Technological breadth and depth of knowledge in innovation: The role of mergers and acquisitions in biotech

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Abstract

We analyze the diffusion and integration of external knowledge by distinguishing between the depth and breadth of technological knowledge in combination with the type of partner and channel of exchange. Using a latent variable structural equation model with a sample of 202 US biotechnology firms between 1990 and 2009, we investigate the extent to which the M&As with different partners contribute to the depth and breadth of the focal firm's knowledge base. Our analysis also addresses potential endogeneity issues and shows that acquisitions of related firms mainly increase the depth of knowledge, while acquisitions of unrelated firms develop the breadth of knowledge.

1. Introduction

There is a general consensus about the fact that innovation, one of the most relevant drivers of economic growth, is deeply affected by mergers and acquisitions (M&As) strategies (e.g. Bena & Li 2013; Cassiman et al. 2005; Katz & Shelanski 2005; Phillips & Zhdanov 2013).

However, despite the relevance of the impact of M&As on innovation input and output, both in the short and long term, few academic efforts have focused on this topic, and the findings of the studies are far from conclusive. For instance, M&As reduce the duplication of efforts and costs in research activities, thereby encouraging firms to reduce their investments in research and development (hereafter R&D) (Bloom et al. 2013; Hoberg & Phillips 2010; Reinganum 1983), but at the same time, the M&A process also influences its member firms to exploit economies of scale or scope in research enhancing R&D investment (Amore et al. 2013; Brown et al. 2012; Ferreira et al. 2012). Thus, the net effect on innovative input is puzzling. Furthermore, member parties frequently assert that M&As can improve their research performance because of new and better processes or products, which in turn enlarge their technological diversity and their innovative capabilities (Cassiman et al. 2005). Conversely, there is some evidence that shows that acquiring firms target those firms that are developing similar products with related technological skills (Bena & Li 2013), which can have a negative impact on the variety of new products, long-run innovative growth and market competition (Ornaghi 2009).

Therefore, given the conflicting results in prior literature on innovation, we believe that the impact of M&As on innovation output deserves further attention. Our paper aims to contribute to this debate by focusing on the direct consequences of M&As on firms'

technological activities to better understand the production of technological knowledge through M&As. More precisely, our main research question is: How does the corporate takeover affect the creation of the technological breadth and depth of knowledge - the horizontal and vertical knowledge dimensions - which can simplify our understanding of diffusion of the technological knowledge through M&As and their interdependence?

Many recent studies on the technological innovation process emphasize the development of the technological breadth and depth of knowledge (e.g. Alexy et al. 2013; George et al. 2008; Hughes & Kitson 2012; Katila & Ahuja 2002) and find that an important strategy for successful innovation is to search for external ideas that have commercial value. Technological breadth refers to the variety of areas explored to develop a particular subject, while technological depth refers to the analytical sophistication or specialization of the complex subject associated with the difficulty conceptualizing expertise or competence (Wang & Von Tunzelmann 2000). In other words, breadth is the broader set of different components embodied in an innovation, and depth is the degree of specialization embodied in the knowledge components of that innovation. In industrial organization terms, both breadth and depth represent the vertical and horizontal features of the innovative process, where the former is related to the *variety* of the innovation and the latter is related to the *quality* of the innovation. Thus, it is also important to have a proper *measure* of the breadth and depth of the technological knowledge of firms, particularly in technology-intensive industries.

Using a unique dataset from a sample of 202 biotechnology firms headquartered in the US, we show how acquiring firms through M&As develop the two distinct dimensions – depth and breadth – of technological knowledge by choosing their potential targets. We consider all the patents filed by these firms in the US patent office and other countries

between 1984 and 2009 as products of inventions. We measure the depth by the extent to which a patent draws upon a certain technology (identified by the International Patent Classifications or IPC codes) more intensively than others and the breadth[1] by the range of new technologies (IPC codes) included in the patents. We aggregate the patent-year level data to the firm-year level for technological depth and breadth of these firms during the study period.

This paper contributes to the innovation literature in several ways. First, there exists only a limited number of studies that focus on the direct consequences of M&As on firms' technological activities (Cassiman et al. 2005; Valentini 2012). As previously mentioned, because of the conflicting results in the existing literature, it is difficult to understand the production of technological knowledge through M&As. Our paper provides additional insight into the role of M&As in the creation of knowledge, thus bridging the gap in the related literature (e.g. Alexy et al. 2013; Henderson & Clark 1990; Katz & Preez 2008; Laursen & Salter 2006)

Second, and most importantly, the paper contributes methodologically by developing a unique measure of the technological breadth and depth of knowledge from the IPC codes. Based on the previous measure (Katila & Ahuja 2002; Moorthy & Polley 2010), which uses backward patent citations, our measure differs from this as we measure the breadth and depth directly from the IPC codes of patents to detect the technological breadth and depth of the firms. In addition, as we observe only innovation output of firms through new products and patents (not the innovation decision or process), using the latent variable structural equation model (LVSEM), we capture better results of knowledge production.

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[1] We found only a few patents without IPC codes and excluded them from the data. Furthermore, their effect is negligible compared to the total patent numbers in my database. Sometimes the patent may not have main IPC codes as the invention cannot be fit into a specified IPC file, but the patent has a set of secondary IPC codes.

Our econometric model also addresses potential endogeneity issues in the strategic initiative decisions of the knowledge development process for the focal firms.

Third, the present paper provides relevant implications for business strategies and economic policies, both in the short and long term. This paper suggests that firms must be selective in choosing their M&A partners and targets because their knowledge acquisition and integration have significant impact on the breadth and/or depth of the R&D activities as well as on the dynamics of the whole innovative process.

