**SHAPING THE PATH TO INVENTIVE ACTIVITY:**

**THE ROLE OF PAST EXPERIENCE IN R&D ALLIANCES**

**M.C. Di Guardo1, K.R. Harrigan2**

1 Department of Business and Economics, University of Cagliari, Cagliari, Italy

diguardo@unica.it

2 Columbia Business School, Columbia University, New York, NY (USA)

krh1@columbia.edu

ABSTRACT

A firm’s past experiences with R&D alliances exert a positive effect on an invention’s impact. Experience with R&D alliances increases the breadth of knowledge classes that firms cited in their subsequent patent applications. Past experience with R&D alliances has a non-significant effect on the breadth of different technological classes that will subsequently cite a firm’s patented inventions.

As expected, results suggest that – in the area of R&D -- alliances formed by experienced partners are more likely to produce inventions that synthesize knowledge from more diverse inputs (*originality*). Experienced alliance partners are more likely to generate useful inventions with a greater innovative impact on others’ subsequent inventions – knowledge that can be built upon – when they collaborate with others in alliances. Results are indeterminate with regard to whether innovation via an R&D alliance increases an invention’s degree of applicability across diverse scientific and technological fields that might cite its patent.

**SHAPING THE PATH TO INVENTIVE ACTIVITY: THE ROLE OF PAST EXPERIENCE IN R&D ALLIANCES**

**1. GROWTH VIA ALLIANCES**

Firms must grow over time. Typically firms grow through internal innovation (organic) or acquisition (transactions), but some firms grow through collaboration (alliances). Whatever their growth mode may be, firms must become ever more nimble in a knowledge-based economy at harnessing innovative processes effectively because knowledge is the currency of greatest value in the global competitive environment. Among all organizational outputs, innovation is fundamental not only because of its direct impact on the viability of firms (Franko, 1989; Cho & Pucik, 2005), but also because of its profound effect in fomenting economic and social change (Mowery & Rosenberg, 1989; Nelson & Winter, 1982).

In this paper, we consider how firms become proficient at managing R&D strategic alliances -- where proficiency is assessed in terms of the *quality* of the outcomes from their inventive processes using patterns of patent citations. We expect that inventive outcome differences observed among firms may be attributed to experience effects. Our results offer new insights concerning the fundamental drivers of technological breakthroughs and invention quality.

The strategic management literature (e.g. Eisenhardt & Schoonhoven, 1996; Hill & Rothaermel, 2003; Rothaermel & Deeds, 2006) acknowledges that alliances are a means of extending knowledge boundaries of firms, and acquiring capabilities, especially in the case of technology-related ventures (e.g. Inkpen & Dinur, 1998; Inkpen & Pien, 2006; Kale et al., 2000; Khanna et al., 1998; Makhija & Ganesh, 1997; Powell et al., 1996; Tsang, 2002). Does past alliance experience improve firms’ performance? We believe that past alliance experience improves subsequent alliance performance (Hoang & Rothaermel 2005; Shan, Walker, & Kogut, 1994) and, in particular, increases value creation (Anand & Khanna, 2000; Kale et al., 2002; Kale & Singh, 2007). However the relationship between alliance experience and performance has been controversial (Shi et al. 2011) as prior studies have found past alliance experience to be positively-related to performance (Child & Yan, 2003; Lavie & Miller, 2008; Rothaermel & Deeds, 2006; Zollo, Reuer, & Singh, 2002), nonsignificant (Garcia-Canal, Valdes-Lianeza, & Arino, 2003; Merchant & Schendel, 2000), and even U-shaped (Sampson, 2005). It would appear that alliance performance has often fallen short of expectations (e.g., Bleeke & Ernst, 1993; Kogut, 1989) and there are concerns that alliances expose firms to greater technological uncertainties (Sampson, 2007).

 Even in the face of difficulties, firms collaborate when growth via internal development becomes more difficult and ultimately insufficient for responding fast enough to the needs of local and global markets because they need access to other firms’ technologies quickly and at a cost that is lower than organic growth requires (Rigby & Zook, 2002). The practice of forming alliances with domestic partners has become far more acceptable than was once reported in Harrigan’s (1985) pioneering inquiry. Corporate partnering has become a popular way to gain new knowledge that is considered to be superior to contracting out (Chesbrough, 2003; Granstrand, Bohlin, Oskarsson, & Sjoberg, 1992; Powell, Koput, & Smith-Doerr, 1996; Rigby & Zook, 2002) because it provides access to the specific complementary technological resources needed to facilitate faster development of innovations. Better yet, firms’ innovations can enjoy improved market access through partners’ distribution channels -- if their inventions should prove to be commercializable (Hagedoorn, 1993; Hagedoorn & Schakenraad, 1994).

