Title: Industry Cognitive Distance in Alliances and Firm Innovation Performance

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Industry Cognitive Distance in Alliances and Firm Innovation Performance

ABSTRACT

This paper focuses on the role of industry cognitive distance in innovation alliances on firm innovation performance. Drawing from the literature on technological cognitive distance in alliances we elaborate on the role of industry cognitive distance between partners and its impact on managerial attention to investigate the role of numbers of alliances of low (intra-industry) and high (inter-industry) industry cognitive distance on firm innovation performance. Intra-industry alliances offer lower opportunities for innovation compared to inter-industry alliances and are less demanding on firm management due to higher cognitive similarity between partners from the same industry. We propose that trade-offs between innovation opportunities and management efforts result in an inverted U and a U shaped relationship between the number of intra- and inter- industry alliances and innovation performance respectively. We find support for both hypotheses in the context of the UK bio-pharmaceutical sector.

INTRODUCTION

The importance of alliances and cooperative agreements on innovation is well documented in the literature on innovation processes (e.g. Dodgson, 1994; Freeman, 1991; Tether & Tajar, 2008) and the role of external sources of knowledge in innovation (Chesbrough, 2006; Powell et al., 1996; Tether, 2002). Several streams of literature attempt to explain the reasons behind success or failure of alliances to enhance firm performance. A prominent stream of the literature proposes that the extent of similarity in the partners' knowledge bases is key to firm performance and innovation as it facilitates communication between partners and can be conducive to innovation (Lane & Lubatkin, 1998; Mowery et al., 1996; Sampson, 2007). However, some scholars comment on the tendency of this stream of literature to perceive distance between partners' knowledge bases as a liability (e.g. Sampson, 2007) and its failure to consider that such distance can generate variation which contributes to firm innovation (Nooteboom et al., 2007). Nooteboom et al. (2007) developed the construct of cognitive distance to analyse how resource heterogeneity among alliance partners affects partner learning in alliances. Cognitive distance encapsulates differences across organisations in perception, sense making, interpreting, understanding and evaluating their environments and differences in organisational purpose and focus, and it has multiple dimensions: technological, organisational (Nooteboom et al., 2007; Wuyts et al., 2005), and industry specific (Enkel & Gassmann, 2010; Enkel & Heil, 2014; Li & Vanhaverbeke, 2009). Noteboom et al. (2007) focused on technological cognitive distance and the interplay between increasing levels of underlying resource heterogeneity and of lowering absorptive capacity on cross-partner learning.

This paper builds on the work of Nooteboom et al. (2007) by exploring industry cognitive distance (Enkel and Heil, 2014; Enkel and Gassmann, 2010; Li and Vanhaverbeke, 2009) in

alliances and how low and high levels of distance affect firms' abilities to manage such alliances as their numbers increase and, in turn, influence firms' innovation performance.

The present work contributes to the literatures on the role of cognitive distance in alliances and on the broader literature on the impact of innovation search strategies, by distinguishing between alliances with partners within and outside a firm's main industry of operation. This distinction captures low and high levels of cognitive distance respectively, and contributes to the literature on innovation search, which adopts a parallel distinction (Katila, 2002) to examine the impact of depth and scope of search strategies respectively. This is in turn important because innovations result from combination of existing knowledge (Kogut and Zander, 1992) with similar knowledge providing lower novelty, and combinations of knowledge which is dissimilar, for example from firms in different industries, providing higher novelty.

In considering the challenges to alliance management and coordination arising by cognitive differences we employ the concept of managerial attention (Ocasio, 1997). The alliance literature draws insights from the attention-based view to explore for instance, how firms prioritise sourcing of external knowledge from formal and informal relationships and manage diversification in alliances (de Leeuw et al., 2014; Fernhaber & Li, 2013). Hence we further contribute to existing alliance research employing the attention-based view (de Leeuw et al., 2014; Estrada et al., 2016; Fernhaber & Li, 2013), by analysing how the combination of high industry cognitive distance and increasing alliances may require attention to the management of alliances in order to enjoy higher innovative performance.

We develop two testable hypotheses on the role of low and high levels of industry cognitive distance in alliances on firm innovation performance by considering the different levels of

novelty and managerial challenges posed by such alliances. We argue that the relationships between intra-/inter- industry alliances and firm innovation performance show an inverted U and U shape respectively. We test and find support for our hypotheses in the context of the UK bio-pharmaceutical sector between 1991 and 2001, a period of high alliance activity, as collaborations in research and technology sharing are prevalent at the early stages of development of new technologies, such as biotechnologies (Al-Laham et al., 2010; Cainarca et al., 1992; Karamanos, 2012), with collaboration becoming the dominant mode of organising innovation in the sector (Powell et al., 1996). Moreover, this is an interesting setting to explore the role of industry cognitive distance in alliances on innovation performance as the bio-pharmaceutical sector comprises of firms across various industries that employ biotechnologies as new methods of discovery (e.g. Orsenigo et al., 1998; Walsh, 2004).

THEORETICAL BACKGROUND

Industry Cognitive Distance in Alliances and Firm Innovation Performance

Knowledge heterogeneity is central to firm innovation, and accessing knowledge outside a firm's boundaries can stimulate innovation as it provides opportunities for knowledge combination which can boost novelty and creativity (Kogut & Zander, 1992). Nooteboom et al. (2007) developed the construct of cognitive distance in alliances to explore cross-partner learning. They argue that increasing cognitive distance enhances knowledge variation and the level of novelty in alliances, providing greater opportunities for innovation but at the same time, it diminishes partners' absorptive capacities and their abilities to benefit from such variation (ibid.). These opposing effects generate a concave relationship between cross-partner cognitive distance and partners' learning (Nooteboom et al., 2007; Wuyts et al.,

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2005). Nooteboom et al. (2007) focused on the technological dimension of cognitive distance in alliances.

