11 Strategic alliances and knowledge flows between firms

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One of the established results in the literature on strategic alliances stresses that firms learn from each other and, as such, alliances are important means through which knowledge flows in industries. The alleged positive relation between alliances and learning has resulted in a vast amount of research carried out to determine the conditions and contexts which facilitate learning processes. In this chapter, we focus on three factors which can be important: the duration, the scope of the alliance and the initial technological overlap between partners. Our results reveal that initial technological overlap has a positive relation with learning, and there is an inverted-U relation between learning and alliance duration.

Introduction

The impact of strategic alliances on organizational learning has been a fruitful field of study during the last 20 years. On the one hand, there exists a significant literature confirming the transfer of knowledge and capabilities through alliances. One the other hand, some studies cast doubt on this alleged positive impact of alliances, highlighting the barriers that firms face in learning from their partners (Hamel, 1991; Crossan and Inkpen, 1994) and underlining the importance of alliance management capabilities (Schilke and Goerzen, 2010). Overall the research reveals that the effectiveness of knowledge flows between partners is highly contingent on the environment and the specific characteristics of firms.

As far as environmental factors are concerned, the central factors which shape knowledge flows can be related with the stability of the industry, the tacitness of the knowledge base and the stage in the industry life cycle. At the same time, alliance management capabilities and strategies (Schilke and Goerzen, 2010), the network positions of partners (Phelps, 2010), prior experience with partners (Gulati *et al*., 2009) and firms' overall alliance portfolio (Duysters and Lokshin, 2010; Jiang *et al*., 2010) as well as the balance the firms achieve between exploring and exploiting (Lavie and Rosenkopf, 2006; Hoang and Rothaermel, 2010) are some of the factors which shape the extent to which firms can learn from their partners.

While a variety of factors seem to shape learning processes, the duration of an alliance has been a less studied factor. Most of the studies on alliance duration focus on the determinants of contract duration, rather than the performance effects in the post-alliance phase. The importance of alliance duration mainly stems from the perception of partners in terms of the commitment of their resources. While instability of the industry, rapid technological change and uncertainty can increase the costs of committing resources for long periods (Simonin, 1999), long term relations can also have the benefit of permitting partners to develop shared understandings and a common knowledge base during the execution of the contracts. In addition, the extent to which such long term relations impact the learning from alliances is likely to be moderated by the initial common knowledge base between partners.

The aim of this chapter is to explore these aspects of learning in alliances, through the analysis of 128 technology based alliances which took place between 1984 and 1987, in a variety of industries. In particular, we investigate the extent to which knowledge transfers depend on the duration of the alliance, the scope of the alliance and the initial similarities between partners in terms of their knowledge bases.

The next section presents a theoretical background, as well as our hypotheses. In the third section we explain the data and methodology. And the last section is devoted to some discussions of our results.

Background

Back in the 1980s, a fairly rich literature on strategic alliances focused on the rationales for firms to enter into partnerships in the domestic and global context. The rationales behind alliances were investigated in various ways, both through in depth studies and large scale empirical analysis. In this sense the rationales behind alliances can be explained through a transaction cost perspective, which however falls short of covering strategic behavior of firms, and organizational learning (Kogut, 1989). Organizational learning as a motive behind strategic alliance formation has been since then studied by many researchers, utilizing a wide variety of methodologies and contexts of study. While a large body of literature confirms the knowledge flows between firms through alliances, some cast doubt on the difficulties associated with learning (Hamel, 1991; Crossan and Inkpen, 1994).

During the 1990s, this literature on alliances and organizational learning was to be complemented by the network perspective. Particularly, a leading study is by Powell *et al.* (1996) who emphasized the role of inter firm networks as locus of innovation. They state that firms network with each other not only because they lack resources and need to access others, but because they seek to explore and exploit each other's knowledge bases. In addition, and more importantly, it is the firms' position in this network that has a strong influence on the extent of success. The incorporation of the network approach into the alliance and organizational learning areas proved to yield a very fruitful area of inquiry, resulting in a vast body of work, investigating how network positions relate to learning by firms in the form of exploration and exploitation (Burt, 1992; Ahuja, 2000; Rowley *et al*., 2000; Gilsing *et al*., 2008; Phelps, 2010).