 R&D alliances have developed as an important complement to firms’ ongoing innovation processes (Arora and Gambardella, 1990; (Cassiman and Veugelers, 2005), especially in dynamic technological environments where firms’ internal resources alone are insufficient for achieving breakthrough innovations (Ahuja & Lampert, 2001; Phene, Fladmoe-Lindquist, & Marsh, 2006). Firms hope to internalize positive knowledge spillovers from learning through R&D alliances (D’Aspremont & Jacquemin, 1988) and to gain tacit knowledge from seeing innovation process details that they would not normally be privy to when contracting out their needs.

Successful partnering in R&D alliances improves a firm’s relational capability which, in turn, has been linked to improved alliance performance (Dyer & Singh, 1998; Ireland, Hitt, & Vaidyanath, 2002 Heimeriks and Duysters, 2007; Schilke & Goerzen, 2010). Increased experience with R&D alliances increases the firm’s absorptive capacity which allows its personnel to exploit and transform the new knowledge that they acquire and assimilate when working with alliance partners (Cohen & Levinthal, 1990; Zahra & George, 2002). Finally although the relationship between past experience with R&D alliances and inventive output is as yet not well established, successful experiences with R&D alliances can offer firms access to the types of resources that are important for patenting and converting inventions to commercializable innovations (Ahuja, 2000).

To take on the challenge of establishing a link between alliance experience and the quality of inventive output, we considered the impact of firms’ past experiences with R&D collaboration -- using measures that go beyond simple counts of inventions (Di Guardo & Harrigan, 2012). Our reason for evaluating inventive activity using new performance measures is that all inventions are not equally useful and valuable; while producing new ideas and knowledge is a necessary condition to sustain superior performance, it is not sufficient. There can be huge variance in invention quality and economic impact. The distribution of valuable patents, for example, is extremely skewed (Hall et al., 2001); the top 10% of all patents garner 48-93% of the financial payoffs (Scherer & Harhoff, 2000). Investors typically value firms based on the quality of the patents that they own rather than on the number of their inventions (Deng et al., 1999; Hall et al., 2005). Consequently we focus on measures of patent quality as our performance variables and consider factors that shape the quality of firms’ inventive activities (Trajtenberg, Jaffe, and Henderson, 1997; Hall, Jaffe, and Trajtenberg, 2001; Fleming, 2002). We test our hypotheses using data from the U.S. pharmaceutical industry and use patent citation attributes as our performance proxies for the quality of firms’ inventions.

**2. THEORY AND HYPOTHESES**

How do we gauge the quality of inventive activity? Inventions can be analyzed along three relevant dimensions: their usefulness, originality, and generality. The *usefulness* of an invention denotes its impact on future inventions and inventors (as well as its economic value); *usefulness* captures the extent to which new – somehow related – inventions will have to build upon or refer to an invention as a building block to subsequent innovations and can be approximated by the citations that a patent garners. The *originality* of an invention indicates the extent to which an invention synthesizes ideas from different knowledge streams – especially from a mix of inputs that departs from the current state of knowledge (Fleming, 2001; Hall, Jaffe, & Trajtenberg, Argyres & Silverman, 2004). The *generality* of an invention signifies its degree of applicability across a range of different scientific and technological fields.

These distinctions which characterize the quality of inventions are important because excessive emphasis on innovativeness has overshadowed a more-appropriate focus on innovation performance (and the value of underlying inventions that are produced). Inventions vary greatly in quality and half of all (*or as many as nine out of ten*) new products end up ultimately being financial failures (Andrew & Sirkin, 2003). The quality of the inventions that a firm produces strongly affects their survival and prospects for long-term success (e.g. Henderson, 1993; Christensen, 1997).

* 1. Quality of inventive activity

Invention is usually conceived as the first step in an innovation process that Schumpeter (1939) defined as the commercial application or adoption of an invention and he noted that “the making of the invention and the carrying out of the corresponding innovation are, economically and sociologically, two entirely different things” (p. 85). Following Fleming (2001), we focus our analysis on inventions, the prerequisite for technological innovations, in assessing the quality of firms’ inventive activity.

