4 illustrates the obtained results, while Section 5 contains some concluding remarks.

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ration, especially in innovation, is that under some conditions there may be opportunities and incentives for free ridership, or for one party extracting more gain than others, or even expropriating their gain".

[3]With many firms, analytical solution of the dynamic model becomes intractable so we employ an agent-based simulation model (ABM). ABMs have gained an increasing interest in different fields of economic research having an advantage in (i) a more realistic representation of agents' behavior than in a standard representative agent model and (ii) possibility of an extensive and fast simulation analysis for different parameter settings due to the ongoing advances in computational performance.

[4]We do not imply a contrast between absorptive capacity and social capital; rather, we examine the networks generated when cooperation is motivated by knowledge gains rather than social capital.

2 The Model

In the model, a fixed population of firms (N) seeks to generate new knowledge over a certain number of periods within a defined knowledge space. Similar to Baum et al. (2010), a simple representation of firms in a two-dimensional metric space[5] capturing cognitive distance is used. While firms' locations in the underlying space have no particular meaning, they "translate directly into a network of strategic alliances" (Baum et al., 2010, p. 2097), because the distances affect the learning ability and, hence, partnership formation.

In each period, innovations can be generated from new knowledge created within that period.[6] Each firm maximizes its potential to innovate either alone or in cooperation with another firm. The decision to cooperate is influenced by absorptive capacity not only of the firm itself but also of its potential partner. The absorptive capacities, in their turn, depend on the extent to which the two firms' knowledge endowments both resemble and complement each other (cognitive distance). Bilateral partnerships among the firms yield an aggregate network. We are particularly interested in three issues:

i. the kinds of aggregate network structures that emerge: here we examine whether the networks generated by our model display small world properties like many real life networks (Cowan and Jonard, 2004; Verspagen and Duysters, 2004).

ii. the effects of different knowledge regimes on aggregate network structures and performance: here we analyze how the network structures respond to varying degrees of voluntary and involuntary spillovers.

iii. the relationship between firms' network position and their innovation performance: the focus here is on individual firms and the manner in which the structural characteristics of the network relate to their performance.

Four important assumptions are made in the model. First, partnership formation is only a short-term profit-maximising decision. Second, each firm selects only one partner and conducts one R&D project in each period. Partnerships are reconsidered in every period so that previously formed alliances may be discontinued. Third, reciprocity in partnerships is only relevant in terms of shared knowledge; partners' trust and reliability are ignored. Last, firms are well informed about the knowledge base but are uncertain about the investment decisions of other firms.

2.1 R&D investments

For each firm i, we distinguish between investments in directly in R&D (rdi_i^t) for the creation of own knowledge (which is a share, ρ, of total research budget, RD_i), and investments for exploring the environment for new complementary knowledge (aci_i^t):

$$RD_i = rdi_i^t + aci_i^t = \rho_i^t RD_i + (1 - \rho_i^t) RD_i, \tag{1}$$

Allocation of these investments is influenced by the potential quantity and complexity of external knowledge, either within a partnership or beyond it, both of which, in the

[5]A two-dimensional representation is the smallest suitable form allowing for transitivity relations in the metric space and provides a clear graphical representation of network formation and evolution.

[6]Thus, although the new knowledge may be combined with already existing knowledge to innovate, not every new recombination of knowledge is considered to be an innovation.

ures 18-20 in Appendix B, average cognitive distance between partners first falls in δ_c since learning implies that firms move closer in the knowledge space. As δ_c reaches its middle range ($\delta_c \approx> 0.4$), average distance increases. This may be a result of increasing absorptive R&D (subplot (e) of Figures 18-20 in Appendix B), where firms reach further in the knowledge space to find cooperation partners with novel knowledge. In fact, firms first reduce investments in absorbing external knowledge (with smaller distance less investments are required) but then increase them back to roughly the same level. This causes ac_{ij} to rise. The combined dynamics here further illustrates the ambiguous relationship between cognitive distance and absorptive capacity that we analyzed in Egbetokun and Savin (2012).

It is worth noting that aggregate profit reaches its maximum at an intermediate level of δ_c in all matching scenarios (subplot (c)). This happens because firms' learning capacities allow them to benefit from the combination of shorter distances to partners and increasing investments in inventive R&D. However, at high levels of δ_c, aggregate profit drops in spite of the benefits from inventive R&D and involuntary spillovers as well as increasing assimilated voluntary spillovers observed in subplot (f). The reason for this is that the costs of cooperation rise consistently and become more dominant as cooperation becomes more intense. The inverted 'U'-shaped dynamics draws attention to the potential pitfalls of cooperation as emphasised in the empirical literature. Intense cooperation, whether in terms of repeatedness or persistence, limits the potential for recombinant novelty, thereby reducing innovative profits. Again, networks with popularity contest consistently demonstrate the worst aggregate performance which is due to lowest number of alliances (which, in turn, is a result of competition).

4.2.2 Relationship between firms' performance and network position

A widely held belief in the literature on alliances and firm networks is that the diffusion of knowledge in networks characterised by short path lengths is more efficient. Also, it is thought to be beneficial for firms to occupy influential positions - such as having high betweenness centrality which allows them to act as knowledge brokers - in networks. These results are normally explained in terms of social capital. Our model, in which networking is entirely knowledge-driven and any kind of social capital is excluded from consideration, yet shows results which are consistent with the empirical regularities. The value in this is that knowledge and technological fit, rather than just social capital, contribute to the observed performance effects of inter-firm cooperation. An important extension derived from the results here is how the relationship between network structure and innovativeness varies in response to changes in the characteristics of the knowledge space. In this section we discuss the relationship between an individual firm's performance[40] and the structure of the network. Figures 9-11 contain the results for varying levels of involuntary spillovers and Figures 12-14 for varying levels of voluntary spillovers.

In all cases, we report first the correlation between profits and betweenness centrality (subplot (a)). In subplot (b) we illustrate the correlation between absorptive capacity to a partner and betweenness centrality. The same plot shows the correlation of absorptive capacity to external knowledge and betweenness. Subplot (c) shows the correlation between profits and number of partnerships. In subplot (d) the correlation between profits and mean path length is shown. The correlations between the two different absorptive capacities and mean path length are given in subplot (e). Finally, in all of Figures 12-14,

[40] Recall that performance refers to the amount of R&D profit that the firm generates in each period.

subplot (f) shows the correlation between profits and absorptive capacity.

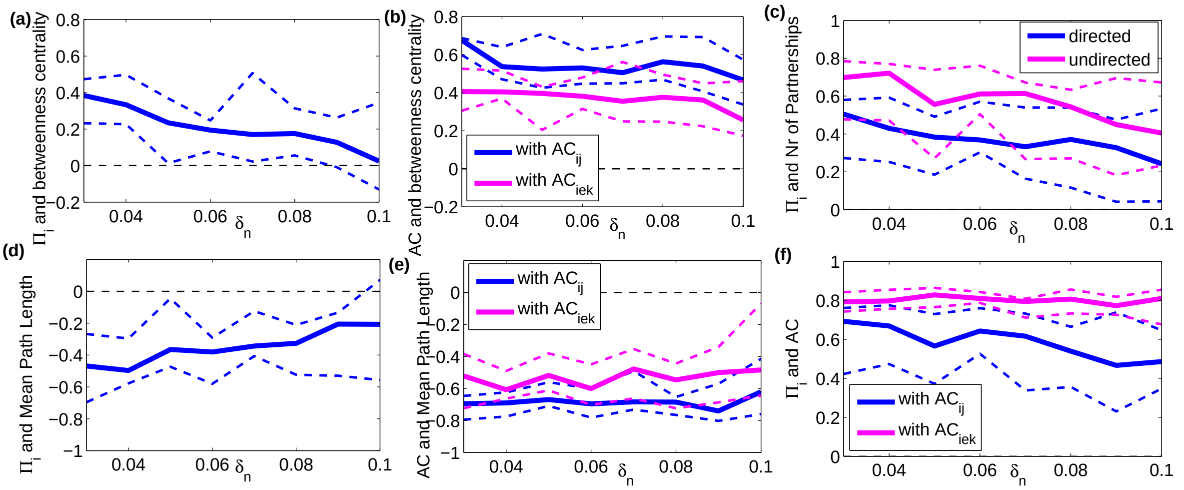

Figure 9: Correlations with firm performance for different δ_n and unilateral partnership

