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Innovation, Recombination and Technological Proximity

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Abstract This article investigates the relation between recombinative capabilities, innovation and alliance strategies for 71 firms in the Information Communication Technologies (ICT) sector, through a panel data analysis. In particular, it explores the impact of two factors on innovation. The first is the recombinative capabilities of firms, which are measured by the breadth of their patents. The second is their alliance strategies, which are measured in terms of technological proximity with partners. The results reveal that recombinative capabilities increase innovative output. However, there is a limit to this positive effect. Beyond this limit, recombinative capabilities reduce innovation intensity. In other words, after a threshold, the wider is the breadth of the firm's patents, the less is the number of them. This relationship also depends on the technological proximity with alliance partners. High recombinative capabilities are best complemented by technologically proximate alliance partners, who permit refinements in existing domains, without augmenting costs of variety management.

Keywords Recombination · Innovation · Strategic alliances · ICT

Introduction

In recent decades, increasing product complexity and rapid innovation in knowledge-intensive industries have been accompanied by richer technological opportunities to recombine knowledge in different configurations. From an evolutionary perspective of the industrial system, recombination of knowledge is a central process in innovation and in the evolution of technologies (Schumpeter 1934; Nelson and Winter 1982), which depend on a complex interplay between economic actors, artefacts and ideas (Arthur 2009; Antonelli et al. 2010).

As it is used in this article, *recombination* refers either to the combination of elements which were previously unconnected or finding new ways of combining

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elements which were already associated (Nahapiet and Ghoshal 1997). Recombination rests on the ability to maintain variety (Weitzman 1998). In particular, recombinative capabilities are related with the internal capabilities of the firm to organise knowledge, measuring the extent to which firms can creatively combine different domains of knowledge in the innovation process. As far as external capabilities of the firm are concerned, local and distant knowledge search mechanisms are important aspects of accessing different knowledge domains (Stuart and Podolny 1996) which happen mainly through collaboration with other actors.

Although these collaborative relations have been studied from a variety of perspectives in innovation studies, one of the questions which received relatively less attention is how recombinative capabilities of firms and the nature of their alliance portfolios shape innovative competences jointly. Distant search is usually associated with exploratory activities, which are risky, yet they can bring very high returns. For sure, these returns depend on the firm's existing capabilities of recombination and how it can integrate new domains into its existing competences. Do high recombinative capabilities complement or substitute distant knowledge domains? How can firms design effective knowledge search strategies, depending on their recombinative capabilities? The effect of recombinative capabilities in innovation activities is extremely important in highly innovative sectors where there are rapid technological changes characterised by different knowledge base.

To explore these issues empirically, we focus on the Information Communication Technologies (ICT) sector. Firstly, ICT sector is characterised by rapid technological and structural change. In addition, the complexity of the technological base implies the critical role of complementarities between firms and the importance of technological diversity to ensure competitive advantage (Rao et al. 2004). In order to estimate how recombination and alliance portfolios influence innovative competences, we analyse panel data of patents granted to 71 ICT firms between the years 1995 and 2003. We collect data from different sources including the European Patent Office (EPO), the DTI Department for Business Innovation and Skills (BIS) research and development (R&D) and the Cooperative Agreements and Technology Indicators (CATI) databases. In this way, we construct an original database of worldwide ICT firms which have highest levels of R&D spending. The sample includes firms such as Ericsson, Oracle and IBM.

The article is organised as follows. "Theoretical Background" section presents the background literature and the hypothesis. It relies on the Schumpeterian notion of innovation to explain the role of recombination in the innovation process. Additionally, we explore the literature on the strategic alliances and learning in order to present the article's hypotheses on the ways in which external alliance strategies of firms interact with their internal recombinative capabilities. "Method and Data" section explains the data and measures used in the empirical investigation. The empirical results are discussed in "Results" section. Some concluding remarks follow.

Theoretical Background

A largely established view in the management and economics literature underlines the complementary nature of internal capabilities and external collaboration (Mowery and Rosenberg 1989; Arora and Gambardella 1994; Powell et al. 1996; Cassiman and

Veugelers 2006). The complementarity perspective explains how firm-specific internal innovative competences are associated with higher competitive advantage, when they are implemented together with an external knowledge acquisition strategy. The role of absorptive capacity in this process is critical; whereby higher in-house R&D investments improve the way firms acquire and build upon the knowledge which they access from outside (Cohen and Levinthal 1990). An inter-firm network is usually taken as a platform in which different fields of specialisation enable not only rapid access to different knowledge domains but also result in increased opportunities for building internal capabilities through recombination of external knowledge with internal competences (Powell et al. 1996). While R&D capabilities are critical in absorbing the knowledge accessed externally, creative use of the acquired knowledge rests on the firms' ability to recombine it with its pre-existing knowledge base. In the rest of this section, firstly, the relation between recombination and innovation is explored. Secondly, the relation between technological proximity with alliance partners and innovation is covered. In this part, we make a distinction between direct effect of proximity on innovation and an indirect effect which works through interaction mechanisms with recombinative capabilities. Figure 1 shows this theoretical construct as well as the hypotheses tested in the study.

