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Location and R&D Alliances in the European ICT Industry

By

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Abstract:
This paper shows empirically that in an intra-industry oligopolistic scenario the location of a firm’s innovative activities plays an important role in determining its partner selection in R&D alliances. Such a role is mainly attributed to a strategic use of R&D alliances as a means to limit knowledge flows and protect competences, rather than to promote knowledge flows. By drawing on a novel dataset matching alliances and patent data for the European ICT industry, the econometric analysis shows that partners’ prior co-location (at both national and sub-national regional level), previous ties and technological overlap matter in the choice of partner, while common nationality has a negative impact on alliance formation.

Key words: Alliances, strategy, efficiency, R&D location

Jel codes: D23, F23, O18, O32, R3

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1. Introduction

This paper seeks to investigate whether and why firms operating in the same industry that already co-locate their industry core R&D activities may also engage in R&D alliances over time.

A large body of studies in the organisational, managerial and economic realm have addressed the issues of alliances determinants. Within these studies, transaction costs and competence arguments have dominated the scene. Transaction cost-based analyses have understood inter-firms partnerships as a means to solve hold-up problems and opportunistic behaviour (Williamson, 1991; Hennart, 1998; Kogut, 1998), while the competence-based perspectives draws heavily on the synergistic argument according to which inter-firm partnerships are a means to access new complementary knowledge for the sake of partners’ technological development and learning (Hagedoorn, 1993; Dyer and Singh, 1998; Inkpen, 1998). However, these large bodies of literature have neglected the spatial aspects associated to partner selection choice. An exception in this scenario is, to some extents, the strategic management-oriented literature which has dealt with the spatial aspect only indirectly, in terms of firms’ network position in order to analyse knowledge flows in the context of inter-firm partnerships (e.g. Hagedoorn et al., 2006).

We argue here that the geography of innovative activity has significant implication for partners’ selection over time, especially in intra-industry analyses where the proprietary aspects of knowledge may complicate strategic competitive interactions. Our focus is on the European information and communication technology (ICT) hardware industry, which is an oligopolistic, R&D intensive sector, where rival firms often do not generally seek spatial proximity for the development of industry core fields of R&D activity. Indeed, there is a tendency to avoid co-location of R&D activities to minimise the loss of technological advantages due to externalities to rivals (Cantwell and Santangelo, 2002). However, when such co-location does occur because of, for instance, location-bound assets, firms do engage in R&D alliances. Our discussion here sheds light on the reasons firms may engage in cooperation as a way of primarily protecting their assets, by carefully planning and monitoring knowledge flows.

We utilise an original dataset developed by merging the MERIT-CATI database on strategic technological partnerships with data on US patents. This enables
us to jointly consider corporate strategic partnering and R&D location at both national and sub-national regional level in the context of the European ICT hardware industry. Strategic technology partnering (STP) as used here refers to inter-firm cooperative agreements which affect the long-term product-market positioning of at least one of the firms involved (Hagedoorn, 1993).

The argument is developed into 6 sections. Section 2 sets the theoretical framework and hypotheses. In section 3, the construction of the dataset and the sample of analysis are illustrated. Section 4 discusses the specification of the econometric models and the variables adopted. The results are reported and discussed in section 5, while section 6 draws some brief conclusions.

2. Theoretical framework and hypotheses

Traditionally, competence-based and transaction cost approaches have provided concurrent interpretations of STPs and their determinants (Dunning, 1995; Madhok 1997). The competence-based literature (Hamel, 1991; Hodgson, 1998; Kogut, 1998) has understood STPs as a matter of promoting inter-firm learning by accessing complementary types of technology in order to enrich the firms’ innovatory and learning process rather than to enhance the overall prosperity of the partners (Hagedoorn, 1993; Chesnais, 1988; Cantwell, 1998; Coombs and Metcalf, 1998; Dyer and Singh, 1998; Inkpen, 1998; Miotti and Sachwald, 2003; Cassiman and Veugelers, 2006). The transaction cost scholars focus on efficiency considerations and the benefits alliances yield in mitigating contracting problems (Glaister and Buckley, 1996; Gulati and Singh, 1998). According to this literature, the advantage in adopting alliances lies in the minimisation of the sum of production and transaction costs due to appropriability hazards inherent in the development, transfer and exploitation of technological knowledge and in its failure-prone characteristics (Caves, 1982). Therefore, the choice of partnering is driven by the joint value maximisation in the sense that firms jointly decide how much to commit to a collaboration depending on their motivations and partner’s characteristics so as to maximise the expected pay-off of the alliance.

Recent attempts to reconcile such perspectives (e.g. see Colombo, 2003) show that valuable complementary insights can be gathered from both transaction costs and competence-based perspectives. Indeed, contractual and competence arguments are
now recognized as connected building blocks for the formulation of a general theory of the firm (Foss, 2003; Foss and Foss, 2005) and, therefore, for the understanding of the determinants of inter-firm partnerships. Similarly, viewing inter-firm collaborations as driven either by mere efficiency (e.g. cost and risk sharing, mutual specialization tasks, consolidation of production capacity) or mere strategic (e.g. entry into a growing business, entry into a new geographical market, developing new capabilities) considerations, is reductive and may miss some major points of inter-firm interactions (Madhok, 1997). Strategic partnering is not just about complementary technologies and the spreading of risk: it is about improving the long-term product-market positioning of the firms, or indeed simply maintaining their product-market positioning. Strategic partnering affords firms a chance to (temporarily) pre-empt competition, in addition to allowing the partners to evaluate the capabilities of the partner firm. Besides which, co-opting competition can also reduce risk. Take the situation where two firms in the same industry are pursuing an important new breakthrough. Neither can be certain that they will win the race to innovate. As such, it may be in their best interest to collaborate, thus ensuring both that they are jointly 'first': half a pie may be considered better in conditions of uncertainty while there is a probability that there may be none at all (Dunning and Narula 2004).