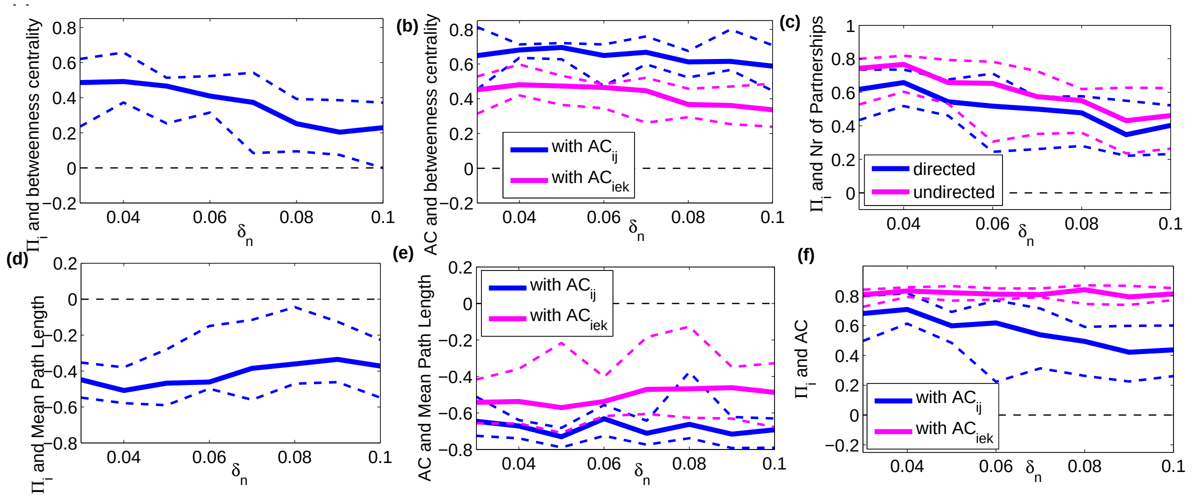

Figure 10: Correlations with firm performancefor different δ_n and reciprocal partnership

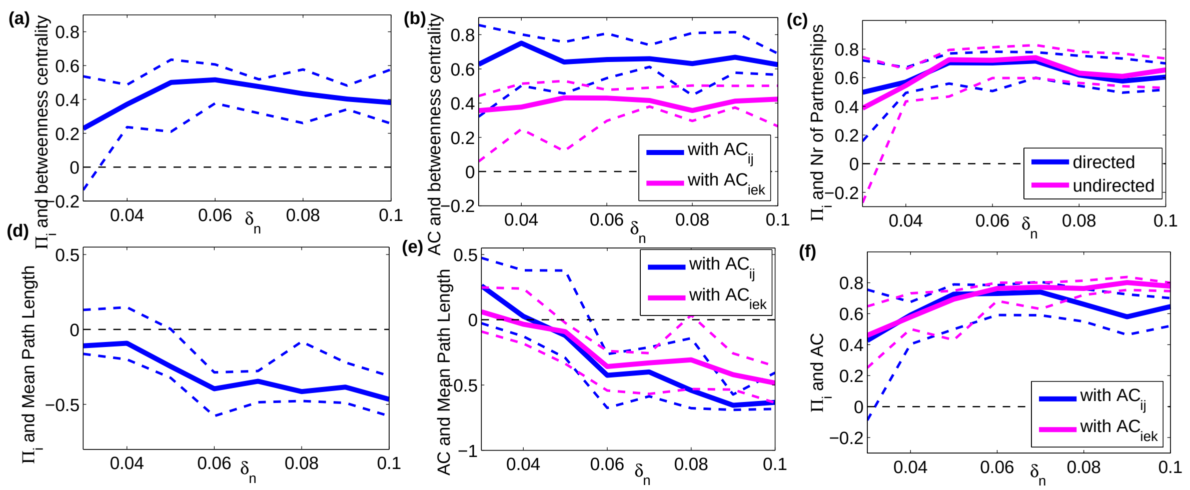

Figure 11: Correlations with firm performance for different δ_n and popularity contest

First, we consider changes in the level of involuntary spillovers (Figures 9-11). In subplot (a), betweenness is positively correlated with performance, suggesting that occupying a brokerage position pays off for the firm. At least in the unilateral and reciprocal matching networks, the highest correlations coincide with very low values of δ_n. The correlation then reduces greatly but remains positive as δ_n increases. The extreme values of δ_n correspond to different stages of an industry's life cycle. Typically, in the early stages, involuntary spillovers are low. In this context, being in a brokerage position improves access to tacit knowledge. In the later stages when knowledge is mostly codified and freely available, although being in a brokerage position is good, it becomes less relevant.

This is quite logical because, in such scenarios, networks are less clustered and brokers tend to become redundant to gain access to spillovers which are freely available. The only real constraint that each firm faces then is its capacity to absorb and not necessarily the absence of a broker in its ego-network. The correlation of profit with mean path length (subplot (d)) tells a consistent story. High values imply late arrival of knowledge and potentially lower innovation performance. However, when freely available knowledge becomes more abundant, the severity of this effect reduces significantly. Simply put, a combination of high betweenness and short path length becomes less critical for performance in mature industries wherein involuntary spillovers are generally high.

The total number of alliances is positively correlated with performance at all levels of δ_n but the strength of the correlation reduces as δ_n increases (subplot (c)). In particular, the correlation of a firm's performance with 'directed' partnerships (that is, when it initiates the partnership) is consistently lower than the 'undirected' partnerships (that is, when it either initiates or accepts a partnership). This is consistent with the empirical finding that too many partnerships can be problematic (Uzzi, 1997; Ahuja and Lampert, 2001), mostly for social capital reasons. In contrast, our result here is driven by changes in the underlying knowledge regime. When intra-industry spillovers are high, it is less efficient to maintain a large portfolio of alliances. As we have noted earlier, this situation is characteristic of the later stages of an industry when firms might be more dispersed and localised spillovers are less useful (Potter and Watts, 2011).

Also, as expected, absorptive capacity is positively correlated with performance (subplot (f)). The reducing correlation of ac_{ij} further emphasizes the view that at higher levels of involuntary spillovers, learning from cooperation becomes less important. Particularly interesting is to observe the correlations of absorptive capacity with betweenness (subplot (b)) and mean path length (subplot (e)). The correlations somewhat reflect the relationship between profits and these network measures. It seems that firms having favourable network positions (high betweenness and short paths) are motivated to build up absorptive capacities. This implies that firms adjust their learning (particularly from partners) depending on their position.

Now we turn to the effect of changes in voluntary spillovers (Figures 12-14). First we observe from the correlation in subplot (a) that betweenness is highly positively correlated with performance. The correlation does not change much with variations in δ_c. This suggests that brokerage positions are consistently favourable in a regime characterised by increasing voluntary spillovers. In such regimes, tacitness is high and cooperation is considered to be essential (von Hippel, 1989). Occupying brokerage positions thus confers some controlling power on firms. Again, it is crucial to note that this result arises not from social capital but out of knowledge-driven alliance formation. In this sense, a high betweenness value can be interpreted as being located in a clustered part of the knowledge space and having influence in the knowledge diffusion process.