Recombinative Capabilities and Innovation

The concept of recombination in the innovation literature is important since Schumpeter identified resource recombination as the principal aspect of the innovation process (Schumpeter 1934; Gilfillan 1935; Nelson and Winter 1982; Bassala 1988; Van den Bergh 2008; Arthur 2009). Recombination refers to the idea that no new knowledge is "manna from heaven"; each piece of knowledge that is used to create something new is essentially combining pieces of knowledge that existed before, albeit disparately in the knowledge space. This ranges from incremental improvements in a technological domain to the most radical changes that disrupt existing product systems. Such radical changes are usually based on the recombination of largely unrelated and distant

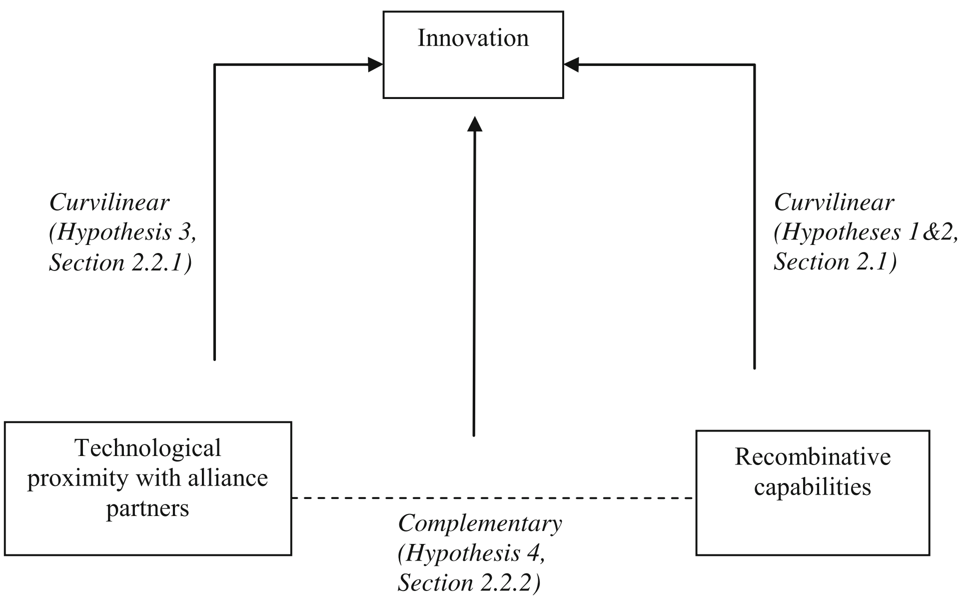

Fig. 1 Theoretical framework and illustration of hypotheses

knowledge elements (Schoenmakers and Duysters 2010). Previous studies have found that technological diversity can increase the innovative potential (Fleming 2002; Miller et al. 2007) through maintaining the availability of a broader set of alternative recombination paths (Weitzman 1998; Fleming 2002; Carnabuci and Bruggeman 2009). But, the extent to which the firm makes use of this diversity depends on its recombinative capabilities. Termed as "recombinant growth" by Weitzman (1998), it is accepted that creative combinations are more likely when there are a wider set of elements to be recombined.

Based on the importance of variety in recombination, innovative performance depends on the extent to which the firm generates variety internally and externally. In this paper, we define recombinative capabilities of the firm as its ability to access variety, process it internally and create novelties by recombining its previous knowledge with what it acquired. In this sense, recombinative capabilities resemble absorptive capacity of the firm (Cohen and Levinthal 1990) yet with an added dimension of creativity in forming synergies between different knowledge domains. Recombination capabilities are internal to the firm, measuring the extent to which firms can creatively combine within their internal boundaries' different domains of knowledge in the innovation process. In this, various factors play a role, ranging from the structure of inventor networks (Fleming and Marx 2006), alliance partner selection, as well as innovation strategies and context, and the nature of knowledge and technology (Galunic and Rodan 1998). Recombinative capabilities are largely firm-specific (Kogut and Zander 1992; Galunic and Rodan 1998; Miller et al. 2007) as they are embedded in the firms' internal routines in storing, retrieving and processing knowledge.

In the literature, recombination is usually assumed to be equivalent to innovation, and one of its sources is taken to be varied. Our first hypothesis is concerned with the alleged positive relation between recombination and innovation.

Hypothesis 1: Firms with higher recombinative capabilities innovate more.

There is a limit to the positive effect of recombination on innovation as diminishing returns to variety might set in (Weitzman 1998; Antonelli et al. 2010). In fact, the positive effect of recombination on innovation will depend largely on the *rate of change* of variety in the firm (Garcia-Vega 2006; Van den Bergh 2008). As knowledge is localised, the rate at which the technical variety in a firm changes is slow. This is largely because of the established and routinised learning processes, which inhibit the rate at which firms can absorb new knowledge in new technical domains, and because of the localised nature of learning (Antonelli 2006). The accumulation of knowledge in new domains can entail coordination costs of managing variety. In return, increasing knowledge breadth of research projects can bring forth reduced potential to manage *different* research projects. Incorporation of different knowledge domains in research can come at a cost of reduced overall number of projects that the firm is capable of handling.

Hypothesis 2: There is a curvilinear relationship between innovative capabilities and recombinative capabilities.

Alliance Portfolios, Technological Proximity and Innovation

Alliance portfolios are one of the most important means through which firms access variety from outside, and thereby, they play a critical role in the innovation process. We explore two ways in which technological proximity with R&D partners influence innovation. The first one is a direct effect through learning. The second one is an indirect effect through recombination.

Direct Effect: Proximity and Innovation

Recent studies show in various industrial contexts that the characteristics of the portfolio of firms' alliance partners influence their innovative performance. Organisational learning (Powell et al. 1996; Lavie et al. 2011) and capability transfer (Mowery et al. 1998) are important mechanisms underlying this effect. Drawing upon March (1991), exploration dimension of organisational learning refers to "experimentation with new alternatives" and the exploitation to the exercise of "refinement and extension of existing competencies, technologies and paradigms" (March 1991: 85). Both exploration and exploitation are knowledge search processes, which can be described as the firms' struggle to identify, select and learn from knowledge that can be both beyond their boundaries. Whether firms treat these to be substitutes or complements has been a matter of debate in the literature (Lavie et al. 2010, 2011).