According to this literature, network position is related with learning, because it determines firms' access to external knowledge. When relations are embedded in a social context (Granovetter, 1985) where knowledge exchange is frequent and face-to-face, partners can build trust, so that concerns for reputation mitigate possible opportunistic behaviors. In addition, such networks which are rich in social capital facilitate the transfer of tacit knowledge since partners can develop shared meanings and a common understanding. These also can improve efficiency because costs of negotiation are reduced (Uzzi, 1997). Consequently, a clustered network structure facilitates the flow of knowledge (Audretsch and Feldman, 1996; Cowan *et al*., 2003).

On the other hand, embeddedness can make firms weaker in coping with external shocks and exclude them from knowledge residing outside their own clusters (Uzzi, 1997). Accordingly, network positions which bridge otherwise disconnected clusters can be better for effectiveness of knowledge access (Burt, 1992). Most scholars today agree that the type of network position conducive to performance depends on the context of inquiry, partner specific characteristics and the environment. In this sense, some studies posit that either of the two network positions is beneficial – but not both – or else a hybrid network position is more beneficial (Baum and Rowley, 2008).

Duration of alliances

While network positions can be highly influential in firms' access to knowledge, the duration of these ties also deserves attention. The impact and the determinants of alliance duration on learning have been studied from the lens of different research streams. Transaction cost approaches are predominantly concerned with the design of contracts between firms. In this view, the duration of a contract may depend on the asset specificity (Joskow, 1987), and the extent to which partners are unable to predict future hazards (Simonin, 1999). When the exchange necessitates parties to make relationship specific investments, long term contracting is a more attractive governance mechanism, in the face of unforeseen hazards that may occur during the execution of the contract. In this sense, longer contracts reduce the ambiguity which may be caused by the inability of the partners to foresee the future (Simonin, 1999), and thus protect against opportunistic behaviors. In addition, in high technology industries, where there is rapid innovation, and technologies are complex, long term contracts are better for learning (Pangarkar, 2003).

While these aspects are influential in the initial design phases of a contract, the final impact of duration on the performance of firms has been less studied. On the one hand, long term alliances allow the development of relationship specific skills and capacities which may facilitate knowledge flows between partners. In addition, long term alliances can be better for the transfer of tacit knowledge since partners can have the opportunity to develop shared understandings. In industries where knowledge is highly tacit, a cohesive network structure facilitates learning (Audretsch and Feldman, 1996; Cowan *et al*., 2003) and that tie age contributes positively to the performance benefits of such closure (Baum *et al*., 2007). In accordance, our first hypothesis is concerned with the positive impact of duration on learning:

> Hypothesis 1: Alliance duration has a positive impact on learning by partners.

While long term contracts can be preferred when there are risks of opportunistic behaviors, when there is a high level of asset specificity, or when knowledge is tacit, they can also be costly. Particularly, environmental instability may increase the likelihood of contract termination (Kogut, 1989). Especially in periods of instability, firms value flexibility when committing their resources for long periods. In such environments, deviations from optimal contract incentives significantly raise the cost of long term contracts (Crocker and Masten, 1988). More precisely, longer alliances allow for learning, but the longer the duration, the higher the cost of inflexibilities.

> Hypothesis 2: There is an inverted-U relation between alliance duration and learning.