2. Literature and research questions

Traditionally, innovation has been conceptualized as a process of creation, accumulation and recombination of knowledge embodied in science and technology. To sustain this innovative process, it is compulsory for a firm to upgrade its knowledge stock (Castellacci & Zheng 2010; Dosi 1988; Herstad et al. 2013; von Tunzelmann et al. 2008). This knowledge stock can be improved either internally, such as by investing in R&D or by internal learning, or it can be externally acquired from sources outside the firm's boundaries, such as by technological co-operation, research joint ventures, strategic alliances and M&A. The present paper focuses on the second possibility, i.e., the firm's ability to reconfigure and integrate external complementary knowledge from an external source through M&As. Mergers occur when independent firms combine their resources and activities to form a new entity, and an acquisition occurs when one firm gains control of the majority of the ownership of the acquired firm.

The relevant question is: How do firms assimilate and integrate technological knowledge after acquiring it? The studies of Cohen and Levinthal (1989, 1990) contribute to the literature in this context. They argue that R&D activities broaden a firm's absorptive

capacity (the *by-product* of the R&D process), which is the assimilation of knowledge from external sources. A number of studies on innovation also show that investment in R&D increases a firm's ability to exploit external technological knowledge (Arora & Gambardella 1994; Henderson & Cockburn 1994; Henderson & Clark 1990). This implies that these firms can assimilate knowledge when the external knowledge aligns with their technological knowledge portfolio and that these firms can transform the knowledge when the external knowledge does not fit with the existing knowledge stock (Todorova & Durisin 2007).

A substantial body of literature recognizes the importance of external and complementary knowledge (Antonelli 2000; Bertrand & Zuniga 2006; Cohen & Levinthal 1990; Laursen & Foss 2003; Lissoni 2001; Teece 1986) acquired through strategic partnerships, research joint ventures and M&As (Adams & Marcu 2004; de Faria et al. 2010). These studies show that inter-firm knowledge spillovers help in the cross-fertilization of new ideas and in the creation of new technology. The speed of technological change and the need for external technological knowledge that can complement internal R&D often motivate firms to extend their resources through M&As (Hagedoorn & Duysters 2002). In a study of 9000 deals between 1990 and 2000, Villalonga and McGahan (2005) find that the likelihood that a firm will choose acquisition over other forms of collaboration increases with the technological resources of the potential targets. The question then is as follows: Is there a process in which M&As directly affect the innovation? Lerner et al. (2003) show that firms can acquire the portfolios of patents from their competitors through M&As. In addition, studies find that firms often acquire alliance partners (Porrini 2004; Zollo & Reuer 2010) of target firms. Hence, the strategic decision of a M&A to acquire new technological knowledge and

capabilities has become a well-institutionalized corporate phenomenon (Larsson et al. 1998; Uhlenbruck et al. 2006).

2.1. Mergers and acquisitions: breadth and depth of knowledge

The consequences of M&As, as previously mentioned, could be two-fold. On the one hand, a firm can engage in more R&D by achieving scale and scope of economies than it could before the acquisition. On the other hand, because of the high R&D budget in the post-M&A period, fundamental research projects receive more attention, and consequently, firms can increase their technological capabilities. Furthermore, if some technological knowledge is tacit in nature and embedded in the organizational routines, M&A becomes the best strategic choice. Additionally, innovative firms are more likely to acquire firms with patents of high commercial importance over an extended period of time (Higgins & Rodriguez 2006), thus indicating a close link between technological knowledge development and M&A activities. Hence, acquiring technologically rich targets provides the acquirer an opportunity to be exposed to new and diverse knowledge (Hitt et al. 1996). The similarity between the technological knowledge of the acquirer and the target facilitates the exchange, combination and exploitation of what is already known (Nonaka et al. 1996). Conversely, acquiring complementary technological knowledge (which is dissimilar in nature) increases the integrating costs (Katila & Ahuja 2002) because of complexity and challenges (Grant 1996). In sum, knowledge development is largely affected by the similarity and complementarity of technological knowledge in M&As. Yet, the common knowledge stocks of both the acquirer and the acquired firm facilitates communication and integration between the two, thereby expanding the scope of exploitation when technological knowledge is similar enough for learning and

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complementary enough to easily understand the uniqueness of the value. This suggests

that innovation is based on intensive research and an existing knowledge dimension, as in

the exploitative innovation case (Quintana-Garcia & Benavides-Velasco 2008). In other

words, technology-based acquisitions stimulate both exploration and exploitation

processes in developing the technological knowledge of the acquirer.

2.1.1. Knowledge creation in technologically related M&As

The above argument raises the following question: What factors determine the

development of the knowledge portfolio of the acquirer? Studies regarding M&As

emphasize that the success of the post-M&A technological output depends on the strategic

fit of the partners. For instance, the technology relatedness of the partners helps to

integrate efficiently the technological knowledge of the R&D divisions of both firms

(Cassiman et al. 2005; Cloodt et al. 2006; Hagedoorn & Duysters 2002).[2]

However, controlling additional technologies and the variety of technologies

becomes more costly than accessing them. Loasby (1998) suggests that the firm can take

advantage of only "crucial and manageable" technologies for the innovation. Thus, the

stronger the firms are in their R&D efforts, the better they can access and exploit new

complementary assets. In this way, the acquirer can only enrich its existing knowledge

from the R&D of target firms in related technology, as the existing technological skills can

leverage the absorptive capabilities with similar external knowledge. In addition, the

technology relatedness in M&As reduces the R&D efforts, shortens the time horizon of

projects and, more importantly, provides an opportunity to emphasize development over

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[2] As previously mentioned, it partly depends on the absorptive capacity of the acquirer (Cohen & Levinthal 1990).

research (Cassiman et al. 2005). Moreover, experience in similar technology domains is likely to make the search process more predictable and more efficient (Lane & Lubatkin 1998).

This gives rise to the following question: How does the similarity in technology between the acquirer and the target firms affect the innovation activities of the firms in the post-merger period? Studies show that there exists an inverted U-shaped relationship between technology relatedness and post-merger innovation performance in the technology-intensive industry (Cloodt et al. 2006). Hence, within limits, the technology similarity within the firm's technology knowledge domain leads to a local search and exploitation of existing knowledge (Stuart & Podolny 1996). This suggests that the technology-based acquisitions of firms in related industries positively affect the depth of technological knowledge.