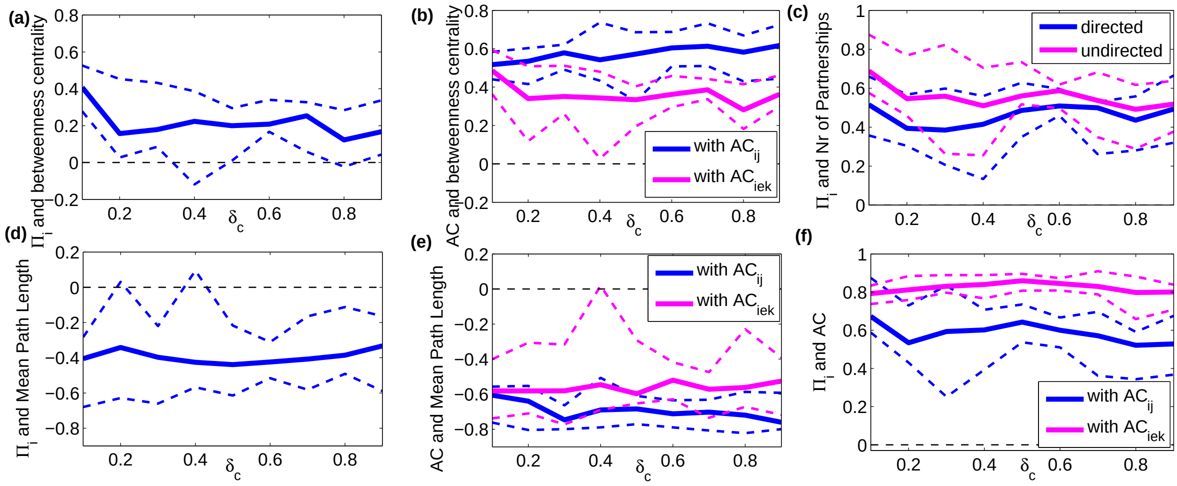

Figure 12: Correlations with firm performance for different δ_c and unilateral partnership

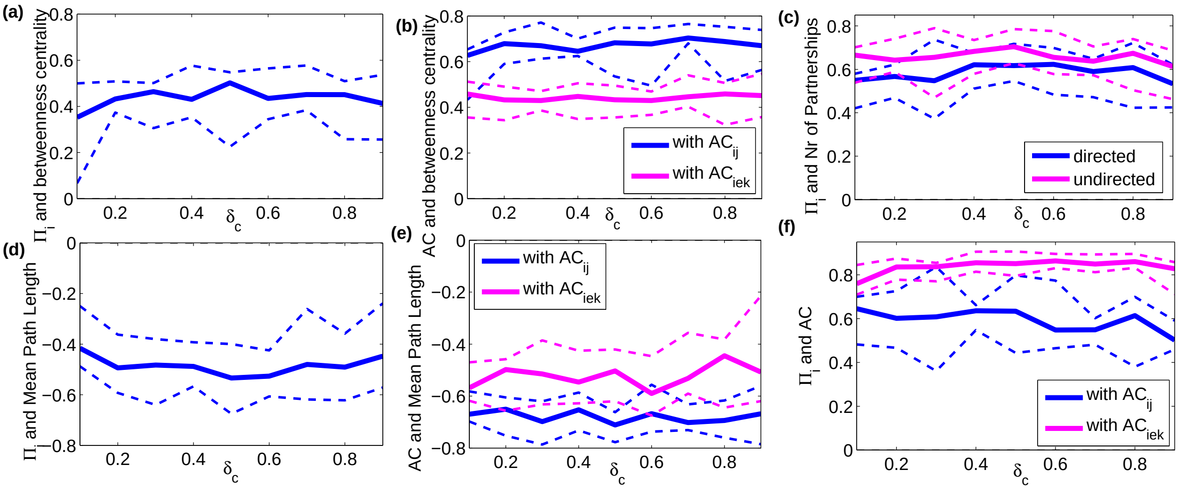

Figure 13: Correlations with firm performance for different δ_c and reciprocal partnership

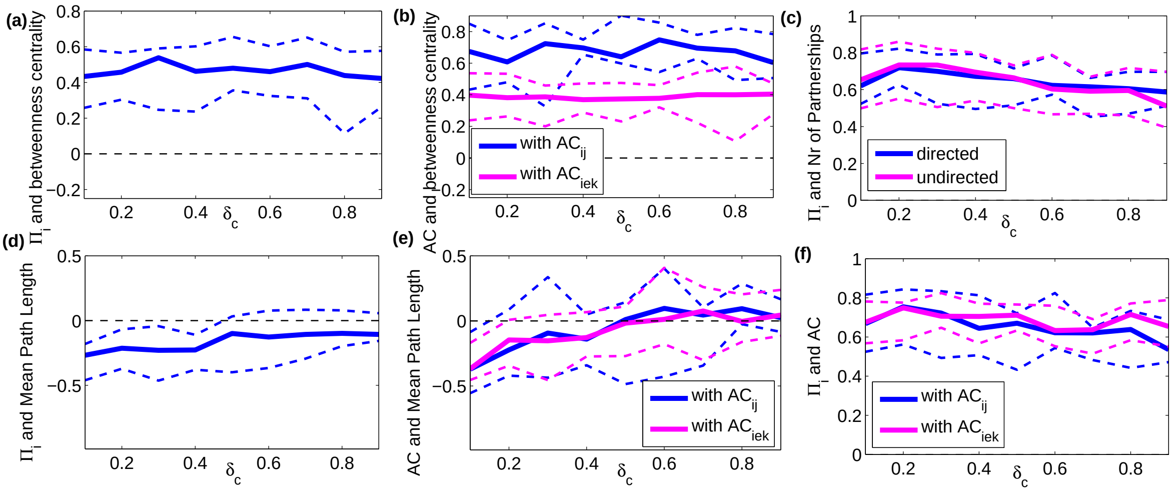

Figure 14: Correlations with firm performance for different δ_c and popularity contest

Mean path length is negatively correlated with performance (subplot (b)) meaning that low accessibility impairs innovativeness. In contrast to involuntary spillovers, this relationship here does not vary much for different voluntary spillovers. In sum, a combination of high betweenness and short path length are consistently important for innovation performance in a highly tacit knowledge regime.

The performance effects of the number of partnerships (subplot (c)) fluctuates as δ_c rises. It is highest at some intermediate values of δ_c, falling otherwise. This seems to reflect an empirically observed problem associated with alliances. As Ahuja (2000) argued, at high levels of embeddeddness, the marginal costs of every additional linkage will outweigh the marginal benefits. Absorptive capacity is consistently positively associated with profits. This correlation does not change much with changes in the amount of voluntary spillovers (subplot (f)). As observed with involuntary spillovers, the correlations of absorptive capacity with betweenness and mean path length somewhat reflect the relationship between profits and the network measures. Taken together with the earlier observation, these results indicate that firms display heterogeneity in building up absorptive capacity depending on the network positions they occupy.

4.3 Robustness checks

To analyse robustness of the results discussed above, a number of alternative settings are examined.[41] First, in the simulation we have set the marginal returns to both inventive and absorptive R&D as equal.[42] It is appealing, however, to try out scenarios where this does not hold (that is, $\psi \neq \xi$). To this end, we set either ψ or ξ equal to 0.75 leaving all other parameters unchanged and repeat the ABM simulation comparing results with the *baseline scenario* (the one described before).

