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THE INFLUENCE OF SOCIAL CAPITAL AND KNOWLEDGE CODIFIABILITY ON SUCH RELATIONSHIP

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Abstract

Alliances are increasingly considered a key issue for innovation, especially in knowledge-intensive firms. While this is true, the mere membership to alliances does not explain innovation performance, and thus the alliance's characteristics that determine high performance must be examined. Our research address the question of how the diversity of partners in a certain alliance for innovation affects innovation performance, and how this influence can be moderated by certain characteristics, such as the social capital and type of knowledge shared among partners.

The empirical analysis of a sample of 90 biotech companies shows that diversity, on its own, does not explain alliance performance. Instead, social capital and codified knowledge, as moderating variables, may help reap the benefits of diversity. This effect is not unlimited, so beyond a certain level of diversity, the moderating variables become less effective.

Keywords: Keywords: Innovation Performance; Social Capital; Knowledge; Partner Diversity.

1. INTRODUCTION

Alliances are increasingly considered a key issue for innovation, given that they enable organizations to exchange valuable knowledge resources and share costs and risks (Dooley, 2007; Gulati, 1998). This phenomenon becomes particularly important in knowledge-intensive industries usually consisting of a set of many different technologies for which unique and differentiated capabilities are required. This is the case for the biotech industry, in which knowledge and resources are distributed across a variety of organizations -universities, research institutions, small biotech firms, large pharma companies, and so on (Hendry and Brown, 2006). In this context, the development costs of new products and the acquisition of the required knowledge and skills are difficult to assume by a single company (Hagedoorn, 1993; Powell and Brantley, 1992). Given the breadth and pace of technological change in this industry, exploring all facets of the R&D without specialized external support is not possible even for large pharmaceutical companies (Pisano, 2006). In turn, biotech companies that support these R&D activities of big pharma firms have to look outside themselves to find the competences to commercialize their innovations, given that they are not likely to be successful in carrying out the entire set of business functions along the value chain (Oliver and Liebeskind, 1997; Powell, 1998). Therefore, the biotech industry is characterized by the existence of multiple inter-organizational agreements among different types of partners trying "to build knowledge at an inter-organizational level" (Nonaka, 1994), in order to achieve their innovation aims.

Thus, alliances do matter for innovation performance in the biotech industry. However, the performance achieved by alliances for innovation does not always meet the companies' expectations, so trying to explain how certain characteristics of these alliances contribute to their success remains as yet a relevant research question (Sampson, 2007).

Our research focuses on alliance diversity, which represents an alliance attribute that may have a particularly relevant effect on performance (Goerzen and Beamish, 2005; Nieto and

Santamaria, 2007). In this sense, it is broadly accepted that the diversity of partners provides opportunities for valuable learning (Teece, 1998) and, specifically in science-based industries, it is claimed that alliances among diverse organizations (universities, small firms, public research institutes and large pharmaceutical companies), convey innovation benefits (Owen-Smith and Powell 2004). Indeed, partners' diversity has become a key feature of alliances in biotech industry. Notwithstanding, research suggests that beyond a certain level of diversity, its benefits could be difficult to reap given the hindrances to share and transfer knowledge among firms that have little in common (Kogut and Zander, 1992; Lane and Lubatkin, 1998).

This controversial effect of diversity on innovation performance is challenging and has attracted the attention of researchers trying to explain how firms can obtain the potential benefits of diversity, as well as counteract its harmful effects. Sampson (2007) analysed how alliance organization (equity joint ventures vs bilateral contracts) moderates the influence of partners' diversity on firm innovation. Terjesen et al. (2011) examined how the interaction between manufacturing capabilities in the alliance and alliance diversity affects venture performance. At the level of alliance portfolio, Duysters et al. (2012) demonstrated that alliance experience and alliance capabilities moderate the diversity-performance relationship. Oerlemans et al. (2013) found that technology management tools moderate the effect of partner diversity and firm's innovation outcomes.

Therefore, the literature referred above suggests that managers can influence the relationship between partner diversity and innovative outcomes through conscious and targeted managerial efforts (Oerlemans et al, 2013); that is to say, by means of some capabilities, tools, alliance forms and so on. Nevertheless, not only may these conscious efforts and actions moderate the effect of diversity, but also certain attributes of the alliance itself could influence how diversity has an impact on innovation performance. Given the difficulties associated with knowledge transfer and learning pointed in the literature on

diversity, we focus on two alliance attributes that may facilitate these processes in alliances comprising very diverse partners.

The first alliance attribute has to do with the quality of relationships among partners. The literature on knowledge and social capital claims that relationships characterized by friendship and trust (the relational side of social capital) provide information and learning benefits (Maurer and Ebers, 2006; Powell et al, 1996). Therefore, organizations involved in alliances characterized by a strong social capital are more likely to obtain the benefits of having very diverse partners (Phelps et al, 2012).

