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ORGANIZING HIGH-TECH R&D – SECRETS OF SUCCESSFUL INNOVATION ALLIANCES

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ABSTRACT: We use the data compiled from the USPTO patent and patent citations concerning the patented knowledge intensive technologies in three areas: cryptography, image analysis and data processing/software. The data is restricted to those patents between the years 1980-2003 that have two or more assignees, i.e. we consider only joint patents. We find some evidence that technological or product market proximity of partners in R&D alliance matters but whether the closeness generates more or less valuable innovations depends on the technology field.

Our data further suggest that the most valuable innovations are generated when there is a certain level of prior patenting experience of the individual innovation partners. Interestingly, the prior patenting experience of the pairs of firms filing the joint patent does not seem to matter. It thus seems that learning from the prior joint patenting that creates more value for innovations is rather firm-specific than alliance-specific. Our findings on prior joint patenting experience generally hint that not only strategic benefits, and those benefits related to the management of joint patenting, can be gained from the R&D alliance experience.

1. Introduction

A firm's success and survival essentially depends on its ability to continuously adapt, develop and regenerate its business activities and product assortment. Reliance on a self-sufficient approach in R&D rarely endures as a viable way for a firm to organize its innovation process – the exploitation of external knowledge and collaboration across the firm boundaries are needed. Potential benefits arising from R&D collaboration are well documented, and in many countries the governments further promote collaborative innovation arrangements among companies by targeting R&D subsidies particularly to the research joint ventures[1].

Firms use their resources to find the best partners for R&D collaboration but success is never guaranteed – both the collaborative arrangements and innovation itself involve a lot of uncertainties. Previously reported research suggests that the failure rates of innovation alliances are relatively high; over half of the R&D alliances fail to achieve their goals (see, e.g., Kale et al, 2002). However, other studies show that it has become more common for companies to patent their collaborative innovative output, and the growth in joint patenting has continued (see, e.g., Hagedoorn, 2003; Ma and Lee, 2008). Using these thoughts as a starting point, this paper addresses and aims at answering an empirically oriented question that is of critical importance for the firms' R&D alliance formation: how is R&D collaboration among companies organized most productively in terms of the quality of innovation? In other words, what are the factors that characterize the most successful innovation alliances?

[1] For instance, in the United States, one of the most important policy means of the Advanced Technology Program has been to fund research consortia. In Finland, Finnish Funding Agency for Technology and Innovation (TEKES) - that is the primary organization providing R&D support for companies – requires that the funded R&D projects of large companies are organized in collaboration with some other firms and/or research organizations.

The empirical studies of Branstetter and Sakakibara (1998, 2002, 2003) represent those few published on the topic and relate closest to our study. One of their major findings using data from both Japanese government-sponsored research consortia from the years 1980 to 1992 and the US data from government subsidized R&D consortia during the time period 1985-1995 is that technological proximity of research partners relates positively to the innovation output of R&D consortia. The studies of Branstetter and Sakakibara deviate from ours in various ways. First, we focus on the question of the *value* of produced innovations using patent citations as an output measure. Second, we approach the problem at the level of innovations though we use firm- and research consortium specific variables as explanatory factors in our empirical estimations. Third, the time span of patented innovations we analyze is more recent and more extensive: our data cover the years 1980-2003. Also, our data is not limited to research consortia in a certain country but cover internationally all research consortia that have patented knowledge intensive technologies in three areas, cryptography, image analysis and data processing/software, in the United States.

We use the data compiled from the USPTO patent and patent citations concerning the patented knowledge intensive technologies in three areas: cryptography, image analysis and data processing/software. The data is restricted to those patents between the years 1980-2003 that have two or more assignees, i.e. we consider only joint patents. Our database provides a rich source of information on joint patenting as firms in high-technology industries are inclined to collaborate in R&D more than those that involve lower technological intensity due to complex and diversified knowledge that the further technological advancements in high-tech fields typically require (see, e.g., Hagedoorn, 1993). The patent data is further complemented with the firm- and alliance-level information concerning each patented innovation. The data comprise more than 4300 joint patents but as we have missing values for firm-specific factors in many cases, the number of observations we have for the estimated models is 1235.

This paper is organized as follows: Section 2 introduces our data and sheds light on the key variable of interest, value of innovations measured by forward patent citations. Section 3 first motivates the factors that may influence the quality of the jointly patented innovations, and then reports and discusses the estimation results. Section 4 summarizes our main results.

2. High-tech innovation alliances - cryptography, image analysis and software

We focus on the performance of R&D alliances that have yielded patented knowledge intensive technologies in the following three high-technology areas: cryptography, image analysis and data processing/software (see Annex for a detailed description of technology fields). Investigating the quality of output of collaborative research in certain high-tech fields is sensible as disproportionately large share of joint patents are filed in high-tech fields (see, e.g., Hagedoorn, 2003). We use the data extracted from the patents filed to the USPTO. The USPTO database has the advantage of being the largest integrated database on patents to which similar patent laws apply for. Patent data gathered from individual countries would involve country-specific differences in patenting law and practice. Also, the United States market is one of the most important, and technologically sophisticated.