The outcome of an inventive process depends on the resources made available to innovators -- both in terms of quantity as well as quality. The invention process is cumulative in nature and exhibits learning curve economies. Access to accumulated knowledge is a key resource in the invention process (Winter, 1997) and knowledge produced in the future relies on the knowledge made available today. Innovative firms who partner with other firms rely on inventors to combine their existing knowledge bases in synergistic ways that explore the unexploited potential of their technologies to create new knowledge that can be commercialized (Grant, 1996; Kogut & Zander, 1992). Working together to create new knowledge increases the base of resources that inventors can subsequently manipulate and gives them access to additional R&D capabilities that could not be obtained in isolation (Nerkar & Paruchuri, 2005). In brief, success breeds success and we expect to find that the more collaboration experience firms have acquired in the past through R&D alliances, the greater will be the quality of inventive output in their subsequent R&D alliances in terms of impact, generality, and originality, where *impact* represents weighted patent citations, *originality* represents the pattern of backward citations that a firm invoked in its patent application, and *generality* represents the pattern of forward citations for a patent. A past experience with R&D alliances is our first independent variable.

Hypothesis 1a. Past R&D Alliance Experience is positively related to the *impact* of the inventive output of the firm’s R&D alliance.

Hypothesis 1b. Past R&D Alliance Experience is positively related to the *originality* of the inventive output of the firm’s R&D alliance.

Hypothesis 1c. R&D Alliance Experience is positively related to the *generality* of the inventive output of the firm’s R&D alliance.

2.2 Novelty of heterogeneity

The strategy literature has shown how firms embedded in an alliance network have a higher rate of establishing alliances (Gulati & Gargiulo, 1999). This is scarcely surprising since firms that are similar in their understanding of technologies are better equipped to collaborate on joint projects (Cohen & Levinthal, 1990; Mowery et al., 1997) with the result of greater alliance formation between similar firms in crowded technology areas (Stuart, 2000). But there is also merit to incorporating diverse stimuli into the innovative process.

Diverse alliance portfolios provide firms with access to a wider range of valuable resources from different types of partners -- thereby enabling firms to benefit uniquely from the specific resource contributions of their different partners (Wassmer, 2010). Partners’ diverse characteristics have a strong influence on whether and how well the firms in an alliance can learn from each other (Sampson, 2007). Exposure to diverse partners broadens the firm’s perspective and increases its ability to see fruitful opportunities that may arise at the confluence of several technologies. This greater experience with diversity, in fact, enlarges the knowledge base of the firm and implies a better quality in the output of its subsequent R&D alliances.

Accordingly we considered the heterogeneity of partner traits when considering the diversity of a firm’s alliance portfolio. Having heterogeneity in the firm’s alliance partners implies a greater variance in the partners’ resources, capabilities, and industrial backgrounds that firms have access to (Goerzen & Beamish, 2005). Heterogeneity is measured as differences in kind, source or category of relevant knowledge or experience among alliance partners and we expect that heterogeneity will positively impact the knowledge bases of firms entering alliances and affect their potential capability to generate new inventions in the collaboration process (Harrison & Klein, 2007). Briefly, greater heterogeneity in the types of partners that firms have cooperated with in the past will positively affect the quality of inventive output in their subsequent R&D alliances in terms of impact, originality and generality, where *impact* represents weighted patent citations, *originality* represents the pattern of backward citations that a firm invoked in its patent application, and *generality* represents the pattern of forward citations for a patent. Past partner heterogeneity is our second independent variable.

Hypothesis 2a. Heterogeneity in a firm’s past experiences with R&D alliances is positively related to the *impact* of inventive outputs from firms’ subsequent R&D alliances.

Hypothesis 2b. Heterogeneity in a firm’s past experiences with R&D alliances is positively related to the *originality* of inventive outputs from firms’ subsequent R&D alliances.

Hypothesis 2c. Heterogeneity in a firm’s past experiences with R&D alliances is positively related to the *generality* of the inventive output of firms’ subsequent R&D alliances.