Alliance portfolios has been a lively field of research during the recent decade, investigating issues like the diversity of partners (Jiang et al. 2010; Lin et al. 2010), foreignness of alliance partners (Lavie and Miller 2008), exploration versus exploitation alliances (Lavie and Rosenkopf 2006; Yamakawa et al. 2011) or technological proximity between the partners (Mowery et al. 1998; Vanhaverbeke et al. 2009), the complexity of portfolios (Duysters and Lokshin 2011) and the links between partners (Dyer and Nobeoka 2000). In this literature, a firm's alliances are seen as complementary, and to make use of synergies between different alliances, it is important to take alliances at the portfolio level. A growing body of research investigates exploratory and exploitative dimensions of firms' alliance portfolios and their effect on performance. The results of this literature reveal that partner diversity is better for explorative innovation (Lavie and Rosenkopf 2006) because it increases the extent to which firm accesses non-redundant knowledge. Some other studies find that rather than the diversity of partners, the extent to which partners are technologically distant from the firm determines its explorative innovation (Nooteboom et al. 2007). For example, Ahuja and Katila (2001) find that recombinative search is better carried out with distant partners.

An important dimension of recombinative capabilities is the extent to which the firm selects partners whose knowledge is complementary to its own. An increasing number of studies detect a curvilinear relation between the technological proximity between two firms and the extent of transfer of capabilities (Schoenmakers and Duysters 2006; Nooteboom et al. 2007; Gilsing et al. 2008; Cowan and Jonard 2009). Moreover, this proximity increases as firms collaborate with each other (Mowery et al. 1998). The underlying logic in this process is that when firms are too close in the knowledge space, they have few to add to each others' knowledge and when they are too far, they cannot access each others' knowledge base, and learning is limited. The next question that we address in this article is concerned with how technological distance between the firm and its partners influence the firm's innovative competences. Based on the above literature on the optimal cognitive distance, we propose that both high levels of technological overlap and low levels of overlap with alliance partners restricts the firm's innovative competences because there can be limited knowledge that the firm is able to acquire from outside.

Hypothesis 3: There is a curvilinear relationship between innovative competences and the average technological proximity between the firm and its alliance partners.

Indirect Effect: Proximity and Innovation

The indirect effect of proximity on innovation works through the recombination capabilities. High recombinative capabilities are best complemented by local search processes, which imply proximate alliance partners. On the other hand, low recombinative capabilities are better complemented by exploratory search processes.

The relation between recombination and innovation depends on the access to new knowledge sources from outside. Exploratory alliances refer to search processes which are highly risky, but at the same time, they can yield higher returns compared to deepening of the knowledge base through exploitative search processes. As such, explorative search processes underline the importance of distant alliance partners, who can bring novelties to the knowledge base of firms and expand the knowledge base of the firm. This expansion will yield higher opportunities for recombination and yield more opportunities for firms who are relatively weak in recombining knowledge.

Despite potential benefits of exploratory alliances, research shows that firms search narrowly within their existing technological domains (Helfat 1994; Stuart and Podolny 1996; Leonard-Barton 1992) in the form of exploitative alliances, which connote technological proximity between partners. In this context, Srivastava and Gnyawali (2011) stress the paradox of capabilities, while partnerships with resource-rich firms can improve the firms' capabilities for radical innovations through accessing variety, competency traps and possible leakages of valuable knowledge can be barriers in the innovation process.

A firm with high recombinative capabilities connotes one that has appropriate knowledge management skills to search for innovative combinations in its pre-existing knowledge domains. While recombinative capability connotes the ability to synthesise distinct and possibly diverse knowledge domains, local search processes underlie refinements in a specific domain. Both processes are highly relevant in the problem-solving activities in the firm, in terms of searching for alternative solutions and selecting the useful ones in the technology space (Arthur 2009). Problem solving is a critical capability in innovation (Vincenti 1990) which requires both a profound understanding of the relevant domain and a capacity to look at the distant technology landscape in selecting alternative solutions. In this sense, for a firm with high recombinative capabilities whose internal routines are oriented towards operationalisation of variety, exploitative alliances with proximate partners can have a complementary effect, in terms of refinements in each of the diverse technology domains. In addition, such refinements are usually associated with incremental innovations which can be critical for competitive advantage of incumbent firms (Banbury and Mitchell 1995).

Stated differently, higher recombinative capabilities are likely to be complemented by local search processes in the innovation process. The local search processes permit refinements in existing domains, without augmenting the costs of variety management in partnerships. Accordingly, we propose the following:

Hypothesis 4: There is a positive interaction effect between technological proximity between the firm and its partners and the firm's recombinative capabilities, as far as they influence innovation.

Method and Data

The model applies the above theoretical framework to the analysis of the ICT sector. There are several reasons behind the selection of this sector as a suitable context to test our hypotheses. ICT is one of the fastest growing sectors of the economy, accompanied by rich technological opportunities, as also revealed by the increasing number of patent applications during the recent decade (Corrocher et al. 2007). The development of the ICT sector has been characterised by a process of continuous and rapid technological change where radical innovations enable a broad range of incremental innovations (Bresnahan and Malerba 1999). One of the most important characteristics of the ICT industry is that the dominant input in production is knowledge. Because knowledge can be inexpensively reproduced (expansible) and it is non-rival (its use by one party does not exclude others from using it), an original design can be reused in meeting different markets, which is a source of economies of scope (Steinmuller 2007). Consequently, knowledge recombination is essential in the industrial dynamics, and it is characterised by a sequence of highly selective process of exploration (Corrocher et al. 2007). The development of the ICT sector has been characterised by the recombination of a variety of knowledge domains, stemming from different technologies (Van den Ende and Dolfsma 2005; Antonelli et al. 2010; Cecere 2009).