Hagenoorn's (2002) data reveals that there has been a clear growth pattern in the number of newly established R&D partnerships from the 1960s until the late 1990s. Our data suggests that there has been only a slight increase in the number of joint patents filed to the USPTO in case of cryptography and image analysis, while we observe a substantial increase in the jointly filed software patents from the 1980s until the late 1990s. The growth in jointly applied software patents is particularly during the 1990s when the software industry grew strongly. The drop in the number of filed patents in the early 2000s arises, by and large, from the date of data gathering, when information from all granted patents that were filed between the years 2000-2003 was not yet available. Our data do not thus cover fully the last four of the sampled years.

Figure 1. Joint USPTO patent applications by technologies

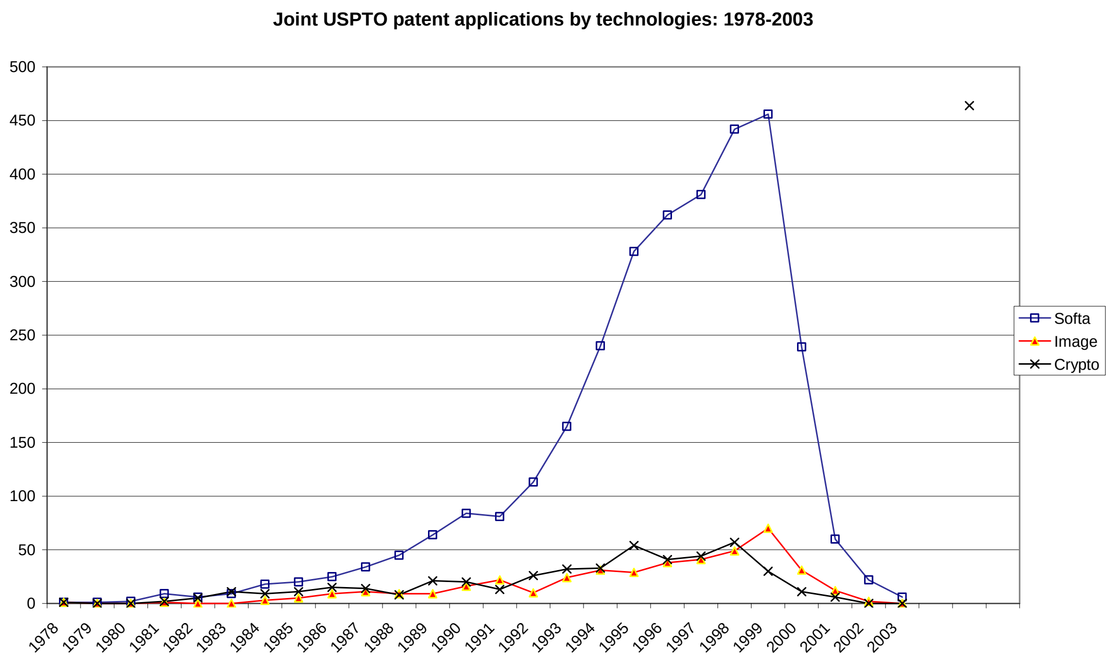
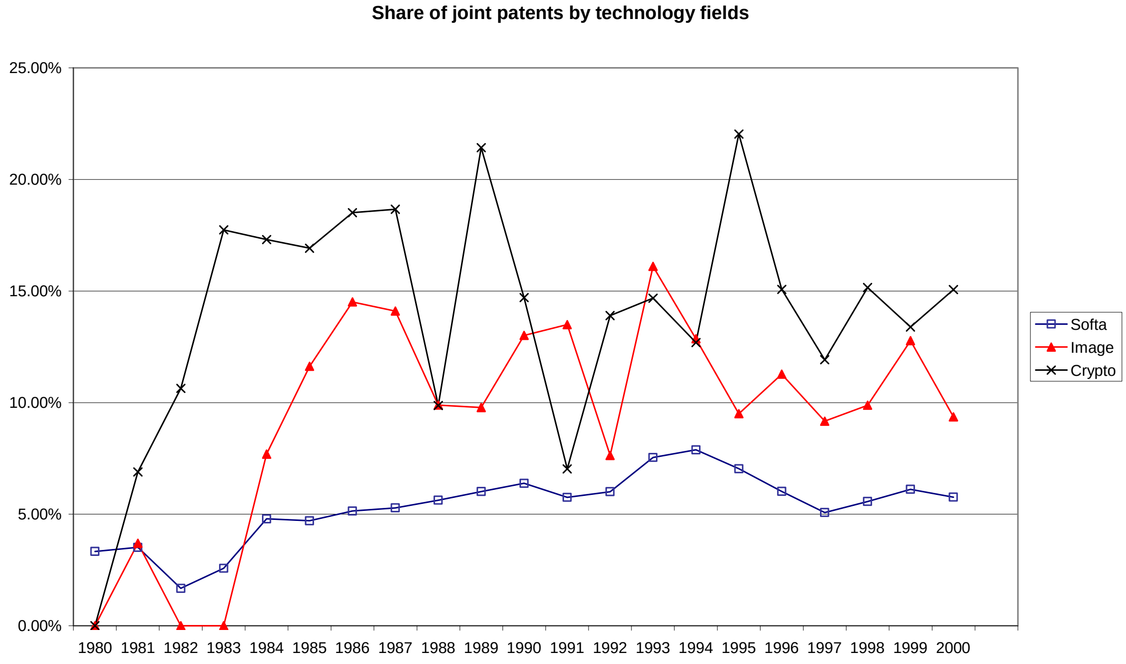