Both the competence and transaction costs approaches tend to neglect the direct role of geographical location in determining the choice of partners in R&D alliances. However, research into networks and organizational learning has indirectly brought location into the picture as the underlying factor explaining that being part of the same spatially localized social network reduces opportunistic behavior and improved knowledge transfer, because partners are “likely to have a greater awareness of the rules, routines, and procedures each follows” (Gulati, 1998, 304). Thus, industry-specific, technological and absorptive capacity issues are tempered by concerns about how cooperative agreements are affected by past partnering experience, and how relationships between partnering firms depend upon a common culture and institutional setting, among others, both of which build up inter-organizational trust (Gulati, 1998; Gulati et al. 2000). The spatial aspect has also been evaluated in terms of compatibility of organisational cultures and social networks which reflect the culture of partners’ location, and these themselves are shaped by the nature of the polity, and the social and economic institutions of that
location (Granovetter, 1985). The discussion of knowledge flows between firms engaged in cross-border joint ventures, likewise, emphasises the notion of relational embeddedness in tempering the process of learning (Kale et al. 2000, Lane et al. 2001, Dhanaraj et al. 2004) by acting as a facilitator in the transfer of tacit knowledge between firms (Dhanaraj et al. 2004).

However, these arguments fail to make the explicit link between spatial location and the choice of partners in R&D alliances, despite considerable research that emphasises that innovative activities of firms are very much dependent on location-specific characteristics (Narula and Zanfei, 2005; Iammarino and McCann, 2006). The general view is that the technological competences of firms tend to be associated with specific locations, and that this changes relatively slowly over time (Cantwell, 1989; Cantwell and Iammarino, 2003) because firms are often ‘locked-in’ to relationships with suppliers, customers and knowledge infrastructure through formal and informal institutions that have taken years to evolve (Narula, 2002). Thus, there tends to be a preference for innovative activities to be associated with specific location-bound assets, which may or may not include quasi-public goods provided though universities and public research institutes (Asheim and Gertler, 2005; Iammarino and McCann, 2006), and, thus to be spatially concentrated (Almeida and Kogut, 1997; Saxenian, 1994).

It should be noted that a discussion of the importance of location requires us to recognise that the benefits of co-locating production or innovation are not unambiguous. The tacit nature of knowledge associated with production and innovation activity implies that “physical” or geographical proximity eases knowledge transmission (Blanc and Sierra 1999). Knowledge spillovers tend to be more intense between parties that are located close to each other in space (e.g., Jaffe et al. 1993; Jaffe and Trajtenberg 1996, 1998; Jaffe et al., 1998; Maurseth and Verspagen, 2002). If this leads to the clustering of innovation activities, it also implies potential threats to competitive advantage by co-located rivals, unlike the unambiguous beneficial effects claimed by Porter’s (1990) theory (see also Bell (2005)). Empirical evidence has shown that the involvement of firms in clusters is extremely sensitive to the nature of the industry structure in which the firm operates (Cantwell and Kosmopolou, 2002). That is, firms operating in the same R&D-intensive oligopolistic industry tend to spatially separate their core innovative activity (Cantwell and Santangelo, 2002). Unintended knowledge outflows from a firm can be quite valuable to its direct
competitors and can therefore be important not to locate close to rivals (Ibid.), or it may result in an adverse selection of co-located firms (Shaver and Flyer, 2000). When, however, the local system provides a combination of factors that contributes to innovation (such as skills, finance, production, user-producer linkages), the fear of knowledge spillovers to competitors may be counterbalanced by location-bound (i.e., associated with firm specific advantages) or location-specific factors, and intra-industry spatial concentration then takes place.

However, this raises an important question: If firms in the same oligopolistic industry are co-locating their core innovative activities, but would rather be spatially separated, why would they engage in R&D alliances with each other over time? One reason to engage in an alliance might be for the partners to plan and manage knowledge outflows and inflows to and from co-located rivals. Firms are unable to properly protect their technological assets which they intentionally or unintentionally share with their neighbours, even though formal property rights have been obtained. This is particularly the case when they are geographically close since, while the marginal cost of transmitting codified knowledge across geographic space does not depend on distance, the marginal cost of transmitting tacit knowledge increases with distance (Criscuolo and Verspagen, 2006). The co-location of innovation activities therefore implies potential threat to competitive advantage of co-located rivals. This argument applies especially to alliances between firms operating in the same industry and core technological fields. In such cases, the need for closely monitoring knowledge transmission is greater, the higher the degree of competition, since co-located rival firms with technologically similar profiles compete both in the output market and the technological realm. Therefore, in these cases partnerships enable firms to directly monitor their co-located market and technological rivals as well as to access to possible complementary capabilities:

H1: The likelihood of concluding an alliance with technological similar firms is greater for pairs of firms that have previously co-located their R&D activity in the core fields of their own industry.

Traditionally competence-based view has identified one of the main determinants of partnering as technological complementarity. Indeed, the dynamic capabilities approach (e.g., Teece and Pisano, 1994; Teece et al., 1997) contends that a pre-requisite to successful inter-firm learning through STPs requires the partnering firms to have an appropriate level of absorptive capacity in the appropriate
competence areas (Lyles and Salk, 1996; Simonin, 1999; Lane et al. 2001), and this implies some similarity in technology profiles. Therefore, it helps if partners firms have a similar general set of prior knowledge so that they can successfully interpret each other’s knowledge, and adjust it to their own context (Mowery et al., 1998; Cantwell and Colombo, 2000; Santangelo, 2000). For these reasons, firms in high tech sectors showing similar research interests are more likely to enter STPs, in which the interaction between partners’ paths of innovative learning enhances their own respective internal development. Thus,

\[ H2: \text{For technologically similar firms, the likelihood of concluding an alliance increases the greater the degree of overlap between their technological profiles.} \]