Cognition and cognitive distance have other dimensions in addition to the technology one, e.g., organisational (Nooteboom et al., 2007; Wuyts et al., 2005) and industry (Li and Vanhaverbeke, 2009; Enkel and Gassmann, 2010; Enkel and Heil, 2014), and this section elaborates on the role of the industry[1] dimension (see also Enkel & Gassmann, 2010) which is central to this paper. Firm cognition is influenced by the path along which organisations evolve, their idiosyncratic knowledge trajectories, the socially constructed nature of firms' knowledge and actions and surrounding environments (see Nooteboom et al., 2007). Firms operating in the same industry are likely to adopt similar mental models and frames, or worldviews, to perceive and interpret their environment and competitors' actions, and, similarly to scientific (Kuhn, 1962) and technological paradigms (Dosi, 1982), they provide industry cohesion and greater degree of correspondence between the types of knowledge employed within industries (Huff, 1982; Spender, 1987). Activities that require the same capabilities for their undertaking tend to cluster within the same industry (Richardson, 1972). The use of industry specific knowledge and capabilities establishes a level of commonality in discernment among industry members, providing a common background, a shared meaning and interpretation. Industry recipes, mental models and dominant logics are some examples of such shared meanings and understandings (Bettis & Prahalad, 1995; Prahalad & Bettis, 1986; Spender, 1987).

As a result it can be argued that cognitive distance is lower in alliances between partners from the same industry (see also Enkel & Gassmann, 2010), and intra-industry alliances provide lower knowledge heterogeneity compared to inter-industry alliances (Nooteboom et al., 2007)[2]. The distinction of intra- and inter- industry alliances reflects the separation

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of external search space between "within" and "outside" a firm's own industry (Katila, 2002) reflecting depth and scope of search strategies respectively.

Industry Cognitive Distance and the Role of Attention-Based View in Managing Increasing Numbers of Alliances

Our study explores the role of increasing number of alliances of low and high industry cognitive distance on innovation and as such it envelopes the impact of the ensuing managerial challenges, as inter-industry alliances can challenge partner management abilities more than intra-industry alliances, requiring higher managerial attention (Ocasio, 1997), especially as the numbers of such alliances increase. Firms have bounded abilities to notice, encode, process and act upon information (Simon, 1955). It is important to understand where firms focus most of their managerial attention as it can influence how decisions and actions are taken and prioritised in organisations (Ocasio, 1997; 2011). Existing literature on alliances argues that cross-partner differences in orientation, involving perception of the purpose and objectives of the alliance, are harder to overcome compared to routine-level dissimilarities, with findings suggesting that placing attention to the latter leads to neglecting the former due to trade-offs and eventually to alliance failure (Estrada et al., 2016). Research on alliances and informal external knowledge sourcing also identifies trade-offs in managerial attention, arguing that when firms form formal relationships they divert their attention towards their management and tend to benefit less or none at all from informal knowledge spillovers arising from co-location (Fernhaber & Li, 2013). Other research emphasises how lower levels of alliance portfolio diversity in terms of partner type composition, are more efficient for the creation of radical innovations compared to incremental, as radical innovations are more demanding in managing knowledge

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integration across partners and this requires higher levels of managerial attention compared to incremental innovations (de Leeuw et al., 2014). Building on this still limited literature on managerial attention and inter-firm collaborations we develop testable hypotheses below here.

HYPOTHESES DEVELOPMENT

Low Cognitive Distance and Intra-industry Alliances

Cognitive similarity reflects resource-knowledge commonalities in technologies (Nooteboom et al., 2007), dominant logics (Enkel and Gassmann, 2010), and processes, which are fundamental for knowledge (re)combination in alliances (Lane & Lubatkin, 1998; Mowery et al., 1996). Intra-industry alliances offer immediate innovation opportunities and applications to existing production processes as partners can combine proximate to existing knowledge (Levinthal & March, 1993; March, 1991). They can enhance firm innovation performance (Rothaermel & Deeds, 2006) by allowing partners to exploit their existing knowledge and technologies, by increasing organisational focus and specialisation (Lavie et al., 2010), by penetrating further existing business lines and markets, generating economies of scale and scope, and timely advancement of technologies (Tether, 2002). The relative cognitive proximity in intra-industry alliances, compared to inter-industry alliances, offers supplementary (Das & Teng, 2000) and complementary knowledge to support firm innovation (Rothaermel & Deeds, 2006). This incremental, exploitative knowledge is valuable to firms within the same industry because they still differ in the ways they utilize industry specific knowledge (Nelson and Winter, 1982).

As cross-partner knowledge proximity eases knowledge sharing and internalisation it is expected that in intra-industry alliances there is recognition and understanding of cross-

partner idiosyncrasies allowing for increased awareness of the requirements for effective interaction (Cohen & Levinthal, 1990; Estrada et al., 2016; Lane & Lubatkin, 1998). As a result, intra-industry alliances, reduce complexity and ambiguity (Rothaermel and Deeds, 2006) and require relatively low managerial attention (Ocasio, 1997; Estrada et al., 2016), allowing firms to retain focus. This may induce firms to dedicate their scarce managerial resources to more challenging tasks (Penrose, 1959). Cross-partner similarities facilitate establishing communication processes and inter-organisational routines (Zollo et al., 2002), with such routines being more effective in managing less challenging alliances, compared to alliances that are more complex or those offering higher potential for learning (Heimeriks, 2010). Overall, the above implies that firms face relatively lower coordination costs and require less managerial resources to manage intra-industry alliances (e.g. Rothaermel and Deeds, 2006).

However, when firms intensify intra-industry search, the creative potential and extent increasingly diminishes (Katila, 2002). It can eventually reach saturation, so that firms may find themselves in a competency trap (Levitt & March, 1988), and experience diminishing returns to innovation performance. Similarly to Ricardian decreasing marginal returns, firms are likely to engage in the most promising and productive alliances first, and then, as they expand their alliances they will enter in less fruitful ones (Rothaermel & Deeds, 2006). Firms can subsequently experience negative returns to their innovation performance as their intra-industry space eventually becomes over-searched, making learning myopic (Levinthal & March, 1993). Therefore, we posit the following hypothesis:

> *Hypothesis 1: There is an inverted U-shaped relationship between the number of intra-industry alliances and firm innovation performance*

High Cognitive Distance and Inter-industry Alliances

Inter-industry alliances offer higher novelty value compared to intra-industry alliances, as they bring together firms with greater diversity in their lines of business, production processes and operating practices (Enkel & Gassmann, 2010), expose partners to knowledge of broader scope, enhancing the chances of renewing internal knowledge (Kogut & Zander, 1992) while accommodating knowledge shifts in other sectors and experimenting with new markets. Industry cognitive differences pose higher uncertainty, risks and managerial challenges, but, at the same time, have a positive association with pioneering innovation in buyer-supplier alliances (Li and Vanhaverbeke, 2009).