2.1.2. Knowledge creation in technologically unrelated M&As

Because an invention is followed by innovation, extraordinary innovation does not occur within a single technological field, but rather within a combination of multiple technological fields (Colombelli et al. 2013; Schoenmakers & Duysters 2010). The studies indicate that the industrial structure has an immense influence on the diversification of production and innovation. Investigating the effects of the related technology of acquired firms on the innovation of acquiring firms or on their mutual innovation, several studies have divided the sample into technologically related acquisitions and technology unrelated acquisitions based on IPC codes and citations of patents (Cloodt et al. 2006; Hagedoorn & Duysters 2002). However, these studies have failed to document the significance of technology similarities and complementarities within the technologically related M&As.

Ravenscraft and Scherer (1987) define complementarity in terms of fewer similarities between the functional areas of the acquiring and the acquired firms. Thus, new technological innovation may occur if there exists dynamics of proprietary or specialized knowledge and skill transfer such that the knowledge disseminates from one unit of one firm to another unit of another firm that is weak in those areas. Consequently, an unrelated or dissimilar takeover outperforms those deals triggered by industry-related bids because of cross-fertilization of multiple dissimilar technologies.

While Makri et al. (2010) discuss the knowledge relatedness with respect to M&As, it is noted that by integrating complementary knowledge, acquiring firms can create additional and supper-additive[3] value synergies that are not captured by technology relatedness. Thus, firms acquire complementary assets (e.g., regulatory knowledge, manufacturing and marketing capabilities) to increase *innovation* capabilities through bilateral dependence between R&D and downstream activities with market-oriented firms in vertical integration (Teece 1988, 1992). However, a horizontal acquisition with firms, such as competitors, in the same industry provides complementary technological knowledge that increases their R&D efforts (Capron 1999). Accordingly, the acquirer can spread its fixed costs over more R&D output and increase the scale of its R&D investments (Bertrand & Zuniga 2006). In addition, acquiring firms can obtain a broader pool of intellectual capital for more synergies in unrelated acquisitions (Park 2003). However, by acquiring the competitors necessary to gain market power, most M&As are not solely about knowledge acquisition nor are they solely about technology-based acquisition. Rather, they are about obtaining the required knowledge needed for innovation. Thus, it is obvious that the acquiring firms obtain more knowledge from the

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[3] See Milgrom and Roberts (1990, 1995)

targets than they actually need. Therefore, technology-based acquisitions of firms in less similar industries can positively affect the *breadth* of technological knowledge.

3. Methodological approach

3.1. Empirical model

This section describes our data analysis approach using the latent variable structural equation model (LVSEM) approach where the structural model evaluates the path significance and the measurement model shows the validity and reliability of the selected factors. The endogeneity issue is overcome by generalized method of moment (GMM) in the robustness test.

We build a theory to investigate the impact of M&As on the development of technological knowledge, which results in a model structure where the innovation (a latent variable) mediates between the firm's involvement in M&A and the firm's technological knowledge development. The acceptability of fit of the full model is evaluated by the LVSEM. We have also tested the partial model that reveals a direct relationship between acquisition and knowledge development as well as an indirect relationship through the innovation variable.

3.1.1. Conceptual framework

Suppose a biotech firm 'k' is involved in a technological knowledge creation decision in two alternative dimensions – building breath or depth in period t.

Considering the situation where the technological knowledge creation through the innovation process is reflected by patenting activities and is important based on the extent

of its participation in the M&A process, we develop the following conceptual model with latent variable construct:

Involvement in Corporate Takeover (INV) → Innovation (INN) → Quality of Knowledge (KNW)
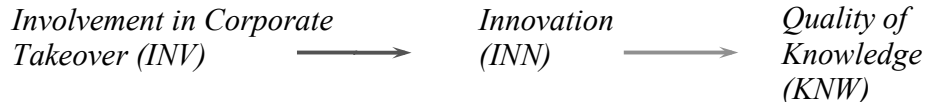
where *INV* is the involvement of the firm in acquiring knowledge from the acquired firms in the M&A process. This consists of three variables, namely, a merger dummy (1 if the firm involves M&As in a particular year, 0 otherwise), the lag of the number of related (or unrelated) acquisitions and the lag of the number of times the firm is acquired.

INN represents the innovation activities of the firm that depend on the lag of R&D intensity, the lag (2 years) of the number of alliances, firm size, firm age, and the lag of financial leverage.

KNW is another latent variable that indicates the knowledge stock of the firm that is developed by the innovation process. This variable is comprised of our main variables of interest – the depth and breadth of technological knowledge.

3.1.2. Structural equation model

Expanding the structural form of the above relationship that describes the decision to create knowledge, we write the following model:

$$INV_{k,t} = \alpha_0 + \alpha_1 MA_{k,(t-1)} + \alpha_2 MA^R_{k,(t-1)} + \alpha_3 MA^T_{k,(t-1)} + \epsilon_{INV} \qquad (1)$$

where MA_k is the vector to capture the effects of the M&A process, MA^R_k is the number of related (or unrelated) acquisitions, and MA^T_k is the number of times the firm is acquired by other firms. α_x is the corresponding vector of parameters. ϵ_{INV} is the error term with usual properties. The above equation holds because the firm's response to the above

independent variables does not influence it to be innovative, but rather, its level of innovativeness causes its response, i.e., to collaborate with other firms (see Figure 1 and 2).