Patents have significant strengths as measures of technological performance. Not only do they represent an externally validated measure of technological novelty with a clear economic significance (Scherer & Ross, 1990), but their correlation with other measures of technological performance, such as new products or innovation counts, has been vetted (Hagedoorn & Cloodt, 2003).[[1]](#footnote-1) Trajtenberg (1990) and Hall, et al (2001) found that a patent’s citation by subsequent patents (whereby each patent documents the “prior art” upon which that particular innovation builds) is an indicator of the impact of the underlying innovation, but also of its economic value. A firm’s patent impact was measured using the weighted number of forward citations received for those patents which were applied for in the years after participation in an R&D alliance.

**3. METHODS**

The ideas we have expounded herein are best explored empirically in the context of a large sample of firms drawn from a common industry background, like ethical pharmaceuticals, because limiting the sample to a single industry insures that the dimensions on which alliance partners are analyzed will be easily comparable. Our sample is drawn from the pharmaceutical industry which lends itself well to analyzing how past experience with R&D alliances affected firms’ subsequent innovative performance for three main reasons: first, firms’ ability to innovate is crucial to commanding a competitive advantage in this industry (Hall & Ziedonis, 2001);

second, alliances are widely recognized as being important to the innovative performance of individual pharmaceutical firms and to the industry’s development as a whole (Langlois & Steinmueller, 1999; Lim, 2010); and third, all relevant players in this industry compete in the U.S. market and must routinely patent their innovations at the U.S. Patent and Trademarks Office, thereby giving a basis for comparing the quality of their inventions (USPTO, 2012; Hall & Ziedonis, 2001).

Pharmaceutical companies often engage in dyadic bilateral R&D alliances (Hoang and Rothaermel, 2005). The emergence of a vast network of R&D collaborative relationships among heterogeneous pharmaceutical companies has been one of the key distinguishing traits in the recent evolution of this industry – which is characterized by rapid technological change, huge investment stakes and radical uncertainty regarding regulatory approvals (Hagedoorn, 1993; Riccaboni & Pammolli, 2002; Rosenkopf & Schilling, 2008; Pisano, 1991; Arora & Gambardella, 1994; Powell et al., 1996; Orsenigo et al., 1998). The history of collaborations within the pharmaceutical industry can be tracked easily – making it a suitable forum for our analysis.

3.1 Data Sources

Data on firms’ R&D alliances which were formed between 1994 and 2000 in the pharmaceutical industry were obtained from the *SDC Platinum* database (Thomson One, 2013). Inclusion in our sample was predicated on the firms engaged in an R&D alliance (a) having as their primary 4-digit SIC code either “2833" (for Medicinals and Botanicals), "2834" (for Pharmaceutical Preparations), "2835" (for Diagnostic Substances) or "2836" (for Botanical Products, Except Diagnostics); (b) having full financial data available for both sponsoring firms from the COMPUSTAT database (Standard & Poor’s, 2013); and (c) having made patent applications (during 1994 through 2000) that subsequently yielded patents. *Factiva Press Releases* *(2012)* were used to verify the existence of and gather additional information about the R&D alliances generated by *SDC Platinum*. Following the methodology of Ahuja (2000), we converted multi-partner alliances into a set of dyads composed of bilateral alliances.

Although we examine the phenomenon of R&D alliances, our dependent variables are measures of inventive quality at the sponsoring-firm-level performance (which we attribute to their past experiences with R&D alliances) -- one observation for each alliance that a sponsoring firm participated in during the window of 1994 through 2000. The values of a respective sponsoring firm's impact, originality and generality indices differ for each respective R&D alliance that sponsoring firms participated in because the performance indices are calculated as of the year of the announcement of each respective R&D alliance. (The alliances firms engaged in sometimes included marketing, production, and/or supply activities in addition to joint R&D activities, but consideration of these additional strategic activities did not enter into our construction of the dependent inventive performance variables.) This selection process yielded a sample of 911 alliances which involved 236 distinct firms who cooperated with each other in sponsoring various combinatorial dyads.

Patent data were obtained from the National Bureau of Economic Research (NBER) U.S. Patent Citations Data File (Hall et al., 2001) and the updates to the database that were provided by the NBER and Professor Bronwyn Hall. The NBER Patent Citations database comprises detailed information on utility patents that were granted during the period 1963 to December 2006; it contains all citations that were made to these patents between the years of 1975 through 2006. The NBER Patent Citations database contains patent number, assignee name, assignee number, filing year, grant year and technological class number for intellectual claims made, but it does not contain the CUSIP numbers of the assignee firms (which are needed to match up financial information from the COMPUSTAT database). We used the name-matching database -- a bridge between the NBER patent and COMPUSTAT databases provided by Hall and colleagues (2001) -- to match patent data with the financial data that was available in the COMPUSTAT database.