The higher level of knowledge incongruence in inter-industry alliances increases complexity in knowledge sharing and coordination as firms form more of such alliances. Parallel research shows that allying with diverse types of partners increases complexity due to cross-partner dissimilarities, escalating managerial challenges and coordination costs (Vlaisavljevic et al., 2015; White & Lui, 2005), while investments in social capital (Vlaisavljevic et al., 2015) or in tighter forms of control can act as moderators or mitigate such costs (Gulati & Singh, 1998). However, formal routines to manage alliances could prove to be less effective when alliances are more complex or offer higher learning potential (Heimeriks, 2010). Thus, although the cognitive distance and knowledge variety in inter-industry alliances is conducive to firm innovation, they also pose high demands on the cognitive abilities of firms (Simon, 1955), requiring greater efforts, investing more resources to combine and absorb knowledge, increasing managerial and coordination challenges (Estrada et al., 2016; Rothaermel & Deeds, 2006). These inefficiencies may also be exacerbated by tensions arising from misalignment in commitments between dissimilar

partners (Yang et al., 2014) or when there are wide differences in the goals and expectations between the two partners (Estrada et al., 2016).

As already pointed out, managerial attention intensifies with increased diversification in alliance portfolios (de Leeuw et al., 2014), as it is the case in the inter-industry alliances. We argue that as alliance coordination and management costs increase, firms' abilities to reap the innovation potential of inter-industry alliances increasingly diminish, leading us to expect that firm innovation performance will taper off as the number of such alliances increases. We propose that this effect may in part be due to the dilution of managerial attention stemming from increasing the number of alliances of higher cognitive distance (Ocasio, 1997; 2011), as searching a space with high number of innovative ideas implies that less attention is paid to fully developing each one of these possibilities and this can impair performance (Koput, 1997). However this pattern can be reversed. As these alliances become even more numerous, unsatisfactory performance will attract managerial attention: management will become more aware of lowering performance and failures and it will intensify closer inspection of alliances with higher cognitive distance (Ocasio, 1997; 2011), dedicating more resources to inform and attend to their coordination. Intensified attention can aid accurate perception of cross-partner differences and avoiding attribution errors which are linked to alliance failures (Estrada et al., 2016). Moreover, higher cognitive distance may require more frequent renegotiations in alliances (Yang et al., 2014) which, in turn, attracts managerial attention. Koput (1997) argued that small increases in managerial attention are likely to have disproportionately positive benefits on innovation, as they counteract the negative effect of previous lower levels of attention on the number of new ideas pursued.

Firms engaged in a higher number of inter-industry alliances will develop higher awareness, experience and understanding of their differences with their partners and become more attentive in recognizing and addressing ambiguity and complexity in alliances (Zollo & Winter, 2002). Firms become more accustomed to identifying and resolving tensions in alliances and in addressing these by modifying existing alliance routines or developing new ones. Moreover, expanding inter-industry alliances enhances the probability of identifying fruitful and novel combinations; as with any creative process with a high scope of novelty, the probability of experiencing success and positive returns increases with the number of trials and consistency in experimenting (Levinthal & March, 1993).

Therefore, we suggest that after initial enhancing innovation performance of inter-industry alliances, increasing managerial and coordination challenges prevent firms to accrue the benefits of increasing novel opportunities and they start experiencing lowering innovation performance. Following increases in managerial attention to these alliances, firms start to benefit again from the increased variety in the pool of knowledge that can be accessed through inter-industry alliances, which, in turn, enhances their innovation performance; as a result, the relationship between the number of inter-industry alliances and firm innovation resembles a U shape. Although there is empirical evidence of a U-shaped relationship between unrelated acquisitions (targeting firms in industries different to past acquisition targets) and firm financial performance (Haleblian & Finkelstein, 1999), and somewhat similar arguments have been developed in research exploring how alliance experience influences acquisition performance (Zollo & Reuer, 2003), we could not identify any prior evidence of a U-shaped relationship in the specific case of inter-industry alliances and innovation. We posit the following hypothesis:

Hypothesis 2: There is a U-shaped relationship between the number of inter-industry alliances and firm innovation performance

DATA AND VARIABLES

Sample

We test the hypotheses in the context of the UK bio-pharmaceutical sector, due to the wide range of industrial applications of biotechnologies as discovery process technologies (Orsenigo, 1989; Orsenigo et al., 1998; Walsh, 2004) and collaboration emerging as a dominant form for organising innovation since the 1990s (Hopkins et al., 2007; Powell et al., 1996). Moreover, the UK bio-pharmaceutical sector provides an interesting empirical setting as it is under-researched relative to the US. We identify the whole population of firms using sector-specific directories which include all firms across various industries that use biotechnologies in their research and focus on life sciences (Coombs & Alston, 2000; 2002). This provides the opportunity to capture a wide range of industry applications arising from firms using biotechnologies either as platform technologies or within specific areas of application. Indeed, since the advent of biotechnologies, successive waves of new technologies were introduced (e.g., screening, gene expression - see Hopkins et al., 2007) and applied in diagnostics, drug development and therapeutics. The underlying scientific development is hierarchical with new firm entry in the sector reflecting the proliferation of research trajectories over time, highlighting the cognitive variety in the sector in terms of pursuing different paths of discovery and positioning at different levels of the scientific evolution hierarchy (Orsenigo et al., 1998).

The bespoke dataset includes 110 publicly listed firms that were in full operation in 2003 that engaged in innovation alliances and for which data is publicly available but not

throughout our time period. We choose to collect data for the 1991-2001[3] period because alliances for research and development and technology sharing are particularly common at the early stages of the development of technologies such as biotechnology (Cainarca et al., 1992; Orsenigo et al., 1998) and it is not affected by the M&A activities which became very frequent in the 2000s. Indeed, recent research on biotechnology also focuses on pre-2001 data (Karamanos, 2012; Al-Laham et al., 2010; Wuyts and Dutta, 2014).