It is noted that the focal biotech firm has an ongoing innovation process that develops and upgrades its knowledge stock. To capture this, we include the latent variable *INN*, which is governed by the following equation:

$$INN_{k,t} = \beta_0 + \beta_1 R\&Dint_{k,(t-1)} + \beta_2 nrAL_{k,(t-2)} + \beta_3 Leverage_{k,(t-1)} + \beta_4 Age_{k,t} + \beta_5 Size_{k,t} + \epsilon_{INN} \qquad (2)$$

The innovation of firm 'k' depends on the R&D intensity (*R&Dint*), the number of alliances (*nrAL*), financial leverage (*Leverage*), firm age (*Age*) and firm size (*Size*). As discussed in the theoretical framework, the firm builds its technological knowledge stock through the innovation process, which is mediated by the corporate takeover (M&As). The following equation attempts to capture this situation.

$$KNW_{k,t} = \gamma_0 + \gamma_1 BREADTH_{k,t} + \gamma_2 DEPTH_{k,t} + \epsilon_{KNW} \qquad (3)$$

$BREADTH_{k,t}$ and $DEPTH_{k,t}$ are detailed in the next section. As there exists a relationship between the latent variables, we write the structural form of the equation that captures the focal firm's knowledge building strategy and its M&A process.

$$KNW_{k,t} = \delta_0 + \delta_1 INV_{k,t} + \delta_2 INN_{k,t} + \upsilon_{KNW} \qquad (4)$$

Assuming that the creation of breadth and depth is correlated with the M&A decision, the following condition holds:

$$Cov\ (\epsilon_{KNW}, \epsilon_{INV}) \neq 0 \qquad (5)$$

The validity of equation (4) depends on the rejection of the exogeneity of the knowledge creation variables with respect to equation (1), which describes the firm's involvement in acquiring external knowledge through M&As.

3.1.3 Breadth and Depth Indicators

Empirical contributions agree on the definitions of the breadth and depth of technology (e.g. Bena & Li 2013; Chircu & Mahajan 2009; Gambardella & Torrisi 1998; Jose et al. 1986; Laursen & Salter 2006; Miller 2006; Moorthy & Polley 2010; Wang & Von Tunzelmann 2000). The technological breadth of knowledge is related to the concept of diversification in a technological space (i.e., variety in the product space), while the technological depth of knowledge is linked to the sophistication of the technology itself (i.e., quality in the product space). Conversely, there are few attempts to measure such breadth and depth concepts, and the literature still lacks in providing common indices.

The breadth index has been calculated by considering an inverse measure of the concentration indicator. For instance, Gambardella and Torrisi (1998) measure the technological diversification by means of the Herfindhal-Hirschman index (H) over patents for five sectors, namely, computers, telecommunications equipment, electronic components, other electronic products and other non-electronic products. A recent study by Gruber et al. (2013) also uses the Herfindahl concentration index to capture knowledge variety. In their influential study, Jose et al. (1986) measure the value of diversification as $DIV = 1 - H = 1 - \sum SLB_j^2$, where SLB_j is the share of a firm's total sales originating in the j line of business, where $j = 1, \dots N$. Furthermore, considering the well-known properties of the H index[4], the author shows that DIV consists of two components, one

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[4] A nice property of the H index is that it measures concentration distinguished by two components, the

based on the number of product lines and the other based on the size of distribution or dispersion of sales shares across product lines.

Thus, the index is $DIV = \left(1 - \frac{1}{N}\right) - \sum\left(SLB_j^2 - \left(\frac{1}{N}\right)^2\right)$.

Focusing on the diversification in the technology space, Moorthy and Polley (2010) explicitly measure technological breadth and depth using an H-type index over the number of patents. Suppose a firm's total number of patents is distributed over N patent classes. Let p be the fraction of patents that are in patent class i. The measure of technological knowledge diversity is $TK = 1 - \sum_{i=1}^{N} p_i^2$. A shortcoming of this index is that it does not provide any indication of the spread of patents across patent classes. However, upon rearranging, we have $TK = \left(1 - \frac{1}{N}\right)\left(1 - \frac{1}{N}\right) - \sum\left(p_i^2 - \left(\frac{1}{N}\right)^2\right) = TK_B - TK_D$. Notice that TK is identical to the index DIV, but it is in the technological space over patents rather than lines of business. Furthermore, it is crucial that Moorthy and Polley (2010) distinguish two components of the technological diversification index, TK_B, which accounts for the technological breadth dimension, and TK_D, which accounts for the technological depth dimension. Thus, a single index encompasses both relevant dimensions of the technology.

Conversely, because we are interested in the distinction between the breadth and depth of the innovation, we keep the two indices separated. However, similar to Moorthy and Polley (2010), we measure technological differentiation by means of patent dispersion using the H index. While our measure of breadth is based on Katila and Ahuja (2002), it

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number of firms in a given sector and the size distribution of the firms themselves. Analytically, $H = \sum s_i^2 = \frac{1}{N} - N\sigma^2$, where $s_i = \frac{x_i}{\sum_{i=1}^{N} x_i}$ is the market share of firm i and $\sigma^2 = \frac{1}{N}\sum\left(s_i - \frac{1}{N}\right)^2$ represents the variance. Notice that in a market with equal size firms $s_1 = s_2 = \cdots = s_N$, H assumes the value of $\frac{1}{N}$.

differs in that we use IPC codes and technology class. Accordingly, our measure of breadth is as follows:

$$BREADTH_{k,t} = \left(\frac{1}{nTech}\right)^2 \frac{\{Unused_{IPC}\}_{k,t}}{\{Total_{IPC}\}_{k,t}}$$

where $Unused_{IPC}$ is the number of new IPC codes that appear (and cannot be found in patents from the last 5 year) in the patents of the biotech firm 'k' in year 't'. We divide this number by the total number of IPC codes of firm 'k' in year 't'. $nTech$ is the number of technology classes in all the patents during the last 5 years[5]. Thus, we have a straight measure of diversification, which is the ratio between the new IPC and the old IPCs at the firm level, without calculating the concentration index and the diversification index. Note that we can have the $BREADTH_{k,t}$ value for every year t and a single index of technological diversification as a summary of the behavior of the firm (not an index for every technological class). The index always varies between 0 and 1, i.e., $0 \leq Breadth_{k,t} \leq 1$.