From a transaction cost perspective, sharing the same institutional context and a common organizational culture allows for greater bandwidth (Heiman and Nikerson, 2004). As argued by Vasudeva (2005) not only must firms have technological and organizational complementarities, there must also be complementarities in the institutional environment for an alliance to be successful. It is important to distinguish between the overlap in institutional context between the nationality of the firm, and the location of its R&D activity. Increasingly, these are not the same (Narula and Zanfei, 2005), and in a globalising world, the R&D facilities of the MNE are not always located at ‘home’. Therefore, we hypothesise that

\[ H3: \text{The likelihood of concluding an alliance is greater for pairs of firms with a common nationality of ownership.} \]

Firms are ‘sticky’ in their choices of hierarchical and network relationships within their milieu. Accordingly, scholars interested in the social network perspectives hypothesise that if a firm were to seek to engage in STP – assuming the appropriate technological congruence that creates the basis for a fruitful knowledge exchange – it might be inclined to select a partner with which they already have some level of relationship capital. Firms’ partner selection often reflects pre-existing relationships and associations also based on interactions which come from a time were firms were more “sticky” than “slippery” (Markusen, 1995). Although alliances and the creation and maintenance of a large network of partners are costly, and firms seek to ‘slim down’ their portfolio of partners to exclude relationships that – while historically important – have become redundant, considerable work in network theory suggests that firms prefer to ally with those firms with whom they have had previous association (Gulati, 1998; Powell and Grodal, 2005) because the market for
information about potential partners – while improving – is still imperfect. Indeed, Gulati (1998) argues that identifying appropriate partners is driven as much by economic advantage as it is by safety. Therefore,

**H4: The likelihood of concluding an alliance is greater for pairs of firms which have previously engaged in an alliance.**

### 3. The data

We use a unique dataset which lies at the intersection of the Reading patent database and the MERIT-CATI database on R&D alliances.

The Reading database records patents granted to 784 of the world’s largest industrial firms in the US between 1969 and 1995. In the database, each patent is classified by the year in which it was granted, the type of technological activity with which it is primarily associated, the location where the R&D activity was conducted and the company to which the patent was granted. Thus, following the USPTO scheme, all patents recorded are classified into 399 original patent classes, of which 30 are ICT patent classes. The location in which the R&D activity was carried out is provided by the patent records through the address of the inventor, and can be separated from the location of the headquarters of the parent company to which the patent is ultimately assigned, which can be inferred through the corporate consolidation of patents. This allows us to conduct the spatial analysis of large corporate research activity at national level and, for European countries, at sub-national regional level. For each of these countries, the sub-national regional entities identified correspond to territorial units as classified by the European Nomenclature of Territorial Units of Statistics (NUTS). Mergers and acquisitions are recognised in the data through the practice in most groups of centralising the patent application procedure in the parent company. In other important cases affecting the ultimate ownership of significant numbers of patents, the change in ownership structure has been incorporated into the organisation of the data, which in some cases involves the creation of a new corporate group and, in others, the expanded consolidation of groups with newly acquired subsidiaries.

The MERIT-CATI database records information on over 10,000 cooperative agreements involving some 4000 different parent companies. The inter-firm agreements collected in CATI are those containing some arrangements for
transferring technology or joint research, while mere production or marketing joint ventures are excluded. The database adopts a standardised classification of agreements by recording several relevant inputs for each alliance such as year of establishment, time-horizon, duration and year of dissolution; capital investments and involvement of banks and research institutes or universities, field(s) of technology and modes of cooperation. The identity of the companies involved in each alliance, the group to which they eventually belong and their nationality is also known. Information technology industries account for a great share of the total number of agreements established by firms especially in the 1980s. Similarly, information technology (computers, industrial automation, telecommunications, software, microelectronics) is among the most important fields in terms of frequency. Information in the CATI database was collected through a literature-based alliances counting by consulting various sources such as newspaper and journal articles, books dealing with the subject, and specialised journals which report on business events.

We focus on 17 European firms from the world’s largest ICT hardware companies for which data on their patenting activity from 1978 to 1995 were available. This period was in turn broken into two sub-periods 1978-1986 and 1987-1995, which hereafter will be referred as \( t \) and \( t+1 \), respectively. The reasons for confining our attention to this period are twofold. First of all, in those years a global trend toward a greater adoption of inter-firm organisational forms of economic and innovative activity has been recorded worldwide (Gerlach, 1992; Dunning, 1995). Secondly, the overall period witnesses the rising of the European technological policy boosting the European ICT industry for the sake of global competition through a policy of subsidised R&D collaboration projects. Many EU-subsidised R&D programmes were aimed at achieving this renewed competitiveness, and indeed, were undertaken by most firms with a view to being able to compete on equal terms with US and Japanese firms. The availability of funds through the establishment of EU subsidised R&D programmes further enhanced the intra-EU collaborative efforts of European companies. Indeed, Hagedoorn and Schakenraad (1993) show that there was a concurrent rise in non-subsidised and subsidised R&D during the later half of the 1980s.