3.2 Dependent variables

*Patent impact*

Following standard practice (e.g., Yayavaram & Ahuja, 2008), firms’ inventive performance is measured by counting the number of patents that were granted to a firm. The cumulative impact of their portfolio of patents is measured as a weighed count of their patents. Citation-based counts are considered to be a reliable and externally validated measure of inventive performance (Griliches, 1990; Yayavaram & Ahuja, 2008) that correlates well with the economic and the social value of a firm’s innovations (Harhoff, Narin, Scherer, & Vopel, 1999), as well as with a firm’s ability to generate new products and science-based inventions (Basberg, 1982; Comanor & Scherer, 1969). Hall et al (2005) found that a firm’s market value increased by 3 percent for every patent citation that it received -- making weighted citations a credible measure of a patent’s impact (Cattani, 2005).

Our first dependent variable, patent impact, is calculated as the number of granted patents applied for in the four-year window after an alliance has been formed, weighted by the number of forward citations that each of these granted patents received. For example, if an alliance began in 1994, the patent impact associated with that particular intellectual collaboration was constructed using those patents that were applied for during the four-year window of 1995 through 1998 – weighted by the citations received for those respective patents. (Ideally analysis should focus only on those patents that were clearly the result of participating in a specific alliance. Given the obstacles to obtaining information on the precise intellectual origins of specific patents, we followed the conventions of Sampson (2007) in constructing patent impact measures.)

The number of citations that a patent receives depends on its age; in our example, the patent whose application was filed in 1995 has a higher probability of being cited than does the patent which was applied for in 1998. To correct for age bias, we normalized every citation-based measure by the average value of the measure itself -- calculated over all the patents belonging to the same technological category whose application was filed in the same respective year. The use of forward citations as a proxy of a patent’s impact is widespread in the literature and our specification of this dependent variable is consistent with it (Trajtenberg, 1990; Stuart, 2000).

*The breadth of innovation: originality*

To acquire a patent, an inventor must submit to the U.S. Patent Office an application that describes a non-obvious and industrially useful invention. A legal requirement for obtaining a patent is that applicants must generate a list of citations to all previously granted patents that made technological claims similar to those claimed in their applications. This backward citation process is supervised by patent examiners, who maintain the integrity of the citation process by verifying that the list of references included in each patent application is complete before a patent can be issued. The function of the citation requirement is to establish the scope of the patent under evaluation: inventors can only claim patent rights to the unique aspects of their inventions. To establish such uniqueness, each application must identify how the proposed invention extends on all patented technological precursors. Like paper citations in an academic context, studies have shown that highly cited patents are inventions which have been the most important inventions in that area (Hall et al., 2001) and a complete patent application will note these most-important technological precursors. When an application for patent is granted, the patent receives technology codes that indicate those knowledge fields where claims of uniqueness have been vetted by the patenting process. These codes designate a particular patent’s core technology; citing technology codes in a patent application that are far beyond the granted patent’s scope indicates that the particular patent has integrated a broad range of knowledge that goes beyond the firm’s typical technology core. The U.S. Patent Office uses about 400 main (3-digit) technology classes in classifying patents, and over 120,000 patent subclasses. However, since 400 classes are far too many for most applications, Hall et al. (2001) have developed a higher-level classification by which the 400 classes are aggregated into 36 2-digit technological subcategories; their classification scheme is included in the NBER Patent Citations database and was used to calculate indices of originality and generality.

 To measure the breadth of innovation, we calculated an originality index. The originality of patent *i* is measured as:

*Originalityi* = 

where *tij* indicates the proportion of the citations *made* by patent *i* to patents that belong to patent class *j*. Then, for instance, if a patent cites previous patents that belong to a narrow set of technologies, the originality score will be low. The notion is that the synthesis of divergent ideas is characteristic of research that is highly original and hence also basic (Trajtenberg et al., 1997), and that originality stems from the breadth of search (Hall et al., 2001). Every citation-based measure is normalized by the average value of the measure itself, calculated over all the patents belonging to the same technological category whose application was filed in the same year.