Data

In this study, data on 71 ICT firms that are collected by the DTI database BIS during the period 1995–2003 are used. This database collects data on the firms that have the highest R&D expenditure worldwide. Comprehensive pieces of information on the most important determinants of firm's innovative competences are collected. The data were obtained from different sources including the EPO database (PATSTAT), CATI database, bnet.com website and firms' own websites. CATI covers around 19,000 technology-based alliances of nearly 9,500 firms. The data is systematically collected since 1986 (although some of the alliances date back to end of 1800s), and it is one of the most widely used databases as far as technology-based strategic alliances are concerned. Although data maybe incomplete, it is considered as one of the most dependable data sources in this field (Schilling 2008). For each firm in the database between 1995 and 2003, the technology-based cooperative agreements were collected. Finally, a total of 71 ICT firms, operating in Electronics, telecommunications and computer sectors, with high technical competences (jointly considering R&D and patent counts) are included. In addition, a total of 349,070 patents granted to these firms during the period 1995–2003 are included.

In order to control for alternative determinants of patenting behaviour which have been identified in the previous literature, a broad set of control variables are utilised. In the following section, the variables and descriptive statistics are presented.

Patent Information

The primary goal of this article is to analyse how technological proximity with partners and their recombinative capabilities jointly affect the innovative competencies of ICT firms. The number of patents of the focal firm is taken to be the dependent variable. For each firm in the dataset, the patents granted by the USPTO in the mentioned period are collected. In addition, the patents granted to the partner firms which were involved in one or more alliances with the focal firm are collected as well.[1] Patents were searched using the firm name, along with familiar abbreviations and evident variations in spelling of firms' names.

Recombinative Capability

One of the independent variables is recombinative capability. Each patent document includes the relevant technology codes related with the subject matter of the patent, which is given by the eight-digit International Patent Classification (IPC) code. In this study, the main and secondary IPC codes of patents are used to derive measures of recombinative capabilities. Recombinative capability of a firm is measured by its capability to combine different technology fields in a *single* patent. The more different types of technology fields a given patent incorporates, the higher is the recombinative value of the patent. For this purpose, all the IPC codes of patents in the sample are converted into one of 30 main technology fields (Schmoch 2008).[2] To measure recombinative value of a patent, the Blau index (1977) is used. Here, the recombinative value b_{ij} of a patent j taken by firm i is given by the following:

$$b_{ij} = 1 - \sum_k a_{ik}^2$$

where a_{ik} is the proportion of technology field k in patent j. Smaller values indicate the dominance of some technology fields over the others in the patent document. On the other hand, high values of the index reflect a higher variety in technology fields which reflect higher recombinative capabilities. Therefore,

[1] We collect also the technological fields of the firms (that are not necessarily included in our sample) involved in a strategic alliance with the firm in our sample.

[2] The mapping between IPC codes and 30 technology fields is based on the study by Fraunhofer Gesellschaft-ISI (Karlsrube), Institut National de la Propriété Industrielle (INPI-Paris) and Observatoire des Sciences et des Techniques (OST, Paris).

the recombinative capability ($\mathrm{Re}com_{it}$) of firm i in year t is given by the average of the Blau index for the patents taken during that year:

$$\mathrm{Re}com_{it} = \frac{\sum_j b_{ij}}{P_{it}}$$

where P_{it} is the total number of patents taken by the firm i in year t. In the regression, the 1-year lagged recombination index is taken to account for the reverse causality. The variable is instrumented by considering the recombination index in time t^{-1}.

Technological Proximity with Alliance Partners

Average knowledge overlap between the firm and its partners (as evident from the patent portfolio) measures the extent to which two firms are proximate in the knowledge space. Knowledge base of a firm refers to the main technology fields that the firm is active in a given year and the intensity of its patenting in this field. Therefore, the knowledge base of the firm measures the breadth of the knowledge as revealed by the range of different technology fields that a firm obtains into patents. In addition, the knowledge base reveals how deep the firms knowledge is in a given technology field, by measuring the weight of the firm's patents which belong to a given technology field. In this sense, technological overlap between two firms captures the extent to which their breadth and depth of competences are similar to each other.

For each of the firms in the database, all the firms that the firm had an alliance with are collected. EPO PATSTAT patent database was then used to collect the patents granted to all the partner firms in the years in which it had an alliance with the firm. In this way, a total of 2,980 alliances for a total of 1,200 firms are included. The cosine index (Breschi et al. 2003) is used to calculate the extent of overlap between the firms' patent portfolio and each of its partners. Here, it is assumed that the more is the overlap between two firms in terms of the breadth and depth of their patent portfolio, the more proximate they are in the technology space. Cosine index between firms i and j, which is used as the independent variable $Tech\mathrm{Pr}ox_{ij}$, is calculated in the following way:

$$Tech\mathrm{Prox}_{ij} = \frac{\sum_{k=1}^{30} a_{ik}a_{jk}}{\sqrt{\sum_{k=1}^{30} a_{ik}^2}\sqrt{\sum_{k=1}^{30} a_{jk}^2}}$$

where a_{ik} refers to the proportion of technology field k in all the patents taken by firm i in a given year. Obviously, $\mathrm{TechProx}_{ij}=1$ indicates that the two firms are exactly the same in terms of their technological profile, and if there is no common technology field between the patent portfolios of two firms, $\mathrm{TechProx}_{ij}=0$. Therefore, high cosine values indicate increased overlap between the knowledge bases of two firms, in terms of their similarity.