For the 17 firms identified, we then sought information on alliances in MERIT-CATI. Note that the data on alliances used in this paper are private, non-subsidised R&D alliances, and explicitly excludes alliances associated with the EU
framework programmes. For 14 of the 17 above-mentioned firms, comparable information on alliances and patents across the sub-periods under consideration were found. The final sample can be regarded as representative of the oligopolistic European ICT industry, and is composed of 3 computer firms and 11 communications companies.iii The oligopolistic nature of this industry can be traced back to the industrial policy of most European nations over much of the XX century granting monopoly or semi-monopoly status to national champions. In the run-up to the Single European Market programme, both firms and policy makers realised that a considerable restructuring was necessary if these MNEs were to be internationally competitive. Leading European firms had begun to cooperate by the mid-1980s (Mytelka and Delapierre, 1987; Mytelka, 1995). This cooperation in R&D was further enhanced by encouragement from the European Commission around this same period, with the commission establishing a ‘Big 12 roundtable’ to develop proposals for new collaborative R&D projects (Peterson, 1991). Despite of this major restructuring, the ICT industry has been mainly dominated by big firms which were the one that benefit most from the EU technology policy of the 1980s. In sum, over this period, the major European players in this already-oligopolistic sector repositioned themselves so as not compete directly amongst each other (Narula, 1999, 2001).iv

The 14 European firms concluded a total of 100 alliances (87% cross-border and 13% domestic), of which 75% involved communications companies only, 6% computer companies only and 19% both of them. Non-equity agreements are the primary form of cooperation in the sample, accounting for slightly more than 80% of the total number of alliances considered in line with a global pattern showing a greater preference for non-equity agreements (Narula and Hagedoorn, 1999, Hagedoorn 2002), especially in the ICT sector (Colombo, 2003).v Alliances between more than two firms are reduced to two-firm (dyadic) agreements by considering all possible combinations of the firms involved.

The geographical distribution of European corporate patenting activity in the ICT technological classes is investigated across Belgium, Germany, France, Italy, the Netherlands, Sweden, Switzerland and the UK and the related 82 sub-national regions, which host more than 98% of research carried out in ICT (Cantwell and Santangelo, 2002). The industry in question exhibits a strong spatial clustering around a few centres of excellence most likely showing some location-bound advantage that make them “sticky”. Table 1, which reports the share of R&D activity in core ICT
fields at both national and sub-national regional levels, clearly shows a pattern of
greater concentration at both geographical levels, although the number of sub-national
regional locations involved over time has increased.

***TABLE 1 ABOUT HERE****

4. The specification of the econometric models and the variables

The econometric analysis estimates discrete choice models on 91 observations
concerning the maximum number of individual linkages between the 14 firms.\textsuperscript{vi} We
utilise a binomial logit estimation.

4.1 Dependent variables

We focus on technologically similar allied firms, drawing upon recent empirical
evidence that measures the importance of firm’s knowledge base through patent data
(Mowery \textit{et al.}, 1996; Cantwell and Colombo, 2000; Santangelo, 2000). Although
patents are clearly codified knowledge, this approach contends that they indicate
corporate learning activity associated with the take-up of new products and processes
in technologically advanced production facilities. In other words, patents capture the
new knowledge associated with the establishment of tacit capability, which applies
such knowledge and makes it operational, and not just the creation of new codified
knowledge as such. Therefore, this literature argues for the complementarity of tacit
and codified knowledge. Following Jaffe (1986) for each pair of allied firms $i$ and $k$
we construct two technological position vectors for time $t+1$ as

\begin{align*}
F_i &= (f_{i1}, f_{i2}, \ldots, f_{i30}) \quad (1) \\
F_k &= (f_{k1}, f_{k2}, \ldots, f_{k30}) \quad (2)
\end{align*}

Where $f_{ij}$ and $f_{kj}$ represent the share of firm $i$ and $k$ in patent class $j$, respectively, (with
$i \neq k$). Technological similarity between firm $i$ and $k$ ($\omega_{ik}$) is, then, measured by the
angular separation or uncentred correlation of $F_i$ and $F_k$ as follows

$$
\omega_{ik} = \frac{F_i' F_k}{\sqrt{(F_i' F_i)(F_k' F_k)}} \quad (3)
$$
Where $\omega_{ik}$ is equal to 1 for allied pairs of firms whose position vectors are identical, is zero for allied pairs of firms whose vectors are orthogonal, and is bounded between 0 and 1 for all other allied pairs. On these grounds, we identify the subset of technological similar allied pairs of firms $i$ and $k$ by considering all allied pairs showing $\omega_{ik} \geq 0.5$, and set the dependent variable ($TECHSIMI_{ik,t}$) equal to 1 for allied pairs for which $\omega_{ik} \geq 0.5$, 0 otherwise.

4.1 Explanatory variables

Recognising that country level data is often too general for any meaningful level of spatial microeconomic analysis, we build a series of variables accounting for partners’ prior R&D co-location in ICT technological fields at both national and sub-national regional level. Drawing on the information provided by the patent document, prior co-location of R&D activity is proxied by:

- $COLOC_{ik,t}$ equal to 1 for pairs of firms $i$ and $k$ co-locating their R&D activity in the ICT patent classes in the same European countries at time $t$.
- $NUTSCOLOC_{ik,t}$ equal to 1 for pairs of firms $i$ and $k$ co-locating their R&D activity in the ICT patent classes in the same European sub-national regions at time $t$.

In order to ensure robust results, for each pair of firms $i$ and $k$ we also measure the intensity of prior co-location of partners’ innovative activities by

- $NCOLOC_{ik,t}$ equal to the number of countries hosting co-localised R&D activity in the ICT patent classes at time $t$.
- $NNUTS_{ik,t}$ equal to the number of sub-national regions hosting co-localised R&D activity in the ICT patent classes at time $t$.

