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Tie formation over the network life cycle: evidence from telecommunications

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Abstract

In this paper we argue that the determinants of tie formation in R&D networks vary over time, driven by technology evolution. In our theoretical argument, we pay particular attention to the role of new firms. Firms entering early into the network are typically established firms; firms entering in the mature phase of network evolution are young and specialized. The theoretical hypotheses we formulated are tested on a sample of 681 technological alliances in the telecommunications industry during the period 1991-2001, which provide general support for our hypotheses.

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1.INTRODUCTION

The aim of this paper is to study the determinants of tie formation in R&D networks. Networks are nowadays considered a central aspect to understand innovation in the more knowledge intensive industries (Powell and Grodal, 2004), both from the managerial and policy perspectives. For that reason, a large body of evidence now exists on the issue, which identified both endogenous determinants (associated to the influence of past network architecture) and exogenous determinants (such as the technological profiles of firms) of tie formation.

However, the extant literature tends to neglect the possibility that the role of the various determinants of tie formation may vary over time. Instead, this possibility appears as relevant, if one considers the empirical evidence of the dynamics of tie formation: networks seem to be characterized by cyclical behaviour, where periods of growth in the number of newly established agreements are followed by periods of sharp decline.

We argue that this cyclical behaviour is driven by the underlying (cyclical) behaviour of technology evolution, and this may lead to a different role of tie formation determinants over time. In our theoretical argument, we pay particular attention to the role of new firms. In our context, newness is considered both in terms of network participation and age. What we claim is that the characteristics of firms entering the network also change over time. Firms entering early into the network are typically established firms, which possess the relevant technological capabilities in the fluid phase of the technology; firms entering in the mature phase of network evolution are young and specialized, providing (typically to incumbents) specific knowledge assets.

The theoretical hypotheses we formulated are tested on a sample of 681 technological alliances in the telecommunications industry during the period 1991-2001. After having divided our sample in an early phase (1991-1993) and a mature phase (1994-2001) of network evolution, we found general support for our hypotheses.

We believe that our results are of particular relevance for knowledge-based entrepreneurship. The existing literature, relying on the evidence of path dependent mechanism of network evolution, stresses the importance of early entry for the viability and growth of new firms. Our results qualify this claim, in the sense that, at a beginning of the network cycle, entry into the network by new firms may be hard for reasons that are related to the stage of technological evolution, which causes their low attractiveness as partners, rather than for their peripheral position in the network. Since we do find also in our data the self-reinforcing effect driving network evolution, our results suggest the existence of a "window of opportunity" for new firms in the network: while entry may be too difficult in the first phase of network evolution, new firms entering early in the network relatively to other new firms may nevertheless obtain a strategic advantage.

The rest of the paper is organized as follows. Section 2 develops our appreciative argument. First we provide some evidence on the existence of network cycles. We then briefly review the determinants on R&D tie formation, with this being functional on the formulation of hypotheses of the relative role of such determinants over time. Section 3 describes our data and introduces the econometric model, while Section 4 presents and comments upon the results. Finally, Section 5 concludes.

2. TIE FORMATION OVER THE NETWORK LIFE CYCLE

Central to this paper is the notion of network life cycle. In management studies and in economics, the notion of life cycle has been traditionally applied to products or industries, reflecting the view that product sales or the evolution of industries go typically over a number of stages, from birth, through growth, to maturity and eventually decline. When applied to industries (Klepper, 1997), different stages are associated to specific patterns of firm entry and exit, innovation and growth rates. Along this line, in this section we intend to sketch an argument on the network life cycle that discusses the networking activity of firms and the identity of firms that are most active in the different stages of the network.

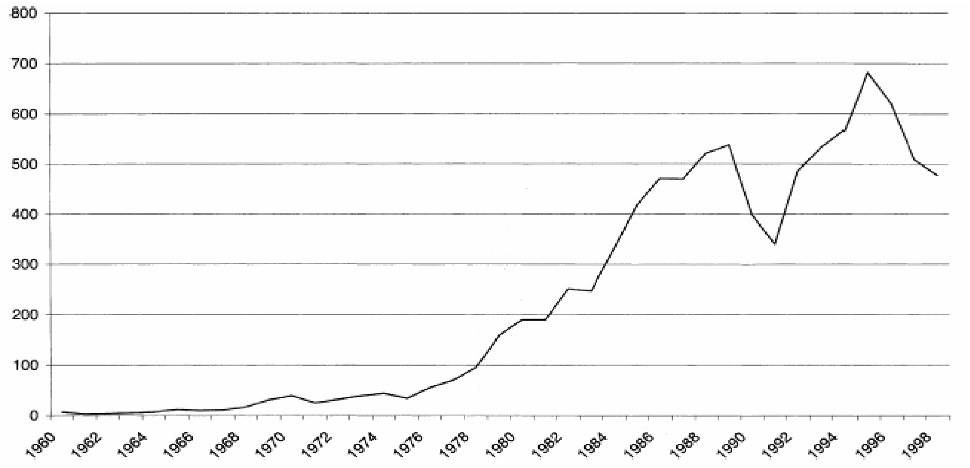
The section is divided in three paragraphs. First of all, we provide some empirical evidence on technological alliances that can motivate, in our view, the life cycle perspective. Then, we provide a brief review of the literature on network dynamics and tie formation, on which our theoretical considerations hinges upon. Finally, Section 2.3 outlines our view of the network life cycle, relating network evolution to the existing view of technological evolution.

2.1 Some evidence on the life cycle of alliances networks

Although historical examples of cooperation in the technological realm are not rare (Allen, 1983), interfirm technological agreements seem to have become relevant only in the relatively recent times. This is what suggests the analysis of large, word-wide literature-based datasets such as the MERIT-CATI database and the SDC Platinum database by Thompson (Zirulia, 2009).