The 1990s marked an era of industrial change with newly established firms and pharmaceutical firms gradually integrating capabilities in biotechnologies via collaboration and alliances (Hopkins et al., 2007). In Europe entry peaked in 1997 and continued till 2003 followed by a period of stabilisation and consolidation with merges and acquisitions (Gottinger, 2010). This is witnessed slightly earlier in the UK with the merger of Glaxo Wellcome and SmithKline in December 2000. As such, the 1990s form a paradigmatic example of how a science-based technology triggered industrial change and the adaptation of established firms via alliances. Focusing the analysis on this era can assist in understanding the impact of other future science driven technologies bringing similar industrial changes and in understanding the adaptation dynamics between emerging and established firms and the role of networked strategies for innovation. Indeed existing research explores parallels between the biotech and nanotech evolutions (e.g. Rothaermel & Thursby, 2007) as both are new discovery technologies with applications in a wide range of existing industries.

Information on innovation alliances is drawn from Recombinant Capital (ReCap.com), a consulting firm specialising in life sciences and from BioScan, which is a sector-specific publication. Both data sources have been used in numerous other studies on this sector

(Hoang & Rothaermel, 2005; Wuyts & Dutta, 2014) and list alliances for research, technology sharing and new product development. Empirical research on alliances, in the main, is not influenced by the type of alliance database (Schilling, 2009).

Variables

Dependent variable: Innovation output

Consistently with literature on the role of alliances in firm innovation performance, we use firm patent counts (e.g. Deeds & Hill, 1996; Sampson, 2005; 2007). Indicators of jointly owned intellectual property rights, such as co-patents, have been found to poorly reflect innovation outputs of R&D alliances (Hagedoorn et al., 2003). As the study focuses on UK based firms (63 firms, 57%) or the UK subsidiaries of multinational enterprises (47 firms, 43%), we collect data on patents successfully filed at the UK Patents and Trademarks Office (UKPTO) between 1991 and 2001. Patents are a good proxy of innovation performance particularly in bio-pharmaceuticals because this is a science-based sector (Al-Laham et al., 2010; Ziedonis, 2008).

Information on patents granted is publicly available through Esp@cenet. We identify patents granted by the UKPTO by matching the name and address of the patent assignee to those of the firms in our sample (Arora et al., 2011). We account for potential changes in addresses and variations in firm names over time by tracing firm records in FAME, a specialist database providing accounts of UK-based firms. Moreover, for patent data assigned at the corporate parent level we use information on inventors' location to identify any additional patents stemming from firms in our sample by selecting those that had at least one inventor employed by a firm in the UK sample. A total of 398 patents were successfully filed by the 110 firms between 1991 and 2001; the relatively low patenting

activity is due to the industry being relatively young at the time of the study, with a third of the firms in our sample being established after 1995, and because of the inherently low discovery rate in this industry, especially in the early years. Finally, we use patent filing date rather than publication date because the former better approximates the time of innovation, as there is, on average, a two-year gap between patent filing and publication dates[4].

Independent variables

Intra- and inter- industry alliances

Industry cognitive distance has been operationalized by using information on SIC code similarity (Li and Vanhaverbeke, 2009; Enkel and Gassmann, 2010), a measure employed in literature on cognitive proximity in alliances, joint ventures, acquisitions (Enkel & Heil, 2014; Haleblian & Finkelstein, 1999; Keil et al., 2008; Luo & Deng, 2009) and innovation search (Enkel and Gassmann, 2010). Other literature focuses on the technological dimension of cognitive distance, as captured by patent cross-citations (e.g. Nooteboom et al, 2007). However such information relies on partners successfully filing for a patent, whereas SIC data, although a broader indicator of firm activity, is available for all partners which is very important in small samples (see also Enkel and Heil, 2014).

We used US instead of UK SIC codes as a high number of alliances involves partners based internationally. The most representative categories of SIC in the sample of 110 firms are: 8731 (23%), 2833 (19%), 2834 (5%)[5]. Of the total 2,442 alliances formed between 1991 and 2001, there is information on partner US SIC for 2,285 (94%) alliances (based on the Thomson Analytics database). The most representative categories of US SIC of alliance partners are: 2834 (39% of alliances with available information), 8731 (20%), 2835 (5%),

2836 (5%). For each firm in the sample we calculate the yearly figures of intra-industry alliances by counting all alliances with partners in the same 4-digit SIC class, and yearly figures of inter-industry alliances by counting all alliances formed with partners with similar SIC in the first 2-digits. This approximation of low and high industry cognitive distance is less refined than a continuous variable measuring the absolute difference between partners SIC codes. However the latter assumes that there is equidistance across different points in the SIC hierarchy and may lead to results with poor interpretative power[6]. There is no standardised approach for measuring industry cognitive distance based on SIC data (in terms of digit level) (Keil et al, 2008; Enkel and Heil, 2014; Haleblian and Finkelstein, 1999), therefore, we undertake a range of robustness checks on our operationalisation which are detailed and discussed in the Appendix[7].

There are 193 intra-industry alliances and 1,777 inter-industry alliances formed in the sample from 1991 until 2001, with firms forming more than one alliance per year (see Table 2). The variables counting the number of alliances for each firm and year are introduced in the regression models as linear and squared terms (that is, *at power 1 and 2*) to test our hypotheses of non-linear effects.

Control variables

Alliance experience

The literature on alliances suggests that accumulated prior alliance experience can be a confounding factor influencing firm returns from alliances (e.g. Hoang & Rothaermel, 2005; Kale et al., 2002). Consistently with this literature, we measure firm alliance experience as the one-year lagged values (Lavie et al., 2011) of the cumulate number of alliances that

firms hold every year by considering that alliances last on average for a period of 5 years (Kogut, 1988). Left censoring to 1991, should not introduce serious biases as firms in our sample formed only 13% of total alliances in the period prior to 1991 (1979-1991 based on ReCap.com). As recent alliance experience may be more valuable compared to experience gained in the distant past, with diminishing returns to experience accumulation in alliances, we use natural logarithms (e.g. Sampson, 2005).

Further controls and variables

We include firm size as control variable, as larger firms with access to more resources might be in a more advantageous position to reap benefits from alliances[8]. We use the number of employees as a measure of firm size due to our focus on the bio-pharmaceuticals sector. A large proportion of firms in this sector are newly established firms and may not generate any sales in the first few years of their life, while they are heavily reliant on the quality of their employees and research output for survival and success (Orsenigo, 1989). This information is gathered from company accounts provided by FAME. We include the amount of investments in R&D to control for the resources invested in innovation generating activities. Information on investments in R&D is gathered from Thomson's Analytics and the UK DTI's R&D Scoreboard.