Technological scope of alliances

In the literature, the scope of collaborations usually refers to the range of different functions that the alliance encompasses (Pisano, 1989; Oxley and Sampson, 2004). There is a fairly rich literature on how the scope of an alliance moderates learning processes. While this definition of scope encompasses different functions, like marketing, R&D, manufacturing and so on, the technological scope of an alliance and its effect on performance has been less studied. Technological scope of an alliance refers to the range of diverse subject matters which the alliance encompasses. The idea here is that, as the width of technological fields expands, so can the potential novelty from the alliance, and also the ambiguity surrounding the subject matter. The relation between technological scope and novelty is based on the Schumpeterian notion of recombination. Recombination refers either to the combination of elements which were previously unconnected, or finding new ways of combining elements which were already associated (Nahapiet and Ghoshal, 1997). One of the building blocks of recombination being variety, it is accepted that the probability of innovation is higher when there is more variety to be recombined (Weitzman, 1998). In addition, radical inventions are more likely to draw upon wider technological fields, than non radical inventions (Schoenmakers and Duysters, 2010).

However, in alliances with a broader scope, partnering firms can face difficulties in specifying the allocation of future property rights. In this sense, broader scope increases the complexity surrounding the alliance, and can result in more frequent changes in the post contract phase (Reuer *et al.*, 2002). In addition, although broader scope can induce firms to invest more in their alliances, it can have lower learning results than alliances with the same function (Amaldoss and Staelin, 2010). As a result, the complexity of alliance scope can augment the motivation to reduce the time span of the contract.

> Hypothesis 3a: There is a negative interaction effect between alliance scope and alliance duration as far as their effect on learning is concerned.

However, we argue that the sign of the interaction effect is indeterminate. Broader scope may enhance uncertainties surrounding the contracts (Simonin, 1999; Reuer *et al.*, 2002), since it increases the ambiguity of systems in general (Reed and De Filippi, 1990; Mosakowski, 1997). In this sense when the scope of the alliance is wider, increased duration can yield better learning by permitting firms to have more time in synthesizing complex projects.

> Hypothesis 3b: There is a positive interaction effect between alliance scope and alliance duration as far as their effect on learning is concerned.

Knowledge complementarities between partners

The knowledge based theory of the firm is considered to be an extension of the resource based theory, stressing the knowledge of the firm as its key resource. Accordingly, complementarities in knowledge between partners are an important motivation behind strategic alliances (Kogut and Zander, 1992; Grant, 1996). Empirical studies in this tradition usually measure firm complementarities through employing the notion of technological distance between firms. It is possible to argue that initial technological overlap is an important determinant of learning, because it means that firms have a certain initial commonality in their knowledge bases, which increases the extent to which they can learn from each other. Accordingly, we propose that:

> Hypothesis 4: There is a positive relationship between initial technological overlap between partners and their learning from the alliance.

At the same time, this positive effect can diminish as initial overlap increases. Two findings in the literature indicate that, first the likelihood of an alliance between two firms is higher when their distance is at an intermediate level (Mowery *et al*., 1998). Second, an inverted-U relationship exists between technological distance between firms and their learning (Schoenmakers and Duysters, 2006; Nooteboom *et al*., 2007; Gilsing *et al*., 2008). Moreover, this distance diminishes as firms collaborate with each other (Mowery *et al*., 1998). The underlying logic in this construct is that, when firms are too close in the knowledge space, they have little to add to each other's knowledge; when they are too far, they cannot access the other's knowledge base, and learning is limited. Johnson and Lundvall (1992) get to a very similar conclusion. Accordingly, we propose that:

> Hypothesis 5: There is an inverted-U relationship between initial technological overlap and learning from the alliance.

It is also possible to argue that the initial technological overlap between partners is mediated by the duration of the alliance. First, a high level of initial technological overlap implies that the tacitness of knowledge is less critical in terms of knowledge transfer. The positive impact of duration on learning can be augmented in this case. In addition, with increased overlap between partners, firms can better cope with the risks of future uncertainties.

> Hypothesis 6: There is a positive interaction effect between initial technological overlap and the duration of alliances as far as their impact on learning is concerned.

Figure 11.1 summarizes our hypotheses.