The second attribute is related to the knowledge shared in the alliance. The literature has suggested that the success of alliances is highly dependent on the ability to create and transfer knowledge within the alliance (Albino et al., 1999). Diverse alliances require the transfer of knowledge between many different actors. Thus, a successful use of such knowledge requires that all partners receive full information without any loss of content whatsoever. Codified knowledge is defined as the one that can be transmitted without any loss of its integrity, when the transmitter and receiver share the syntactic rules necessary for its decipherment (Kogut and Zander, 1992). Therefore, given the complexity associated to diverse alliances (Carlsson, 2010), we expect that the more codified the knowledge, the higher the innovation performance obtained from the alliance will be. This is because this type of knowledge will reduce the complexity of interrelated communications and will make the development of success innovation easier.

Therefore, the aim of this paper is twofold: first, we discuss the controversial effect of alliance diversity on innovation performance, and propose that it could be understood as an inverted U-shaped relationship. Second, we explain that this effect may be moderated by two attributes: the quality of relationships among partners and the type of knowledge shared.

These may facilitate knowledge transfer and learning when alliances involve very diverse partners.

The empirical analysis of a sample of 90 biotech companies shows that while we cannot confirm the direct U-shaped relationship between alliance diversity and innovation performance, it appears when introducing the moderating effects of social capital and knowledge codificability. These findings contribute to the current research on alliances for innovation by providing empirical evidence on why some alliances perform better than others. Also, our results suggest that the study of diversity, as determinant of alliance performance, should not be addressed in isolation. By considering the moderating effect of certain characteristics of the alliance, such as social capital and knowledge, the influence of partners' diversity on innovation performance can be better understood.

The paper proceeds as follows. The next section presents the theoretical background that led us to establish the hypotheses. The following sections test such relationships empirically. Finally, the main conclusions, contributions, managerial implications and limitations are presented.

2. Theoretical background and hypotheses

2.1. The effect of alliance partner diversity on innovation performance

Given that alliances boost firms' knowledge, those firms that have many alliances are likely to be more innovative (Baum et al., 2000). Even so, research suggests that, rather than the number of partners or alliances *per se*, it is the diversity of knowledge to which an organization has access via its partnerships that affects its innovation performance (Baum et al., 2000; Phelps et al., 2012; Zeng et al., 2010). Thus, the composition of the alliance in terms of the diversity of partners is a key factor that may have a particularly relevant effect on performance (Goerzen and Beamish, 2005) and can help to understand why some alliances are more successful than others.

Partner diversity refers to the degree of heterogeneity in the types of partners with which a firm allies (Rothaermel and Deeds, 2006; Terjesen et al., 2011). It includes universities and research labs, suppliers, buyers, competitors, consultants and so on, all of which possess different types of knowledge (Oerlemans et al., 2013).

The literature suggests opposing arguments about how partner diversity affects alliance innovation performance. On the one hand, it is broadly argued that knowledge building requires dissimilar but complementary bodies of knowledge (Boschma, 2005), provided by a set of diverse partners. Indeed, as Dyer and Nobeoka (2000) state, the main reason why a network is superior to a firm is that there is greater diversity of knowledge in the former than in the latter. Partner diversity exposes firms to more pieces of information from which to learn, enhancing the breadth of perspective, the cognitive resources and the problem-solving capacity of the firm (Goerzen and Beamish, 2005). This exposure to diverse ideas and experiences benefits the firms by making them think 'out of the box' and by stimulating learning (Vasudeva and Anand, 2011). Thus, as the level of diversity increases, the opportunities for valuable learning increase as well (Teece, 1998), because partners with diverse capabilities have more to learn from each other than from similar partners (Sampson, 2007). Some studies on biotech industry support this idea that different types of partners, which provide access to diverse information, knowledge and capabilities, are more likely to generate innovation (Al-Laham et al., 2010; Powell et al., 2005). Similarly, Baum et al. (2000) showed that startup biotech firms enhance their performance by configuring alliances into an efficient network that provides access to diverse information and capabilities.

On the other hand, the literature also states that while diversity may represent an opportunity to gain access to new and valuable knowledge, it could become a barrier for the effective inter-organizational learning. That is, the potential benefits of collaboration between highly diverse partners may be difficult to reap, because the costs of sharing and transferring

knowledge may be very high (Kogut and Zander, 1992; Lane and Lubatkin, 1998). Vasudeva and Anand (2011) state that as partners' diversity increases, lower levels of synergies and shared experiences can be exploited and, thus, more learning resources may be needed. Similarly, Oerlemans et al. (2013) state that a high level of partner diversity increases the costs of coordination, monitoring and communication, as well as the probability of opportunism. In fact, what organizational learning theory has largely suggested is that it is the similarities between partners, rather than their differences, that facilitate the absorption of tacit and articulated knowledge, which will in turn affect alliance performance positively (Hedlund, 1994; Parkhe, 1991). It seems that people learn new ideas by associating those ideas with what they already know, while firms will better identify and absorb external knowledge when it is close to their existing knowledge base (Boschma, 2005; Cohen and Levinthal 1990; Lane and Lubatkin, 1998). Therefore, from this point of view, in order to ensure the success of the alliances, the knowledge and technology shared and exchanged among partner firms should have a certain degree of similarity.