STATISTICAL METHODS AND RESULTS

Table 1 reports descriptive statistics and correlation coefficients. Statistics for the full sample show that on average firms formed 4.4 alliances, and in particular almost ten times as many alliances with inter-industry partners (3.9) as with partners in the same 4-digit SIC industry (0.4) (the corresponding median values are 2 and 0 respectively)[9]. This indicates that firms tend to source more external knowledge which is distant rather than proximate,

possibly to take advantage of the varied industry applications of biotechnologies. For the subsample of firms that form intra- or inter- industry alliances the average numbers are 2.5 and 4.2 respectively (median values 1 and 3 respectively). Firms filed on average 0.3 patents between 1991 and 2001, with that number rising to 0.5 if one restricts observations only to the years during which firms form alliances and to 3 if we consider only firms that hold patents. Most correlation coefficients are at acceptable levels (below 0.5) but we find high correlation (0.560) between the number of inter-industry alliances and alliance experience. This is expected because inter-industry alliances capture the majority of alliance activity in the sample. High correlation (0.644) between the variable for total number of alliances and alliance experience is also found, however the mean VIF index of 1.59 suggests that multicollinearity is not an issue[10].

TABLE 1

Descriptive Statistics and Correlation Coefficients

	Mean	S.D.	Min	Max	1	2	3	4	5	6
1. Number of Patents	0.33	1.62	0	20						
2. Inter-Industry Alliances	3.90	4.25	0	26	-0.081					
3. Intra-Industry Alliances	0.42	1.37	0	12	-0.040	0.213				
4. R&D (Mil. GBP)	85.16	262.50	0	1937	0.400	0.169	0.276			
5. Ln Cum Number of Alliances (5 years) One-Year Lagged Values	1.53	1.32	0	4.77	0.067	0.560	0.236	0.180		
6. Firm Size (Number of Employees)	5,928	33,699	1	328,000	0.332	0.376	0.400	0.630	0.348	
7. Total Number of Alliances	4.43	5.30	0	32	-0.0680	0.926	0.399	0.172	0.644	0.440

We use count dependent variable models to examine our hypotheses on an unbalanced panel dataset arising from: a) missing information; b) a third of firms in the sample being established after 1995; and c) the inclusion of lagged variables in the regression models (see Table 2). We estimate both the Poisson and the Negative Binomial models for panel data (Greene, 2003). The results are similar, but we refer only to the Negative Binomial model which is more appropriate in the case of overdispersion[11] (Baltagi, 1995). Table 2 provides estimates for both the Random-Effects (RE) and Fixed-Effects (FE) specifications because the Hausman (1978) specification test does not assist in selecting between the two specifications in limited dependent variable models.

The baseline model with only control variables is presented on the first column of Table 2. Model 1 in the second column estimates the impact of the *total* number of alliances on innovation performance without distinguishing between low and high levels of cognitive distance. The variable is significant and negative, suggesting that not distinguishing for industry cognitive distance would obscure a more nuanced relationship. Indeed, we also include the square value of total number of alliances to test for an inverted U-shaped relationship identified in other research irrespective of type of partner (Rothaermel and Deeds, 2006) but the impact of this variable is insignificant (positive)[12].

TABLE 2

Negative Binomial Panel Date Estimates: Number of Patents Filed (Dependent Variable)

	Baseline Model		Model 1		Model 2		Model 3		Model 4	
	RE	FE	RE	FE	RE	FE[13]	RE	FE	RE	FE
Intra-Industry Alliances					0.95*	1.53**			0.90*	1.31**
					(0.50)	(0.60)			(0.48)	(0.62)
Intra-Industry Alliances Square					-0.14***	-0.19***			-0.13**	-0.16**
					(0.06)	(0.06)			(0.06)	(0.07)
Inter-Industry Alliances							-0.24**	-0.28***	-0.18**	-0.21**
							(0.09)	(0.10)	(0.09)	(0.11)
Inter-Industry Alliances Square							0.007**	0.009**	0.005†	0.005†
							(0.004)	(0.004)	(0.004)	(0.004)
R&D	0.002***	0.002***	0.002**	0.001**	0.003***	0.003***	0.002***	0.001**	0.002***	0.002**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Alliance Experience	0.11	0.04	0.16	0.178	-0.18	-0.23	0.18	0.12	0.06	0.04
	(0.14)	(0.16)	(0.20)	(0.22)	(0.19)	(0.22)	(0.24)	(0.27)	(0.23)	(0.26)
Total Number of Alliances			-0.063**	-0.085**						
			(0.04)	(0.04)						
Constant	-0.76*	-0.601†	-0.599	-0.569	0.17	0.19	-0.21	0.11	0.14	0.17
	(0.46)	(0.48)	(0.67)	(0.71)	(0.66)	(0.69)	(0.75)	(0.82)	(0.72)	(0.76)
Observations[14]	329	124	260	102	232	94	232	94	232	94
Wald Chi^2	20.82	12.39	19.7	12.4	20.23	18.33	22.86	15.57	25.65	22.25
Prob > Chi^2	0	0.002	0.000	0.006	0.00	0.00	0.00	0.00	0.00	0.00
Log Likelihood	-248.33	-147.81	-206.33	-111.49	-187.14	-97.91	-188.17	-99.47	-184.60	-95.26

Standard errors in brackets. Significance levels: *$p<0.1$; ** $p<0.05$; *** $p<0.01$; † $p<0.20$

Table 2 (Models 2 and 3) provides evidence for both the inverted U- and U-shaped relationships between intra- and inter-industry alliances and firm innovation performance respectively. The results hold for both the RE and FE specifications and also when we test the hypotheses both separately and jointly (Model 4), although the significance of the squared term of inter-industry alliances is weaker (20%) in the full model compared to when Hypothesis 2 is tested separately (in Model 3)[15]. The Appendix discusses additional results on the joint impact of intra- and inter- industry alliances.