We infer the degree of overlap of technological specialisation of each pair-wise combination of firms drawing on the information gathered from patent data. More specifically, for each firm $i$ at time $t+1$ we calculate the index of revealed technological specialisation in the ICT patent class $j$ (RTA). Let $P_{ij}$ be the number of US patents granted in a particular ICT patent class $j$ to a European ICT company $i$. Then, $RTA_{ij}$ is given by the following expression

$$RTA_{ij} = \frac{P_{ij}/\Sigma_i P_{ij}}{(\Sigma_j P_{ij}/\Sigma_{ij} P_{ij})}$$ \hspace{1cm} (4)

Only technological patent classes associated with ICT are considered. Thus, for each of the European ICT companies in the sample, $RTA_{ij}$ provides a measure of
technological specialisation in the ICT patent classes relative to all sample firms. Since the RTA index varies around unity, values greater than one suggest a technological comparative advantage of firm \( i \) in the selected patent classes, whilst values less than one indicate a position of comparative disadvantage in the classes in question. Then, the Pearson’s correlation coefficient (\( r_{ik} \) with \( i \neq k \)) was computed between the RTA distributions of any pair-wise combinations of firms \( i \) and \( k \) across the ICT patent classes. This coefficient measures the correlation between the patterns of technological specialisation of partner firms as captured by the RTA values. Positive (negative) correlation denotes greater similarity (dissimilarity) between the technological specialisation of each pair-wise combination of allied firms. Thus, for all pairs of firms \( i \) and \( k \) in the sample we proxy the overlap of technological specialisation by the Pearson’s correlation between the distribution of their RTAs at time \( t + 1 \) (\( TECHOVERLAP_{ik,t+1} \)). Given the complementarity between tacit and codified knowledge discussed above, the distribution of firm’s patents across ICT technological classes reflects the underlying distribution of technological capabilities. Therefore, the Pearson’s correlation coefficient between the RTA distribution of any dyadic combination of firms \( i \) and \( k \) (with \( i \neq k \)) across the ICT patent classes at time \( t + 1 \) is a proxy of the extent of overlapping of partner’s technological capabilities. This implies that \( TECHOVERLAP_{ik,t+1} \) reflects the capability of partner firms to absorb each other’s competences and knowledge.

As far as partners’ common culture and institutional context are concerned, we include a binary variable equal to 1 for pairs of firms \( i \) and \( k \) whose headquarters are located in the same country, 0 otherwise (\( SAMEHOME_{ik} \)). Considerable research has been conducted on the role of prior alliances in relation to the likelihood of partnering (Gulati, 1995; Gulati and Singh, 1998; Garcia Canal, 1996; Oxley, 1997, 1999; Colombo; 2003). Nonetheless, results are far from unanimous. To account for the establishment of previous alliances, we count the number of alliance each pair of firms \( i \) and \( k \) concluded at time \( t \) (\( STP_{ik,t} \)).

In order to control for differences in the internationalisation of R&D activity, for each pair-wise combination of firms \( i \) and \( k \) we also include a variable measuring the average share of patents granted for research conducted outside the home country of the parent (foreign patent share) at time \( t + 1 \) (\( INTR&D_{ik,t+1} \)). For each European ICT firm \( i \), the foreign patent share (\( FS \)) is defined as \( FS_i = \sum_j F_{ij}/\sum_j P_{ij} \), where \( P_{ij} \)
denotes the number of US patents granted in a patent class \( j \) to an European ICT firms \( i \), whilst \( FP_{ij} \) indicates only the number of US patents granted for research conducted outside the home country of the parent firm to \( i \) in the same patent class \( j \).

A summary of all variables adopted is provided in Table 2, while Table 3 reports the descriptive statistics and the correlation matrix.

***TABLE 2 ABOUT HERE***  
***TABLE 3 ABOUT HERE***  

5. Empirical findings

The results of the binomial logit models are reported in Table 4.

As far as partners’ location behaviour is concerned, the econometric results highlight that the likelihood of concluding STPs is greatly affected by prior geographical proximity of research activities in technologies core to a given industry both at the country and sub-national regional level. That is, co-location in core R&D fields was statistically positive significant as proposed in \( H1 \). This holds whatever the geographical level adopted whether the country (as capture by \( COLOC_{ik,t} \) and \( NCOLOC_{ik,t} \)) or the sub-national region (as captured by \( NUTSCOLOC_{ik,t} \) and \( NNUTS_{ik,t} \)). This seems to suggest that, when location-bound assets are important and firms are forced to be sticky with their competitors, co-located firms may engage in alliance formation in order to co-opt and monitor their competitors. In intra-industry R&D agglomerations, the need to protect their proprietary knowledge is dominant since geographical proximity eases knowledge transfer but may also consequently harm their technological competences. Firms need to deal with the fundamental dilemma of managing the tension between knowledge sharing and knowledge expropriation (Heiman and Nickerson, 2004). This is especially so in an oligopolistic industry where firms have a similar technological profile and the dangers of knowledge expropriation through unintended knowledge spillovers is high being the firms both market and technological competitors.

The results also confirm the significance of the competence-based considerations (\( H2 \)) such as technological overlap of firms’ competences (\( TECHOVER_{ik,t} \) throughout Model 1 to 4 in Table 4). Along the lines of previous
research (Mowery et al., 1998; Santangelo, 2000), the greater the overlap of partners’ technological specialisation, the greater the likelihood of an alliance between them for the purpose of technological co-operation.

Unlike our H3, SAMEHOME_{ik} is statistically negatively significant at \( p < 0.05 \) (Table 4), suggesting that firms are ready to take the risk of opportunistic behaviour and hold-up problems when selecting their partners since they prefer to partner with a firm coming from a different system than with a firm of the same nationality. As Narula and Hagedoorn (1999), among others, have noted, firms seek to select the best partner they can find in a given technological area, regardless of nationality. In selecting a partner, a firm has two choices when it seeks to acquire complementary assets through alliances. It can either choose between (say) a firm with which it shares a similar cultural and institutional setting, with which it has built up relational capital and whom it can trust not to be opportunistic. This would therefore be a firm with which it shares a common innovation system even though the learning potential may be lower. Alternatively, however, it can partner with a firm with a higher learning potential, which derives from a different system, but with whom there is a greater chance of opportunistic behaviour. In the latter case, the risk of hold-up problems may be offset by greater learning potential and opportunities to access to new complementary capabilities. Firms may be inclined to take the risk of opportunistic behaviour if they believe that there are chances to enhance their competence portfolio, thus seeking to identify the most appropriate partners from a technological point of view regardless of nationality. The fact that prior co-location of R&D is a positive determinant of the likelihood of R&D cooperation while nationality is a negative one should not be seen as a contradiction. Firms’ R&D facilities are not always located in the same country as their headquarters, (the correlation between COLOC_{ik,t} and SAMEHOME_{ik} is only a 0.38 – see Table 3). Therefore, the implied relational capital due to sharing a common home country institutional context is considerably less important for STP than sharing a common institutional context of their R&D location.