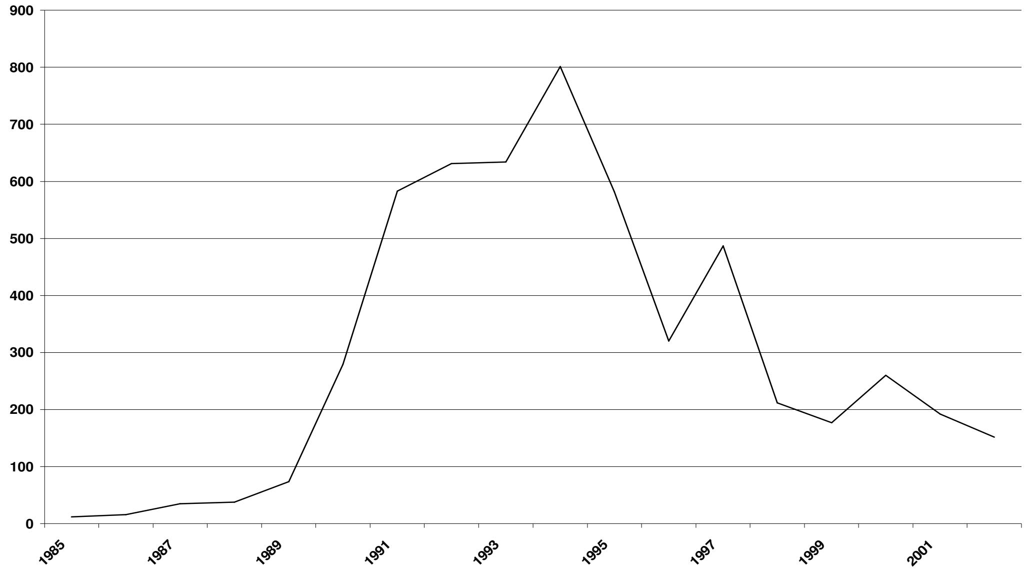
Figure 1 reports the number of newly established agreements, worldwide and for all sectors, as reported in the CATI database (Hagedoorn, 2002). It is shown that, after a limited growth in the 1960s and 1970s, the number of agreements has exhibited significant growth rates in the 1980s, and after that a cyclical behavior with a positive trend in the 1990s.

Figure 1: Newly established R&D partnership (1960-1998) Source: Hagedoorn (2002), MERIT-CATI database.



The SDC Thompson database pictures a slightly different behaviour. After the growth at the end of the 1980s, the cycle at the beginning of the 1990s is not observed, while as long as the period 1998-2002 is concerned (which is not included in Figure 1), the negative trend seems to continue.

Figure 2: Newly established R&D agreements (1985-2002). Source: SDC Platinum, Thompson Financial



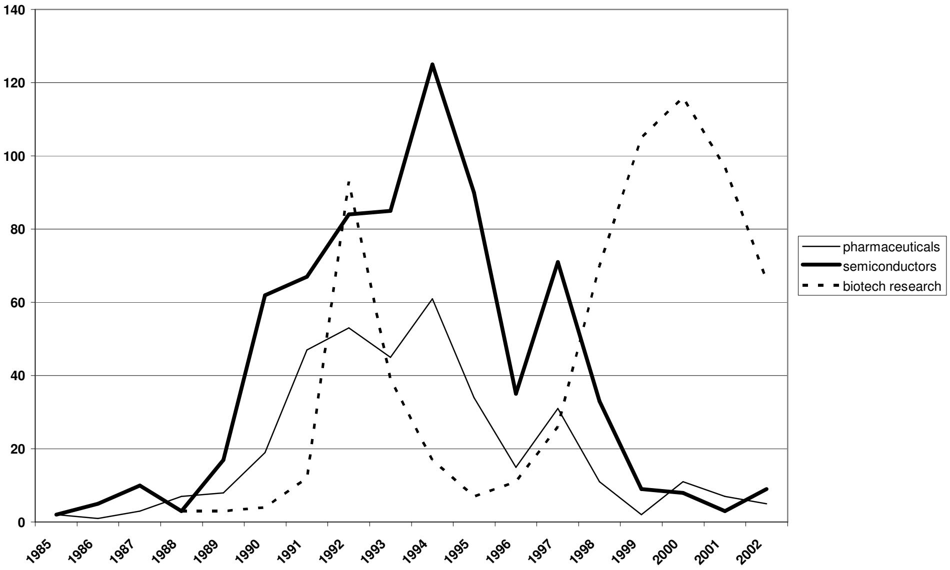
Using the MERIT CATI database, Hagedoorn and van Kranenburg (2003), show that the time series for newly established link (period 1960-1998) is largely of a non stationary nature, and a white noise model quite adequately fits the data. Hagedoorn and Vonortas (2002) find similar results analyzing the time series concerning the subset of alliances including at least a U.S. firm. Moreover, their econometric analysis indicates causal relationships between macroeconomic variables and the number of new agreements.

While aggregate data are suggestive of the general relevance of the phenomenon, it cannot be forgotten that they result from the aggregation of sectoral data, for which the specificities of the technological environment are most likely to have an influence also on the networking activity of firms (Malerba, 2005).

To the best of our knowledge, no previous study has investigated the technology and industry-specific determinants of the long run behaviour of technological alliances. However, descriptive evidence and some historical analysis show that cyclical behaviors are typically observed also at the level of single technology/industry.