Data and methodology

The primary goal of this chapter is to analyze the knowledge flows between firms through their alliances. For this purpose, we collected the technology based cooperative agreements found in the CATI (Cooperative Agreements and Technology Indicators) database between the years 1984 and 1987. The MERIT CATI relational database covers around 19,000 technology based

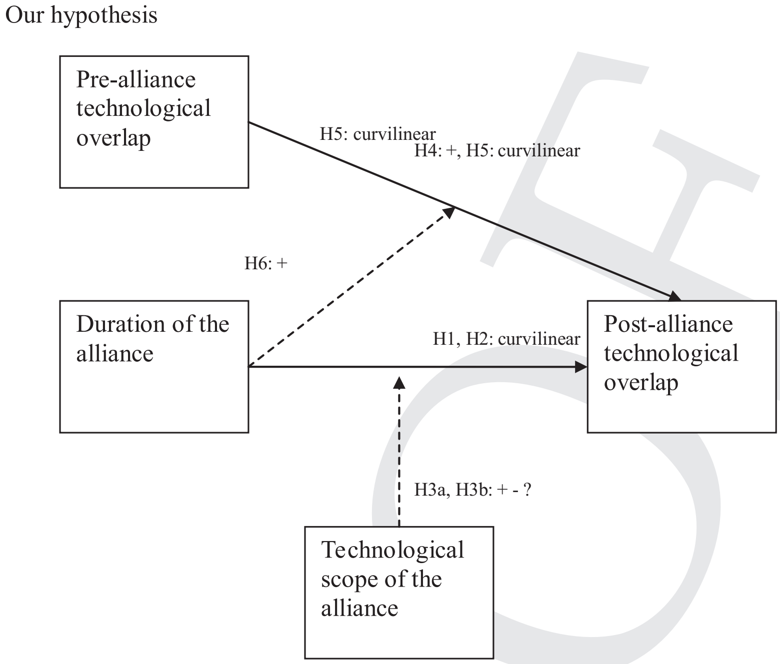

Figure 11.1 Our hypothesis

alliances of nearly 9500 firms. The data have been systematically collected since 1984 (although some of the alliances date back to the end of the 1800s), and it is one of the most widely used databases as far as technology based strategic alliances are concerned. Although data may be incomplete, it is considered as one of the most dependable data sources in this field (Schilling, 2008).

One of the drawbacks of the CATI database is concerned with the duration of alliances, because not all alliances have duration data. Because our main interest is in the longevity of alliances, we included only those alliances in which duration data were available, between 1984 and 1987. Keeping the time period short is important, so as to reduce the impact of time varying factors which might influence learning, capabilities or industry wide determinants of learning. We were further restrained by the availability of data on R&D expenditure for the firms in the sample in the mentioned period, to be used as control variables. We further excluded those firms which had no registered patents either at the beginning of the alliance or at the end. As a result, the total number of dyads in the sample was reduced from 971 to 223. These 223 dyads include a total of 128 technology based alliances,[1] and 143 firms that we include in the regression analysis.

We selected these periods for several reasons. First, these are the years in which alliance activity was very intensive. Second, technological advances in especially Biotechnology and Information Technologies were rather in their early development phases. In this sense, we believe that the *marginal* impact of an additional one year commitment in an alliance could be higher