The arguments above lead to the fact that the relationship between partner diversity and alliance innovation performance is an inverted-U-shape, as has been proposed also by Sampson (2007) and, with a similar logic, by Duyster et al. (2012), Oerlemans et al. (2013) and Van de Vrande (2013) at the level of alliance portfolio. In sum, partner diversity should be wide enough to represent an appropriate base for knowledge transfer and recombination but not so wide as to prevent efficient assimilation (Sampson, 2007). Therefore, what can facilitate the alliance success and development of innovation is a moderate level of diversity. Hence, our first hypothesis is formulated as follows:

Hypothesis 1: The relationship between alliance partner diversity and innovation performance takes the form of an inverted U-shape.

2.2. The moderating role of social capital

As argued, and in spite of its advantages, the wide diversity of knowledge provided by very distinct partners might make effective learning difficult and, as a consequence, it may harm innovation performance. In this section, we argue that social capital, understood as the quality of the relationships among partners, could mitigate the disadvantages of partner diversity and leverage its positive influence on innovation performance. Indeed, Ahuja (2000) states that the benefits of collaboration, that arise from combining skills, sharing knowledge and conducting joint projects, presume the existence of significant trust between partners. In absence of trust and shared norms of behaviour, sharing knowledge and combining skills are likely to be difficult (Coleman, 1988).

The nature and benefits of this type of relationships based on trust have been addressed in previous research under the framework of social capital. Social capital has been defined as the actual and potential resources embedded within, available through and derived from the networks of relationships by an individual or social unit (Nahapiet and Ghoshal, 1998, p. 243). The relational side of social capital on which our research is grounded refers to different types of relationships, be it friendship, trust or respect (Nahapiet and Ghoshal, 1998).

Social capital among partners can contribute to leverage the positive effect of diversity on innovation performance for two main reasons. First, social capital can help mitigate the difficulties in transferring and integrating very diverse knowledge. Overall, the literature has addressed the fact that quality relationships enhance comprehension of the transferred knowledge because trust allows for greater openness and cooperation (Pérez-Nordvedt et al., 2008). In this sense, Tiwana (2008) demonstrated that ties characterized by trust, reciprocity and proximity, help integrate diverse knowledge, skills and capabilities. Individuals connected by this type of ties serve as brokers, translators and interpreters of a broad repertory of specialized knowledge from alliance partners that, in turn, influence the innovation

performance positively. Other authors state that when social capital exists among partners (i.e., trust, reciprocity and social identity), they are more disposed to share and receive knowledge, and are more likely to expend effort to ensure that partners understand knowledge exchanged sufficiently and can put into use the new knowledge acquired (Levin and Cross, 2004; Phelps et al., 2012).

The second reason has to do with the fear of opportunistic behaviour by the partners in the alliance, which represents an obstacle to share knowledge. As Gulati (1998) states, the problem of appropriation concerns in alliances is worsened by a heightened threat of opportunistic behaviour. If trust is not present in the relationship, the focal firm is likely to believe that its partner in the alliance may want to harm them. Thus, the former would be cautious in admitting some lack of knowledge and reluctant to learn from any transferred knowledge owing to fear that it might be wrong or misleading (Levin and Cross, 2004). When allied partners are very diverse and, therefore, the knowledge shared is as well, the information asymmetry makes this fear even a more important concern for firms. In this context, trust and reciprocity provided by social capital can help mitigate this fear. This creates a normative context in which decision-makers do not feel that they have to protect themselves from the opportunistic behaviour of others (Cuevas et al, 2013; Gulati and Singh, 1998; Inkpen and Tsang, 2005; Padula, 2008). By reducing concerns about loss of proprietary skills and knowledge, social capital encourages firms to be more willing to share knowledge and learn from their partners, even when they are very diverse and information asymmetry exists.

Summarizing, closeness and trust in the relationships among partners (the relational side of social capital), will help avoid some drawbacks when there is partner diversity, by facilitating the comprehension of shared knowledge as well as by reducing the fear of opportunistic behaviour. As Phelps et al. (2012) state, given that social capital among alliance

partners will enhance the transfer of knowledge, the organization involved in such alliance will improve its ability to benefit from diverse partners. Thus, we propose that:

Hypothesis 2: The inverted U-shaped relationship between partner diversity and innovation performance is positively moderated by social capital among partners.

2.3. The moderating role of knowledge codifiability

As we have mentioned, alliances are complex organizational forms involving the transfer of resources between organizations with diverse knowledge and capabilities. Obviously, different types of alliance with different kinds of partners will involve different degrees of complexity, and organizations must put their abilities into practice in order to achieve effectiveness in their knowledge exchange. The knowledge-based view of the firm (Grant, 1996; Kogut and Zander, 1992, among others) argues that developing innovations by setting up alliances requires effective mechanisms to facilitate inter-organizational transfer of knowledge (Inkpen, 1996; Zander and Kogut, 1995). Therefore, this section is devoted to explain how knowledge codifiability could reduce the complexity of these organizational forms and enhance the curvilinear relationship between diversity and innovation performance.