With respect to the *DEPTH* index, we stress the difference from Moorthy and Polley's (2010) TK_D index. They measure the depth of technology as the distance between the concentration of the R&D effort measured by the squared number of patents (as a *H*-type index) and the medium value (as if all patent classes were the same size). Conversely, we provide a more precise index that accounts for the IPC code repetitions weighted by the relative role of each IPC code. Thus, our depth index is as follows:

$$DEPTH_{k,t} = \left(\frac{1}{nTech}\right)^2 \frac{\sum_{j=(t-5)}^{t-1}\{Repeated_{IPC}\}_{k,t}}{\{Total_{IPC}\}_{k,t}}$$

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[5] Calculated following the technology-IPC concordance of Observatoire des Sciences et des Techniques (OST), Paris, France.

where *Repeated$_{IPC}$* represents the number of repetitions of the IPC codes in the last 5 years. Depth can vary from 0 to any number. Similar to the breadth index, the depth index is also based on Katila and Ahuja (2002), but we used IPC codes instead of backward citations to account for patents of radical innovation that may not have any backward citations.

3.2. *Data*

Our initial data consist of 385 publicly traded biotechnology firms headquartered in the US and obtained from the patent board[6] by looking at the patent descriptions of these firms. In particular, these firms are involved in human therapeutics (*in-vivo* or *in-vitro*) discoveries between 1985 and 2009. With some exceptions to the year of the firm's foundation, almost all of the firms were founded during this period. Thus, all the patents[7] of these firms are applied to USPTO or EPO[8]. These patents are the first applications in either of the patent offices. We consider the date of patent filing with the patent office to capture the immediate effect of the invention. From PATSTAT[9] (April 2010), we extract the primary as well as the secondary IPC codes for each patent. We discard those patents that do not have any IPC codes, and we calculate the depth and breadth based on the formula presented in the previous section for the years between 1990-2009.

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[6] US-based leading independent provider of the best research tools and matrices for patent analysis and intellectual property investment
[7] We have checked from the patent board that there were no patent applications filed in 2010 by these firms.
[8] United States Patent and Trademark Office (USPTO); European Patent Office (EPO)
[9] EPO worldwide patent statistical database created by the European Patent Office covers the patent offices of more than 80 countries.

We obtain alliance data for these firms from Recombinant Capital[10]. These data are based on two criteria. First, the alliance involves cross licensing, and second, it involves R&D and co-development agreements. Because of these restrictions, the number of firms with alliance information drops to 202. For these 202 firms, we retrieve all the announcements of completed acquisitions from Thomson Reuter's Security Data Corporation (SDC). The acquisitions meet the established criteria in that (i) they were announced between 1990 and 2009 and completed no later than the end of 2009, (ii) the deal value as equal to or greater than US$ 1 million, and (iii) the acquirer purchased more than 50% of the target. The SDC database also provides us with the four digit North American Standard Industrial Classification (SIC) codes of the acquirers and the targets. Finally, we extract the financial data of these 202 firms from Compustat North America (Standard & Poor's Research Insight). Finally, we aggregate all the data to the firm-year level and obtain an unbalanced panel of 202 firms with 14909 patents from 1990 to 2009, resulting in 4040 firm-year observations for the analysis.

3.3. *Variables*

3.3.1. *Constructs and indicators or variables*

The first part of the indicator is related to *technology-based M&As*. These variables consist of several parts and determine the latent construct involvement in corporate takeover (INV). The focal firm can acquire a firm (target) or can be acquired by some other firm. In the high-tech industry, such as biotechnology, the objective of the acquirer is, through the R&D efforts of the targets, to fulfill the acquirer's future plan of discoveries and breakthrough inventions. Accordingly, we have taken those cases where

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[10] A California-based biotechnology consulting company that incorporates detailed description of alliances of the global biotech and pharmaceuticals industries since 1973. The database is based on SEC (10-K, 10-Q, S-1 and 8-K) and FDA filings, press releases, and industry conferences.

the focal firms are the acquirer. To capture the effect of the acquisition, we use a dummy variable that is equal to 1 if the focal firm make an acquisition announcement in the year before it applies for a patent and is 0 otherwise. Furthermore, to distinguish the effect of knowledge diffusion through the M&A, we create two variables – *technology-related*, which includes the number of target firms with similar technology, and *technology-unrelated*, which includes the number of target firms with dissimilar technology. Following Higgins and Rodriguez (2006), we consider technology *unrelated* targets as those firms engaged in over-the-counter or generic drugs, consumer products, medical devices and products and manufacturing facilities. Conversely, the technology *related* targets are those cases where the target firms belong to the industry, 2833 to 2836 (SIC), and are engaged in only biopharmaceutical activities. We assume a one -year lag for both of these variables. As other firms can acquire a percentage of ownership of the focal firms, we control for the *number of times it is taken over* in the one year before it applied for a patent.

The indicators used for the latent variable innovation (INN) are discussed herein. We use firm-specific control variables that might impact the knowledge stock of the firm. Scherer (1965) finds that patenting is an increasing function of *firm size*. Larger firms often have multiple projects running simultaneously and can thus potentially better exploit external knowledge[11] (Schmidt 2010). Therefore, we control for firm size using the logarithm of total assets. As Hall et al. (2005) argue that the heterogeneity across the biotech firms is due to differences in R&D spending, we include *R&D intensity*. Because the financial condition of the firms affects their innovation activities, we control for

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[11] Smaller firms can take more risks than larger firms. Additionally, they are flexible to changes in the technological environment.

leverage, measured by the ratio of debt to equity. As the economic conditions that affect the innovation activities may change over time, we also include year dummies. The *firm age* is included to control for the effect of experience in innovation of the firms. Furthermore, as the firms also engage in alliances for scientific research and innovation purposes we control the *number of alliances with a two-year lag*.

For the latent construct quality of knowledge (KNW), we use patent data[12] to identify the types of technology used for a particular invention. A patent is one of the most prominent vehicles to diffuse and appropriate knowledge. We include breadth and depth variables at this point. Katila and Ahuja's (2002) study is exceptionally noteworthy in measuring the depth and breadth variables using the backward patent citations data. However, when the firm develops a breakthrough invention, by nature of the invention and the patent, it may not have any citations to prior works (backward citations). Therefore, rather than considering backward citations[13] of patents, as Katila and Ahuja (2002) do, we use IPC codes that directly measure the combinations of technology used in the inventions. Additionally, unlike Lerner (1994), who used 4-digit IPC codes for the study of patent scope in the biotechnology industry, we use 8-digit IPC codes, as two IPC codes can differ at many levels[14].