The existence of previous alliances between partner firms seems to affect the likelihood of concluding STPs, confirming H4. Therefore, the finding supports the view placing great emphasis on prior ties (Gulati and Singh, 1998). Although in the industry in question, the fast pace of technological change is characterised by continuous experimentation and re-combination, partners maintain their historically important network of alliances and relationships. It is worth noting that in high tech
sectors, strategic efficiency drives alliance partner selection much more, and in the long run there is limited need for redundant contracts (Kranenburg et al., 2006a). Indeed, the results of Sampson (2005) confirm this, showing that while existing ties are important, they are less important over time. The fact that having participated in previous alliances greatly increased probability of engaging in future ones indicates that even if EU subsidies were not available co-located firms would still cooperate, as a means to protect as well as enhance their technological assets. First, because if firms were to go it alone, they forgo the opportunity to observe what the other firms in the same industry are up to. Second, firms do not always have recourse to patenting as a means to protect new and rapidly evolving technologies, and often rely on co-inventing with a potential competitor (Levin et al. 1987).

6. Conclusions

Despite the number of in-depth studies on STP, our knowledge of the relationship between location and the propensity to engage in STP is still incomplete. While the strategic and efficiency issues have been widely studied in the literature, the role of location in STP – while acknowledged – have not hitherto been systematically investigated. This study, therefore, contributes to the literature on R&D alliance formation by explicitly accounting for geographical aspects within an industry that is highly geographically concentrated. To some extent, this can be seen as a contribution to the economics and management literature which has so far neglected the spatial dimension. The understanding of geography of location bears great implications for the competitiveness of both firms and local systems. Indeed, thus far, location has been presumed not to play a significant role in technology partnering (Cantwell and Iammarino 2003), and we have argued here that this may have to do with the importance nuance of differentiating between national context in terms of ownership, and that of institutional context of innovation, which are not always the same.

Furthermore, we have examined STP within a high-tech industry (such as ICT) where protecting and limiting knowledge flows is of equal - if not greater – strategic motivation for engaging in R&D alliances, compared to the more commonly discussed objective of enhancing knowledge flows. Our results suggest that when location-bound assets are important and firms are forced to be obliged to be spatially proximate with their competitors, co-located firms may engage in alliance formation
in order to co-opt and monitor their competitors. In interpreting these results, it is important to place them in the context of European ICT industry, and the fact that during the period in question the European Commission (through its Framework Programmes) was promoting R&D collaboration by public and private EU-based institutions – which, however, are not captured by our data – significantly relaxing anti-competitive regulations and providing subsidies to collaborative R&D so as to allow this sector to compete more effectively, both on world markets and within the EU (Peterson and Sharp 1998). The subsequent decline in the popularity of intra-EU alliances relative to EU-US alliances in this sector by the early 1990s (Narula 1999, Narula and Duysters 2004) reflects that this restructuring has largely been completed, with an even more oligopolistic structure, after a wave of acquisitions, divestments, and an adjustment of product specialisations by the main players.

From a policy perspective, there are two important implications that can be raised. First, creating regional systems of innovation and strong location-specific assets can promote agglomerative behaviour by firms, although not necessarily with the outcome conventionally associated with the co-location of rivals. That is, instead of increased knowledge flows between firms due to spatial proximity, firms can also utilise STP to monitor, gauge and control the strategic positioning of their technological profiles vis-à-vis their competitors. In other words, firms in an oligopolistic industry may follow the adage, ‘keep your friends close and your enemies closer’.

Second, the evidence reviewed here suggests that policies to promote industry restructuring of less competitive sectors, and those that are aimed at building stronger regional systems of innovation should not necessarily be seen separately. Although we do not have data on the nature and location of joint innovative activities, we venture to hypothesise that the familiarity with institutions associated with a common milieu promotes an inertia that has ramifications beyond spatial co-location.

The study suffers from some shortcomings. First, because we lack information on patent citations associated with specific alliances, we are not able to measure the extent of knowledge flows between firms. Second, our dataset does not include any information on the actual motives underlying individual alliances. Third, the results are gathered with regard to a particular industry over a very specific (and limited) period, and in this respect they may be industry- and context-specific.
References


Table 1 - R&D activity in ICT patent classes carried out by European ICT firms in European locations, 1978-86 and 1987-95

<table>
<thead>
<tr>
<th>Location</th>
<th>1978-86</th>
<th></th>
<th>1987-95</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>%</td>
<td>number of regions hosting co-location of R&amp;D in ICT</td>
<td>%</td>
<td>number of regions hosting co-location of R&amp;D in ICT</td>
</tr>
<tr>
<td>Germany</td>
<td>0.34</td>
<td>6</td>
<td>0.33</td>
<td>9</td>
</tr>
<tr>
<td>UK</td>
<td>0.16</td>
<td>8</td>
<td>0.15</td>
<td>9</td>
</tr>
<tr>
<td>Italy</td>
<td>0.01</td>
<td>0</td>
<td>0.03</td>
<td>3</td>
</tr>
<tr>
<td>France</td>
<td>0.29</td>
<td>5</td>
<td>0.23</td>
<td>10</td>
</tr>
<tr>
<td>The Netherlands</td>
<td>0.14</td>
<td>1</td>
<td>0.13</td>
<td>0</td>
</tr>
<tr>
<td>Belgium</td>
<td>0.01</td>
<td>1</td>
<td>0.03</td>
<td>2</td>
</tr>
<tr>
<td>Switzerland</td>
<td>0.01</td>
<td>1</td>
<td>0.01</td>
<td>2</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.05</td>
<td>1</td>
<td>0.09</td>
<td>3</td>
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<tr>
<td>Total</td>
<td>1.00</td>
<td>23</td>
<td>1.00</td>
<td>38</td>
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Table 2 - Variables description