The independent variable that we use for the alliance portfolio of firm i is the average of its technological distance with its alliance partners in time t^{-1} (lagged of 1 year) which permits to consider for endogeneity. In the literature on inter-firm networks, the diversity of partners is taken as an important determinant of innovative competences of firms (Lavie and Rosenkopf 2006). Surprisingly, the dataset shows that firms are quite consistent in a given year, in terms of their strategy of partnership. In other words, there is little variety in the overlap of a firm with each of its partners. This is why an average distance over all firms can be taken as a measure of the firms' partner selection strategy for a given year. In order to estimate the complementarity between the recombination capabilities and technological proximity, we include in the regression the interaction effect of these two variables.

Firms' Characteristics

Detailed information on yearly basis is obtained from the DTI (BIS) R&D database which provides detailed data on the largest firms in the world. Firstly, the annual R&D expenditure of each firm in millions of pounds is included and instrumented by considering the 1-year lagged R&D expenditure deflated by GDP price index.[3] R&D expenditure measures both the effect of firm size and the innovation input. Smaller firms can have more willingness to exchange internal information. Larger firms are expected to have larger financial means with respect to smaller firms. However, large firms can have some rigidity which hampers the explorative knowledge activities (Gilsing et al. 2008). Secondly, dummy variables are included indicating the company headquarters which allows to take into account the difference among the different continents, namely, Europe (EU), USA (US), Japan (JAPAN) and other countries (OTHER). The reference variable in the regression is the dummy variable EU. Additionally, the number of alliances that firms undertake is included to take into account the learning effect of being involved in large number of strategic alliances.

Industry Classification and Age of the Firms

In addition to the variables described above, industry differences and firms' age in the patenting behaviour are taken as other control variables. This data is collected from the firm's website or on the bnet.com website. Based on the North American Industry Classification System (NAICS) code of the firms, a set of dummy variables are created. These are based on the three-digit NAICS code that consider the different group of firms distinguishing between semiconductors, producers of machinery manufacturing and printing and related support activities and so forth. These categories are not a precise assignment of the activities of the firms, but they can capture some sector-specific characteristics.

Descriptive Statistics

Before presenting the estimation results in the "Results" section, Table 1 presents some descriptive statistics of the sample. In total, the sample contains 71 R&D intensive

[3] As there are some missing variables in the measure of R&D expenditure, the sample is reduced to 245 observations.

Table 1 Descriptive statistics

Variable	Description	Mean	Standard deviation	Min	Max
Patent	Number of total patents granted to firm i in time t innovative competencies	344.660	569.628	1	4,158
Recom$_{it-1}$	Measured by the Blau index for a single patent. The average is taken over all patents of firm i in time t^{-1}	.0364	.0347	0	.275
Recomsq$_{it-1}$	Recombination index in square	.0025	.0060	0	.076
Techprox$_{it-1}$	Technological proximity with alliance partners is intended to measure the average knowledge overlap between the firm i and its partners in time t^{-1}	.5697	.2500	0	.993
Techprox in sq$_{it-1}$	Technological proximity in square	.3868	.2633	0	.986
Recom$_{it-1}$*TechProx$_{it-1}$	Interaction effect recombination index multiplied by technological proximity-Cronbach method	.0203	.0185	0	.1284
$R\&D_{it-1}$	Natural log of the deflated R&D investment of firm i in time t^{-1} in million pounds	6.152	1.648	−1.251	9.285
Number of alliance	Number of alliances per year	1.706	3.292	0	22
Age	Based on the establishment year of the firm	52.35	36.53	11	163
Agesq	Age in square	4,073.4	5,297.3	121	26,569
NAICS 334	Industrial segment of the firm NAICS 334	.5054	.5004	0	1
NAICS 541	Industrial segment of the firm NAICS 541	.1268	.3330	0	1
NAICS 32;33	Industrial segment of the firm NAICS 32; 33	.0970	.2962	0	1
NAICS 511-8	Industrial segment of the firm NAICS 511;8	.1127	.3164	0	1
USA	Dummy variable sets to one if the firm is based in US	.5352	.4991	0	1
JAPAN	Dummy variable sets to one if the firm is based in Japan	.2394	.4271	0	1
OTHER	Dummy variable set to one if the firm is based in other countries	.0704	.2561	0	1

NAICS North American Industry Classification System firms which have at least one strategic alliance agreement recorded in the CATI database. The smallest firm has 600 employees and the largest 668,000 employees. Appendix 1 presents the correlation matrix of the all variables in the sample. Table 2 reports the breakdown statistics of variables according to industrial sectors. Approximately 50 % of the firms in the sample are established in the USA, about 24 % of the firms are based in Japan and only 16 % are located in Europe.