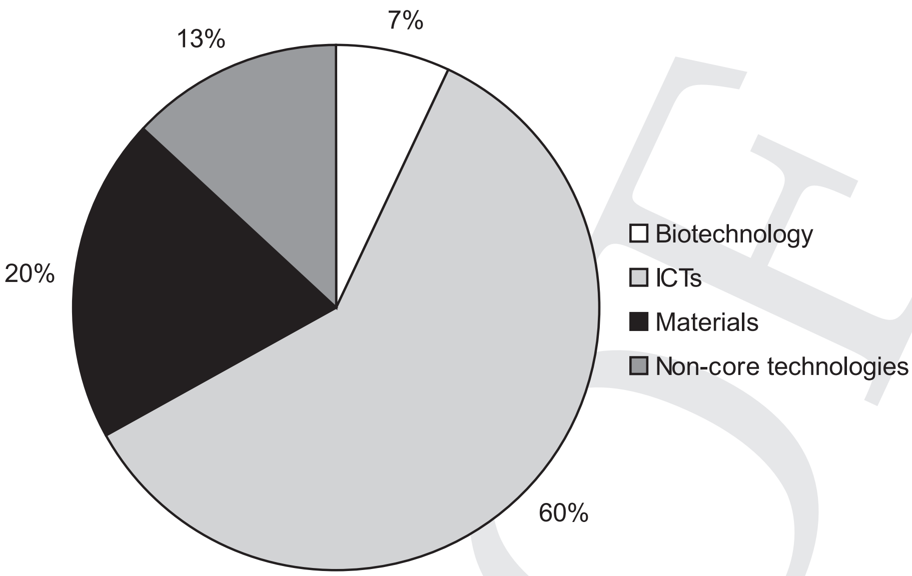

Figure 11.2 Sectoral distribution of alliances in the study

in these early development periods, rather than its effect in more stable phases of the industry. Figures 11.2 and 11.3 shows the breakdown of alliances with respect to sectors and continents.

To explore the learning aspects of alliances, we collected all the patents of the firms in the sample from the EPO PATSTAT database. Thus, we gathered variables that measure the firm's patent portfolio such as number of patents and their citations.

For the regression analysis, we had to keep the period limited (1984–1987), but we also carried out some exploratory analysis covering a broader time horizon, to see the general trends with respect to the variables that we are interested in. For this purpose, Figure 11.4 shows the relationship between learning from the alliance and the duration for all the alliances in which we had the data on duration, between the years 1965 and 1990. Learning is here taken as the difference between initial and final technological overlap between firms (see the section "Dependent variable" below for details on calculation).

As the figure reveals, the extent of negative and zero learning diminishes as the duration of alliance increases. In other words, positive learning is more likely the longer the duration of the alliance. However, it is difficult to draw robust conclusions because the number of observations is not homogeneous with respect to years.

Dependent variable

As a proxy for learning, we used the cross citation index that is commonly found in the literature (Mowery *et al.*, 1998; Schoenmakers and Duysters,