3.3.2. *Descriptive statistics*

Tables 1(a-b) and 2 show the descriptive statistics of the data and the pairwise correlation among the variables, respectively. In Table 1a, we see that the depth varies between 0 and 23.5, while the breadth ranges from 0 to 1. Both variables are continuous. We also find the

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[12] For the importance and applicability of patent data for inventions, see Griliche's (1990) survey
[13] In the case of breakthrough inventions that do not depend on prior works, it may be impossible to capture the depth and breadth of knowledge by backward citations.
[14] A short discussion is given in Appendix 2.

presence of influential outliers of depth and breadth variables. Accordingly, these two

variables are winsorised at 1% (0.5 percent on both sides). As breadth is a ratio of new

IPC codes (not used in the last 5 years) in the focal patents of firm k in year t, the value of

the index cannot exceed 1, where 1 indicates that all IPC codes of that particular year are

new. Examining the average age of these firms, we find that these firms are not new firms

as their average age is 22 years. With respect to Table 1b, we note that the maximum

number of alliances is 23, while the maximum number of M&As is one-third the number

of alliances.

Table 2 shows a matrix of correlation residuals, that is, the difference between the

adjusted (observed) correlation matrix and the reproduced (fitted) correlation matrix. It

determines whether any factor has an extremely weak predictive capacity. For instance, if

a residual is much larger than zero (in absolute value), the model will have difficulty

reproducing the original correlations with that factor. However, in our case, the table

appears fairly strong.

[Table 1a and 1b about here]

[Table 2 about here]

3.4. Measurement model and results

Following Anderson and Gerbing (1988), we begin by testing whether our structural

model has an acceptable goodness-of-fit. As the Cronbach's alpha underestimates the

reliability in the presence of multidimensional measures, it is convenient to check the

unidimensionality of the construct (Bollen 1989). Thus, to find a descriptive assessment of

unidimensionality, we apply exploratory factor analysis to the variables used in this

analysis. The three well-defined latent variables (INV, INN and KNW) reveal that the

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eigenvalues greater than one accounted for 70% of the variance of the indicators (variables). The factor pattern coefficients are 0.75, 0.87, and 0.82, respectively, (not reported) and indicate that each factor influences as few variables as possible. The small magnitude of the fitting of the cross-factor loading also indicates that we cannot reject unidimensionality. Thus, we start by fitting a confirmatory factor analysis (CFA) model. Our model includes ten items that describe the three latent variables. The items include merger dummy, number of related (or unrelated) acquisitions, number of times the focal firm is taken over (targeted), R&D intensity, alliance, firm size, firm age, leverage, depth and breadth. The CFA model allows each item to have its own unique variance, thus enabling us to obtain a better measure of the latent variables. We use maximum likelihood estimation. The results from the CFA is also show evidence of unidimensionality.

3.4.1a *Model fit*

The goodness-of-fit index with the acceptable threshold values is presented in Table 3a. Although the chi-square is statistically significant at the traditional level, which is acceptable given that we have 202 biotech firms with over 4000 observations - a relatively large sample (Bagozzi & Yi 1988). All the item loadings for each construct in the paths of the measurement model are significant (p<0.01). Comparing previous studies (Hu & Bentler 1998; Hu & Bentler 1999; Sharma et al. 2005), we see that the overall fit of the measurement model is acceptable. The measures indicate that the optimized model is effectively supported by the data.

[Table 3a about here]

3.5 *Estimations from structural equation model*

This section presents details of the econometric analysis undertaken using structural equation modeling (SEM) and the results. SEM is the preferred method of analysis in this study as it allows the study of multiple relationships simultaneously, provides a measure of overall model fit, and explains the significance of each of the relationships among the variables (Kline & Rosenberg 1986). Unlike multiple regression and path analyses, SEM accounts for the effects of measurement error in multi-item variables. Moreover, the output indicates whether the model is supported by the data as a whole and includes a significance test for the various individual relationships. Furthermore, the approach is effective when testing models that are path analytic with mediating variables and that contain latent constructs that are being measured with multiple indicators.

[Insert Figure 1 about here]

The standardized direct effect in Table 3b shows the potential relationship for the structural model and path significance of related and unrelated acquisitions. The first and second columns present the related-technology and associated critical ratio. The third and fourth columns present the unrelated-technology and associated critical ratio. Regarding the relationship between involvement and innovation, in the technology-related M&A, the impact is -0.73, and in the technology-unrelated M&A, the impact is -0.62. This implies that an increase in the takeover decision is expected to decrease by 0.73 (for related M&A) and 0.62 (for unrelated M&A) in innovation activities. This is consistent with a number of studies that indicate a negative effect in the post-merger period. Interestingly, knowledge development is also positively affected by this M&A decision through the innovation

process, thus implying that acquiring another firm contributes to the depth and breadth of technology of the focal firm.

[Insert Figure 1 about here]

[Table 3b about here]

We report the estimates from the measurement model as well as the standardized loadings and the t-statistics (critical ratio) to assess the significance of these loadings in Table 3c. The standardized direct effect of knowledge development on the knowledge dimension indicates that an increase in knowledge quality, developed through the technology collaboration and M&As, leads to a 0.73 (related M&A) and a 0.34 (unrelated M&A) increase in technological depth and a 0.42 (related M&A) and a 0.82 (unrelated M&A) increase in technological breadth. These results clearly indicate that M&As tend to increase both the depth and the breadth of technological knowledge. However, related acquisition increases the depth of knowledge more strongly than the breadth of knowledge, while the opposite results are found for unrelated acquisition. These results are consistent with our expectations.