What we find is the for $\xi = 0.75$ investments in inventive R&D become naturally more lucrative (ρs rise close to 90%), firms' absorptive capacities in all the scenarios reach on average lower values as in the baseline setting (between 0.2 and 0.6), which makes partnerships less efficient and their number drops by almost one half. The latter results in lower weighted small world ratios (due to lower clustering coefficients). However, rescaled small world ratios remain robust and are consistently above one at least in the unilateral and reciprocal partnership formation rules. Similarly, patterns of correlations identified in the baseline scenario between R&D profits and network positions (betweenness and mean path length) and also the positions and firms' absorptive capacities remain stable. 40%-60%), which results in somewhat higher average absorptive capacity values (particularly, in the popularity contest matching) - between 0.7 and 0.8 - and larger numbers of R&D alliances in all the scenarios considered (about 25% higher than in the baseline setting). Small worlds ratios of the emerging networks remain robust: while rescaled values consistently exceed one (even in the popularity contest matching), the weighted values are slightly higher (due to higher clustering). The patterns of correlations both between firms' network positions and profits, and network positions and learning capacities remain stable.

Second, we have assumed that firms have perfect knowledge about cognitive distance between them and others. In other words, firm i knows how far it is from j in the knowledge space and j also has the same information. To see, how crucial this assumption is, we introduce some uncertainty in this knowledge by adding some uniformly distributed error term ϵ reaching in its absolute maximum 50% of the distance between two firms,

[41] Detailed results are available upon request, but are not included in the paper for the sake of brevity.

[42] In doing this we were aiming to obtain more general results not giving any preference to one of the investment directions.

$\epsilon \in [-\frac{1}{2}d_{i\cdot}; \frac{1}{2}d_{i\cdot}]$.[43] This estimation error is added to the distances both to voluntary and involuntary spillovers (i.e. to d_{iek} as well) during the mathing scenarios and, hence, affects the partner choice and the investment decision. However, the R&D profits are then estimated with actual distances.

What we observe is that the main findings (on the small world properties, interdependencies between firms' network positions and profits/learning capacities) remain remarkably robust (not only qualitatively, but quantitatively). Among the most noticeable changes are:

- clearly lower quality of expectation about other firm's investment decision (correlation between $E^i(\rho_j)$ and ρ_j is about 50% only). This could have been expected since the uncertainty in the distances' evaluation affects the investment decision and, hence, the latter becomes less predictable;

- some lower average absorptive capacities of firms (0.4-0.6 for unilateral and reciprocal matching, 0.2-0.4 for popularity contest). Again, failing to estimate the distance exactly naturally leads to under-/over-investments in absorptive R&D and, hence, lower absorptive capacities (recall the inverted 'U'-shaped function in (7));

- some lower aggregate R&D profits of firms (by 10-20% maximum compared to the baseline scenario) which is primarily due to lower absorptive capacities.

It is worth to mention that increasing ϵ further (up to 100% of the distance between two firms), the emerging networks loose their small world properties, while firms' profits plummet further down. Thus, the ability to approximate the distance with a sufficient precision is found to be a very important competence firms must have to be efficient.

In brief, one can conclude that the main findings remain robust for different settings, although naturally it becomes impossible to try out all the different parameter combinations given the complexity of the model and the number of parameters included. A possible further step along this line would be to estimate some of the model parameters as described, for instance, in Gilli and Winker (2003); Winker and Gilli (2004). However, due to lack of suitable and readily available data, this is left for further research.

5 Conclusion

As an important determinant of learning, absorptive capacity plays a key role in firm-level innovativeness. Its role in the formation of R&D partnerships, and the resulting networks, is however, not well understood. This paper starts with the observation that earlier work on alliances has heavily focused on social capital explanations and that recent works which attempt to overcome this limitation seem to understate the role and the complexity of the absorptive capacity phenomena neglecting an important source of heterogeneity between firms resulting from it. We develop and simulate an agent-based model in which social capital is absent and alliances are formed based on knowledge fit depending on endogenous absorptive capacity. Three different matching scenarios are tested, one of which - the popularity contest - presents a simplified representation

[43] In this way, the higher the distance between the two firms, the larger the potential error in estimating the cognitive distance between them.

of competition.[44] The remarkable result from the modeling exercise is that well-known empirical characteristics of networks are replicated by this ABM. What this tells is that disregarding the knowledge dimension in trying to explain the emergence, evolution and performance effects of networks gives, at best, a partial picture of reality.

The networks generated in the model display small world properties which respond to different extents to changes in the underlying knowledge regimes. The effects of these networks on performance vary depending on whether the knowledge space is characterised by intense cooperation and high voluntary spillovers (regime of high tacitness) or by relative dispersion and high involuntary spillovers (regime of high codification). In particular, in a regime of high tacitness, it seems to be more profitable for firms to occupy some kind of brokerage (high betweenness) and easily accessible (short path length) positions. This effect is less pronounced in a regime of high codification. Thus, at different stages of an industry's history, firms require different network strategies to achieve and maintain competitiveness through innovation.

A particularly important result relates to the role of absorptive capacity in network evolution. We observed a consistently strong and positive correlation between firms' absorptive capacity and their network centrality. This implies that being in a favourable network position relies on a higher level of absorptive capacity than being on a periphery. The consistently negative relationship between absorptive capacity and mean path length tells a consistent story. Efficient knowledge diffusion within a network requires that firms build up sufficient levels of absorptive capacity. To maximise their benefits, therefore, firms tend to adjust their absorptive capacity depending on their network positions. This heterogeneous behaviour is pronounced at extreme spillover levels.

Echoing recent studies (Cowan et al., 2007; Baum et al., 2010), our model further advances the possibility that empirically observed properties of inter-firm networks may be due to the characteristics of the knowledge space rather than purely social capital. Beyond this, however, we identify a time-varying characteristic of the knowledge space which helps to explain the network properties - that is, variations in the amount of knowledge spillovers. Network structures observed in mature industries characterised by high amounts of involuntary spillovers affect firm-level performance differently from the structures observed in early-stage industries characterised by high amounts of voluntary spillovers. By extension, network-based policy mechanisms (such as clustering initiatives) need to take into account the stage of an industry's development.

Our study may serve as a basis for a large number of extensions. Among those, one may set firms' R&D budgets dependent on their past profits, instead of time invariant and randomly allocated. Besides, we hope that the results of this modeling exercise will guide a fresh wave of empirical investigations. In partiular, analysis of strategic alliances in industries where networking is pervasive (such as biotechnology, pharmaceuticals and information and communication technologies) may benefit from the results stated above.

[44] What we generally find in this way is that competition reducing the number of alliances detrimentally affects firms' innovativeness. On the complexity of modeling competition in this type of models see, e.g., Baum et al. (2010, p. 2108).

Appendices

A Formal Definitions on Network Analysis

The definitions of the networks and its characteristics used in this study are consistent with the latest studies in this research area (see, e.g. Baum et al., 2010). However, some minor differences are possible. This section is meant to clarify them.

A.1 Networks

The simulated population of firms N and the L links (or 'partnerships', or 'alliances' throughout the paper) over 100 periods represent the resulting *network*. The two firms (*nodes*) are connected if there exists a *link* l_{ij} in the network L. The more links to distinct partners firm i has, the larger its *neighbourhood* (firms to whom i is directly connected) $Ne_i^L = \{ij \in L, i \neq j\}$, which is sometimes denoted as *degree* (the number of links to distinct partners held by i: l_i). The *average degree* of a network, therefore, is simply an average over all nodes' degrees. Another related measure in this context is *density* measured as the sum of all links presented in the network L divided by the number of all possible ties (repeated alliances do not count here), i.e.

$$Density^L = \frac{\sum l_{ij} \in L}{N(N-1)/2}$$

with $N(N-1)/2$ being the total possible number of (undirected) links in the network.

A.2 Unweighted measures

Considering network characteristics we are most interested in the following three:

- The *clustering coefficient* measured as an average over neighbourhood clustering of each firm in the network, where the neighbourhood clustering of firm i is the proportion of neighbours who are neighbours of each other, i.e. are directly connected:

$$c_i = \frac{\sum l_{jh} \in L : j, h \in Ne_i^L}{l_i(l_i - 1)/2}.$$

- The *mean path length* is the average of all pairwise shortest distances between two nodes in a given network (computed by means of the Dijkstra's algorithm). The more the distinct nodes are located on the shortest path, the larger the resistance of the path. To cope with infinite distances (if the population of firms is split in two distinct networks), we equalize them to the maximum distance within the network containing the node and adding one more unit to the distance, i.e. making the distance largest available within the given network.