*The breadth of impact: generality*

 To measure the breadth of an innovation’s impact, we measured generality. The generality of patent *i*, following Trajtenberg, et al. (1997), is measured as:

*Generalityi* = 

where *sij* indicates the percentage of citations *received* by patent *i* that belongs to patent class *j*, out of *ni* patent technological classes. Therefore, if patent *i* is cited by subsequent patents that belong to a wide range of technological fields, the measure will be high, whereas if most citations are concentrated in a few fields, the measure of generality will be close to zero. A high generality score suggest that a patent had an impact that influenced subsequent innovations in a widespread variety of technological fields.

3.3 Independent variables

Our hypotheses depend on two independent variables – a firm’s past level of experiences with R&D alliances and the heterogeneity of traits of the firm’s past alliance partners. We specified several control, categorical and dummy variables to correct for effects that may not be adequately captured by our independent variables.

*Past experience with R&D alliances*

As a proxy for differing experience levels with past alliances we used the number of R&D alliances that each sponsoring firm had entered into -- up to the five years prior to the start of the focal collaboration. This approach is in line with prior research (Kale & Singh, 1999; Tsang, 2002, Rothaemal, 2005) and there is growing consensus in the literature that five years is the correct period to examine since it is considered to be the average period in which an alliance can still contribute to the experience level of the firms (Kale et al., 2002; Li & Rowley, 2002; Zollo et al., 2002).

*Heterogeneity in past R&D alliance partners*

To measure the relative heterogeneity of the past partners with whom a sponsoring firm collaborated, we computed a diversity index that will reflect higher values when a firm enters into a broader variety of alliances with diverse partners. We measure partner heterogeneity encountered in previous R&D alliances as:

*Heterogeneityi* = 

where *hij* is the number of firmi’s past partners in a specific segment of the market (using past partners’ four-digit SIC codes as indicators of their diversity) and *n* is the number of partners in the same segment of market.

3.4 Control variables

Our specifications included two potential covariates (that were not collinear with each other) that may affect the measures of firms’ innovative performance. Control variables included: (1) a size correction to control for heteroskadasticity which is specified as the logarithm of a firm’s sales in the year when its R&D alliance began, and (2) a correction for firms’ R&D outlays to control for evidence of commitment to innovation that is evidenced by past investments (Ahuja, 2000; Hall & Ziedonis, 2001) which is specified as the ratio of R&D expenses divided by sales.

3.5. Categorical and dummy variables

Our specifications included categorical variables to capture (1) effects from prior experiences of working with the same partner (suggested by Hoang & Rothaermel, 2005) which is specified as the simple number of R&D alliances that a sponsoring firm has concurrently with the same partner and (2) effects from having multiple alliances with different partners operating in the same year which is specified as the simple number of R&D alliances that a sponsoring firm has concurrently with a variety of partners. Dummy variables were added to capture effects from (1) scope effects (Oxley and Sampson, 2004) that may occur where R&D alliances also involve other value-adding activities, such as manufacturing or marketing, and (2) contractual form (Harrigan, 1995) where equity joint ventures are designated as “1” and non-equity alliances are coded as “0.” Annual exogenous shocks and other time effects were captured using a set of dummy variables for each year where the base case equals “1994.”

3.6 Additional corrections

We corrected for potential multicollinearity in early specifications by calculating variance inflation factors (VIFs) based on the pooled data (Wooldridge, 2002). Since our sample includes several observations referring to the same sponsoring firm – sometimes in the same years of alliance initiation – we computed a robust standard error for each coefficient to correct for the effect of clustered data.

In Table 1, we report the summary statistics and pair wise correlations of the key variables of interest. DISCUSSION OF TABLE 1

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**4. RESULTS**

Table 2 reports the best specifications for our three dependent variables. In column 1, the specification for patent impact refers to the extent to which new – somehow related – inventions

will have to build upon or refer to the firm’s patents. In simple regression specifications testing patent impact, the effect of sponsoring firms’ experience with past R&D alliances always had a positive coefficient and was statistically significant. We found evidence of intervening variables when testing simple specifications of the effect of heterogeneous past partners on patent impact (because the variable’s coefficient was always negative and statistically significant). When we combined the effects of both independent variables in specifications that included our two control variables (plus the categorical and dummy variables), the signs of sponsoring firms’ experience with past R&D alliances and of the effect of heterogeneous past partners on patent impact both became positive (as expected) and statistically significant. We conclude that there is some support for hypotheses 1a and 2a.