Figure 2 shows that thought the software industry has witnessed a constant increase in the absolute number of joint software patent alliances, the relative (about 5 %) share of joint patents of all patented software innovation has not changed much since the mid 1980s. In 2000, less than 6% of granted software patents were filed jointly by two or more companies. Instead, the evolution of image analysis and cryptography fields relies more strongly on the inter-firm R&D collaboration. During the 1980s, the relative shares of the joint patents in these two technology fields increased dramatically, and during the 1990s the jointly filed patents were fluctuating around 10 % of all image analysis patents and around 15% of cryptography patents.

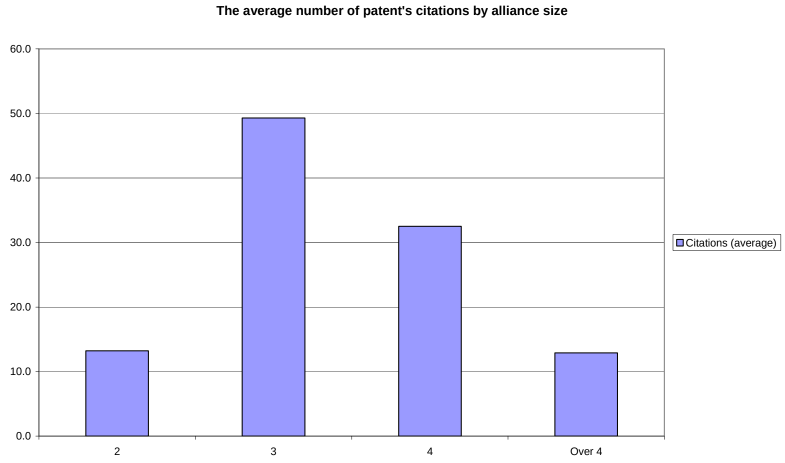
Figure 2. Share of joint patents of all patents



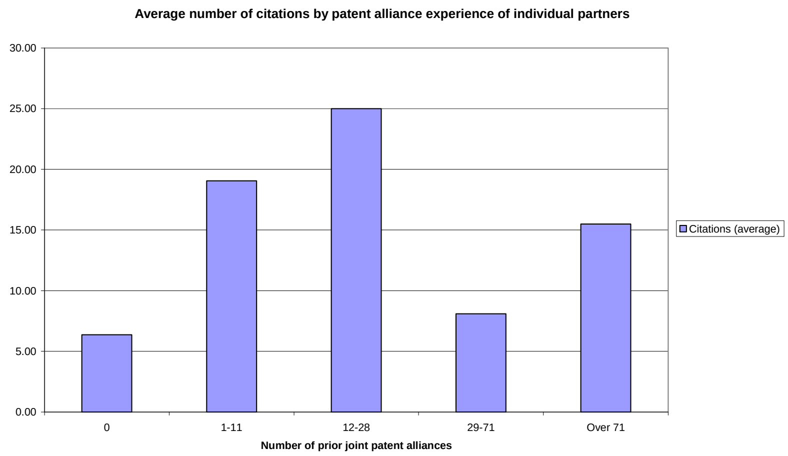
We are also interested in how the size of the patenting alliance and the prior joint patenting experience of the alliance partners relates to the quality of patented innovation. Figures 3a-3c illustrates the average number of forward citations per patent by the number of the alliance partners and by the firm- and alliance-specific joint patenting experience. This descriptive analysis hints that the quality of the produced innovation increases when the third partner joints the R&D alliance but again decreases when four or more partners participate in the innovation alliance. Figure 3b hints that when the patent alliance participants have no prior experience on joint patenting, they produce less valuable innovations than in those innovation alliance in which at least some of the firms have previously filed joint patents with the other firms. The relationship seems not be linear though, and when the maximum number of prior joint patenting partnerships exceeds 28, the benefits seems less clear. Figure 3c illustrates that the average number of forward citations varies less with the order of magnitude of the prior alliance experience of the firm pairs filing the joint patent. All these findings are descriptive, and need to be confirmed with the empirical analysis that simultaneously controls for various factors that may affect the quality of innovation output.