Among the control variables, investments in R&D has a positive significant effect consistently with the innovation literature and the notion that higher R&D efforts will result in more inventions (Cohen, 1995). The small coefficient indicates that the return of R&D investments (measured in million GBP) to patents is, on average, very small, a result which has been observed also in other studies of the biotechnology sector (Vlaisavljevic et al., 2015). However, alliance experience is not found to be significant in any model. This is somewhat surprising, but it could reflect a lack in firms' abilities to use lessons from past alliances in improving the performance of new (inter- or intra-industry) alliances[16].

DISCUSSION AND CONCLUSIONS

Based on the literature on cognitive distance between alliance partners (Noteboom et al., 2007) and the attention-based view of the firm (Ocasio, 1997), we investigated how low and high levels of industry cognitive distance affect innovation performance as firms expand their intra- and inter- industry alliances. Our research contributes to the literature on cognitive distance (e.g. Nooteboom et al., 2007; Wuyts et al., 2005) by exploring the industry dimension in the context of alliances and firm innovation, and to the literature on innovation search strategies of depth (within industry) and scope (outside main industry) (Katila, 2002). An

indirect contribution of our work to exiting literature arises from our (somewhat implicit) treatment of the interplay between firm abilities to manage an increasing number of alliances and the opportunities for firm innovation arising from different levels of knowledge variation at low and high levels of industry cognitive distance. As it is a common challenge in multiple firm-level studies (e.g. Fernhaber and Li, 2013), our work does not directly measure managerial attention, however, it contributes to the alliance research employing the attention-based view (de Leeuw et al., 2014; Estrada et al., 2016; Fernhaber & Li, 2013), by exploring how managerial attention helps understand the patterns of returns to innovation from alliances of high industry cognitive distance.

We identify that increasing numbers of alliances of *low* industry cognitive distance are subject to diminishing and potentially negative returns to innovation performance.   This complements existing empirical literature on diminishing and eventually negative returns to firm innovation performance from external sources of innovation (e.g. Laursen and Salter, 2006), increasing diversity in type of partner (Vlaisavljevic et al., 2015) and from various actors along the vertical and horizontal firm boundaries (Rothaermel and Deeds, 2006) and extends such literature to the case of intra-industry alliances (potentially direct competitors). Our results for the impact of alliances with *high* industry cognitive distance add to such literature. They suggest that as the number of inter-industry alliances increases, increased managerial attention can reverse unsatisfactory innovation performance, potentially leading to improvements, which in turn could command and justify greater managerial attention, due to further positive feedback effects. This contention offers a more refined understanding of how managerial attention may gradually build inside firms and how, eventually, (alliance) management may become more attentive and purposeful. This may potentially offer an additional explanation behind the development of alliance routines which may warrant future

attention in the literature on alliance capability development (Kale & Singh, 2007; Schreiner et al., 2009). Further qualitative research could explore the organisational processes leading to the development of alliance management routines.

Several managerial implications arise from our study which could also be relevant in the context of other technologies that share similarities with biotechnologies. First, our study indicates that firms will experience different impacts on their innovation performance from alliances depending on whether these present low or high industry cognitive distance from the partner. Firms in our sample which engaged in intra-industry alliances, form 2.5 of such alliances on average (1 for the median firm), which lies below the inflection point (3.3) of the inverted U-shaped relationship. This suggests that there could be opportunities for further expansion of such alliances and for achieving higher returns to innovation by moving closer to the inflection point. Indeed, firms in the bio-pharmaceuticals sector have being forming alliances mainly with firms in different industries, benefiting from applications of biotechnologies across a wide range of industrial sectors (e.g. Rothaermel & Deeds, 2004; 2006). Empirical evidence on the role of alliances with direct competitors is sparse for this sector (e.g. Rothaermel & Deeds, 2006), as research has mostly focused on up-stream and downstream alliances (e.g., Rothaermel & Deeds, 2004). Our study suggests that firms may not exploit the full potential of the research synergies that can arise from alliances with partners within the same industry.

Second, the firms in our sample engaging in inter-industry alliances manage 4.2 alliances on average, or 3 for the median firm per year, which is far below the inflection point (15.7) of their U-shaped relationship to innovation. A closer look at the significance at different segments of the U-shaped relationship (Haans et al., 2015 tests reported in the Appendix)

shows that an expansion beyond the inflection point may lead firms to gradual but not remarkably high improvements in innovation performance. Our results are indicative of two possibly successful strategies for inter-industry alliances. The first strategy, entails maintaining a fairly restricted number of inter-industry alliances at levels where the management and coordination challenges do not reduce the benefits of inherent heterogeneity. The second strategy involves an expansion strategy which results in somewhat improved innovation performance. The choice between these strategies may depend, among other factors, on the plethora of inter-industry alliance opportunities available, firm corporate strategy, financial viability, the level and direction of competition. Wuyts and Dutta's (2012) results run in parallel with our suggestion of a dual strategy, as they show that both a focused and an expansive approach in sourcing technology diversity in alliances can benefit the production of drugs of superior therapeutic value.

We recognize some limitations in this study, which we cannot address with our data, some of which may be explored in future research. Our study has tested hypotheses in a specific industry, country and period. Future studies could investigate the role of industry cognitive distance in alliances and firm innovation performance in other sectors, countries and periods. Using measures that could capture the content and degree of novelty of innovation performance could provide further insights on whether inter-industry alliances lead to more breakthrough innovations compared to intra-industry alliances; this would require capturing the innovation outcomes from specific alliances and a much comprehensive sample. Analysing co-patenting could offer a potentially fruitful avenue in this direction; however, co-patenting applications are sparse and existing research finds a poor association between co-patenting and joint R&D agreements (Hagedoorn et al., 2003). Moreover, using alliance counts to capture alliance experience neglects the fact that alliances tend to vary in size (value

and duration) and may contribute differently to firm learning and building experience to manage alliances. Finally, our operationalization of industry cognitive distance based on SIC codes shares the limitations of this classification system. However, relying on SIC data is consistent with other studies using SIC to proxy for search depth and scope (Katila, 2002; Katila and Ahuja, 2002), in the context of alliances and acquisitions (Luo & Deng, 2009; Keil et al., 2008; Haleblian and Finkelstein, 1999; Li and Vanhaverbeke, 2009) and to explore the role of cognitive distance in breakthrough innovations (Enkel & Gassmann, 2010).