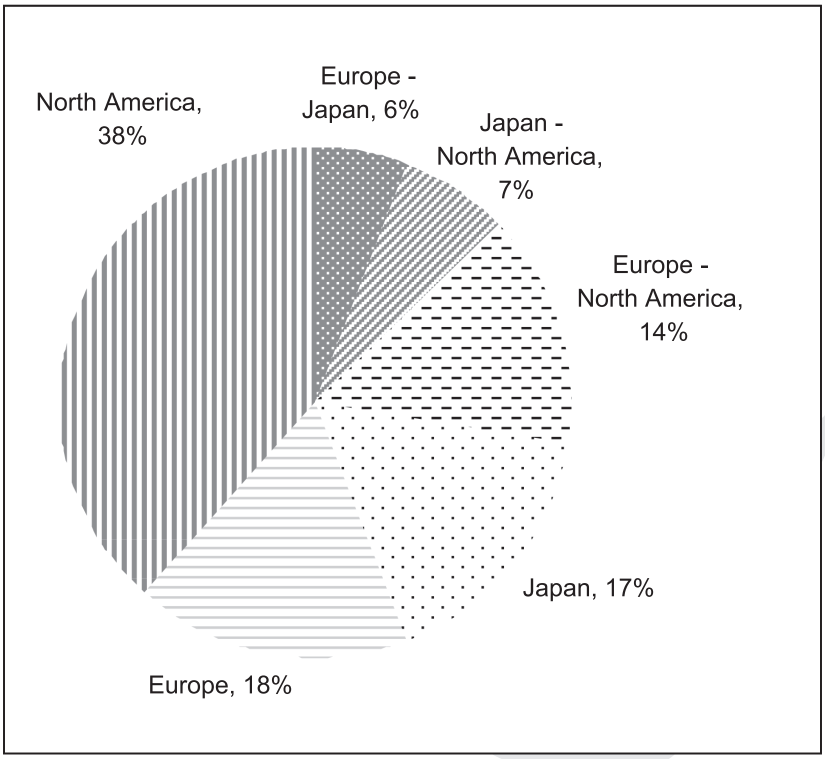

Figure 11.3 Country distribution of the dyads covered in the study

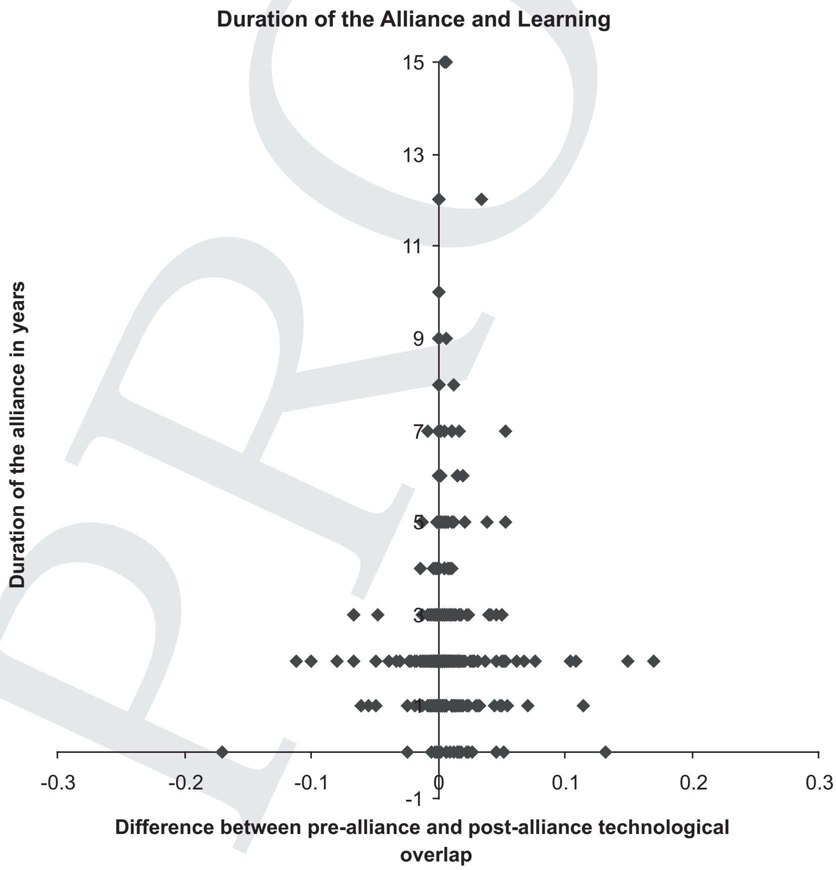

Figure 11.4 Duration and learning

2006; Rothaermel and Boeker, 2008). In particular the cross citation index between firms i and j is given by

$$common\ citation\ index = \frac{citations\ in\ firm\ i\text{'s}\ patents\ to\ firm\ j\text{'s}\ patents}{total\ number\ of\ citations\ in\ firm\ i\text{'s}\ patents} + \frac{citations\ in\ firm\ j\text{'s}\ patents\ to\ firm\ i\text{'s}\ patents}{total\ number\ of\ citations\ in\ firm\ j\text{'s}\ patents}$$

This ratio is calculated taking into account the patents of all the firms in the study. Two sets of patents were collected for each firm in a dyad. First, we collected those patents that the firms applied for and were granted in the five years preceding the alliance beginning (Mowery *et al*., 1998). In addition, we collected the patents that were applied for in the five years after the end of the alliance. Therefore, we took into account the duration of each alliance separately in data collection. In this way, we obtained approximately 86,000 patents. The difference between the common citation rates will give the relative rise – or fall thereof – of the cross citation rates before and after the alliance. In other words, cross citation rate gives a proxy for the extent to which firms move towards or away from each other in the technology space. The dependent variable used in the regressions is the post cross citation rate, which is the cross citation rate covering the five years after the alliance was ended.