We also estimate separate models for the confirmatory analysis, with and without constraining the parameters across the two groups – related technology and unrelated technology (not reported). The standardized direct effect of knowledge development on the dimension of knowledge indicates that an increase in knowledge quality, developed through technology collaboration and M&As, leads to a 0.61 (related M&A) and a 0.24 (unrelated M&A) increase in technological depth as well as a 0.50 (related M&A) and a 0.74 (unrelated M&A) increase in technological breadth.

As we control for the knowledge diffusion prior to the M&A through alliances that may affect the impact the knowledge development process as well as the existing knowledge on the innovation process, we further modify our model by including an extra path - from the INV to KNW and from KNW to INN. Moreover, we also drop the variables with very low loading values, such as the patent stock. With these modifications, all factor loadings in our optimized model show a good fit to the data, and all three structural equation models converge without problems. The average variance extracted for each construct is greater than 0.63, and the CFI of the measurement model increased to 0.963.

[Insert Figure 2 about here]

[Table 3c about here]

In our model, the innovation that affects the knowledge stock of the firms has no specific cause. In the presence of a single specified cause of the dependent construct, the squared multiple correlations (SMC) move toward the coefficient of the direct effect. Bentler (1995) argues that with multiple causes of the dependent variables, an SMC should be estimated as one minus the standardized error variance of the construct. The SMC for the INN is (1-0.86)=0.14, which suggests that 14% of the variation in innovation can be attributed to involvement. The SMC for KNW is (1-0.59)=0.41. This means that 41% of the variations can be attributed to involvement in the involvement – knowledge relationships. Thus, a structural relationship for INV and INN is weaker than that for INV and KNW.

In sum, although we did not find a strong direct impact of firms' involvement in M&As on the depth and breadth of knowledge, our data reveal the positive indirect

influence of knowledge development through innovation on two knowledge dimensions - technological breadth and depth.

3.6 *Additional test to address endogeneity*

In this section, we apply different model specifications to determine the robustness of our results. First, we note that variance inflation factors (VIFs) of all variables are below 5, confirming that there are no multi-collinearity problems among the variables.

As we do not have detailed information with respect to the properties of error terms, maximum likelihood estimators may be imperfect. To eliminate the effect of firm specific fixed effects, a first differenced equation by two-stage least square (2SLS) can be used (Anderson & Hsiao 1981). However, the 2SLS estimator is asymptotically inefficient and does not account for all available orthogonal restrictions (Bertrand & Zuniga 2006).

As a solution to this situation, Arellano and Bond (Arellano & Bond 1991) proposed a first differenced generalized method of moments (GMM) for a dynamic panel model. The approach generates the orthogonal restrictions by introducing all possible lags of explanatory variables as instruments. However, Bond (2002) shows that this first differencing may perform poorly if the series is close to being random walks. Later, Arellano and Bover (Arellano & Bover 1995) suggest that the moment conditions can increase the efficiency of the estimator by adding the original equations, by levels, to the system. Thus, we use the following model:

$$KNW_{it} = \beta_0 + \beta_1 KNW_{k,(t-1)} + \beta_2^{ex} X_{k,\tau}^{ex} + \beta_3^{en} X_{k,t}^{en} + \lambda_k + \phi_t + \varepsilon_{i,t} \qquad (6)$$

$$k = 1, 2, \dots N \ firms \ and \ \ t = 1, 2, \dots T \ years$$

where $KNW_{k,t}$ is the depth or breadth for firm k in year t, $X_{k,\tau}^{ex}$ are exogenous firm level controls, and $\tau = t \ or \ (t-1)$ and $X_{k,t}^{en}$ are endogenous firm level time-variant main

explanatory variables of interest. Because the production of knowledge is a continuous process, the outsourcing of knowledge by strategic alliances and technology-based M&As depends on the previous year's knowledge base, $KNW_{k,(t-1)}$. This lagged dependent variable captures the dynamic adjustment of knowledge production. λ_k is the measure of time-invariant variables affecting the depth and breadth used in the innovation activities. ϕ_t is the time-varying shocks. β_1, β_2^{ex} and β_3^{en} are the parameters to be estimated, where β_3^{en} determines the effect of alliances and M&As, and β_2^{ex} determines the impact of firm level controls.

The procedure is called a system GMM in which the additional moment conditions of the system GMM estimator corresponds to the model at the level with a lagged difference of endogenous variables as instruments[15].
The additional moment conditions are:

$$E[(KNW_{k,(t-1)}(\lambda_k + \varepsilon_{k,t})] = 0 \; for \; t = 3, 4, \dots, T$$

$$E[X_{k,(t-1)}(\lambda_k + \varepsilon_{k,t})] = 0 \; for \; t = 3, 4, \dots, T$$

With respect to the differenced equations, lagged and future differences of the R&D expenses, propensity to patent, sales growth and the last three years' number of alliances are used as instruments. Firms generally invest more effort in current technological activities if the demand for their products, based on the current technologies, is increasing (Wu & Shanley 2009). For this reason, we use the knowledge stock of the focal firm as one of the instruments in the model, and we operationalize the variable by considering the patent applied from the last 5 years. These instruments are valid because they are correlated with the firms' R&D activities but not with the time-invariant effect or current

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[15] Because in equation (2) the variable Size is endogenous, we also control for this in the system GMM.

error terms. Blundell and Bond (Blundell & Bond 1998) suggest that the estimator can also solve weak instrument problems. To analyze the effect of M&As on knowledge production using equation (8), we apply a two-step system GMM.

Because the data reveal a large number of patents for the years 1995 and from 2000 to 2002, a regression is run on a reduced sample that eliminating the data for these 4 years. Additionally, we control for sub-industry because within the biotech industry there are many *sub*-industries, such as biological products, *in vitro* and *in vivo* diagnostics, medicinal chemicals, etc. The biotechnology industry is highly concentrated in some US states, such as California, New Jersey, Massachusetts, among others. Therefore, we control for these states. Following the definition of exploration alliances, as given by the literature (Koza & Lewin 1998; Lane & Lubatkin 1998; Rothaermel 2001; Rothaermel & Deeds 2004), we include the effect of exploration alliance as an interaction term with the number of acquisition variables. A firm's learning process and its nearness to tacit knowledge motivates the exploration alliance (Lane & Lubatkin 1998), which, in turn, improves the absorption capacity of the firm. We estimate the model using the sample from the two-step system GMM. Table 4 reports the results for the effect of acquisitions and the interplay between alliances and M&As. We find the results are robust, and there is no significant shift in the direction of the effect.