- The *betweenness centrality* of firm i in the network L is the proportion of the shortest paths between any two other nodes in the network which pass through i ($p_{h,i,j}$) to total number of shortest paths between these two nodes ($p_{h,j}$):

$$b_i = \frac{\sum_{h,j \neq i} p_{h,i,j} \in L}{p_{h,j}}.$$

A.3 Weighted measures

To take into account the number of times each partnership was over the last 100 periods, we construct a cumulative matrix of firms' past alliances W (an example of such matrix with the distinction between direction of links is illustrated in Figure 2). Hence, each element of the matrix has a weight $0 \leq w_{i,j} \leq 100$, with $\forall i \neq j$, $\sum w_{i,j}$ capturing the *strength* of the link, i.e. its weighted degree.

Using the matrix W all three network characteristics described in Section A.2 can be 'weighted'. For the *weighted clustering coefficient* there is a large variety of ways of doing this (a brief but comprehensive review is provided by Saramäki et al. (2007)). In this study we implemented the version described in Onnela et al. (2003), which is similar to the one used in Baum et al. (2010) (e.g., by taking into account weights of all links of triangles in which firm i is involved). In particular, weighted clustering coefficient of each node is defined as the geometric average of subgraph link weights:

$$c_i^w = \frac{1}{l_i(l_i - 1)} \sum_{j,h} \left(\hat{w}_{ij}\hat{w}_{ih}\hat{w}_{jh}\right)^{1/3},$$

where $\hat{w}_{ij}$ are node weights normalised by the maximum weight in the network L: $\hat{w}_{ij} = w_{ij}/\mathtt{max}(w)$. Thus, $c_i^w \in [0,1]$ due to the normalisation and if $\hat{w}_{ij} \in [0,1]$ an unweighted clustering coefficient can be recovered. Furthermore, contribution of each triangle to c_i^w is proportional to the weight of each link in the triangle.

As for *weighted mean path length*, the Dijkstra's algorithm finds the least resistance paths with the distinction that the each link's resistance equals the inverse weight, $w'_{i,j} = 1/w_{i,j}$, indicating the lowest resistance by the most frequently activated partnership.

Finally, the *weighted betweenness centrality* again uses each link's resistance set equal to the inverse weight.