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\text{TECHSIMI}_{ik, t+1})</td>
<td>equals 1 for similar allied pairs of firms (i) and (k) at time (t+1), 0 otherwise.</td>
</tr>
<tr>
<td>(\text{TECHOVERLAP}_{ik, t+1})</td>
<td>Pearson correlation coefficient between the RTA distributions across the ICT patent classes of any pair-wise combinations of firms (i) and (k) at time (t+1).</td>
</tr>
<tr>
<td>(\text{STP}_{ik,t})</td>
<td>number of alliance each pairs of firms (i) and (k) concluded at time (t).</td>
</tr>
<tr>
<td>(\text{SAMEHOME}_{ik})</td>
<td>equals to 1 for pairs of firms (i) and (k) whose headquarter is located in the same country, 0 otherwise.</td>
</tr>
<tr>
<td>(\text{COLOC}_{ik, t})</td>
<td>equals 1 for pair-wise combinations of firms (i) and (k) co-locating their R&amp;D activity in ICT patent classes in the same countries at time (t), 0 otherwise.</td>
</tr>
<tr>
<td>(\text{NCOLOC}_{ik, t})</td>
<td>number of countries hosting co-localised R&amp;D activity in ICT patent classes at time (t) for each pair of firms (i) and (k).</td>
</tr>
<tr>
<td>(\text{NUTSCOLOC}_{ik, t})</td>
<td>equals 1 for pair-wise combinations of firms (i) and (k) co-locating their R&amp;D activity in ICT patent classes in the same sub-national regions at time (t), 0 otherwise.</td>
</tr>
<tr>
<td>(\text{NNUTS}_{ik, t})</td>
<td>number of regions hosting co-localised R&amp;D activity in ICT patent classes at time (t) for each pair of firms (i) and (k).</td>
</tr>
<tr>
<td>(\text{R&amp;DINT}_{ik, t+1})</td>
<td>average value of the patent foreign share of each pair of firms (i) and (k) at time (t+1).</td>
</tr>
</tbody>
</table>
Table 3 - Descriptive statistics and correlation matrix of the explanatory variables

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<tr>
<th>Variables</th>
<th>Mean</th>
<th>S. D.</th>
<th>Min</th>
<th>Max</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
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<tbody>
<tr>
<td>1  TECHSIMI_{t-1}</td>
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<td>0.383</td>
<td>0</td>
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<td></td>
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<tr>
<td>2  TECHOVERLAP_{t-1}</td>
<td>0.063</td>
<td>0.257</td>
<td>-0.518</td>
<td>0.779</td>
<td>0.176</td>
<td>1.000</td>
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<td></td>
<td></td>
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<tr>
<td>3  STP_t</td>
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<td>1.013</td>
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<td></td>
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<td></td>
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<td>4  SAMEHOME_t</td>
<td>0.209</td>
<td>0.409</td>
<td>0</td>
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<td>-0.095</td>
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<tr>
<td>5  COLOC_t</td>
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<td>0.496</td>
<td>0</td>
<td>1</td>
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<td>0.168</td>
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<td>0.349</td>
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<td>7  NUTSCOLOC_t</td>
<td>0.462</td>
<td>0.501</td>
<td>0</td>
<td>1</td>
<td>0.325</td>
<td>0.287</td>
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<td>0.501</td>
<td>0.784</td>
<td>0.697</td>
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<td>8  NNUTS_t</td>
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<td>0.305</td>
<td>0.137</td>
<td>0.448</td>
<td>0.402</td>
<td>0.624</td>
<td>0.649</td>
<td>0.796</td>
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<tr>
<td>9  R&amp;DINT_{t+1}</td>
<td>29.453</td>
<td>17.406</td>
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<td>70.923</td>
<td>0.109</td>
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<td>0.077</td>
<td>0.109</td>
<td>0.139</td>
<td>0.246</td>
<td>0.325</td>
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Table 4 - Results of the binomial logit analysis (marginal effect, standard errors in parentheses)