Our research opens up an important set of questions for future research. Firm innovation performance from intra- and inter- industry alliances is likely to influence a firm's desire to invest in such type of alliances in subsequent points in time. Finally, since searching different industry spaces alludes to proximate (exploitation) and distant (exploration) search (Luo & Deng, 2009), or to the depth and scope of search (Katila, 2002; Katila & Ahuja, 2002), our study may also provide broader insights on the management of innovation search and the literature on organisational ambidexterity, which explores whether and how firms can juxtapose exploitation and exploration, together with the approaches to jointly manage such search processes (Gupta et al., 2006; Lavie et al., 2010; March, 1991; Raisch et al., 2009).

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Appendix A

Robustness and Post-Estimation Tests

We carried out a number of post-estimation and robustness tests to explore sensitivity of our results to the operationalization of intra- and inter- industry alliances.

First, we estimated two-stage least squares relationships for the number of patents and numbers of intra-/inter- industry alliances respectively, to handle potential endogeneity between alliance size and firm patenting performance (Lavie et al., 2011). Treating patents and intra-/inter- industry alliances as quasi-continuous variables, we included instrumental variables in two-stage least squares estimations (Greene, 2003; Hamilton & Nickerson, 2003). The two-stage least square relationship for intra-industry alliances (Hypothesis 1) provides coefficients with the expected signs, but not significant, when the two-year lagged values of patent stock is included as an instrument in the first stage. The two-stage least squares relationship for inter-industry alliances (Hypothesis 2) includes two-year lagged values of R&D expenditures, cumulative alliance experience (natural log) and patent stock as instruments and it provides consistent results with the models in Table 2. The choice of instruments was guided by considerations around model fit. In the case of intra-industry alliances, it was also constrained by the small number of observations because the model would not converge and this did not allow including the same instruments as in the case of inter-industry alliances. Results are available upon request.

We also perform further tests to scrutinize the concave relationships (Haans et al., 2015; Karim, 2009; Lind & Mehlum, 2007). Having tested the significance of the coefficients in the regression models, the second step is to test for the significance and magnitude of the slopes of the extreme points. We analyse the concavity of the inverted U shaped

relationship between intra-industry alliances and firm innovation performance based on the RE estimates of Table 2 (Model 2) which has a higher Chi^2 value and more degrees of freedom. We first test the slopes of the extreme points for appropriate magnitude and significance. For intra-industry alliances the coefficient $\beta+2\gamma x_{low}$ at the lowest extreme point (0) is positive (0.95), confirming the positive upward slope for the left point of the inverted U curve. A two-tail test suggests that the left hand side slope is significantly different from zero (Chi^2(1)= 3.60 with probability 0.0578). The coefficient at the highest extreme point (12) is negative ($\beta+2\gamma x_{high}$=-6.59), confirming the negative downward slope for the right point of the inverted U shaped curve. A two-tail test for the significance of the right hand side slope is also significant (Chi^2(1)=4.48 with probability 0.0344). Subsequently we perform the Sasabuchi test (Sasabuchi, 1980) for the inverted U shape function (Karim, 2007). This involves testing whether an inverted U shaped curve is observed by testing two hypotheses: a) that the slope of the left extreme is not positive and/or b) that the slope at the right extreme is not negative (Bayene & Moineddin, 2005; Karim, 2009). A one-tail test confirms both that the left extreme slope is positive (probability 0.0289) and that the right extreme slope is negative (probability 0.0172). We finally test for the significance of the inflection point. The 95% confidence interval for the inflection point 3.28 (equal to -$\beta/2\gamma$) using the Fieller's method (Fieller, 1954) is [-0.48, 7.63] with the value of the inflection being within these values.

We follow the same steps for the RE estimates of Model 3, for inter-industry alliances. The coefficient at the lowest extreme point (0) is negative ($\beta+2\gamma x_{low}$=-0.27) confirming the negative slope for the left point of the U curve. A two-tail test for the significance of the left hand side slope passes significance levels (Chi^2(1)= 6.26, prob= 0.0123). The coefficient at the highest extreme point (26) is positive ($\beta+2\gamma x_{high}$= 0.16), confirming the positive slope

for the right part of the U shaped curve. Although a two-tail test for the significance of the right hand side slope fails to pass significance levels (prob=0.1766), the coefficient is significant at a one-tail test (Chi^2(1)= 1.83 (prob= 0.0883). Then we perform the Sasabuchi test (Sasabuchi, 1980) for the U-shape function (Hypothesis 2).   This involves testing whether a U-shaped curve is indeed observed by testing two hypotheses: a) that the slope of the left extreme is not negative and/or b) that the slope at the right extreme is not positive. The one-tail test confirms that both the left extreme slope is negative (probability 0.0062) and the right extreme slope is positive (probability 0.0883). The Sasabuchi test confirms statistically the curvature and shape of the hypothesised U-shaped relationship. We then test for the significance of the inflection point using the Fieller's method. Based on the estimates the inflection point is equal to 15.69 ($-\beta/2\gamma$) and the 95% confidence interval for the inflection point is [10.51, 156.12]. The inflection point is within the values of the 95% confidence interval, indicating that our results are meaningful for the sample of firms used.

Overall, the Sasabuchi (1980) test supports the hypotheses of concave relationships between intra-/inter- industry alliances and firm innovation performance. Significance is confirmed with one-tail tests while sections of the curves are also found to be significantly different from zero when performing two-tail tests. The Fieller's tests support that both inflection points are meaningful for the sample of firms observed.

We carried out robustness checks on the operationalization of intra- and inter- industry alliances. We added alliances between partners with no similarity in their main SIC (this involves only a dozen alliances) to inter-industry alliances and alliances between partners with same SIC at the 3-digit level (a total of 315 alliances) to intra-industry alliances. Results

remained robust overall (they are available upon request). We also added alliances between partners in the same 3 digit SIC to inter-industry alliances; results were similar, but showing weaker significance. Due to this ambiguity in the categorization of alliances between companies with the same 3 digit SIC we decided not to include them in the analysis.

We carried out sensitivity analysis to the hypothesised shape of the relationships between firm patents and intra-/inter- industry alliances by adding a cubic term in both Models 2 and 3 to explore whether our estimates capture segments of curvilinear S-shaped relationships. The cubic terms failed to pass significance levels in both models. We also estimated a full model which includes the product of intra- and inter-industry alliances to explore their combined effect. The product variable appears insignificant in both the RE and FE specifications. In this model, Hypothesis 1 is still supported, and for Hypotheses 2 the square value of inter-industry alliances (Hypothesis 2) appears with considerably lower significance (35%).