B Further Results

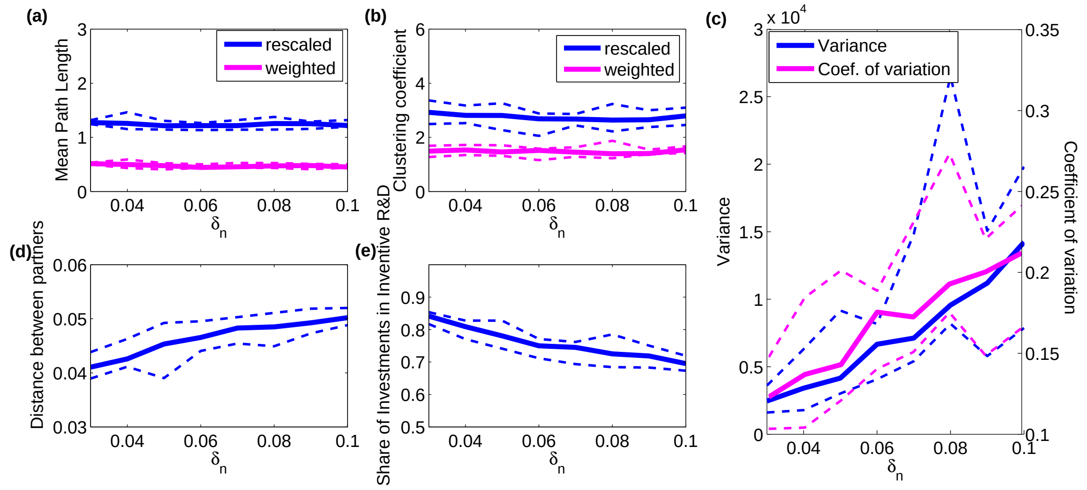

Figure 15: Network characteristics for different δ_n and unilateral partnership

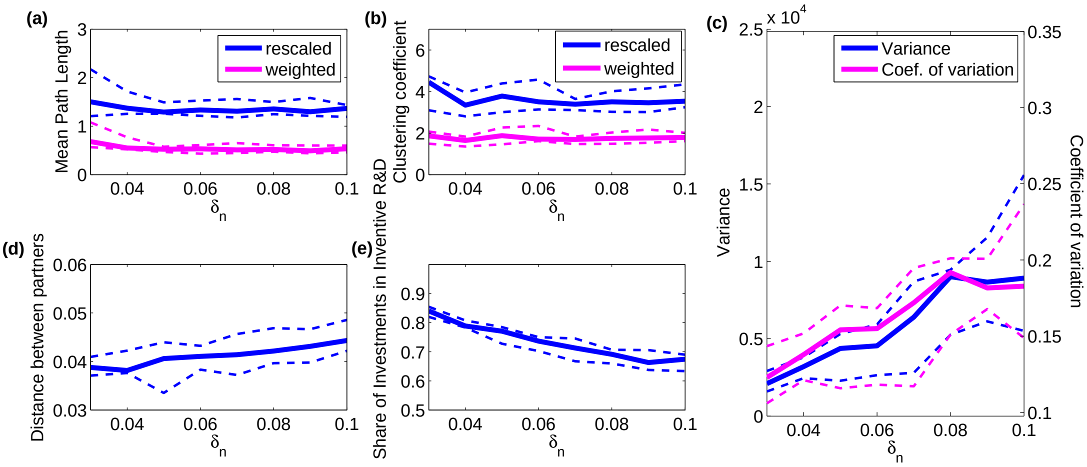

Figure 16: Network characteristics for different δ_n and reciprocal partnership

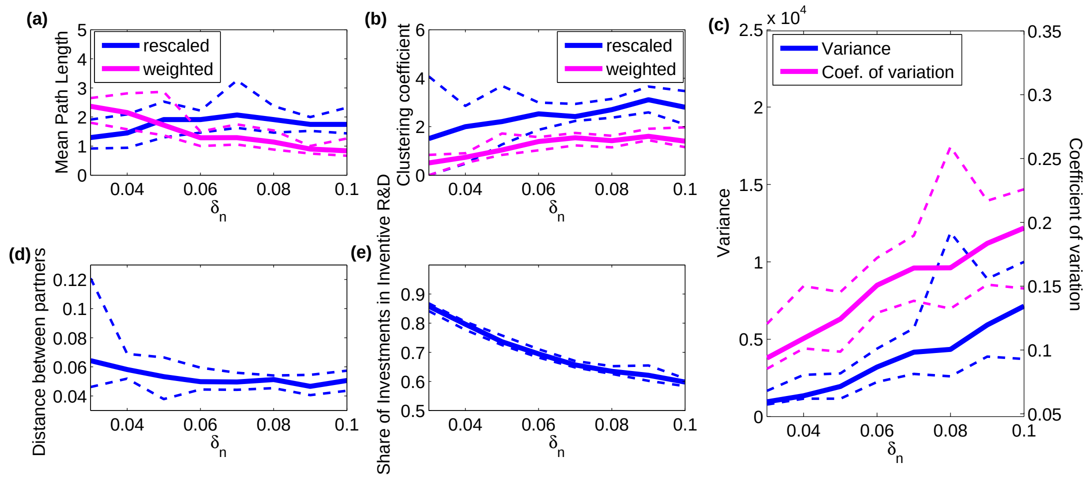

Figure 17: Network characteristics for different δ_n and popularity contest

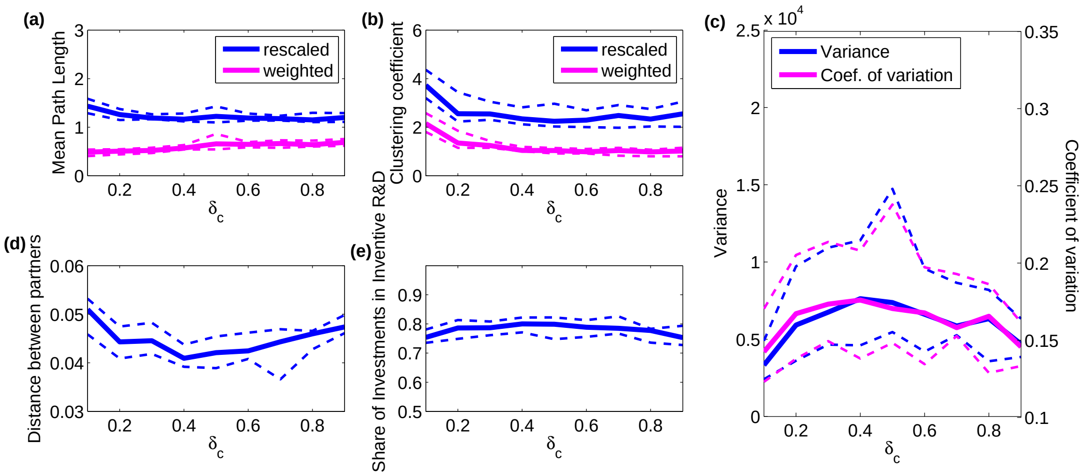

Figure 18: Further network characteristics for different δ_c and unilateral partnership

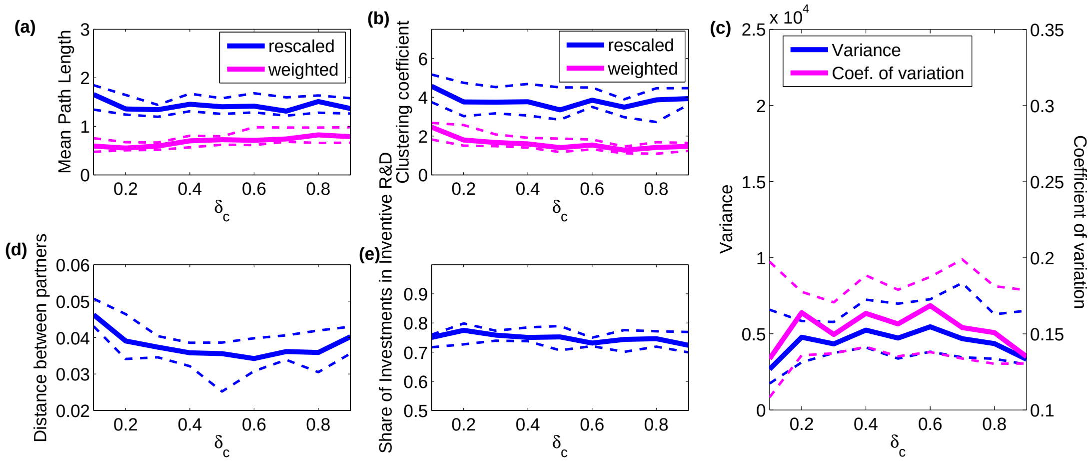

Figure 19: Further network characteristics for different δ_c and reciprocal partnership

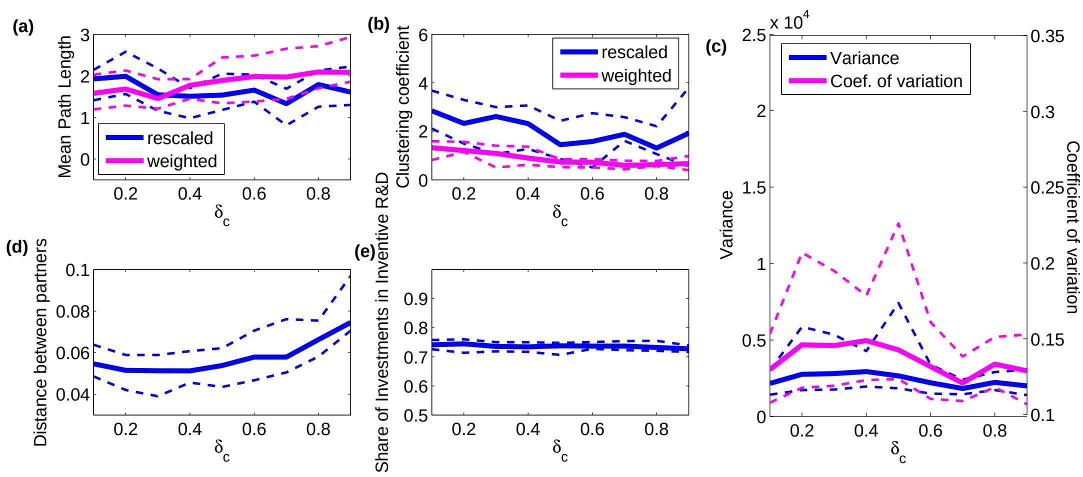

Figure 20: Further network characteristics for different δ_c and popularity contest

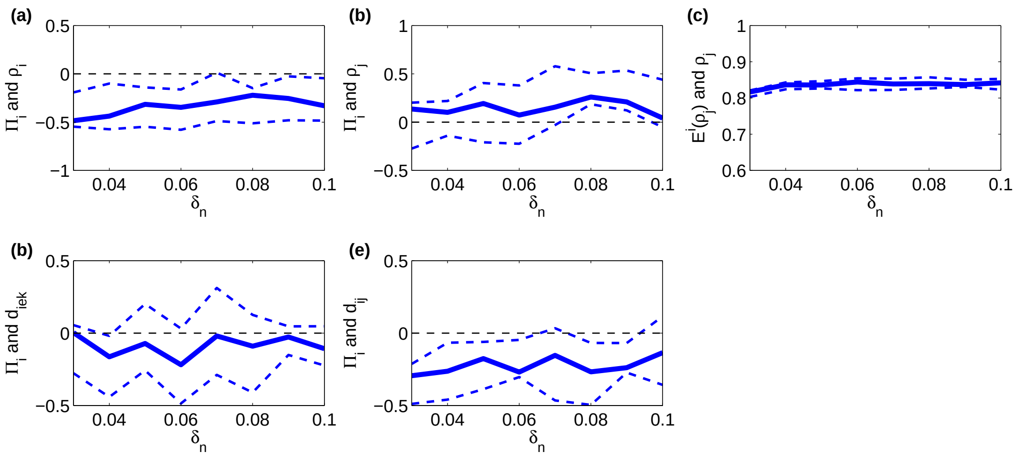

Figure 21: Further correlations with firm performance for δ_n and unilateral partnership

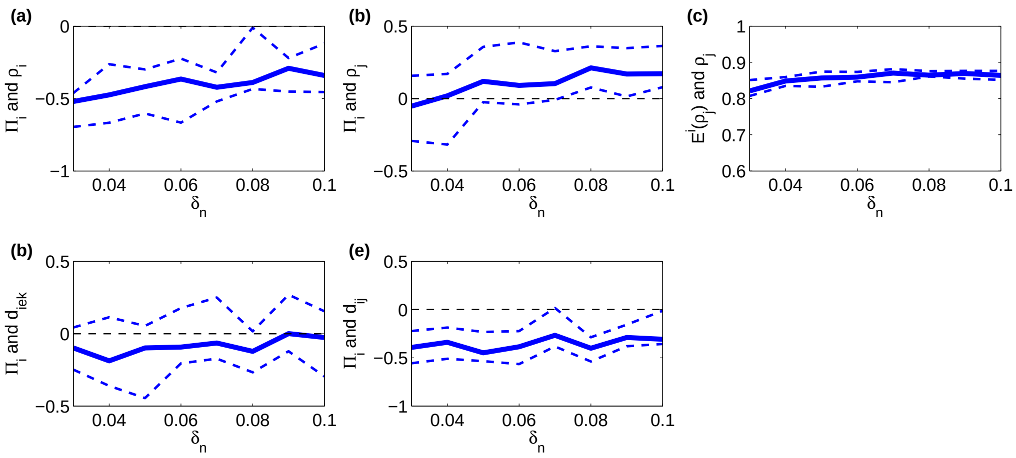

Figure 22: Further correlations with firm performance for δ_n and reciprocal partnership