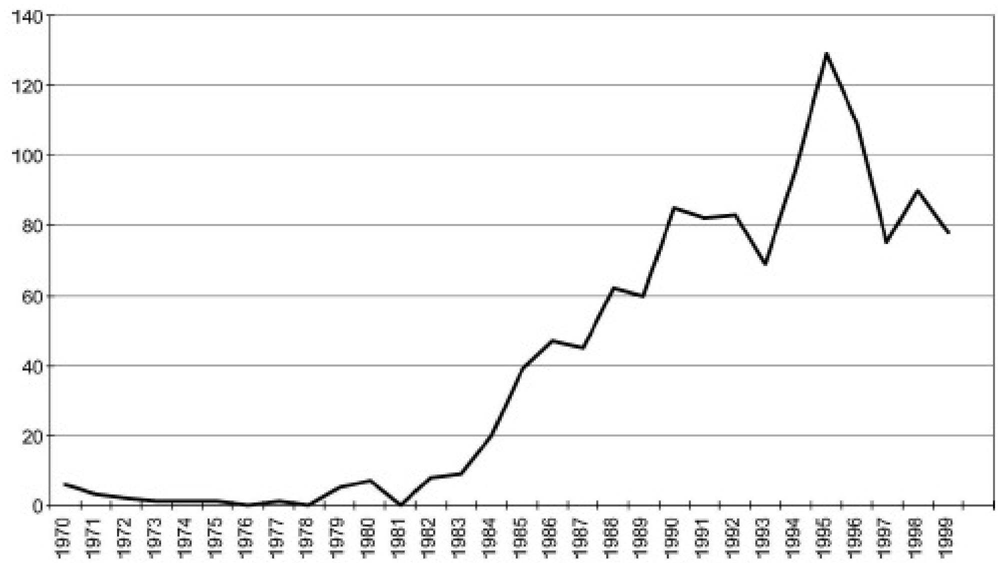
Figure 3 reports the absolute number of new agreements in three sectors (semiconductors, pharmaceuticals, biotech research) as reported in SDC database. Cycles are evident.

Figure 3: Newly established R&D agreements: selected sectors. Source: SDC, Thompson Financial



Cloodt et al. (2010) look at the evolution of the R&D network in the global software industry from 1970 to 1999. The networking activity was almost absent during the 70s, where the prevailing business model involved vertical integration and internal control of new technologies in the computer hardware industry (Bresnahan and Malerba, 1999), and leading computer companies manufactured not only computers but they also produced the microelectronics, provided operating systems, application software and software services that came with these computers. In contrast, a significant upsurge in the number of agreements is observed in the 80s, with the growth of the PC-based mass-market software segment during the 1980 and the emergence of Internet in the 90s. However, it is remarkable that a negative trend (the negative side of the cycle) seems to appear from 1995.

Figure 4: Newly established R&D agreements in the software industry. Source: Cloodt et al. (2010)



2.2 The determinants of tie formation: a brief survey of relevant previous literature

While the literature on the various forms of R&D cooperative agreements has a long tradition (e.g. Contractor and Lorange, 1988), it is only recently that a network perspective has gained attention, spurred by the massive contributions of sociologists to the field (Powell et al., 1996).

Early studies were most interested on the firm level, trying to identify firms' and industries' characteristics affecting firms' propensity to enter into collaborative agreements, their total number of agreements and partners, and the impact of firms networking strategies on technological and economic performance. A network perspective, instead, leads to tackle two interrelated questions i) the determinants of tie formation among nodes (i.e. firms or other organizations); ii) the structural properties of the R&D network. In this section we focus on question i), although it is clear that the answer to this question has obvious implication for ii). The literature is now sufficiently rich to generate some well consolidated stylized results.

One way to classify the determinants of tie formation is to distinguish between exogenous and endogenous determinants, where exogenous and endogenous refer to the influence of existing network architecture.

As for the exogenous determinants, most studies have focused on technology, trying to assess the probability of two firms forming a collaborative link, as a function of their technological distance, usually measured through their patent portfolios.

A quite general result is that firms need to be close in the technological space for being good partners (e.g., Stuart, 1998; Vonortas and Okamura, 2009). First of all, technological similar firms are more likely to find useful the knowledge possessed by their partners. In addition to that, as long as firms use technological alliances in order to learn, they need to have pre-existing knowledge in the partner's field of expertise (i.e. the "absorptive capacity") in order to take advantage of its capabilities. Moreover, cognitive proximity is required for effective communication to occur. Nevertheless, if firms are technologically too close, opportunities for learning may decrease: firms need to be sufficiently dissimilar for technological complementarities to be exploited through collaboration (Nooteboom, 1999). Mowery et al. (1998) is one paper that, in a sample of 151 international joint ventures, in several sectors, find evidence of such an effect.

Endogenous determinants of tie formation are probably those that have attracted more attention in recent works.

First of all, a quite robust result in the literature is that firms tend to ally with previous partners (Gulati, 1995; Stuart, 1998; Gulati and Gargiulo, 1999, Vonortas and Okamura, 2009). Firms, with familiarity, build trust, lower transaction costs and limit the risk of opportunistic behaviors. At the same time, they can develop routines and codes which favour the effectiveness of communication with the partner and control the flows of knowledge.

Indirect links among firms appear to be important as well. Common previous partners can play several roles (Gulati and Gargiulo, 1999): first, they constitute sources of information about potential partners for new collaborations; second, they reduce the asymmetric information among the potential partners, providing an indirect reputation effect; finally, firms that share many common partners can develop a common language for cooperation, practices and routines. From the point of view of network structure, the positive impact of indirect links on tie formation tends to create cliques, or more in general cohesive sub-groups of firms within the network. The existence of cohesive sub-groups has been shown in a number of paper, including. Nohria and Garcia-Pont (1991), who consider 35 leading firms and 133 alliances in the automobile industry, and Gomes-Casseres (1996), who showed that competition in the personal digital assistants market has been characterized, since its inception, by alliance groups of firms coming from different sectors.

Another endogenous mechanism that has been explored is related to “structural holes” argument by Ronald Burt (Burt, 1992). According to Burt’s theory, non redundant contacts are more likely to give the nodes involved timely access to diverse sources of information, as well control over such information, in order to secure them more favourable terms in the opportunities they choose to pursue.