Independent variables

We used a range of independent variables in the models. The duration of the alliance (DUR) is given as the difference between the beginning and the ending of the alliance. The scope of the alliance (SCOPE) is a simple sum of the different technology fields (core and non-core technologies) that the alliance encompasses. The initial technological overlap (OVERLAP_B) is the cross citation rate between the two firms forming the dyad, spanning the five years before the year of the alliance agreement.

In addition we used a range of control variables to account for the total number of patents of the firms in the beginning of the alliance and at the end of the alliance, the average annual sales ratio of the firms in the dyad, as well as the ratio of their average annual R&D intensity. We include dummy variables, for distinguishing between the main technology field of the alliance and to control for whether the two companies are from the same country. Table 11.1 provides some descriptive statistics of the data.

The model utilized is as follows:

OVERLAP_E = f (OVERLAP_B, SCOPE, DUR, Country, Biotech, IT, Materials, R&D, TotalPatents)

Table 11.1 Descriptive statistics

Variable	*Description*	*Mean*	*SD*	*Max*	*Min*
OVERLAP_E	*Technological overlap at the end of the alliance*	0.0097	0.0188	0.109	0
OVERLAP_B	*Technological overlap at the beginning of the alliance*	0.0050	0.0138	0.0952	0
OVERLAP_B SQ	*Overlap at beginning squared*	0.0002	0.0009	0.0091	0
DUR	*Duration of the alliance*	2.0090	0.8718	5	0
DURSQ	*Duration squared*	4.7928	4.3326	25	0
SCOPE	*Scope of the alliance*	2.8198	0.6753	6	2
Total Patents Beg	*Total number of patents of two firms in the period of five years before the alliance*	444.937	573.999	2448	0
Total Patents End	*Total number of patents of two firms in the period of five years after the alliance*	897.599	1083.217	4991	6
Country	*Dummy indicating whether country of origin of two companies are the same*	0.5946	0.4921	1	0
BIOTECH	*Dummy indicating biotechnology field*	0.0691	0.2436	1	0
IT	*Dummy indicating information technology field*	0.5991	0.4912	1	0
MATERIALS	*Dummy indicating materials technology field*	0.199	0.400	1	0
R&D	*R&D intensity ratio between two firms*	0.529	0.278	0.999	0
Sales	*Sales ratio between two firms*	0.275	0.287	0.983	0

Results

The regression results of models 2, 3, 4 and 5 reveal first that there is an inverted-U relationship between alliance duration and final technological overlap between partners. This corroborates our hypotheses 1 and 2. In other words, while the duration of the alliance can have a positive impact on learning, this positive effect diminishes for longer terms.

The regression models highlight no significant interaction effect between alliance duration and scope, rejecting hypotheses 3a and 3b. Hypothesis 6 is also rejected, which tests for the positive interaction effect between initial technological overlap and duration of the alliance.

As far as the effect of initial technological overlap on final overlap is concerned, we do not detect a significant curvilinear relation. Rather, the models 1–5 show that initial technological overlaps between partners have a positive effect on learning, which corroborates Hypothesis 4. There is no diminishing effect on learning as partners are closer to each other at the beginning of an alliance. As a result, Hypothesis 5 is not confirmed.

All the models show that the R&D ratio between firms has a negative and significant impact on learning. In other words, the more asymmetric firms are in terms of their R&D investments, the less they learn from each other as a result of the alliance. In addition, the models detect a significant effect neither for sector nor country variables. One of the interesting results is concerned with the significant positive impact of initial number of patents, and the final learning levels. This result reflects the importance of initial technological capabilities of firms in learning processes.