The Model

The dependent variable is a count variable which corresponds to the number of patents granted by firm i in year t. Poisson regression is a baseline model for count data (Hausman et al. 1984)—see Table 3. The results of the Poisson specification compared to negative binomial model show that the standard errors reflecting efficiency gain due to better model identification (Cameron and Trivedi 2009). The Hausman test confirms the use of random effect. The covariate recombination and technological proximity are centred on their means before computing the interaction term (e.g. Gronbach 1987). Appendix 2 details the results of the negative binomial estimation. The Poisson estimating equation is specified as follows:

$$\begin{aligned} Patent_{it} = \alpha + \mathrm{Recom}_{it-1} + \mathrm{Re}comsq_{it-1} + Tech\mathrm{Prox}_{it-1} + Tech\mathrm{Pr}oxsq_{it-1} \\ + \mathrm{Recom}_{it} * Tech\mathrm{Prox}_{it} + RD_{it-1} + \delta_i + \varepsilon_{it} \end{aligned}$$

with $Patent_{it}$ being the number of patents of the firm i in time t, δ_i are the set of ith firm characteristics which measures the firm-specific heterogeneity and ε_{it} represents the error which is assumed to satisfy the usual regression model conditions. The most important explanatory variable recombination, technological proximity and research development are instrumented with the lagged variables.

Table 2 Detailed data on firms by NAICS segment

NAICS category	Firms	Examples
Professional, scientific and technical services (NAICS 541)	9	3COM, ALCATEL, GEMPLUS, INFINEON TECHNOLOGIES
Computer and electronic product manufacturing (NAICS 334)	36	Atlmel, LG Electronics, Nokia, Sony, Symantec
Office machinery manufacturing and printing and related support activities (NAICS 32, 33)	7	Avid Technology, Dainippon Screen MFG, Xerox
Producing and distributing information and cultural products; transmission and processing of data or communications (NAICS 511-8)	8	Ericsson, I2 Technologies, Oracle
Professional, scientific and technical Services	11	3M, Amazon, IBM, Siemens
Other NAICS[a]		

NAICS North American Industry Classification System

[a] Reference variable in the regression

Table 3 Results of the Poisson panel estimation: dependent variable number of patents

	Poisson random effect (1)	Poisson random effect (2)	Poisson random effect (3)
Recom_{it-1}	2.366* (1.282)	7.892*** (1.696)	7.924***(1.695)
Recomsq_{it-1}	−64.869*** (7.294)	−105.722*** (10.758)	−107.152*** (10.791)
TechProx_{it-1}	1.866*** (0.104)	1.687*** (0.111)	1.694*** (0.111)
TechProxsq_{it-1}	−1.716*** (0.080)	−1.454*** (0.084)	−1.458*** (0.084)
Recom_{it-1}*TechProx_{it-1}	8.150*** (1.610)	3.981** (1.965)	4.003** (1.963)
$R\&D_{it-1}$		−0.055*** (0.015)	−0.042*** (0.015)
Number of alliances		0.007*** (0.001)	0.007*** (0.001)
Age			0.039** (0.017)
Agesq			−0.000 (0.000)
NAICS 334			−0.493 (0.589)
NAICS 541			0.296 (0.887)
NAICS 32, 33			−0.909 (0.700)
NAICS 511-8			0.047 (0.752)
USA			−0.096 (0.705)
JAPAN			0.562 (0.727)
OTHER			1.356 (0.919)
_cons	4.452*** (0.168)	4.717*** (0.215)	3.293*** (0.942)
lnalpha _cons	0.613*** (0.140)	0.699*** (0.142)	0.494*** (0.145)
Time dummies	Yes	Yes	Yes
Wald Chi 2	9,060.96	8,682.67	8,707.30
N	295	249	249

Standard errors (in parentheses) adjusted for clustering on id—firms

NAICS North American Industry Classification System

*p<.10; **p<.05; ***p<.01

Results

Table 3 presents the results for the estimation of innovative competences measured by the firms' number of patents. To check the robustness, different estimations are carried out. The first regression reports the baseline models. Regressions 1 and 2 estimate the equation using only time-varying variables. Regression 3 includes also the time unvarying variables. Additionally, annual dummy variables are included in all estimations to consider changes over time; they can capture the increasing importance of innovative competencies or changing institutional conditions which favour the creation of innovative competencies. Appendix 2 presents the regressions with the Poisson fixed effects estimations and the negative binomial regression both the fixed and random effects.

The results show that firms with high recombinative competencies (Recom_{it-1}) are more innovative, confirming hypothesis 1. However, there is a limit to this positive effect. After this limit, higher technology breadth in patents implies reduced overall patenting intensity, as revealed by the negative coefficient of the variable (Recomsq_{it-1})—hypothesis 2. One of the explanations for this effect is increased costs of managing variety, not only different knowledge domains covered by individual projects but also, and perhaps more importantly, in managing different projects. Stated differently, there is a trade-off between the recombinative potential of patents and the total number of them. The more is the recombinative value, the less is the overall number of patents. At this point, it is important to understand whether patents with high breadth have a higher value added. This is because reduced patenting potential can be compensated with an increase in the value of a small number of granted patents. This trade-off points to the well-known quality-quantity trade-off. Yet, analysing the quality of patents with high recombination potential is out of the scope of current article. But, some studies in the literature can be guiding at this point. For example, Schoenmakers and Duysters (2010) find that radical inventions incorporate a higher number of knowledge domains. The results in this study contribute to this finding, by stating that as the recombinative value of patents increase beyond a threshold, the firms' patenting intensity falls. However, this also depends on the firms' external knowledge search processes.

These results should be interpreted together with the impact of technological proximity with partners. Hypothesis 4 is concerned with the indirect effect of proximity on innovation, which works through recombinative capabilities. The coefficient of interaction effect between recombination and proximity Recom_{it-1}*TechProx_{it-1} is positive and significant. The more is the recombinative value of patents, the better it is to have proximate partners. These imply that the negative possible effects of recombination on innovation (beyond the threshold) can be compensated by an alliance strategy which favours proximate partners. Firms can better cope with coordination costs of variety, when their alliance partners are composed of firms who are similar in terms of technological profile. In other words, proximate partners delay the point at which recombination produces diminishing patenting intensity. Although the model does not yield any specific causal mechanisms which can explain why this is the case, it is intuitively reasonable to conclude that while distant partners add coordination costs over and above the current costs of recombination, proximate partners permit refinements in existing domains, without further augmenting costs of variety coordination.