Rosenkpof and Padula (2008) consider the evolution of the network of the mobile communication industry in the period 1993-2002. In part of their analysis, the authors study the determinants of the formation of “short cuts” across clusters, and found that those are more likely to be activated by firms with similar level of centrality.

Finally, the probability of ties involving nodes that are new to the network has been studied. Barabasi and Albert (1999) developed a model in which new nodes enter the network over time, and form links towards incumbent nodes with probabilities that are proportional to the existing number of links of the incumbent nodes. They show that such “the rich-get-richer” dynamics generate a power law distribution of degrees (i.e. most nodes have few links and few nodes have many links), which is often observed in real world networks. Studies that find evidence for preferential attachment mechanisms and/or scale-free networks are Krebs (2004) for the Internet Industry, Riccaboni and Pammolli (2002) for networks in life sciences and ICT

While our knowledge of the determinants of tie formation is relatively well established, much less is known about the importance of tie formation determinants over the network life cycle, i.e. over the periods of growth and then decline in the number of established agreements; which, we claim, is intrinsically associated to the evolution stages of the corresponding technologies. To the development of hypotheses on this theme is dedicated the next section.

2.3 Towards hypotheses on tie formation determinants over the network life cycle

Nowadays, it is common to look at technological through the lens of concepts such as technological trajectories and regimes (Nelson and Wiinter, 1982) technological guideposts (Sahal, 1981) or technological paradigm (Dosi, 1982), which are all based on the idea that processes of knowledge accumulation go through stages that are different quantitatively (e.g. in terms of rate of progress) and qualitatively (e.g. in terms of uncertainty).

All these concepts share the view that it is possible to distinguish between two phases. In the first phase, uncertainty, both at technical and commercial level, is high, different paths of research are explored, various methods and principles compete. In this “fluid” phase, technological progress is initially low, but then, also thanks to a process of knowledge recombination, technological accumulation “takes off”. Technology then enters into a second phase of stability, when uncertainty is reduced, common methods and principles of search prevails and a dominant design is established. In this second phase, technological progress continues to remain significant, until opportunities start to be deployed and the technology reaches maturity.

What are the determinants of tie formation over this evolution? First of all, it must be acknowledged that technological alliances and networks are most common when the knowledge base required to innovate is complex, hinging upon different technical and scientific fields. In the fluid phase, we conjecture that only firms that are highly competent in one of the fields required to innovate, and are highly complementary, have the incentive to form a link, thus entering the network. In this phase, the cost of forming ties, i.e. the barriers to network entry, is high, since uncertainty is high and the required investments may be large. In other words, we will hypothesize that exogenous determinants of tie formation are initially prevalent, in addition to the obvious consideration that the influence of the existing network structure cannot be too large when the network is almost empty.

One question that can emerge relates to the identity (i.e., old, established firms versus young firms) of the first firms forming ties. Our a-priory is that established firms are the most likely to be first entrants into the network. First of all, this is likely to be case when technological discontinuity is competence-enhancing. Second, established firms may possess the complementary assets that, together with technical expertise, provide value to the collaboration, thus increasing their incentives to form and their attractiveness as partners. Finally, incumbents may be the large, diversified firms more likely to bear the risk of uncertain investments. On the other hand, if the technological discontinuity is competence-destroying, young, specialized firms may play a role since the beginning, due to their unique expertise.

As the technology evolves into the maturity phase, and also market conditions are most established, barriers to entry into the network reduce, mainly due to the reduction in uncertainty. More opportunities to form alliances are created, also to the process of knowledge recombination: once the basic “architecture” of the technology has been reached, firms can start to work and cooperate on specific problems: the network moves from the exploration phase to the exploitation phase. In this stage, also young and firms, relatively less competent, may find entry into the network profitable.

As the number of potential partners increases, the endogenous determinants of network evolution become more and more important as a partner selection criteria, allowing to reduce the uncertainty on potential partner characteristics, create a common language in the cluster, favor ex post cooperation. Endogenous mechanisms induce a path-dependent, relatively predictable evolution of the network, which favours incumbents, in the sense that firms already in the network, ceteris paribus, prefer to link each other. Entry opportunities, however, may be guaranteed by the operating of the exogenous mechanisms, since, for instance, young firms may play the role of preserving technological variety in the network, thus spurring technological progress even in the mature phase. Nevertheless, the path dependent mechanisms provide an advantage to early entry in the network in this phase.

Finally, when technological opportunities are more and more deployed, technologically progress slow down, reducing the rate of new ties formation, until the network cycle concludes.

3. DATA AND METHODOLOGY

3.1. Sample and Data

Our hypotheses developed in Section 2 has been tested using longitudinal data on R&D strategic alliance in the telecommunication industry from 1991 to 2001.

The data on the alliances were collected from the SDC Platinum Database developed by Thompson Financial, which includes all, worldwide contractual arrangements in which two or more entities have combined resources to form a new, mutually advantageous business arrangement to achieve predetermined objectives.

We select 681 alliances according to three main rules. First, each alliance included at least one US participant. In this way, any technology developed during the alliance is more likely to be patented at the US patent office, which is our data source for the technological variables. Second, to be included in the sample, each alliance had to operate in the telecommunication industry, as indicated by its primary SIC of activity (3661, 3663, 4812, 4813). Notice that we did not impose restrictions on *firms'* SIC codes. Third, the objectives of the alliance concern technological related objectives. In the dataset, each alliance has been classified by Thompson according to its content. We selected only R&D-related agreements namely Exclusive Licensing, Cross Licensing, Cross Technology Transfer, Licensing, Technology Transfer, Research and Development.

Figure 5 reports the behaviour of R&D alliances in our sample, together with the data on non R&D ("commercial") alliances in the same SIC codes.