Figure 3. Forward citations of sampled patents by alliance size and alliance experience

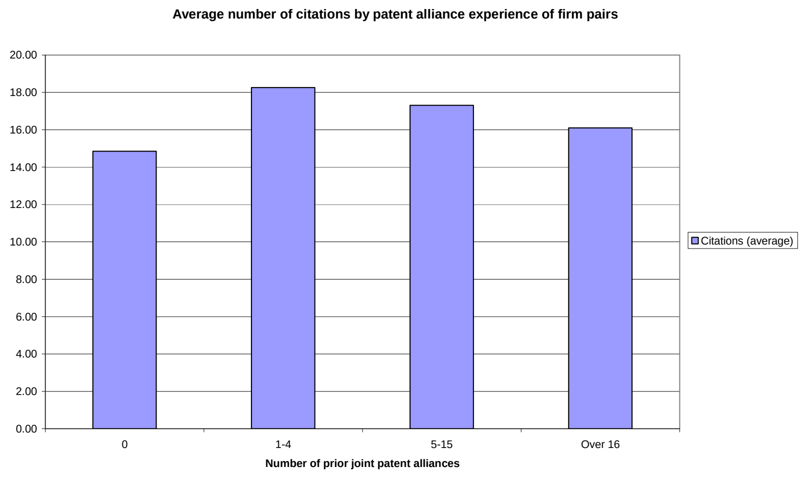
3.a. Forward citations by alliance size



3.b. Forward citations by the number of prior patent alliances of individual partners



3.c. Forward citations by the number of prior patent alliances of alliance firm pairs



Innovation in software is known to be extremely highly cumulative (see, e.g., Hall and MacGarvie, 2006). We observe, on average, 15.5 forward citations per jointly filed software patens. Our data show that similar to the software patents, image analysis has relatively high citation (average) counts: 15.4 citations per patent. The cryptography patents are cited even more often than the patents in the fields of software and image analysis: 69.6 citations, on average. According to the t-test, this number is also statistically significantly larger than the average numbers of software and image analysis patent citations.

3. Why some R&D alliances are more successful than others?

3.1 Theory

We derive from economic theory the following innovation productivity function of R&D alliances for our empirical estimations:

$$I_{it} = \alpha_0 + \alpha_1 R\&D_{it} + \alpha_2 PROXIMITY_{it} + \sum_{3}^{n} \alpha_j C_{it} + \varepsilon_{it} \qquad (1)$$

, where I is innovation output, i denotes observation unit (i.e. R&D alliance) and t is the application year of the patent. Equation (1) suggests that the innovation output of an R&D alliance is a function of two major factors, the R&D expenditures and the proximity (product market&technological and geographical proximity) of the research partners, and a set of control variables, C. The error term of equation (1) captures uncertainty that is inevitably part of an innovation process.

The R&D expenditures of the firms participating to a research consortium form the key input affecting the quality of produced innovation. Also, R&D spending increases firm- and alliance specific capabilities to use external sources of information. The R&D process involves personal and organizational learning, and the accumulation of (tacit) knowledge that improves the firms' ability to exploit external innovations and information. In other words, a firm's own R&D increases its absorptive capacity (Cohen and Levinthal, 1990). The order of magnitude of a firm's absorptive capacity is a function of both the quality of its human capital (e.g. the educational background, skills and know-how of the firm's employees) and its intellectual property (e.g. patented and trademark-protected assets). The greater ability for knowledge absorption leads to higher innovative capacity. Various empirical studies have suggested that firms' own R&D activities improve their absorptive capacity further increasing their innovation output and productivity (see, e.g., Jaffe, 1986; Griffith et al., 2003). Thus, we expect that the greater the R&D intensity of the research partners, the better the absorptive capacity of the alliance. We use the average R&D intensity of the patent assignees (the variable RD_INTENSITY), i.e. the mean of the patent assignees' R&D expenditures divided by their turnover, to explore the relationship between innovation quality and R&D investments.

Product market proximity means that firms are closer competitors with one another and thus the profits from an innovation may be reduced. When the firms are functioning in totally different product market areas it is possible that each firm can gain some monopolistic benefits from innovation in its own markets, whereas competing firms have to settle for duopoly or oligopoly rents from innovation. The presence of partners that are direct competitors of a firm in the market for end products may also hinder the diffusion of information and knowledge in the R&D project. The participants of an innovative alliance may each try to prevent their own valuable knowledge leaking to other companies and control information they share with their research partners (Oxley and Sampson, 2004). Consequently, less valuable knowledge becomes available for joint research use and both the quantity and quality of an input to the innovation process shrinks due to distrust between the collaborators. This problem may be particularly prominent when the product market proximity of the research partners is strong.

Thus, it is possible that the organization of R&D via an innovation alliance, particularly the one between close competitors, relates negatively to the value of innovation.

However, it is also possible that a firm organizes R&D collaboration with its close competitors to avoid costly patent races and cross-licensing negotiations (particularly in high-tech sectors characterized by interdependent and cumulative technologies). Competing firms' R&D collaboration may further arise from network effects, standard setting and monopoly power that the participants of a R&D joint venture may gain. These effects may reduce the collaborating firms' disincentive to provide information and their own know-how to their alliance partners, and thus the R&D alliances between close product market competitors may be as efficient as other research consortia between companies.