Another way in which the interaction effect between proximity and recombination can be taken is by considering the direct learning effects from proximity. According to hypothesis 3, there is a curvilinear relationship between technological proximity with alliance partners TechProxsq_{it-1}, and the firms' patenting propensity. This curvilinear relation has already been confirmed in the literature (Schoenmakers and Duysters 2006). The direct relationship works through learning. Learning is limited when partners are either too distant or too proximate. Our results also reveal that increased recombinative potential can counteract the negative potential effects of too much proximity with alliance partners.

Looking at the regression results further, the point at which technological proximity starts inhibiting innovation depends on the level of recombination.[4]

[4] According to Estimation (2), $\frac{\partial P}{\partial TechProx} = 1.67 - 2.9\,TechProx + 3.98\,recomb$

Higher recombinative capabilities delay the point at which proximity no longer contributes to the firms' knowledge. In other words, when firms' recombinative capabilities are higher, they can support more proximate partners probably through better abilities to synthesise and incorporate the *few* domains which the partner has but which the firm does not. Yet, if the partners are distant, in addition to recombination costs, the firms incur costs of variety management, which can reduce the overall patenting intensity.

As far as control variables are considered, the results show a negative and significant effect of lagged R&D expenditure on innovative capabilities. This result can be justified with the fact that our sample is composed of large firms in the ICT sector, for which there can be inertia in knowledge creation at work. There is no particular effect of country and sector variables.

Concluding Remarks

The aim of this article is to advance our understanding of how firm-level recombinative capabilities and alliance portfolios together determine innovative capabilities. The results highlight how the recombinative capabilities and proximity with partners influence the innovative competences of firms in the ICT sector, as well as interactions between the two.

Recombinative capability is taken as one of the essential determinants of innovative competences, referring to the firms' ability to access variety, process it internally, and create novelties by recombining its previous knowledge with what it acquired. Recombination capabilities measure the extent to which firms can creatively combine different domains of knowledge in the innovation process.

A summary of the results of this paper is as follows. In the ICT sector, there are increased opportunities for recombination due to technological and industrial dynamics, which support a broad and complex knowledge base. Given rich opportunities for recombination, two factors play an important role in innovation: (1) firm-specific capabilities to recombine different knowledge domains and (2) firms' alliance strategies in accessing variety from external sources. Recombination in general has a positive effect on innovative capabilities. The more the firm's patents incorporate a wide range of knowledge domains, the higher is its potential to patent. However, there is a threshold to this effect. After this threshold, recombination has a negative effect on patenting. This can be explained through increased costs of coordination of variety. In other words, the higher is the scope of patents, the less is the number of them. In addition, this threshold depends on the firm's alliance strategy. Technologically distant partners can augment costs of variety coordination. Therefore, the negative impact of recombination on innovation can be offset with an alliance strategy which favours proximate partners. In this way, firms can deepen their competences in existing domains and make a better use of the few non-overlapping domains with partners.

One of the implications of this paper is concerned with the alliance portfolio management. Our results show that in general, high recombinative capabilities are associated with increased innovative performance, however, up to a point. Pass this point, it is better to accompany high variety with an alliance portfolio composed of technologically proximate partners. At the same time, if the firm is too specialised with poor recombinative skills, an alliance portfolio composed of technologically more unfamiliar partners yield increased innovative competences.

To what extent are the results obtained in this paper valid for other industries and contexts? The data that is used in this paper is from the ICT industry, which has peculiarities concerning the nature of knowledge and organisations. These peculiarities are particularly concerned with the complexity and the segmented nature of the ICT industry, which permits increased recombination. An example is the software sector, where rich economies of scope permit using one design in a variety of different contexts, which increases possibilities of recombination through analogous thinking. Consequently, while it is difficult to draw robust conclusions that might be applicable in other contexts, the article offers some insights especially for knowledge-intensive industries in which the knowledge base is wide and diverse and in which collaboration in research is a critical aspect of innovation.

Finally, there are a few points about the article which should be underlined in interpreting these results. The article does not take into account other internal organisational variables, which can shape recombination process. For example, management design, organisational culture, institutional context or the structure of networks among inventors in the firm can have a significant impact on recombination and innovative performance. In this sense, collection of more fine-tuned information at the firm level through interviews and direct observations is a potentially valuable research direction for the future. A second point is related with approximating innovative competences of firms with their patents. Although there is a very rich literature which uses this approximation, one should be careful in interpreting the results. In particular, high patenting propensity may not be a sign of high innovative competences in all sectors. In this sense, sectoral differences in patenting propensity are quite significant. Focusing on the ICT sector partly alleviates this problem, since it is a sector in which patenting propensity is very high. One of the future research areas could be to investigate how recombination is linked with the launching of new product announcements, which could be taken as an alternative measure of innovation.

Finally, one should keep in mind the problems associated with generalising from the statistical analysis of large datasets, especially in organisational level studies. While the results from regressions help to draw some reasonable insights about the underlying mechanisms, case studies carried out at the individual firm level are potentially very valuable to verify these results. As far as future research directions are concerned, detailed case studies are of particular significance to understand the precise mechanisms of recombination process and its implications for innovation.