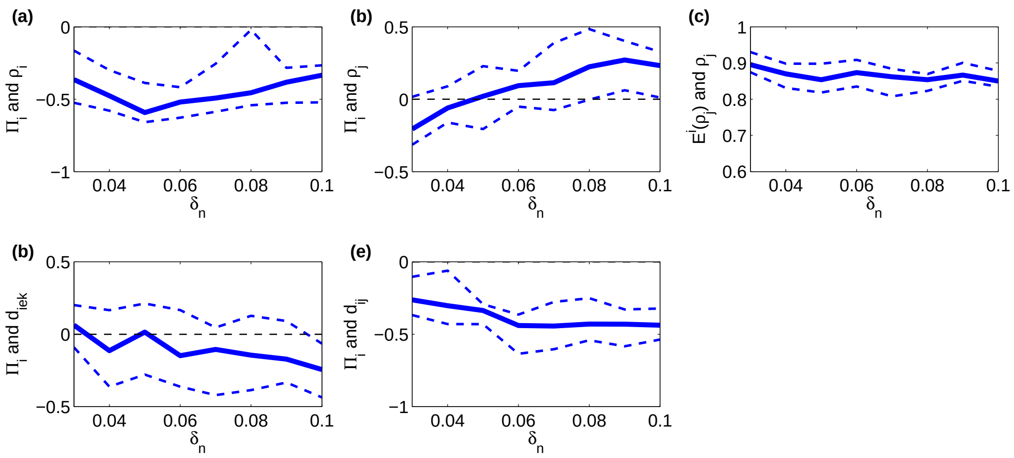

Figure 23: Further correlations with firm performance for δ_n and popularity contest

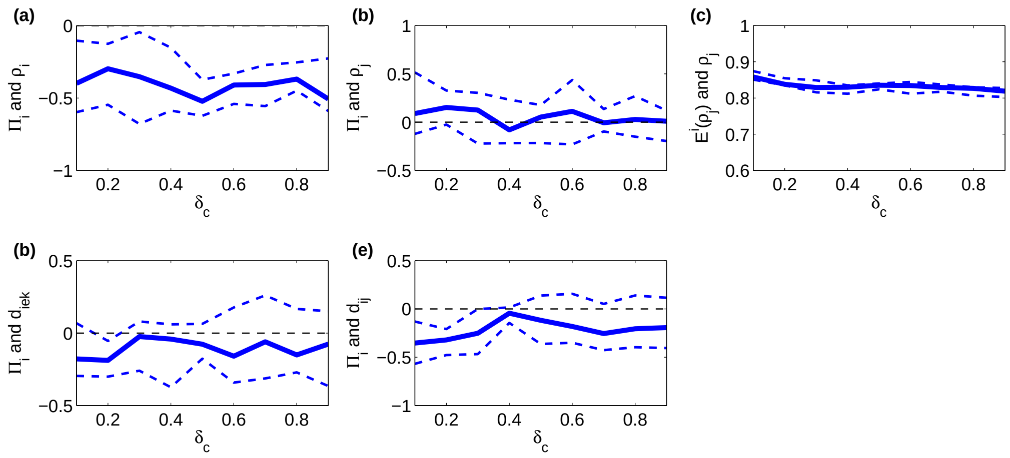

Figure 24: Further correlations with firm performance for δ_c and unilateral partnership

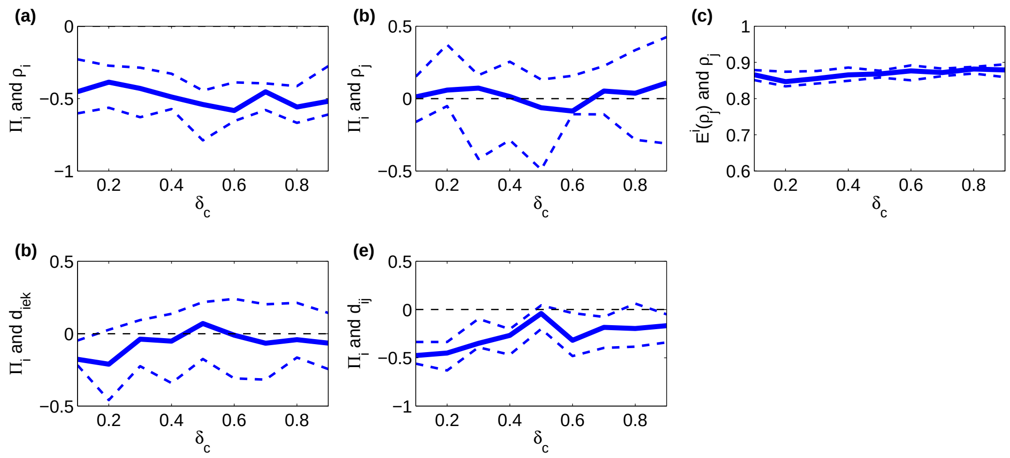

Figure 25: Further correlations with firm performance for δ_c and reciprocal partnership

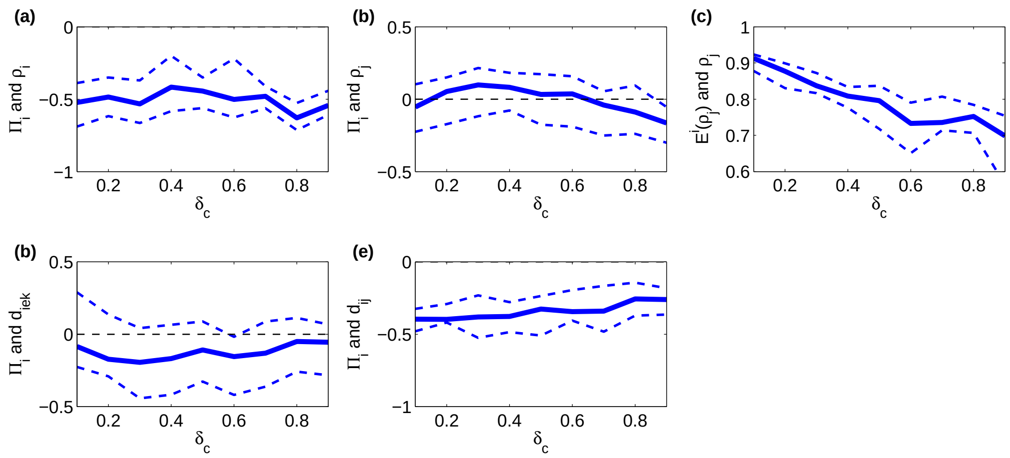

Figure 26: Further correlations with firm performance for δ_c and popularity contest

References

Ahuja, G. (2000). Collaboration networks, structural holes, and innovation: A longitudinal study. *Administrative Science Quarterly*, 45(3):425–455.

Ahuja, G. and Lampert, M. C. (2001). Entrepreneurship in the large corporation: a longitudinal study of how established firms create breakthrough inventions. *Strategic Management Journal*, 22(6-7):521–543.

Antonelli, C., Krafft, J., and Quatraro, F. (2010). Recombinant knowledge and growth: The case of ICTs. *Structural Change and Economic Dynamics*, 21(1):50–69.