In column 2, the specification for patent originality refers to the breadth of synthesis of divergent ideas that a sponsoring firm’s patents made in their respective Patent Office applications. We found evidence of intervening variables when testing simple specifications of the effect of sponsoring firms’ experience with past R&D alliances on patent originality because the coefficient (although positive) was not statistically significant. For simple specifications of the effect of heterogeneous past partners on patent originality the coefficient was negative and not statistically significant. Simple specifications testing the effect on patent originality of an interactive variable built from the two independent variables produced the expected positive coefficient that was statistically significant. When we tested specifications of patent originality that combined the effects of both independent variables with the two control variables (plus the categorical and dummy variables), the signs of sponsoring firms’ experience with past R&D alliances and of the effect of heterogeneous past partners on patent originality both became positive (as expected) but statistically significant only at the 10-percent level. We conclude that there is weak support for hypotheses 1b and 2b.

In column 3, the specification for patent generality refers to the breadth of influence that a sponsoring firm’s patents had on subsequent innovations in a variety of technology classes. We found evidence of intervening variables when testing simple specifications of the effect of sponsoring firms’ experience with past R&D alliances on patent generality because the coefficient (although positive) was not statistically significant. For simple specifications of the effect of heterogeneous past partners on patent generality the coefficient was negative and not statistically significant. Simple specifications testing the effect on patent generality of an interactive variable built from the two independent variables produced the expected positive coefficient but it was not statistically significant. When we tested specifications of patent generality that combined the effects of both independent variables with the two control variables (plus the categorical and dummy variables), the signs of sponsoring firms’ experience with past R&D alliances and of the effect of heterogeneous past partners on patent originality both became positive (as expected) but not statistically significant. We conclude that there is no support for hypotheses 1c and 2c.

5.

**DISCUSSION AND CONCLUSION**

Our investigation of how sponsoring firms’ past experiences with R&D alliances in the pharmaceuticals industry affects the impact of their subsequent patents, as well as their patents’ originality and generality, built upon findings by Trajtenberg, et al (1997), Fleming (2001), and Hall, et al (2001). Results indicating that sponsoring firms’ past experiences with R&D alliances positively affect patent impact add to the debate which has heretofore found mixed results for this question. Our finding that the heterogeneity of firms’ past alliance partners positively affects the impact of their subsequent patents is new. We have no highly-significant findings regarding the effects of sponsoring firms’ past experiences with R&D alliances and the heterogeneity of firms’ past alliance partners on their subsequent patent originality and generality.

 We speculate that having a rich variety of past experience with R&D alliances can help sponsoring firms to avoid “competency traps” (Levitt & March, 1988), “core rigidities” (Leonard-Barton,1992), and the “not-invented here” attitude (Katz & Allen, 1982) which inhibits a firm’s willingness to integrate external knowledge when working with diverse partners to create useful inventions. We believe that the most effective learning is received when firms work with a diverse mix of alliance partners in a wide variety of R&D alliances.

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TABLE 1. Means, Standard Deviations, and Correlations