Knowledge could be defined in a wide sense as what is known (Grant, 1996) or, using Nonaka and Takeuchi's (1995) proposal, as the validated understanding and beliefs in a firm about the relationship between the firm and its environment. Among the existing knowledge-based issues, the distinction between tacit and explicit knowledge is important to understand organizational knowledge (Nonaka and Takeuchi, 1995). This is a familiar category (Gopalakrishnan, Bierly and Kessler, 1999; Grant, 1996; Nonaka, 1994; Polanyi, 1966) and generally describes the extent to which knowledge is or is not codifiable (Galunic and Rodan, 1998). Polanyi (1966) classifies human knowledge into two categories. On the one hand, he distinguishes explicit or codified knowledge, which is the knowledge that can be transferred through a formal language; that is, the knowledge that can be transmitted without the loss of

its integrity if the transmitter and receiver share the syntactic rules necessary for its decipherment (Kogut and Zander, 1992). On the other hand, Polanyi defines tacit knowledge as having a personal quality that makes its formalization and communication difficult (Nonaka, 1994). Therefore, as knowledge tacitness increases, knowledge transfer becomes more complex (Windsperger and Gorovaia, 2011) to such an extent that it may become a barrier for knowledge transfer (Szulanski, 1996).

Knowledge transfer among companies provides opportunities for mutual learning and inter-organizational cooperation, which stimulate the creation of new knowledge and, at the same time, contribute to the organizational ability to innovate (Nielsen, 2005). This knowledge can be captured and codified in manuals, processes and software (explicit knowledge). While authors as Von Krogh et al. (2000) proposed that tacit knowledge, not explicit knowledge, is generally the source of a firm's innovation, when talking about alliances, especially with diverse partners, explicit and easy to transmit knowledge will help the success of innovation performance (Kogut and Zander, 1992). This is because explicit and hence codifiable knowledge can be efficiently transferred (Windsperger and Gorovaia, 2011). As we have previously mentioned, diverse alliances involve the transfer of knowledge between many different participants. A successful use of such knowledge requires that all partners receive the same information without any loss of meaning; in turn, as knowledge codifiability increases, the complexity associated with knowledge transfer in diverse alliances is reduced. Then, by simplifying knowledge transfer, companies could obtain the maximum benefit of diverse alliances.

Based on the previous ideas, we propose that the more codifiable the knowledge, the easier it will be to transmit knowledge among diverse alliance partners. Therefore, we propose that knowledge codifiability enhances the relationship between alliance diversity and innovation performance. Thus,

Hypothesis 3: The inverted U-shaped relationship between partner diversity and innovation performance is positively moderated by knowledge codifiability.

3. Data and methodology

3.1. Research Design and Sample

The nature of biotechnology activities, result of cross-industrial and cross-disciplinary scientific synergies, has led biotechnology companies to an extensive reliance on external collaborations that tend to take place in regional clusters. By clustering, biotechnology firms seem to benefit from being connected to a broad set of actors with expertise from different positions in the value chain (Chiaroni and Chiesa, 2006; Oliver and Liebeskind, 1997).

The population for this study is composed of biotechnology firms belonging to the main five clusters in Spain: Bioregion (Andalusia), Biobasque (The Basque Country), Biocat (Catalonia), Bioval (Valencia) and Madrid Biocluster. We built the database of companies of these clusters by matching the database of ASEBIO (Spanish Association of Biotechnology Companies) and the information found on the websites of the cluster agencies.

For our research, only companies that have biotechnology as its main activity have been considered, leading to a population of 285 firms. Data were collected through a personal survey during 2012 and 2013. Questionnaires were addressed to the CEO and/or the person responsible for R&D activities, and questions were referred to the most important alliance for innovation that the firm had established in the last five years. After eliminating those cases with missing data, ninety valid responses were obtained, which provided a usable response rate of 31.6%.

3.2. Measures

The measures were selected for this research after a wide literature review on innovation, alliances, social capital, knowledge and biotechnology firms. The questionnaire has been

pretested with a small sample of companies in order to make sure that the questions were well understood by managers and were relevant to the industry under analysis.

3.2.1. Dependent variable

Innovation performance of alliance. It was measured using Rese and Baier (2011) scale that assesses the new product performance with respect to the products developed in the networks. As Rese and Baier suggest, this subjective assessment of performance can be sufficiently reliable if alliances have been rather recently formed and other precise performance indicators are not available. Managers assessed the outcome of the alliance with the following three items: IP1: it fulfilled the program or the deadline. IP2: it fulfilled the budget. IP3: the time was efficiently used. The response scale was a seven-point Likert scale ranging from "totally disagree" (1) to "totally agree" (7).