Figure 5: Newly established R&D and non R&D agreements in our sample

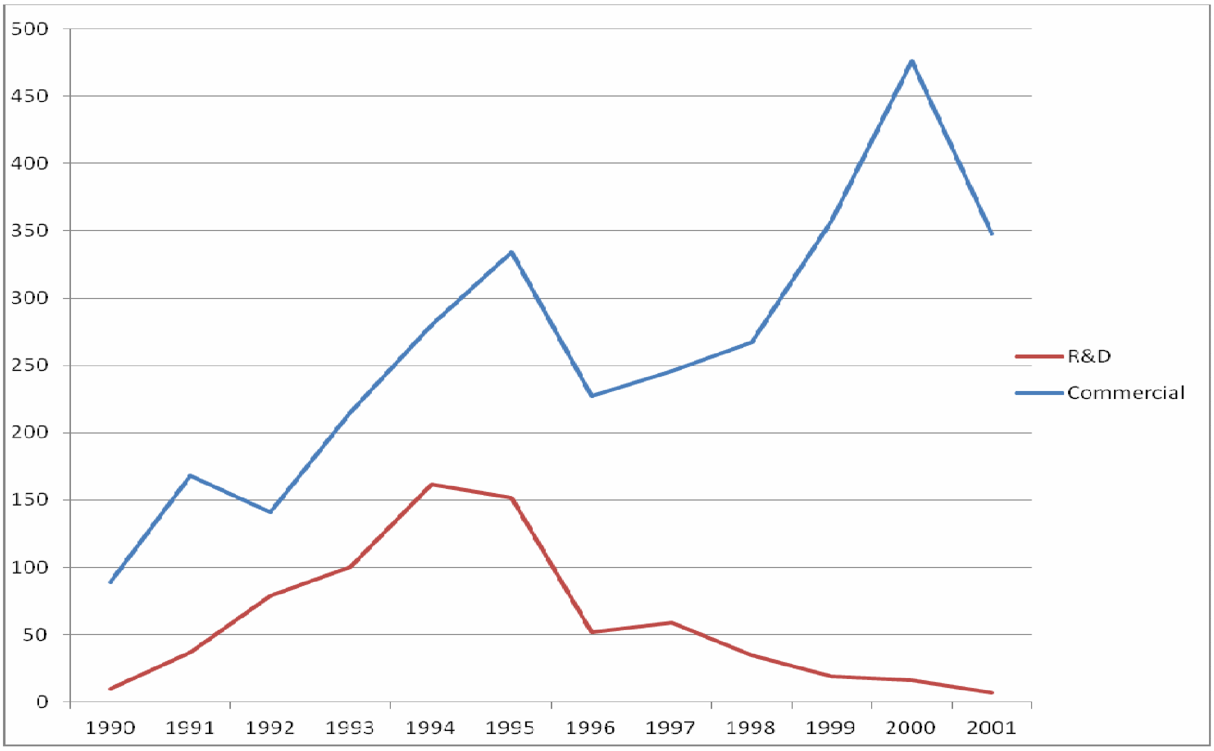
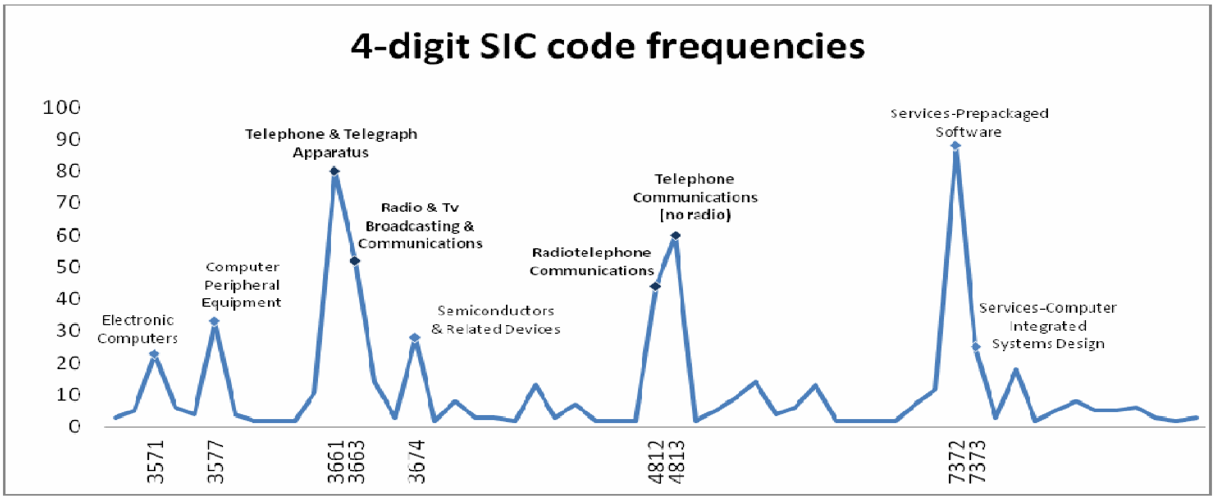


Figure 5 shows quite clearly the reason why we selected the period 1991-2001 for our analysis. From the point of view of R&D tie formation, this decade corresponds to a network cycle. In 1990, the number of newly established R&D agreements was 10. After that year, the number of new alliances growth significantly each year, reaching the peak of 162 newly formed agreements in 1994. From that year on, we observe instead a negative trend. In 2001, the number of new agreements was 7, remaining at these low levels also in the following years.

Consistently with our argument in Section 2, this period, and then the network cycle, corresponds to an era of great technological ferment in telecommunications. Contemporaneous to the processes of market liberalization, which in the US found their crucial passage in the 1996 Telecommunications Act, these years saw the full development of the Internet era. In 1990 the first incarnation of the World Wide Web was introduced. In 1993 we observed with the development of the first user friendly internet interface, i.e. Mosaic, the first World Wide Web Browser. In 1994, the first *commercial* web browser (Netscape Navigator) was launched, marking the shift from the academic[1], technological development to the commercial one (Fransman 2003).