Furthermore, *technological proximity* may facilitate R&D collaboration; if the firms function in the same industry, it is easier for the research partners to absorb knowledge spillovers and to understand both explicit and tacit knowledge delivered or shared by the R&D alliance members. However, when the two firms are functioning in the exactly same field, the R&D joint venture may increase the technological opportunity of each company (i.e. the probability of a firm to innovate given the resources it invests in R&D) but be associated to a smaller variety of innovative technological solutions than in the case of a R&D joint venture of two firms coming from diverse fields. Theoretically, a certain mix of similarities enhancing knowledge transfer between research partners and technological diversity enabling the utilization of complementary knowledge - and sometimes producing unforeseeable discoveries that may further form the basis of a radical innovation – are likely to form the most favourable conditions for the successful innovative alliances. However, what is the optimal mix or how close/distant the R&D partners should locate from one another is an empirical question we aim at tackling in our empirical exploration.

We have information on the primary and secondary industries (i.e. SIC codes) of the alliance partners which we use for creating the following three dummy variables: i) SAMEP_4DIGIT which takes value 1 if two or more of the alliance partners are operating in the same primary industries at the 4-digit level, 0 otherwise, ii) SAMES_4DIGIT which takes value 1 if none of the alliance partners operate in the same primary industries, and two or more of the alliance partners are operating in the same secondary industries at the 4-digit level, and iii) SAMEP_2DIGIT which takes value 1 if two or more of the alliance partners are operating in the same primary industry at the 2-digit level, 0 otherwise. These dummy variables are primarily measuring the alliance partner’s product market proximity, but as discussed above, industries also differ in their technology and knowledge bases. Thus, these dummy variables also capture some variation that relates to the technological proximity of the alliance partners.

In addition to the product market and technological proximity, *the geographical proximity* of the alliance partners may also influence for the success of R&D collaboration via the conditions it establishes not only for knowledge sharing but also for the development of trust between the collaborating partners. The closer the partners are located to each other, the easier it is to organize frequent face-to-face meetings which are usually needed to transfer tacit knowledge among the project partners. Personal interaction further decreases uncertainties related to the intentions and competences of a firm’s innovation partners and enables formation of the trust that is a precondition for knowledge exchange and learning (see, e.g., Gallie and Guichard, 2005). The closer geographical proximity among the R&D collaborators is thus generally expected to increase knowledge sharing in the R&D project and enhance trust between the collaborators and thus to improve the outcome of the project. We measure geographical proximity by the variable GEOGR_PROXIMITY that takes value 1 if two or more of the alliance partners have headquarters located in the same country, and 0 otherwise.

Various other innovation alliance specific factors may also influence the successfulness of R&D collaboration among companies. One of those factors is *the alliance experience* of the collaborating partners. Anand and Khanna (2000) find learning effects in managing R&D joint ventures: their study shows that a greater number of prior R&D joint ventures positively relates to the order of magnitude of firms' abnormal stock returns. Their empirical study suggests that experience in joint R&D ventures of the alliance partners creates value for the firms via organizational learning. As the data of this study concerning the stock price movements cover only 40 days after the alliance announcement, it measures rather the expected performance consequences of the alliance formation than actual changes in firm performance. The study of Kale et al (2002) demonstrates that the alliance formation and experience are not only positively related to the initial positive stock market response but further positively correlated to the long-term performance of a company.

The study of Hagerdoorn et al. (2003) suggest that the collaborating firms' *prior experience with joint patenting* rather than R&D alliance experience relates positively to the number of its subsequent joint patents with other companies. These findings hint that some firms may strategically choose to apply for joint patents and that the firms learn it via their prior experiences how to apply for and manage joint patents.

If a firm's prior experience of joint R&D and patenting also generates more efficient or fruitful innovation collaboration, not only strategic learning and management of joint patents, we should observe positive relationship between the number of alliance partner's prior joint patents and the value of their innovation output. Since this relationship may be non-linear – for instance, there is some threshold level of the joint R&D experiences after which the innovation performance of the alliance does not improve - we introduce a set of dummy variables to for the prior joint patenting. We have constructed the dummy variable for the cases when the patenting alliance is the first (in our sampled data) for all alliance partners (the variable ALLIANCE_EXP_0) and other dummy variables for the alliance experience (ALLIANCE_EXP_1-11, ALLIANCE_EXP_12-28, ALLIANCE_EXP_29-71, ALLIANCE_EXP_OVER71) using the intervals corresponding 25%, 50% and 75% quartiles of the variable measuring the maximum number of *prior* joint patenting alliances of the patent alliance partners (see Table 1 for the detailed description of the variables.). We use the dummy variable ALLIANCE_EXP_1-11 as the reference variable.