3.2.2. Independent Variables

Partner diversity. Based on Oerlemans et al. (2013), we asked about the number of partners in each of these categories: a) universities, research institutes and centers; b) customers; c) providers; d) competitors; e) others and f) pharmaceutical firms. Thus, the variable partner diversity would range from 1 to 6, depending on how many different categories of partners participate in the alliance. Besides, given that the number of partners in each category slightly increases the diversity of partners in the alliance (i.e. three universities as partners implies more diversity than having only one), we corrected the previous measure by constructing and adding an index that captures this internal diversity.

Social Capital was measured using Molina and Martinez (2009, 2010) scales. In order to ask managers about the type of relationships maintained with their partners, the following ten items were used: SC1: we share the same goals and interests in joint projects. SC2: we are motivated to pursue collective goals in joint projects. SC3: there is a shared vision on the

environment and the key factors of success. SC4: we believe that the future of our company is related to companies with whom we have established an alliance. SC5: we have developed some type of strategy or common plan for joint projects. SC6: we trust that the companies with whom we are in partnership do not take advantage of the alliance or behave opportunistically. SC7: companies with whom we have the alliance maintained the commitments made. SC8: we are sure that there will be agreement, even when there is not a written contract that specifies the obligations of each party. SC9: in general, there is a climate of cooperation and mutual trust among the participants. SC10: we feel a special obligation to be supported in difficult situations and to support each other. The response scale was a seven-point Likert scale ranging from "totally disagree" (1) to "totally agree" (7).

Knowledge codifiability was measured using Subramaniam and Venkatraman (2001) scale. The five items for this dimension of the characteristics of the knowledge used in the development of innovations were: KC1: there exists a useful manual that describes the processes. KC2: the information and decision rules are stored in electronic databases. KC3: knowledge about the alliance is sufficiently explained in writing. KC4: new staff can learn easily talking to staff involved in the alliance. KC5: new staff can learn easily by studying the existing manual. The response scale was a seven-point Likert scale ranging from "totally disagree" (1) to "totally agree" (7).

3.2.3. Control variables

R&D department size was measured by the numbers of permanent employees in the R&D department as reported by firm's respondents. ***Age*****:** following Sørensen and Stuart (2000), we also controlled for firm age (2013 – company foundation date). ***Leader*****:** we have considered relevant to control for who the leader of the alliance is; this is a dummy variable, with 1 if the observed firm is the leader of the alliance and 0 if not. We have also controlled for the

different ***clusters*** used in the analysis (Andalusia, Catalonia, Valencia, Basque Country and Madrid).

4. Analyses and results

Given that the measurement scales used were based on an exhaustive review of the relevant literature concerning the constructs under study, we can affirm their content validity. An exploratory factor analysis was performed separately for each construct, using principal component analysis, selecting factors with eigenvalues greater than one. All the items of each construct loaded in only one factor (unidimensionality).

With regard to reliability, Cronbach's alpha exceeded the minimum value of 0.7 recommended by Nunnally & Bernstein (1995) for all the measures with at least two items. Thus, these measures seem to be reliable and valid Table 1 shows means, standard deviations and correlations for the study variables. Concerning correlations, we note that there is a high correlation between innovation performance and social capital, between innovation performance and codifiability, and between size and age. To ensure that multicollinearity was not an issue, Value Inflation Factors (VIFs) were computed (but are not reported here because of space limitations). No VIFs were greater than 2, indicating that we did not encounter multicollinearity.

Table 1: Means, standard deviations and correlation matrix

	Mean	s. d.	N	1	2	3	4	5	6	7
1. Age	9,44	9,00	90	1						
2. R&D Size	15,54	53,18	90	0,75**	1					
3. Leader	0,76	0,43	90	0,14	0,04	1				
4. Social Capital	5,79	0,96	90	0,06	0,03	-0,11	1			
5. Codifiability	4,80	1,32	90	0,10	0,10	-0,14	0,22*	1		
6. Innovation Performance	5,37	1,23	90	0,14	0,16	-0,11	0,47**	0,46**	1	
7. Diversity	1,93	1,17	90,00	0,10	-0,02	-0,22*	-0,16	0,20	-0,11	1

† p < .1; * p < .05; ** p < .01; *** p < .001;

Our hypotheses were tested using hierarchical regression analysis because an interaction effect only exists if the interaction term gives a significant contribution over and above the direct effects of the independent variables.

The results are displayed in Table 2. The base models displayed in the first column explain a non-statistically significant share of the variance.