In terms of firms,[1] our sample include 709 firms distributed over 88 different 4-digit SIC-codes. The distribution of firms by primary SIC code is represented in Figure 6. The great heterogeneity of areas of activity (and technological capabilities) perfectly exemplifies the recombinatory process that determined the emergence of the new technological paradigm in telecommunications.

Figure 6: Distribution of firm primary SIC codes in our sample

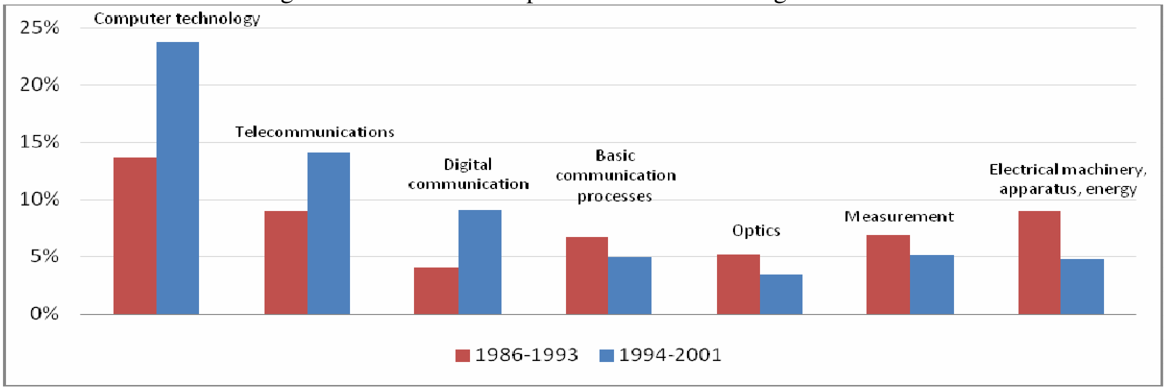


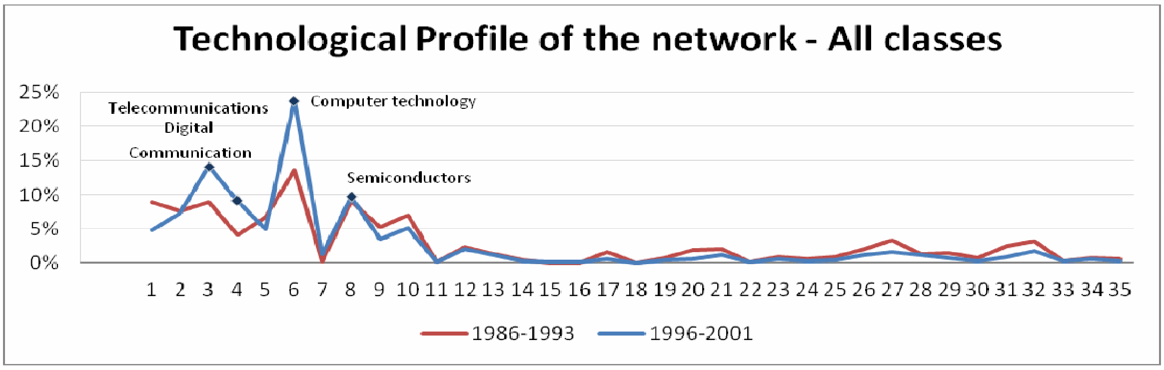
In addition to alliances data, we also collected and used data on firms' attributes. First of all, to measure technological knowledge we used patent data which are a valid and robust indicators of knowledge creation (Trajtenberg 1987), especially in environment like the telecommunication industry where the propensity to patent is significantly is high (Cohen et al. 2000). Even if primarily patents represent a codifiable portion of a firm technical knowledge, yet they correlate with measures of tacit knowledge (Brouwer and Kleinknecht, 1999). Data on patents were obtained from Patstat and only derives from the USPTO. Using data from a single source increase consistency, reliability and comparability across firms and we select the U.S. patent office for a number of reason. The first reason concerns the high quality of the service provided, not only in terms of the rigor and procedural fairness used in the granting process, but mainly due to the reputation of the USPTO for providing effective intellectual property protection (Pavitt, 1988). Second, firms have strong incentives to obtain patent protection in the world's largest market for high tech products. We chose the application date rather than the grant date since the actual timing of the patented inventions is closer to the application date than to the (subsequent) grant date. This is so because inventors have a strong incentive to apply for a patent as soon as possible following the completion of the innovation (Hall et al., 2001). Because patents are often assigned to subsidiaries, coherently with what we did in the sample we aggregated patents at the ultimate parent level.

In the sample 432 (61%) firms have at least one patent in the period considered. Overall, we count 342,452 patents in all the 35 IPC classes. Figure 7 reports the share of patents in the most represented technological classes, distinguishing between the early period 1986-1993 and the late period 1994-2001. Over the two periods it is immediate to notice a shift toward the new technologies, with computer technologies and digital communication doubling their relative weight. At the same time, we observe a tendency of technological specialization of the network: the heterogeneity in terms of patents drastically decrease and the distribution tends to shrink around few classes. Both facts are consistent with a process towards maturity in the technological development.

[1] Since in the SDC database subsidiaries are listed separately from parent firms, we aggregated firms at the ultimate parent level.

Figure 7: Distribution of patents across technological classes





Our choice of not limiting the analysis to large, leading firms but also to include small, young firms which actively participated in the development of the technology, but might exit from the industry soon after their alliance, because of acquisition or other reason, has a drawback in terms of availability and reliability of economic and financial data, such as size or R&D investments. For that reason, our main effort has concerned the collection of the foundation dates for all the firms in the sample, which is the other firm attributes we will use in our regressions. Several sources has been used. For the most important corporations the main source is the official web site. For the smallest companies two strategies have been employed. A preliminary research has been made using dedicated search engines.[2] Secondly we used the information reported in the original article to track back the name of the key CEO, that in most cases coincided with the founder. We cross-referenced this last piece of information with http://www.linkedin.com/, and often we found in the resume the establishment date of the founded company we were looking for. We lack information on the foundation for 103 firms over 738.