We explored potential lagged relationships between intra-/inter- industry alliances and firm patents as the impact of alliances on firm innovation performance may not be immediate, with some research identifying a two-year lagged relationship (Hagedoorn & Schakenraad, 1994). Coefficient signs were consistent with our hypotheses but significance was weak for inter-industry alliances and there was no significance for intra-industry alliances[17]. It is worth recalling that the patents in our dataset are based on filing rather than publication date and that, on average, there is a two-year lag between these dates, which could explain why a lagged relationship is not identified herein, compared to other research that uses publication dates of granted patents (ibid).

[1] By industry we mean specific industrial sectors at 4 digit level in the Standard Industry Classification (SIC).

[2] This does not imply neglecting the considerable heterogeneity that exists among industry members (Nelson, 1991; Nelson & Winter, 1982). Firms from the same industry still differ in terms of practices and other firm specific factors, such as managerial, strategic, organizational, incentive structures and HR practices, which may go beyond the production, technological and market knowledge typical of a given industry (Nelson & Winter, 1982). Indeed, each firm possesses unique endowments and experience that affect the interpretation and implementation of such overarching principles and the application of industry specific knowledge and technologies, with such differences driving collaboration

[3] There were 204 firms operating in the bio-pharmaceutical sector in total, of which 94 did not engage in innovation alliances until 2001 based on ReCap and BioScan.

[4] Any variations in firms' propensity and opportunities to patent over time (see e.g. Basberg, 1987; Griliches, 1990; Pavitt, 1985; for comprehensive reviews of using patent data) can be ameliorated by employing panel data estimators (e.g. fixed effects models) and focusing on single country samples, as it overcomes any differences on patenting due to institutional and technological settings (Cantwell, 1989).

[5] Description of US SIC: 8731 "Commercial Physical and Biological Research"; 2833 "Medicinal Chemicals and Botanical Products"; 2834 "Pharmaceutical Preparations"; 2835 "Diagnostic Substances"; 2836 "Biological Products, Except Diagnostic".

[6] For illustrative reasons, a measure based on the absolute differences of alliance partners SIC codes would imply that there is an equal distance of 10 points in industry cognitive space between a firm with main SIC 2834 "Pharmaceutical Preparations" and its two alliances partners with main SIC codes of 2844 "Perfumes, Cosmetics and other Toilet Preparations" and 2824 "Manmade Organic Fibbers, Except Cellulosic" respectively. Moreover, there are considerable barriers and concerns in effectively interpreting results based on such absolute differences of SIC codes.

[7] We carried out robustness checks for our operationalization (including alliance partners in the same 3-digit SIC class) which we report and discuss in the Appendix. A different approach could calculate the difference between SIC codes of alliance partners. However this approach would be heavily affected by the position in the SIC classification, and not capture in a clean way cross-partner industry cognitive similarity. We investigated the possibility of using the industry relatedness index developed by Bryce and Winter (2009) which is based on relatedness information embedded in multiproduct organisation decisions (as captured by SIC) of diversified US manufacturing firms. However, the index (which is publicly available via: http://marriottschool.byu.edu/strategy/bryce/) is developed only for a limited range of SIC (codes 2000-3999) and it does not include the 8371 SIC under which most dedicated biotech firms are classified, making the index unsuitable for our study.

[8] Firm size is not included in the regression models reported in the results table (see Table 2) because of a parsimonious deletion wise approach: this variable appeared not to have a significant effect and due to the desire to increase degrees of freedom it was excluded from all final regression analyses (Table 2).

[9] The sum of inter- and intra- industry alliances is less than that for our "total alliances" variable, as for some partners the SIC code is missing.

[10] The VIF for alliance experience is 1.8, 1.71 for number of total alliances, and 1.24 for investments in R&D. VIF estimates are based on the pooled dataset.

[11] Overdispersion is tested across all the three models that test our hypotheses of Table 2 by using a STATA routine performed on the pooled time-series cross-sectional dataset. It examines the deviance of the error terms against the degrees of freedom using a Chi^2 distribution. A significant Chi^2 statistic shows significant overdispersion in the dataset. The values of the Chi^2 statistic and their probabilities are: $Chi^2 = 223.87$ (Prob=0.000), $Chi^2 = 215.14$ (Prob=0.000) and $Chi^2 = 217.01$ (Prob=0.000), for models 2, 3 and 4 respectively.

[12] Mean model VIF index for the pooled dataset is 5.74. Moreover, as previous research is on cross-sectional data we pool the cross-section and time-series dimension of our panel and estimate the same relationship and obtain insignificant results for both the linear and square term of total number of alliances. Results for these models are available upon request.

[13] Effective sample size is smaller for the fixed-effects specification due to the computational requirements of first differencing.

[14] Missing values are excluded listwise.

[15] Research on discrete dependent variable models suggests that significance levels of up to 20% can guide inclusion of variables with important interpretative power (Mickey & Greenland, 1989). Statistical power could be enhanced by increasing sample size, the variability in the data, or possibly by increasing the "alpha" value in the confidence interval (Cohen et al., 2003). In our case, it is unfeasible to increase size or variability,

as we have included the whole population of firms in the sector for which data is available; therefore an increased "alpha", or confidence interval, is the only option. Other research estimating discrete dependent variable models on alliance data using quadratic terms also relies on an increased "alpha" and significance at 20% levels (Hoang & Rothaermel, 2005).

[16] To shed more light, we investigated a possible differential impact between general and partner-specific experience (Gulati et al., 2009), as recurrent partnerships may lead to faster learning, and because there may be efficiency gains from investments in relationship specific assets and knowledge exchange mechanisms (Zollo et al., 2002). Our results are not significant across all models. We also investigated the role of prior alliance experience with intra-/inter- industry partners when testing the effect of alliances with the respective type of partner. Both hypotheses were supported, but the alliance experience variables were insignificant. Further robustness and post-estimation tests are provided in the Appendix.

[17] Specifically, significance was at 70 and 80% for the linear and square terms of intra-industry alliances respectively and 36 and 13% for the linear and square terms for inter-industry alliances respectively.