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Variable | Mean | S.D. | Min | Max | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
| 1. | Alliances pastexperience | 8.89 | 10.10 | 0 | 38 | 1 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 2. | Partners’ heterogenety | 0.56 | 0.31 | 0.10 | 1 | -0.57 | 1 |  |  |  |  |  |  |  |  |  |  |  |  |
| 3. | Log assets | 5.91 | 2.84 | -2.41 | 10.62 | 0.71 | -0.51 | 1 |  |  |  |  |  |  |  |  |  |  |  |
| 4. | R&D intensity | 4.61 | 36.42 | 0.05 | 998.3 | -0.09 | 0.10 | -0.15 | 1 |  |  |  |  |  |  |  |  |  |  |
| 5. | Number of alliances in the same years | 3.03 | 2.52 | 1 | 12 | 0.64 | -0.39 | 0.60 | -0.08 | 1 |  |  |  |  |  |  |  |  |  |
| 6. | Past experience with the same partner | 0.04 | 0.23 | 0 | 1 | 0.11 | -0.07 | 0.08 | -0.02 | 0.07 | 1 |  |  |  |  |  |  |  |  |
| 7. | Alliance scope | 0.37 | 0.48 | 0 | 1 | 0.01 | 0.05 | 0.03 | -0.03 | 0.05 | 0.09 | 1 |  |  |  |  |  |  |  |
| 8. | Alliance form  | 0.11 | 0.31 | 0 | 1 | -0.02 | -0.09 | -0.06 | 0.00 | 0.05 | 0.04 | 0.01 | 1 |  |  |  |  |  |  |
| 9. | Year dummy 95 | 0.16 | 0.36 | 0 | 1 | 0.05 | -0.06 | -0.06 | 0.00 | 0.03 | 0.04 | 0.05 | 0.00 | 1 |  |  |  |  |  |
| 10. | Year dummy 96 | 0.09 | 0.29 | 0 | 1 | 0.05 | 0.01 | 0.05 | 0.00 | -0.06 | 0.00 | -0.08 | 0.07 | -0.14 | 1 |  |  |  |  |
| 11. | Year dummy 97 | 0.16 | 0.36 | 0 | 1 | 0.07 | -0.04 | 0.02 | -0.03 | 0.08 | -0.01 | 0.02 | 0.00 | -0.19 | -0.14 | 1 |  |  |  |
| 12. | Year dummy 98 | 0.13 | 0.33 | 0 | 1 | 0.00 | 0.03 | 0.03 | 0.00 | -0.08 | -0.05 | -0.01 | -0.06 | -0.17 | -0.13 | -0.17 | 1 |  |  |
| 13. | Year dummy 99 | 0.11 | 0.32 | 0 | 1 | 0.01 | -0.01 | 0.06 | -0.02 | -0.06 | 0.07 | 0.04 | 0.01 | -0.16 | -0.12 | -0.16 | -0.14 | 1 |  |
| 14. | Year dummy 00 | 0.07 | 0.25 | 0 | 1 | -0.03 | 0.01 | 0.10 | -0.02 | 0.03 | -0.05 | 0.01 | 0.06 | -0.12 | -0.09 | -0.12 | -0.10 | -0.10 | 1 |

TABLE 2.

Dependent variables: change in patents quality.

Results of robust regression. (Robust standard errors in parentheses).

|  |  |  |  |
| --- | --- | --- | --- |
|  | (1) | (2) | (3) |
|  | Patent Impact  | Patent Originality | Patent Generality |
| **Alliances past experience**  | 82.87 (28.15) \*\* | 0.00 (0.00) \* | 0.00 (0.00) |
| **Partners’ heterogenety** | 1100.90 (456.45) \*\* | 0.02 (0.00) † | 0.02 (0.02)  |
| Log assets | 0.15 (0.05) \*\* | -0.00 (0.00) | -0.00 (0.00) |
| R&D intensity | 0.09 (0.52) | 0.00 (0.06) | 0.00 (0.00) |
| Number of alliances in the same years  | 113.11 (95.71)  | 0.00 (0.00) | 0.14 (0.12) \* |
| Past experience with the same partner | 58.87 (155.55) | 0.02 (0.04) | 0.01 (0.01) † |
| Alliance scope | 171.24 (124.26) | 0.01 (0.01) | 0.00 (0.00) |
| Alliance form (JV=1) | 170.00 (173.94) | 0.02 (0.01) | 0.00 (0.01) |
| Year dummy 95 | -528.46 (197.06) \*\* | .047 (0.01) | .047 (0.01) |
| Year dummy 96 | -794.07 (271.89) \*\* | .047 (0.02) \*\*  | .047 (0.02) \*\*  |
| Year dummy 97 | -1106.66 (337.6) \*\* | .046 (0.02) | .046 (0.02) |
| Year dummy 98 | -1278.77 (364.85) \*\* | .072 (0.01) \*\*\* | .072 (0.01) \*\*\* |
| Year dummy 99 | -1488.16 (398.90) \*\* | .051 (0.02) \*\* | .051 (0.02) \*\* |
| Year dummy 00 | -1728.38 (511.07) \*\* | .077 (0.02) \*\*\* | .077 (0.02) \*\*\* |
|  |  |  |  |
| N. of observations | 911 | 911 | 911 |
| F | 6.96\*\*\* | 2.35\*\* | 11.66\*\*\* |

† *p* < .10 \* *p* < .05 \*\* *p* < .01 \*\*\* *p* < .001

1. Nonetheless, the use of patents also presents some limitations. Some inventions are non patentable and others are not patented. Levin et al. (1987), *inter alia*, show how the propensity to patent inventions shows significant discrepancies across industrial sectors. As patenting patterns are to a great extent dependent on industry characteristics, we focus on one single industrial sector. The external factors that affect the propensity to patent are likely to be stable within the same context (Ahuja & Katila, 2001). [↑](#footnote-ref-1)