3.2 Dependant Variable and Case Control Design

Our empirical research addresses how the determinants of tie formation change over the evolution of the network, so we model the probability that a specific couple of firms enter in an R&D agreement (as we define it in the previous section) as a function of a set of covariates. Since the unit of analysis is the dyad-year, we coded a dichotomous variable for any given year which takes value equal to 1 if the two firms sign an agreement 0 otherwise.

[2] In particular, www.bbb.org (Council of Better Business Bureaus), http://investing.businessweek.com, http://www.crunchbase.com,http://business.highbeam.com/, http://companydatabase.org, www.allbusiness.com/, http://www.manta.com, http://www.referenceforbusiness.com.

The problem in this kind of setting is decide how to define the zeros, the potential dyads that did not realize. The first step was to define a risk set, i.e. the firms that were likely to participate in the network: for every year we include in the risk set all the firms that in that year entered at least one alliance. The drawback of this strategy when the network has a large number of nodes, like in our case, is that considering all the potential dyads (even if year by year), generates enormous sparse matrices hence increasing the difficulty of estimation and variable construction (since the variable is at the dyadic level). In particular it does not correctly account for non-independence across cases, as each firms enter in the analysis many, many time. The large number of repeated occurrences of each firm can lead to systematic underestimation of the standard errors for firms attribute that do not change from dyad to dyad (Sorenson and Stuart 2001). In our samples 685 alliances generates 995 realized dyad and over 1.1 million of potential unrealized ones. To deal with this issue, in line with other prior research (Sorenson and Stuart 2001), we adopt a case-control approach: for every realized dyad-year we randomly select 2 potential dyad that did not realize from the risk set of the same year. A first remark on the sampling strategy: our choice respects King and Zeng (2001) suggestion not to collect more than 2-5 times as many 0s as 1s because the marginal contribution to the explanatory variables information content for each additional 0 starts to drop as the number of 0s passes the number of 1s.
The use of a matched sample introduces a new problem. Logistic regression can yield biased estimates when the proportion of positive outcomes in the sample does not match the proportion of alliances in the populations. Because logistic regression is a multiplicative model the bias does not simply affect the intercept term. Rather, bias can affect all coefficient estimate. In particular, uncorrected logistic regression using a matched sample tends to produce underestimates of the factors that predict a positive outcome (King e Zeng 2001). We correct this potential bias using the method proposed by King and Zeng implemented by Tomz in the relogit Stata Procedure (Tomz et al.,2003).

3.3 Explanatory Variables

3.3.1 Network construction and network variables

To compute the network related variables, we constructed yearly adjacency matrix representing the relationship between actors in the network. Since the data lack information about the termination of the alliances we assumed a five year moving windows for alliance duration hence each adjacency-year comprehend all the dyadic relations that took place in the prior 5 years. This choice reflects the findings from prior research that suggests that the lifespan for alliances is usually no more than five years (Gulati, 1995). The first year for which we have data on alliance (1990) does not enter in the regression and was only used to construct the initial network for the 1991 risk set. The following structural measures were computed: distance between the nodes in the dyad and centrality measures.
The distance is defined as the shortest path between the two nodes and, clearly, is defined only for those pair of firms for which both participants are present in the network the year prior to the alliance (i.e. incumbent in the network). To overcome this problem we translated the distance in a series of dummy variables that could account for the issue of disconnected firms. For incumbents we coded three variables

- *Direct Tie* – equal to 1 if the distance equal 1 (meaning that the two firms formed a prior direct tie), 0 otherwise
- *Indirect Tie* – equal to 1 if the distance equal 2 (indirect tie), 0 otherwise
- *Not Con* – equal to 1 if the pair is formed by two incumbent in two different disconnected components, 0 otherwise.

We then create another variable to assess the effect of being a new possible dyad in the network, for which the distance is undefined, rather than an already possible one (composed by two incumbents in the network). *New Dyad* is set to 1 if at least one of the member in the dyad is new to the network (i.e. never entered in an alliance), 0 otherwise.

To assess if the network is characterized by homophily, i.e. the tendency of firms to ally with firms with a similar status in terms of centrality, or social asymmetry (Ahuja et al. 2009), we moved from the dyadic level to the ego-network of the single firm: degree asymmetry is coded as the absolute value of the difference between the normalized degree centrality of the two firms

3.3.2 Technological variables

In our hypotheses technology is an important determinant of tie formation, in particular technological proximity between firms. We measured it by using Jaffe's index. Consider firms as located in a multidimensional technology space, captured by a K-dimensional vector ($f_i=[f_{i,1},....,f_{i,K}]$ where $f_{i,j}$ represents the fraction of firm i's in patent class j. To measure the *technological proximity* ($p_{i,j,t}$) of firm i and j, the Jaffe's index is defined as the angular or uncentered separation of the vectors for firm i (f_i) and firm j (f_j) at time t. This proximity measure has the following properties: it takes value 1 for firms whose positions vectors are identical, it is zero for firms whose vectors are orthogonal, and it is bounded between 0 and 1 for all other pairs. In other words, it is closer to unity the greater the degree of overlap of the two firms research interests (Jaffe, 1986). This distance is correctly defined only when both the firms in the dyad have at least one patent. Since only around 60% of our sample has a positive number of patent we interact the technological proximity with a dummy variable, *Patenting Dyad,* coded as 1 if both firms patent.

3.3.3 Age composition of the dyad

To investigate whether in the two different periods the entry of young firms enhance the probability of concluding an agreement we introduced the variable *young* which is defined as the age of the youngest firm in the dyad.