Table 1. Description of the explanatory variables

Description of variable	**Variable name**	**Mean**	**St. dev**
The average R&D intensity (R&D/turnover) of the research alliance.	RD_INTENSITY	0.52	-2.45
Product market&technological proximity: Dummy variables that get value 1 if i) two or more of the alliance partners are operating in the same primary industries at 4-digit level, ii) none of the alliance partners operate in the same primary industries, and two or more of the alliance partners are operating in the same secondary industries at 4-digit level, and iii) two or more of the alliance partners are operating in the same primary industry at 2-digit level, and 0 otherwise.	i)SAMEP_4DIGIT ii)SAMES_4DIGIT iii)SAMEP_2DIGIT	0.15 0.05 0.36	0.35 0.22 0.48
Geographical proximity: Dummy variable that gets value 1 if the headquarters of (at least) two of the alliance partners are located to the same country, 0 otherwise.	GEOGR_PROXIMITY	0.64	0.48
Alliance experience of firms: The dummy variables that get value 1 the maximum number of the prior joint patenting alliances (in the sampled data) the firms filing the patent have participated into is: i) 0 ii) 1-11, iii) 12-28, iv) 29-71, v) over 71, and 0 otherwise.	i) ALLIANCE_EXP_0 ii) ALLIANCE_EXP_1-11 iii) ALLIANCE_EXP_12-28 iv) ALLIANCE_EXP_29-71 v) ALLIANCE_EXP_OVER71	0.02 0.25 0.24 0.25 0.25	0.12 0.43 0.43 0.43 0.43
Alliance experience of the alliance partner pairs: The dummy variables that get value 1 the maximum number of the prior joint patenting the pairs of firms filing the patent (in the sampled data) have participated into is: i)0 ii) 1, iii) 2-4, iv) 5-15, iv) over 15, and 0 otherwise.	i) ALL_PAIR_EXP_0 ii) ALL_PAIR_EXP_1 iii) ALL_PAIR_EXP_2-4 iii) ALL_PAIR_EXP_5-15 iv) ALL__PAIR_EXP_OVER15	0.25 0.12 0.18 0.21 0.25	0.43 0.32 0.38 0.41 0.43
Log number of assignees that have filed the joint patent.	ALLIANCE_SIZE	0.75	0.17
Log total number of subsidiaries of the alliance partners.	SUBSIDIARIES	3.25	-2.75
The dummy variable that gets value 1 if patented technology is software, and 0 otherwise.	SOFTWARE	0.87	0.34
The dummy variable that gets value 1 if patented technology belongs to the field of cryptography, and 0 otherwise.	CRYPTO	0.08	0.27
The dummy variable that gets value 1 if patented technology belongs to the field of image analysis, and 0 otherwise.	IMAGE	0.05	0.22
The dummy variable that gets value 1 if one or more of the firms filing the patent function in the industrial machinery and equipment industry (SIC35), and 0 otherwise.	SIC35	0.25	0.43
The dummy variable that gets value 1 one or more of the firms filing the patent function in the electronic and other electrical equipment and component industry (SIC36), and 0 otherwise.	SIC36	0.58	0.49
The dummy variable that gets value 1 one or more of the firms filing the patent function in the communications industry (SIC48), and 0 otherwise.	SIC48	0.15	0.36

The dummy variable that gets value 1 one or more of the firms filing the patent function in the business services industry (SIC73), and 0 otherwise.	SIC73	0.41	0.49
Year dummies that get value 1 if the year is the same when the patent was applied, and 0 otherwise.	APPLYEAR_1991… APPLYEAR_2003		

It is also interesting whether it is the individual innovation partners' joint patenting experience that matters, or is it rather the alliance-specific experience that is important for the creation of (more) valuable innovations. We control for the prior alliance-specific experience of the innovation alliance partners by the dummy variables that capture the maximum number of times the patent alliance partners have previously filed joint patents with one or more of the other alliance partners. These variables are constructed similar to the above dummy variables for the firm's prior experience of joint patenting. The dummy variable ALLIANCE_EXP_0 gets value 1 if none of the alliance partners have prior joint patents with the others, and 0 otherwise. See Table 2 for the description of the other dummy variables for the prior joint patenting experience of the pairs of firms filing the joint patent: ALL_PAIR_EXP_1, ALL_PARIR_EXP_2-4, ALL_PAIR_EXP_5-15, ALL_PAIR_EXP_over15.

Table 2. The estimation results of the negative binomial models for the count of forward citations of the patented technologies

	ALL TECHNOLOGIES	**SOFTWARE**	**IMAGE ANALYSIS & CRYPTOGRAPHY.**
VARIABLE	**Coeffient** **t-value**	**Coeffient** **t-value**	**Coeffient** **t-value**
RD_INTENSITY	-0.06 -1.47	-0.11 -2.77	0.07 0.61
SAMEP_4DIGIT	0.39 1.47	0.57 2.23	-1.37 -1.91
SAMES_4DIGIT	0.15 0.65	0.41 1.54	0.11 0.09
SAMEP_2DIGIT	-0.75 -3.78	-0.85 -4.25	-0.65 -0.87
GEOGR_PROXIMITY	0.14 0.92	0.14 0.97	0.58 0.94
ALLIANCE_EXP_0	-0.17 -0.46	-0.19 -0.49	0.33 0.17
ALLIANCE_EXP_12-28	0.39 2.51	0.29 1.91	1.02 1.76
ALLIANCE_EXP_29-71	0.03 0.20	0.07 0.42	0.60 0.91
ALLIANCE_EXP_OVER71	0.02 0.10	0.00 0.02	0.02 0.03
ALL_PAIR_EXP_1	-0.09 -0.63	-0.06 -0.39	-0.76 -1.10