Discussion and prospects for future research

Learning from alliances depends on range factors, as a very rich literature reveals. In this chapter, we focused on the impact of duration, technological scope and the extent of overlap in the partners' knowledge profiles. One of our results reveals an inverted-U relationship between the duration of alliances and the final technological overlap. This can partly explain the discussions in the literature with respect to the impact of duration on learning. While longer term alliances can be preferable in terms of partners' opportunities to build shared meanings as far as complex tasks are concerned, they are also disadvantageous when technology evolves fast and along uncertain paths. In the latter case, firms may prefer not to commit their resources for long periods. Indeed, these factors seem to suggest an inverted-U shaped function between duration and performance, which our data also confirm. According to our results, there is no significant interaction effect between duration and initial technological overlap, and neither is there an interaction effect between alliance scope and duration. However, this might also be related with the measurement of technological scope. Coverage of a wide range of fields in the alliance may not imply that the alliance is more

Table 11.2 Some results of the OLS regressions

	Dependent variable: OVERLAPE				
	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 5*
Intercept	−0.007	−0.012	−0.013	−0.013	−0.020
	−0.392	*−1.026*	*−1.103*	*−1.118*	*−1.156*
Overlap B	0.446	0.428	0.453	0.234	0.234
	*1.95**	*1.91***	*1.86***	*2.76***	*2.74***
Overlap B SQ	−3.185	−2.994	−2.808		
	−0.974	*−0.934*	*−0.882*		
Scope	0.003				0.002
	0.282				*0.558*
Scope SQ	0.000				
	−0.108				
Duration		0.011	0.012	0.012	0.013
		*2.35***	*2.37***	*2.37***	*2.12***
Duration SQ		−0.003	−0.003	−0.003	−0.003
		*−2.57***	*−2.60***	*−2.59***	*−2.54***
Duration * Overlap B			−0.022		
			−0.193		
Duration * Scope					−0.0001
					−0.387
Country	0.002	0.001	0.002	0.002	0.002
	0.835	*0.489*	*0.637*	*0.658*	*0.818*
R&D	−0.007	−0.006	−0.006	−0.006	−0.006
	−1.627	*−1.71**	*−1.78**	*−1.83**	*−1.69**
Total Patents B	0.000	0.000	0.000	0.000	0.000
	*1.98**	*1.79**	*1.76**	*1.92**	*1.99**
Total Patents E	0.000	0.000	0.000	0.000	0.000
	1.224	*1.568*	*1.610*	*1.69**	*1.570*
Biotechnology	0.011	0.012	0.012	0.012	0.012
	1.010	*1.163*	*1.135*	*1.180*	*1.157*
Information Tech	0.007	0.007	0.007	0.007	0.007
	0.780	*0.734*	*0.713*	*0.729*	*0.717*
Materials	0.005	0.003	0.003	0.003	0.003
	0.525	*0.275*	*0.265*	*0.295*	*0.328*
n	209	209	209	211	209
F	7.44	8.15	8.12	9.72	7.07
t-*tests in italics*					

complex in terms of its knowledge content. One of the questions that can be addressed in the future is whether these results are valid also in relatively mature industries.

Last but not least, a brief note on data and methodology. Although utilizing alliance and patent data can give insight into broadly observed regularities, and they are commonly used in the innovation literature, we should be careful in interpreting the results. Hamel (1991: 84), in exploring the measurement problems related to learning from alliances states that:

> Because patterns of causality are extremely complex in most real-world administrative systems, traditional deductive-analytic methodologies force the researcher to declutter the phenomenon by: (1) substituting crude proxies for difficult-to-measure determinants or outcomes; (2) assuming away some of the multidimensionality in causal relationships; and/or (3) narrowing the scope of research. In doing so, much of the potential value of the research is lost. The problem is not that the resulting theories are under-tested (i.e. they fail a test of rigor), but that they are under-developed (i.e. they are so partial in coverage that they illuminate only a fragment of the path between choice, action and outcome).

In this sense, our study should be taken as exploratory, in the sense of highlighting a possible impact of duration, which seems intuitively plausible. However, generalizations are always difficult. Case studies can be a useful complementary approach to validate findings from large databases, and our study suggests that duration and technological scope of alliances can play a role in the learning processes, a relationship which deserves investigating with individual case studies as well.

Notes

1 CATI includes a variety of alliance types. In this study we took into account only the technology based alliances, and we excluded equity based alliances.

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