<table>
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<tr>
<th>Variables</th>
<th>Model 1</th>
<th></th>
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<th>Model 4</th>
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<tr>
<td></td>
<td>dF/dx</td>
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<td>dF/dx</td>
<td>Z</td>
<td>dF/dx</td>
<td>Z</td>
<td>dF/dx</td>
<td>Z</td>
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<td>TECHOVERLAPik,t</td>
<td>0.251</td>
<td>2.350 **</td>
<td>0.268</td>
<td>1.960 **</td>
<td>0.191</td>
<td>1.790 *</td>
<td>0.283</td>
<td>2.320 **</td>
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<td></td>
<td>(0.107)</td>
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<td>(0.136)</td>
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<td>(0.107)</td>
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<td>(0.122)</td>
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<td>STPik,t</td>
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<td>0.060</td>
<td>1.310</td>
<td>0.054</td>
<td>1.820 *</td>
<td>0.042</td>
<td>1.390</td>
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<td>(0.029)</td>
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<td>(0.045)</td>
<td></td>
<td>(0.030)</td>
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<td>(0.030)</td>
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<tr>
<td>SAMEHOMEik</td>
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<td>-2.200 **</td>
<td>-0.109</td>
<td>-1.730 *</td>
<td>-0.134</td>
<td>-2.380 **</td>
<td>-0.146</td>
<td>2.450 **</td>
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<tr>
<td></td>
<td>(0.054)</td>
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<td>(0.063)</td>
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<td>(0.056)</td>
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<td>(0.059)</td>
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<td>COLOCik,t</td>
<td>0.192</td>
<td>2.880 ***</td>
<td></td>
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<tr>
<td></td>
<td>(0.067)</td>
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<td>NCOLOCik,t</td>
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<td></td>
<td>0.097</td>
<td>2.210 **</td>
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<td>(0.044)</td>
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<td>NUTSCOLOCik,t</td>
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<td>0.248</td>
<td>2.900 ***</td>
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<td></td>
<td>(0.086)</td>
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<td></td>
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<td>NNUTSik,t</td>
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<td></td>
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<td></td>
<td>0.077</td>
<td>2.170 ***</td>
</tr>
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<td>(0.035)</td>
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<tr>
<td>R&amp;DINTik,t+1</td>
<td>0.000</td>
<td>0.270 (-0.002)</td>
<td>0.001</td>
<td>0.270 (-0.002)</td>
<td>0.000</td>
<td>-0.200 (0.002)</td>
<td>0.000</td>
<td>0.000 (0.002)</td>
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<tr>
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<tr>
<td>No of obs.</td>
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<td>91</td>
<td></td>
<td>91.000</td>
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<td>91</td>
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<tr>
<td>Log pseudolikelihood</td>
<td>-32.658</td>
<td></td>
<td>-34.077</td>
<td></td>
<td>-32.039</td>
<td></td>
<td>-34.052</td>
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</tr>
<tr>
<td>Wald chi2(5)</td>
<td>15.360</td>
<td>***</td>
<td>16.24</td>
<td>***</td>
<td>16.75</td>
<td>***</td>
<td>17.79</td>
<td>***</td>
</tr>
<tr>
<td>Pseudo R2</td>
<td>0.228</td>
<td>0.1947</td>
<td>0.2429</td>
<td></td>
<td>0.1953</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**** p < 0.01  
** p < 0.05  
* p < 0.10
### Table A1 - List of companies in the sample (nationality of ownership in brackets)

<table>
<thead>
<tr>
<th>Company Name</th>
<th>Nationality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bosch (G)</td>
<td></td>
</tr>
<tr>
<td>CII-Honeywell Bull (FR)</td>
<td></td>
</tr>
<tr>
<td>Compagnie General d'Electricité (FR)</td>
<td></td>
</tr>
<tr>
<td>Genral Electric co. (UK)</td>
<td></td>
</tr>
<tr>
<td>LM Ericsson (SE)</td>
<td></td>
</tr>
<tr>
<td>Nixdorf Computer (G)</td>
<td></td>
</tr>
<tr>
<td>Olivetti (IT)</td>
<td></td>
</tr>
<tr>
<td>Philips (NL)</td>
<td></td>
</tr>
<tr>
<td>Plessey (UK)</td>
<td></td>
</tr>
<tr>
<td>Racal Electronics (UK)</td>
<td></td>
</tr>
<tr>
<td>Siemens (G)</td>
<td></td>
</tr>
<tr>
<td>Standard Telephone and Cables - STC (UK)</td>
<td></td>
</tr>
<tr>
<td>Thomson-Brandt (FR)</td>
<td></td>
</tr>
<tr>
<td>Thorn EMI (UK)</td>
<td></td>
</tr>
</tbody>
</table>

*Legend:*  
G: Germany.  
FR: France.  
IT: Italy.  
NL: The Netherlands.  
SE: Sweden.  
UK: United Kingdom.
The use of patenting in a common third country, that is, the US, allows a more reliable international comparison on a similar basis (e.g. Soete and Wyatt, 1983; Archibugi and Pianta, 1992). Furthermore, foreign patents (e.g. European) are expected to be of a higher quality than domestic patents (i.e. US), as it is reasonable to assume that only inventions and innovations with the highest expected profits will be patented abroad due to the time and costs involved in doing so.

In order to ensure as much comparability as possible, the NUTS 1 level is used to identify Belgian, Dutch, German and UK regions, while as far as French, Italian and Swedish regions are concerned, the NUTS 2 level is adopted. In the case of Switzerland, no NUTS subdivision is available for as Switzerland is a non-EU member. Therefore, in the Reading database, Switzerland is geographically subdivided in 12 regions according to proximity to big cities. Despite the aim of ensuring that comparable regions appear at the same NUTS level, the same level of disaggregation in various countries still implies considerable differences between regions in terms of area, population, economic weight or administrative power, and so it is necessary to choose the most appropriate NUTS level in each case to reduce the effect of inter-country differences in the classification scheme (Eurostat, 1995; Dunford, 1996). The 3 Belgian régions, the 4 Dutch landsdelen, the 22 French régions, the 16 German länder, the 20 Italian regioni, the 8 Swedish riksområden and the 11 UK standard regions seem to allow some comparability as far as innovative activity is concerned.

Companies were classified according to their primary field of production. A list of the firms in the sample is provided in Table A1.

To some extent, cooperation allowed these firms to reposition themselves vis-à-vis their competitors in Europe through the series of M&A that occurred in the run-up to the single market as well as the re-positioning of firms’ technological profiles (Mytelka 1995), and this was reflected in a decline in intra-EU alliances after the late 1980s, and a subsequent rise in cooperation with non-EU partners.

In this study, we focus both on non-equity forms of cooperation (such as joint research pacts, joint development agreements, R&D contracts, mutual second-sourcing agreements, second sourcing agreements, cross-licensing and complete merger of firms) and equity forms of cooperation (such as joint venture, research cooperation, minority holding and cross-holding).

The maximum number of individual linkages between the 14 European ICT firms is given by the algorithm \( \frac{N(N-1)}{2} \), where \( N \) is the total number of companies under analysis. This algorithm gives all the possible pair-wise combinations of allied companies above the diagonal of the matrix.

Thus, challenging the existing mixed evidence in this regard (Kale et al., 2000; Garcia Canal, 1996; Oxley, 1997, 1999a).