ALL_PAIR_EXP_2-4	-0.16 -0.99	-0.17 -1.08	-0.99 -1.37
ALL_PAIR_EXP_5-15	-0.11 -0.64	-0.20 -1.15	-0.29 -0.39
ALL__PAIR_EXP_OVER15	-0.01 -0.03	-0.06 -0.25	-0.26 -0.27
ALLIANCE_SIZE	1.43 4.33	1.63 5.43	0.33 0.20
SUBSIDIARIES	-0.04 -1.28	-0.03 -1.12	-0.02 -0.22
CRYPTO	0.31 1.21		1.28 3.21
IMAGE	-0.75 -2.16		
SIC35	-0.56 -2.70	-0.58 -2.79	-0.61 -0.53
SIC36	-0.92 -4.76	-0.70 -3.66	-2.22 -2.90
SIC48	-0.58 -2.52	-0.55 -2.64	-0.62 -1.10
SIC73	0.00 -0.02	-0.16 -1.00	1.24 1.32
APPLYEAR_1991	-0.08 -0.28	-0.40 -1.64	0.22 0.24
APPLYEAR_1992	-0.50 -2.43	-0.32 -1.45	-0.25 -0.21
APPLYEAR_1993	-0.44 -1.62	-0.49 -2.40	0.70 0.53
APPLYEAR_1994	-0.72 -4.22	-0.53 -3.80	-0.30 -0.34
APPLYEAR_1995	-0.87 -4.83	-0.62 -3.88	-0.96 -0.93
APPLYEAR_1996	-0.57 -2.31	-0.45 -2.02	-0.52 -0.59
APPLYEAR_1997	-1.33 -5.01	-1.04 -4.46	0.26 0.20
APPLYEAR_1998	-1.98 -7.05	-1.68 -6.35	-1.66 -1.54
APPLYEAR_1999	-3.25 -10.66	-2.75 -10.24	-36.71 -26.45
APPLYEAR_2000	-4.32 -8.97	-3.83 -8.28	-37.08 -32.79
APPLYEAR_2001	-22.11 -58.15	-24.08 -64.58	
APPLYEAR_2002	-4.31 -4.05	-3.63 -3.38	-37.59 -21.99
APPLYEAR_2003	-21.64 -28.29	-23.31 -30.98	
CONSTANT	3.45 9.07	3.05 8.29	2.64 1.30
/lnalpha	0.69	0.57	0.77
alpha	2.00	1.77	2.16
Number of observations	1235	1076	159
Log-likelihood	-3701.02	-3214.46	-436.67

More R&D partners may mean more diverse knowledge to be used in the innovation process. We therefore expect that the larger patenting alliances (i.e. those with a greater number of alliance partner firms) produce more valuable innovations. The variable ALLIANCE_SIZE measures the (log) number of assignees that have filed the joint patent.

Firms not only use knowledge they absorb from their R&D partners but also various other sources of information may matter in the innovation process. One of the most notable source from which knowledge may ‘leak’ into a company are the other companies it owns. A firm that has subsidiaries has access to innovations and knowledge developed in the affiliated companies. The greater the number of a firm’s subsidiaries, the larger ‘open’ innovation network the firm possesses, and the easier it is for the firm to use external knowledge and innovation for its own R&D activities. Consequently, we expect that those R&D alliances that have a larger the network of companies owned by the research partners tend to produce more valuable innovations. We measure the (log) number of subsidiaries of the alliance partners by the variable SUBSIDIARIES.

We also control for the technology field by the dummy variables CRYPTO and IMAGE that takes value 1 if the patented technology belongs to the field of cryptography and image analysis, respectively, leaving the software patents as the reference group.

We also control for the industrial sectors at 2-digit (SIC) level, and the application years of the patents. As our analysis takes place at the innovation level, and we have multiple assignees for each patent, we also typically have multiple industrial sectors for one observation. We have resolved this problem by forming industry dummies for the 2-digit level industry codes SIC35, SIC36, SIC48 and SIC73 such that these dummy variables get value 1 if one or more of the patent assignees functions in the given industrial sector, and 0 otherwise. About 86% of the sampled companies are active in the industrial machinery and equipment industry (SIC35), the electronic and other electrical equipment and component industry (SIC36), communications industry (SIC48) or the business services industry (SIC73). We use the rest of the industries – of which each comprises less than 5 %, and typically less than 1%, of the sampled companies – as the reference group.

3.2 Empirical findings

We estimated the negative binomial model for our dependent variable, the count of the forward citations of the patented technologies. We estimated first the model for the whole data, and then models by technologies, one limited to software patents and the other comprising only image analysis and cryptography patents[2], as we were also interested in whether there are technology-specific differences in the relationship between the explanatory variables and the value of innovations. Table 2 reports the estimation results.

First of all, we may note that the average R&D intensity of the alliance partners related negatively, but not statically significantly to the value of produced innovation. In other words, those innovation alliances in which the firms have invested in relatively more to R&D do not seem to produce more valuable innovations than others.