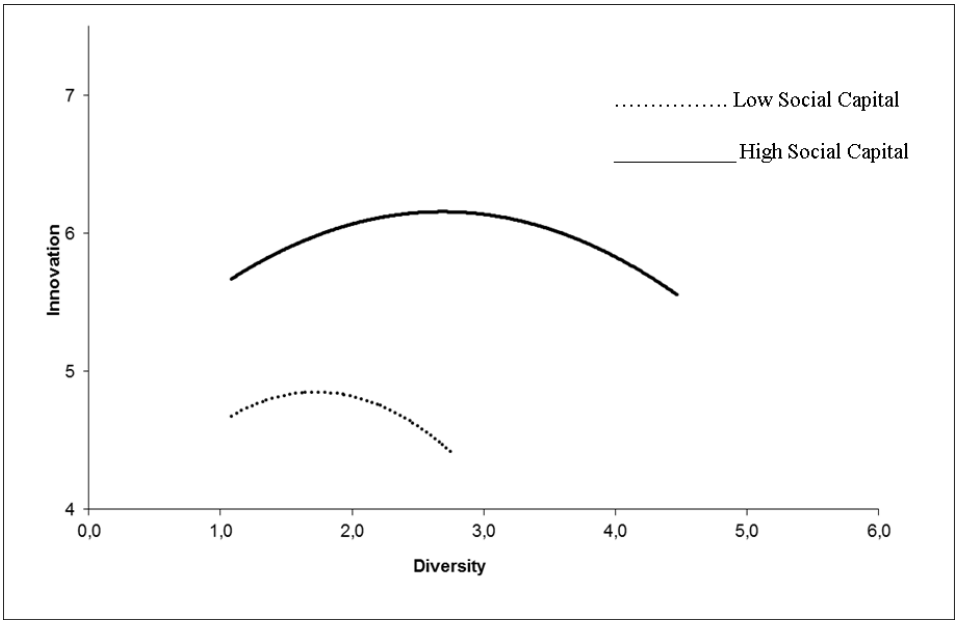
Table 2: Regressions

Dependent variables	Base Model		Independent Model		Contingent Model 1		Contingent Model 2		Contingent Model 3		Contingent Model 4		Contingent Model 5	
	Coefficient	*t* statistic	Coefficient	*t* statistic	Coefficient	*t* statistic	Coefficient	*t* statistic	Coefficient	*t* statistic	Coefficient	*t* statistic	Coefficient	*t* statistic
Control variables														
Cluster1	-0,192	-0,403	0,313	0,783	0,331	0,825	0,337	0,836	0,358	0,914	0,339	0,845	0,316	0,797
Cluster2	-0,185	-0,367	0,509	1,201	0,475	1,112	0,481	1,123	0,535	1,282	0,439	1,026	0,365	0,860
Cluster 3	-0,351	-0,615	-0,054	-0,116	-0,025	-0,052	-0,041	-0,087	0,073	0,160	-0,035	-0,076	-0,018	-0,038
Cluster 4	-0,093	-0,167	0,220	0,475	0,191	0,412	0,248	0,525	0,337	0,731	0,166	0,356	0,060	0,129
Age	0,012	0,522	0,008	0,435	0,009	0,456	0,007	0,353	0,009	0,483	0,006	0,318	0,009	0,483
R&D Size	0,002	0,572	0,001	0,196	0,001	0,209	0,001	0,278	0,001	0,203	0,001	0,303	0,001	0,177
Leader	-0,341	-1,070	-0,196	-0,729	-0,208	-0,772	-0,206	-0,765	-0,100	-0,376	-0,235	-0,872	-0,259	-0,971
Main effect variables														
Social Capital			0,501 ***	4,000	0,485 ***	3,805	0,330	1,390	-0,384	-0,988	0,492 ***	3,862	0,495 ***	3,935
Codifiability			0,370 ***	4,228	0,368 ***	4,188	0,367 ***	4,165	0,358 ***	4,180	0,576 **	2,824	1,305 **	2,789
Diversity			-0,167	-1,652	0,092	0,269	-0,537	-0,607	-4,054 *	-2,302	0,733	1,109	5,024 †	1,955
Diversity^2					-0,044	-0,795	-0,013	-0,190	0,588 *	2,172	-0,035	-0,625	-1,006 †	-1,779
Interactions														
Div X CS							0,085	0,771	0,776 *	2,422				
Div^2 X CS									-0,122 *	-2,289				
Div X Cod											-0,132	-1,132	-0,938 †	-1,951
Div^2 X Cod													0,181 †	1,726
Model														
R^2	0,216		0,638		0,642		0,645		0,674		0,649		0,666	
Adjusted R^2	-0,035		0,332 ***		0,329 ***		0,325 ***		0,361 ***		0,331 ***		0,348 ***	
F statistic		0,574		5,425		4,966		4,578		4,862		4,675		4,656
^R^2			0,360 ***		0,005		0,005		0,038 *		0,010		0,022 †	
Change in *F*				16,010		0,632		0,595		5,239		1,281		2,979

† p < .1; * p < .05. ** p < .01. *** p < .001; *** High-performance work practices

The main effects model in the next column makes a significant contribution over and above the base models ($\Delta R^2 = 0.36$, $p < 0.00$). Here, we can see that both social capital and codifiability have a positive influence on innovation performance. On the other hand, diversity has a negative influence. The contingent model was included next. As can be seen in table 2, it does not lead to an improvement in R^2. Therefore, we do not find support for hypothesis one.