Audretsch, D. and Feldman, M. (1996). Innovative clusters and the industry life cycle. *Review of Industrial Organisation*, 11:253–273.

Bala, V. and Goyal, S. (2000). A noncooperative model of network formation. *Econometrica*, 68(5):1181–1229.

Baum, J., Shipilov, A. V., and Rowley, T. J. (2003). Where do small worlds come from? *Industrial and Corporate Change*, 12(4):697–725.

Baum, J. A. C., Cowan, R., and Jonard, N. (2010). Network-independent partner selection and the evolution of innovation networks. *Management Science*, 56(11):2094–2110.

Blueschke, D., Blueschke-Nikolaeva, V., and Savin, I. (2013). New insights into optimal control of nonlinear dynamic econometric models: Application of a heuristic approach. *Journal of Economic Dynamics and Control*, 37(4):821 – 837.

Burt, R. (2004). Structural holes and good ideas. *American Journal of Sociology*, 110(2):349–399.

Cantner, U. and Meder, A. (2007). Technological proximity and the choice of cooperation partner. *Journal of Economic Interaction and Coordination*, 2:45–65.

Cohen, W. and Levinthal, D. (1989). Innovation and learning: The two faces of R&D. *The Economic Journal*, 99(397):569–596.

Coleman, J. (1988). Social capital in the creation of human capital. *American Journal of Sociology*, 94:95–120.

Cowan, R. (2005). Network models of innovation and knowledge diffusion. In Breschi, S. and Malerba, F., editors, *Clusters, Networks and Innovation*. Oxford University Press.

Cowan, R. and Jonard, N. (2004). Network structure and the diffusion of knowledge. *Journal of Economic Dynamics and Control*, 28(8):1557–1575.

Cowan, R., Jonard, N., and Zimmermann, J. (2007). Bilateral collaboration and the emergence of innovation networks. *Management Science*, 53(7):1051–1067.

Davis, G. F., Yoo, M., and Baker, W. E. (2003). The small world of the American corporate elite, 1982-2001. *Strategic Organization*, 1(3):301–326.

de Jong, J. and Freel, M. (2010). Absorptive capacity and the reach of collaboration in high technology small firms. *Research Policy*, 39(1):47–54.

Dosi, G. (1988). The nature of the innovative process. In Dosi, G., Freeman, C., Nelson, R., Silverberg, G., and Soete, L., editors, *Technical Change and Economic Theory*, pages 221–238. Pinter London.

Egbetokun, A. and Savin, I. (2012). Absorptive capacity and innovation: When is it better to cooperate? Technical Report 2012-056, Jena Economic Research Papers.

Fabrizio, K. (2009). Absorptive capacity and the search for innovation. *Research Policy*, 38(2):255–267.

Gilli, M. and Winker, P. (2003). A global optimization heuristic for estimating agent based model. *Computational Statistics & Data Analysis*, 42(3):299–312.

Gilsing, V., Nooteboom, B., Vanhaverbeke, W., Duysters, G., and van den Oord, A. (2008). Network embeddedness and the exploration of novel technologies: Technological distance, betweenness centrality and density. *Research Policy*, 37(10):1717 – 1731.

Gulati, R. (1995). Social structure and alliance formation patterns: A longitudinal analysis. *Administrative Science Quarterly*, 40(4):619–652.

Hammerschmidt, A. (2009). No pain, no gain: An R&D model with endogenous absorptive capacity. *Journal of Institutional and Theoretical Economics*, 165(3):418–437.

Koberg, C. S., Detienne, D. R., and Heppard, K. A. (2003). An empirical test of environmental, organizational, and process factors affecting incremental and radical innovation. *The Journal of High Technology Management Research*, 14(1):21–45.

Lin, C., Wu, Y.-J., Chang, C., Wang, W., and Lee, C.-Y. (2012). The alliance innovation performance of R&D alliances: the absorptive capacity perspective. *Technovation*, 32(5):282 – 292.

Moran, P. (2005). Structural vs. relational embeddedness: Social capital and managerial performance. *Strategic Management Journal*, 26(12):1129–1151.

Mowery, D. C., Oxley, J. E., and Silverman, B. S. (1998). Technological overlap and interfirm cooperation: implications for the resource-based view of the firm. *Research Policy*, 27(5):507–523.

Nooteboom, B. (1999). Innovation and inter-firm linkages: new implications for policy. *Research Policy*, 28(8):793 – 805.

Nooteboom, B., Haverbeke, W. V., Duysters, G., Gilsling, V., and van den Oord, A. (2007). Optimal cognitive distance and absorptive capacity. *Research Policy*, 36(7):1016–1034.

Onnela, J.-P., Chakraborti, A., Kaski, K., Kertesz, J., and Kanto, A. (2003). Dynamics of market correlations: Taxonomy and portfolio analysis. *Phys Rev E*, 68(http://www.ncbi.nlm.nih.gov/pubmed/17358454).

Pittaway, L., Robertson, M., Munir, K., Denyer, D., and Neely, A. (2005). Networking and innovation: a systematic review of the evidence. *International Journal of Management Reviews*, 5(3-4):137–168.

Potter, A. and Watts, H. D. (2011). Evolutionary agglomeration theory: increasing returns, diminishing returns, and the industry life cycle. *Journal of Economic Geography*, 11:417–455.

Powell, W. (1998). Learning from collaboration: knowledge and networks in the biotechnology and pharmaceutical industries. *California Management Review*, 40(3):228–240.

Powell, W., Koput, K., Smith-Doerr, L., and Owen-Smith, J. (1999). Network position and firm performance: Organizational returns to collaboration in the biotechnology industry. *Research in the Sociology of Organizations*, 16(1):129–159.

Rosenkopf, L. and Schilling, M. (2007). Comparing alliance network structure across industries: observations and explanations. *Strategic Entrepreneurship Journal*, 1(3-4):191–209.

Rowley, T., Behrens, D., and Krackhardt, D. (2000). Redundant governance structures: an analysis of structural and relational embeddedness in the steel and semiconductor industries. *Strategic Management Journal*, 21(3):369–386.

Saramäki, J., Kivelä, M., Onnela, J., Kaski, K., and Kertesz, J. (2007). Generalizations of the clustering coefficient to weighted complex networks. *Phys Rev E Stat Nonlin Soft Matter Phys*, 75(http://www.ncbi.nlm.nih.gov/pubmed/17358454).

Schilling, M. and Phelps, C. (2007). Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. *Management Science*, 53(7):1113–1126.

Storn, R. and Price, K. (1997). Differential evolution: a simple and efficient adaptive scheme for global optimization over continuous spaces. *Journal of Global Optimization*, 11(4):341–359.

Uzzi, B. (1997). Social structure and competition in interfirm networks: The paradox of embededdness. *Administrative Science Quartely*, 42(1):35–67.

Verspagen, B. and Duysters, G. (2004). The small worlds of strategic technology alliances. *Technovation*, 24(7):563 – 571.

von Hippel, E. (1989). Cooperation between rivals: informal know-how trading. In Carlsson, B., editor, *Industrial Dynamics, Technological, Organizational and Structural Changes in Industries and Firms*, pages 157–176. Kluwer Academic Publishing, Boston.

Watts, D. J. and Strogatz, S. (1998). Collective dynamics of small-world networks. *Nature*, 393(6684):440–442.

Winker, P. and Gilli, M. (2004). Applications of optimization heuristics to estimation and modelling problems. *Computational Statistics & Data Analysis*, 47(2):211–223.

Wuyts, S., Colombo, M., Dutta, S., and Noteboom, B. (2005). Empirical tests of optimal cognitive distance. *Journal of Economic Behaviour & Organization*, 58(2):277–302.

Zahra, S. and George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy of Management Review*, 27(2):185–203.