4. RESULTS

Table 1 reports the results. We consider three models, with different explanatory variables. For each model, we run two separate regressions, one for the early period of network evolution (t≤1993) and one for the late period (t≥1994).

INSERT TABLE 1 HERE

First, we comment upon the explanatory variables related to the endogenous mechanism of network evolution. In line with previous literature, both the variable *Direct Tie*, measuring familiarity between partners, and *Indirect Tie*, measuring the existence of a common acquaintance, have usually a positive and significant effect on the likelihood of tie formation (the exceptions being *Direct tie* in the early period of Model 2 and Model 3 and *Indirect tie* in the early period of Model 1). More interestingly in our view is the comparison between the early and the late period. In any model, the effect of *Direct Tie* is of larger magnitude in the later period of network evolution. One way of interpreting this result is that the effect of "familiarity" may be characterized by a sort of increasing returns: the more two firms have collaborated in the past, the more they trust each other and build those communication codes and routines that favor collaboration. For the variable *Indirect Tie*, instead, the coefficient is larger in the first period (except in Model 1, where the two coefficients are rather similar). One of the effect that the variable is usually said to capture is the informative advantage in the search process for new partners. In that interpretation, one could argue that when the network is mature, the informational asymmetries among firms that are incumbent in the network are less severe, and then less important is the role of common partners.

The variable *New Dyad* is not significant in the early period of network evolution, but it is always significant with a positive coefficient in the second period. In other words, consistently with our argument developed in Section 2, new entry in the network is favored when the network (and the technology) is mature, and variety is preserved by firms exploring new technological trajectories.

As for the variable *Not Con*, belonging to different components turns out to have a significant negative impact on the probability of tie formation, both in the early and the late period of network evolution (although the effect is larger, in absolute value, in the second period, which may be explained by the fact that in this period there exists one component, the main component, which is very large compared to the others).

Finally, the variable *Degree Asymmetry* has a positive effect on tie formation.

We turn now on technological variables. The fact that the two firms have both positive stock of patents has a positive impact in the first period, and a non significant (and negative) effect in the second period. Once again, this is line with our appreciative theory: in the mature phase, entry in the network is possible even for firms that do not have (yet) accumulated a relevant stock of valuable knowledge (partially the result can also be due to the greater importance of software firms, they often do not patents).

The variable *TechProximity* has always a positive impact on the probability of tie formation, and such impact is larger in the second period: when the technology is mature, collaboration is more of exploitative nature, and firms tend to collaborate with more similar firms. The square terms for this variable are never significant.

The last variable in the regressions, *Young*, has a positive and significant coefficient in the first period, and negative, but still significant, in the second period. The interpretation of this result is consistent with the explanation for the variables *New Dyad* and *Degree Asymmetry*, and again, with our appreciative theory: while the agreements in the early phase of network evolution typically involves established firms, entry into the network for young firms is easier in the mature phase.

5. CONCLUSIONS

Relying on the existence of cyclical behavior in the process of R&D network evolution, this paper has argued that the role of the various determinants of tie formation may be expected to vary over time, depending on the stage of technology evolution. Our theoretical hypotheses have found confirmation in an empirical analysis on technological agreements in telecommunications in the period 1991-2001. Particular attention has been attributed to characteristics of new entrant into the network. While firms entering early into the network are typically established firms, new firms find easier conditions of network entry in the mature phase of network evolution, when they can provide incumbents specific knowledge assets.

The analysis so far can clearly be strengthened. For instance, the simple distinctions in two periods of network evolution may be regarded as a bit arbitrary and more formal tests could be tried in order to find the "structural break" in the determinants of tie formation. Nevertheless, we think we made a contribution, both conceptual and empirical, to the ongoing development of a full-fledged theory of network evolution applied to interfirm technological level, which is still lacking and would be important both at the managerial and policy level.

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Tab 1: Rare event logit models of the likelihood of a pair of firm entering in an R&D alliance

	Model 1 t≤1993	Model 1 t≥1994	Model 2 t≤1993	Model 2 t≥1994	Model 3 t≤1993	Model 3 t≥1994
Direct tie	1.111*	2.236***	1.092	1.999***	1.094	2.069***
	(0.646)	(0.379)	(0.700)	(0.397)	(0.700)	(0.405)
Indirect Tie	1.349	1.408***	1.597*	1.159***	1.549*	1.170***
	(0.838)	(0.266)	(0.904)	(0.261)	(0.921)	(0.262)
Not Con	-0.748**	-1.322***	-0.615*	-1.166***	-0.600	-1.177***
	(0.363)	(0.211)	(0.369)	(0.215)	(0.371)	(0.216)
New Dyad	-0.207	0.443***	0.136	0.863***	0.113	0.876***
	(0.309)	(0.129)	(0.319)	(0.137)	(0.321)	(0.137)
Degree Asymmetry	0.057**	0.357***	0.040*	0.309***	0.041*	0.322***
	(0.023)	(0.027)	(0.024)	(0.029)	(0.024)	(0.030)
Patenting Dyad			0.421**	-0.271	0.393*	-0.258
			(0.208)	(0.193)	(0.208)	(0.193)
Tech Proximity (Interaction)			2.257**	3.475***	2.281**	3.494***
			(1.060)	(0.870)	(1.061)	(0.873)
$(\text{Tech Proximity})^2$ (Interaction)			-1.337	-1.283	-1.340	-1.365
			(1.160)	(0.866)	(1.159)	(0.871)
Young					0.006**	-0.012***
					(0.002)	(0.003)
_cons	-6.750***	-7.553***	-7.466***	-8.160***	-7.542***	-8.022***
	(0.300)	(0.126)	(0.324)	(0.143)	(0.329)	(0.145)
N	1610	3425	1610	3425	1592	3379
ll						
df_m	5	5	8	8	9	9
aic	.	.	.	.	.	.
bic	.	.	.	.	.	.

Standard errors in parentheses
* p<.10, ** p<.05, *** p<.01