Figure 1: Interaction between social capital and diversity

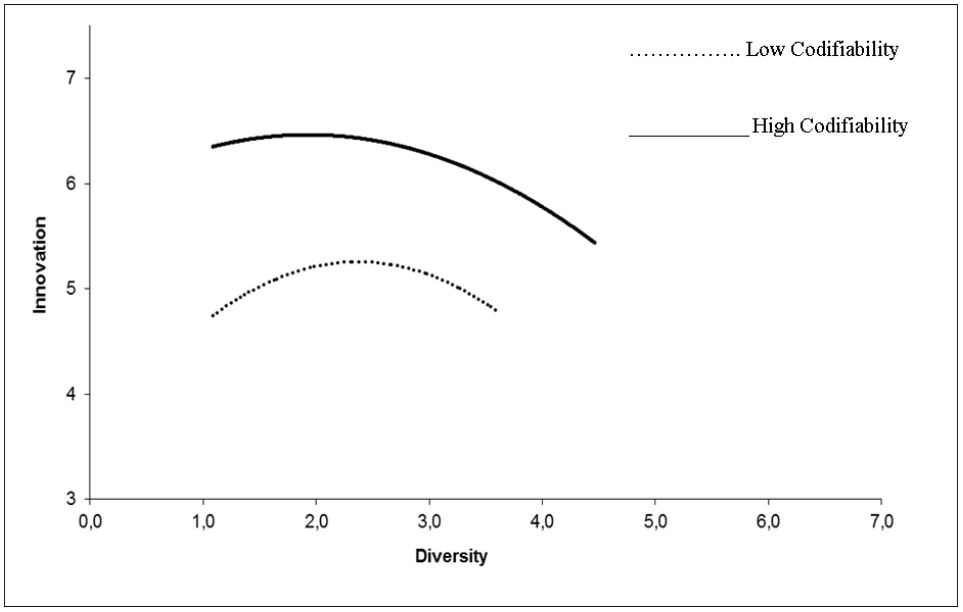


The two interactions were entered separately for each dependent variable, as recommended in the literature (Cohen and Cohen, 1983). The first interaction, the one between diversity and social capital, is reported in Contingent Model 3 and makes a significant contribution over and above the main effects ($\Delta R^2 = 0.04$, $p < 0.05$). The regression coefficient for the interaction between squared diversity and social capital ($\beta = -0.12$; $p < 0.05$) is significant. To determine the nature of the significant interaction, we plotted the effect diversity on the dependent variable for values of the social capital set at the mean and one standard deviation above and below the mean, as suggested by Cohen and Cohen (1983). This plot is reported in Figure 1.

The first curvilinear interaction model attempts to validate the existence of a nonlinear relationship between diversity and social capital over innovation performance. Figure 1 shows that this curvilinear relationship appears when it is moderated by social capital and, as proposed in hypothesis 2, the relationship is higher when social capital is higher. Therefore, we find support for hypothesis 2.

The second interaction, the one between diversity and codifiability, reported in Contingent Model 5 makes a significant contribution over and above the main effects ($\Delta R^2 = 0.02$, $p < 0.1$). The regression coefficient for the interaction between squared diversity and codifiability ($\beta = 0.18$; $p < 0.1$) is significant. To determine the nature of the significant interaction, we plotted the effect of diversity on the dependent variable for values of the codifiability set at the mean and one standard deviation above and below the mean, as suggested by Cohen and Cohen (1983). This plot is reported in Figure 2.

Figure 2: Interaction between codifiability and diversity



The second curvilinear interaction model attempts to validate the existence of a nonlinear relationship between diversity and codifiability over innovation performance. Figure 2 shows that this curvilinear relationship appears when it is moderated by codifiability and, as proposed in hypothesis 3, the relation is higher when knowledge codifiability is higher. Therefore, we find support for hypothesis 3.

5. Discussion and Conclusion

Although the relevance of the alliances for innovation performance has become a common place in the research on innovation, especially in intensive knowledge industries, the literature shows that not all the alliances are equally effective. Thus, the study of why some alliances contribute more than others when it comes to improve performance represents a relevant issue (Sampson, 2007). Our research provides empirical evidence on some characteristics of the alliances that determine high innovation performance.

Our research has addressed the question of how the diversity of the partners in a certain alliance for innovation affects innovation performance, and how this influence can be moderated by certain characteristics of the alliance, such as the social capital and type of knowledge shared among partners.

Our results suggest that the influence of partner diversity on innovation performance is even more complex than the inverted U-shaped effect we proposed, in the sense that it should not be considered in isolation but in interaction with other features of the alliance.

Our proposal of a curvilinear effect tried to bring together the statements highlighted in the literature about the opportunities and hindrances that diversity conveys. Indeed, the idea that a very low as well as a very high level of partner diversity can be detrimental for the performance of the alliance makes sense. If the level of partner diversity in the alliance is very low, knowledge

stocks may overlap too much and innovation may be inhibited, since possible new combinations of existing knowledge may have been exhausted (Sampson, 2007). In the opposite extreme, very diverse partners in the alliance, while providing greater access to diverse information, also involve ineffective communication and coordination, reducing the ability to use the diverse knowledge to which they have access (Phelps et al, 2012). Thus, we expected that firms could reap more benefits from their innovation alliance when the level of partner diversity was moderate.