The estimated coefficients of the variables SAMES_4DIGIT is not statistically significant suggesting that the alliance partners functioning in the same secondary industries do not produce significantly more or less valuable innovations than other firm combinations. The estimated coefficient of the variable SAMEP_4DIGIT is positive and statistically significant in the case of software patents, but negative when we estimated the model for image analysis and cryptography patents. We find thus some evidence that it depends on technology field whether technological and product market proximity of partners in R&D alliance produces more or less valuable innovation. In case of software, the variable SAMEP_2DIGIT is negatively and statistically significantly related to the number of forward citations of a patent. So, definitely for software innovations, highest value is created when the R&D partners are rather homogenous in regard to their industrial specialization.

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[2] We didn’t estimate the models for cryptography and image analysis patents separately due to the small sample size - the negative binomial model for the citation counts for the cryptography patents didn’t converge.

We find that among the dummy variables capturing the order of magnitude of the patent alliance experience of the firms and the firm pairs filing the joint patent, the only one that is statistically significant is the variable ALLIANCE_EXP_12-28. It seems that the most valuable innovations are generated when there is a certain level of prior patenting experience of the individual innovation partners. Instead, when the prior joint patenting experience exceeds this level, it seems that the value of the produced innovations decreases again. One possible explanation for this is that those firms that file substantially more joint patents that average companies are those for which the strategic creation of patent pool is relatively more important than for the others. In other words, their propensity to patent is higher than, on average, and they then tend to also patent lower quality innovations than other companies.

None of the dummy variables capturing (greater than zero) experience of the alliance partner pairs is statistically significant. Given the estimation results concerning the alliance experience of individual firms, our data suggests that learning from the prior joint patenting that creates more value for innovations is rather firm-specific than alliance-specific.

The order of magnitude of the patenting alliance seems to matter in the creation of software innovations: the greater is the number of the firms participating in the R&D alliance that has filed software patent in the USPTO, the more valuable is the patented technology. In case of cryptography and image analysis, the alliance size does not seem to be significantly related to the quality of patented innovation.

The geographical proximity variable appears not to be significant; the variable SAME_COUNTRY does not explain statistically significantly variation in the dependent variable. It is possible that our rough measure of the geographical proximity of the alliance partners does not sufficiently capture the geographical proximity of the researchers behind the patented technologies. We would need more precise information on the location of the individual inventors to make strong conclusions of the importance of the geographical proximity for the quality of innovation.

4. Conclusions

Our empirical exploration on joint patenting among the three high-technology fields, software, cryptography and image analysis, illustrates that the number of jointly filed patents has notably increased in absolute terms since the late 1980s. However, change over time, particularly after the mid 1980s, in the proportion of joint patents of all patents granted has been less dramatic. Our data also suggest that the evolution of cryptography and image analysis fields rely clearly more strongly on inter-firm R&D collaboration than software.

We find some evidence that technological or product market proximity of partners in R&D alliance matters but whether the closeness generates more or less valuable innovations depends on the technology field. In case of software innovations, the highest value is created when the R&D partners are rather homogenous in regard to their industrial specialization. Similar industrial specialization of the R&D alliance partners in the fields of cryptography and image analysis seems to, instead, produce less valuable innovations. We do not find any evidence supporting the significance of geographical proximity of R&D alliance partners but as our proxy variable for geographical proximity is rather poor, strong conclusions cannot be made.

Our data further suggest that the most valuable innovations are generated when there is a certain level of prior patenting experience of the individual innovation partners. Interestingly, the prior patenting experience of the pairs of firms filing the joint patent does not seem to matter.

It thus seems that learning from the prior joint patenting that creates more value for innovations is rather firm-specific than alliance-specific. Possibly, those firms that have previously patented with other companies have developed working and collaboration practices (possibly, e.g., in exchange of information and sharing of knowledge), which they can share with the other alliance partners, and create an innovation environment enabling more efficient and fruitful research collaboration. Our findings on prior joint patenting experience generally hint that not only strategic benefits, and those benefits related to the management of joint patenting, can be gained from the R&D alliance experience.

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Annex. Definition of technology fields: cryptography, image analysis, software

*Cryptography (*US patent class 380) includes equipment and processes which (a) conceal or obscure intelligible information by transforming such information so as to make the information unintelligible to a casual or unauthorized recipient, or (b) extract intelligible information from such a concealed representation, including breaking of unknown codes and messages.

Image analysis (US patent class 382) is the generic class for apparatus and corresponding methods for the automated analysis of an image or recognition of a pattern. Included herein are systems that transform an image for the purpose of (a) enhancing its visual quality prior to recognition, (b) locating and registering the image relative to a sensor or stored prototype, or reducing the amount of image data by discarding irrelevant data, and (c) measuring significant characteristics of the image.

Software (US patent classes…). As software innovations became patentable in the USPTO only in the early 80s, our data basically cover all US patented software until the year 2003. Definition of software here. (See also Hall&MacGarvie, 2007)