Appendixes

Appendix 1

Table 4 Correlation matrix

		1	2	3	4	5	6	7	8	9
Patents	1	1.0000								
$Recom_{it-1}$	2	0.0024	1.0000							
$Recomsq_{it-1}$	3	−0.1250	0.9054	1.0000						
$TechProx_{it-1}$	4	0.2122	−0.0578	−0.0836	1.0000					
$TechProxsq_{it-1}$	5	0.1545	−0.0996	−0.1160	0.9634	1.0000				
$Recom_{it-1}$*$TechProxsq_{it-1}$	6	0.1229	0.8142	0.7338	0.4096	0.3704	1.0000			
$R\&D_{it-1}$	7	0.6226	−0.0235	−0.1215	0.2730	0.1943	0.1063	1.0000		
Number of alliances	8	0.6899	−0.0600	−0.1431	0.2491	0.1938	0.0768	0.5854	1.0000	
Age	9	0.3010	0.1861	0.1333	−0.0662	−0.1090	0.1329	0.4246	0.2260	1.0000
Agesq	10	0.2204	0.1611	0.1229	−0.0997	−0.1311	0.0817	0.3297	0.1659	0.9696
NAICS 334	11	−0.0476	−0.0023	−0.0358	0.0267	0.0228	0.0184	−0.0641	0.0594	−0.1409
NAICS 541	12	−0.0236	0.0374	0.0422	0.1422	0.1836	0.1059	0.0265	−0.0491	0.0140
NAICS 33 other	13	−0.0871	0.1196	0.1510	−0.2018	−0.1791	0.0170	−0.1318	−0.1572	0.2220
NAICS 51 other	14	−0.1058	−0.1187	−0.0843	0.0268	0.0003	−0.1151	0.1392	−0.0125	−0.1550
USA	15	−0.0468	−0.1527	−0.1132	0.0171	0.0484	−0.0965	−0.2081	0.1494	−0.3853
JAPAN	16	0.1748	0.1390	0.0791	0.0027	−0.0101	0.1239	0.2360	−0.0848	0.4135
OTHER	17	0.0159	−0.0208	−0.0474	−0.0421	−0.0247	−0.0383	−0.0951	−0.0404	−0.1666

Table 4 (continued)

	10	11	12	13	14	15	16	17
Patents								
Recom$_{it-1}$								
Recomsq$_{it-1}$								
TechProx$_{it-1}$								
TechProxsq$_{it-1}$								
Recom$_{it-1}$*TechProxsq$_{it-1}$								
$R\&D_{it-1}$								
Number of alliances								
Age								
Agesq	1.0000							
NAICS 334	−0.1528	1.0000						
NAICS 541	0.0037	−0.3558	1.0000					
NAICS 33 other	0.2254	−0.3418	−0.1266	1.0000				
NAICS 51 other	−0.1414	−0.3964	−0.1468	−0.1410	1.0000			
USA	−0.3636	0.1328	−0.1671	−0.0946	0.1222	1.0000		
JAPAN	0.3430	−0.1467	0.0446	0.2619	−0.1815	−0.6455	1.0000	
OTHER	−0.1588	0.2193	−0.0781	−0.0750	−0.0869	−0.2176	−0.1371	1.000

Number of observations 249

Appendix 2

Table 5 Poisson estimations and negative binomial estimations: dependent variable innovation capabilities

	Poisson random effect (a)	Poisson random effect (b)	NBER random effect (c)	NBER fixed effect (d)	NBER random effect (e)
$Recom_{it-1}$	2.249* (1.283)	7.954*** (1.696)	8.300** (4.181)	6.208* (4.100)	9.507* (5.641)
$Recomsq_{it-1}$	−63.488*** (7.292)	−107.126*** (10.786)	−96.104*** (24.990)	−80.345*** (23.872)	−83.591** (35.614)
$TechProx_{it-1}$	1.860*** (0.104)	1.692*** (0.111)	2.006*** (0.615)	1.923*** (0.617)	1.034* (0.535)
$TechProxsq_{it-1}$	−1.710** (0.080)	−1.457*** (0.084)	−1.785*** (0.520)	−1.702*** (0.523)	−0.811* (0.457)
$Recom_{it-1}$*$TechProx_{it-1}$	8.096*** (1.611)	4.004** (1.964)	9.311* (5.235)	9.540* (5.254)	0.916 (6.719)
$R\&D_{it-1}$		−0.043*** (0.015)			0.197*** (0.068)
Number of alliances		0.007*** (0.001)			0.009 (0.008)
Age					0.022* (0.013)
Agesq					−0.000 (0.000)
NAICS 334					−0.862*** (0.315)
NAICS 541					−1.012** (0.404)
NAICS 32, 33					−0.534 (0.423)
NAICS 511-8					−1.545*** (0.394)
USA					0.652** (0.286)
JAPAN					0.521 (0.334)
OTHER					2.731*** (0.561)
_cons			0.273 (0.244)	0.328 (0.243)	−0.999 (0.661)
ln_r _cons			−0.450*** (0.146)		−0.151 (0.173)
ln_s _cons			1.525*** (0.225)		1.950*** (0.315)
Time dummies	Yes	Yes	Yes	Yes	Yes
Wald Chi 2	9056.87	8684.00	150.34	147.14	257.00

Table 5 (continued)

	Poisson random effect (a)	Poisson random effect (b)	NBER random effect (c)	NBER fixed effect (d)	NBER random effect (e)
N	295	249	295	295	249

Standard errors in parentheses

$*p<.10$; $**p<.05$; $***p<.01$

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