In spite of the logic of this reasoning, we could not demonstrate that partner diversity has a direct effect on the innovation performance of the alliance. Thus, partner diversity, on its own, does not explain higher performance in alliances for innovation, even when a curvilinear effect is being considered. This unexpected result increases the interest of understanding the role of some characteristics of the alliance (social capital and knowledge shared) that could interact with partner diversity.

Regarding social capital, we demonstrate that its interaction with partner diversity improves the innovation performance of the alliance. We proposed that social capital (in the sense of close and trustful relationships among partners) can leverage the benefits of diversity by helping to reduce the difficulties when exchanging very diverse knowledge as well as by mitigating the fear of opportunistic behaviour. Thus, what our results suggest is that firms that trust their partners in their alliances are more willing to make efforts to share, receive and understand knowledge that is dissimilar to what the firm already knows. At the same time, in alliances comprised of diverse partners, problems associated with information asymmetry are likely to emerge. In this sense, social capital in the alliance would create a normative context that would reduce the fear of disloyal behaviours among partners.

The specific shape of the diversity-social capital interaction effect (an inverted U) also deserves attention. When social capital is considered, the influence of diversity on performance is as originally expected; that is, a moderate degree of partner diversity is what best contributes to the achievement of high innovation performance. Beyond a certain level of diversity, innovation performance decreases. What is important to highlight here is that when there is a high level of social capital in the alliance, the performance is always higher than for a lower level of social capital.

Regarding the moderating effect of knowledge codificability, our results show that partners' diversity can improve innovation performance when the alliance partners share codified knowledge. As we suggested, it seems that codificability can help reduce the complexity of knowledge transfer among diverse partners by facilitating that all of them receive the same information without loss of meaning. All this makes such complex relationships more effective and simple. Only a common understanding of the knowledge that is being shared and transferred among diverse partners may contribute to improve the innovation performance of the alliance.

Even so, and similar to social capital, while knowledge codifiability always improves the diversity-performance relationship for both high and low levels of knowledge codifiability, moderate levels of partners diversity get higher results.

Our research contributes to the literature in different ways. First, we provide insights about the role of diversity in the specific context of alliances for innovation in the biotech industry. Given that diversity of partners entails both opportunities and disadvantages, research on this topic has provided heterogeneous results, and the necessity of a common understanding of the impact of partners' diversity on performance has been claimed (Goerzen and Beamish, 2005). Be that as it may, one could think that the effect of diversity is mainly dependent on the specific

context in which the alliance occurs as well as the type of outcome that is being considered. More specific studies can help gain better understanding of how this alliance attribute contributes to better performance. Thus, in the biotech industry (characterized by a high number of small and young knowledge-intensive firms that are highly clusterized and specialized in a specific area of science), diversity on its own does not explain a superior performance in alliances for innovation. Therefore, research on partner diversity, as determinant of alliance performance, cannot be addressed in isolation.

This lack of a clear effect of diversity in the context analysed emphasises the role of moderating variables, which represents our second contribution. Previous research had already explored how diversity interacts with the alliance organization (Sampson, 2007) and with some firm capabilities and tools (Duyster, 2012; Oerlemans, 2013; Terjersen, 2011), which can be seen as conscious and targeted managerial efforts (Oerlemans, 2013). Our research demonstrates that some intrinsic characteristics of the alliances (how the relationships among partners are and what type of knowledge they share) also help to explain the role of diversity in the alliances for innovation in the context analysed. Both social capital and codified knowledge leverage the benefits of having diverse partners.

6. Managerial implications and limitations

Some relevant managerial implications can be derived from our research. Firms involved in alliances for innovation must be aware of the fact that diversity has to be appropriately managed in order to reap the benefits of sharing knowledge with different partners. Besides other tools and capabilities that firms can deploy, managers should monitor other intrinsic characteristics of the alliance. Promoting close and trustful relationships among partners and making efforts to codify the knowledge to be shared will help to reduce usual problems associated with diversity.

Managers must also be aware that these beneficial effects of diversity, social capital and codified knowledge working together are not unlimited. If the alliance is comprised of partners that are too diverse, problems of coordination, difficulties for understanding very heterogeneous knowledge and fear of opportunistic behaviour, may not be reduced by these attributes of the alliance.

This research has some limitations. First, other variables not included here could explain the complex issue of innovation performance. Furthermore, given the complexity of issues such as knowledge and social capital, other characteristics could be taken into account. Second, the Spanish sample does not guarantee that the results obtained can be generalized to other countries. Third and finally, the use of cross-sectional analysis provided results at just one point in time, and thus longitudinal studies would be necessary to clarify whether our results change over time.

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