[Insert Table 4 about here]

4. Conclusion

In this paper, we attempt to investigate the impact of technology-based M&As and prior alliances on the depth and breadth of knowledge by considering the dynamics of knowledge production. We use a sample of US biotechnology firms that were engaged in human therapeutics between 1989 and 2009. Overall, the results suggest that prior alliance with universities or research organizations and acquiring unrelated technological firms increases the breadth and diversity of the firm's technological knowledge. Furthermore, prior alliances with competitors in the same industry (other biotech firms) and related technology-based acquisitions increase the depth of knowledge. This has important implications as it shows that firms must be very selective in choosing their partners and targets, as their knowledge stock has significant impact on the breadth and/or depth of the R&D activities of the firm. As the mutual collaboration agreements are incomplete contracts, an optimal level of integration is needed for the firms to be productive. Moreover, the prior literature shows that there exists an inverted U-shape relation between the number of partners and the knowledge creation process. In other words, the speed of knowledge expansion may decrease gradually as the firm reaches its maximum amount of manageable technology. Thus, in addition to a positive relation between alliances and depth of knowledge, firms also increase their breadth of knowledge.

Most often, firms have shorter time-horizons for alliance partnership than they do for R&D in a high-technology industry. Thus, it is challenging to leverage the internal depth and breadth of knowledge by external sources through alliances. Our findings indicate that the biotechnology firms can increase their depth of knowledge by outsourcing

knowledge from partners in a similar industry, that is, by allying with competitors or by engaging in M&As with biotechnology or pharmaceutical firms. However, engaging in strategic alliances with rival firms may lead to the leaking of critical information or technological knowledge, which may jeopardize the existing competitive advantage of the biotech firms. Thus, managers may need to allocate more resources to internal R&D to build up technological breadth before they seek particular complementary knowledge from rivals to increase the depth of the firms. Accordingly, they may be able to prevent unwanted spillovers of knowledge to potential competitors.

Because of the diversity among the firms in the technological knowledge that separates the types of M&As based on industry, we find that related M&As (among similar industries) and unrelated M&As (among dissimilar industries) positively impact the creation of depth and breadth of knowledge, respectively. This result serves as a useful perspective in the M&A literature that focuses on the technological knowledge development related to M&As (e.g. Cloodt et al. 2006; Danzon et al. 2007; Desyllas & Hughes 2010; Hagedoorn & Duysters 2002; Makri et al. 2010).

Although, the existing studies have ignored the relationship between the firm's involvement in M&As and the development of breadth and depth of technology through innovation, our study suggests that there exists a critical link between the M&A and the internal knowledge development process.

The findings also have important economic and policy implications. First, these results indicate that the firm should not only consider the potential benefits of such corporate takeovers for present innovation and financial objectives but that the firm should take into account the additional costs of strengthening its knowledge development

process for future cost-effective innovation programs. Second, our study reveals another significant approach towards choosing the target for acquisition whether technologically related or unrelated, as this has a major impact on the breadth and depth of the knowledge stock of the firm. Thus, the focus for the short-term benefit from an M&A may yield negative outcomes (Cloodt et al. 2006), while in the long-term, if the firm's objective is to develop breadth and depth ex ante the innovation process, such a collaborative approach will result in the firm's success.

This paper has certain limitations. First, we used the reported R&D expenses to control for the knowledge development process. Compustat reports only internally sponsored R&D. Although these data can reveal the effect of internal finance constraints of small firms, for larger firms with better access to external R&D investments, the data fail to capture the effect of other research grants and external research support that biotech firms may have obtained to complement their internal R&D. Second, patent data are considered to be noisy as they cannot take into account all the inventions that a firm is currently working on and that contribute to the knowledge development process. However, as a number of studies have used patent data as codified indicators of inventions, the results of the present study, which are based on all documented innovation activities, are comparable with a substantial body of prior research[16]. Third, because the inventors' and firms' names were not matched in the PATSTAT database, the data do not provide patent information of the client firms involved in strategic alliances. It would be interesting to investigate whether both partners are jointly working on the invention process and whether this could allow for a more direct measure of knowledge spillovers.

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[16] See a number of studies (Cassiman et al. 2005; Grimpe & Hussinger 2008; Jaffe et al. 1993; Valentini 2012)

Fourth, as the present study is limited to one industry, future studies may investigate other industries or analyze cross-industry samples to determine if and how much the results herein are specific to the biotech industry. Despite these limitations, we believe that the study has provided valuable insights to the success of M&A portfolios.

To conclude, the empirical results of this paper substantially support the theoretically developed expectations and highlight the R&D collaboration strategies of high-tech firms that combine technological knowledge from different types of partners and collaborations (alliances and M&As), while also integrating knowledge for developing depth and breadth. Accordingly, this study helps to clarify the complex strategic selection process of partner and target firms for the joint production of technological knowledge, and it sheds some light on the complicated symbiotic relationship between alliances and M&As in innovation activities. We hope that our findings may assist policy makers in optimizing M&A decisions and that our suggestions for future research may stimulate future academic research.

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Appendix 1: Variable definitions

	Variables	Data Source
1.	Depth: During the last five years, the average number of times the firm repeatedly used the IPC codes in the patents	PATSTAT
2.	Breadth: Proportion of the new IPC codes in the focal year's patent, not used in the previous five years' list of patents	PATSTAT
3.	Alliance: Number of alliances $_{(t-2)}$	Recombinant Capital
4.	Merger: Acquisition dummy variables	Thomson SDC
5.	Related: Number of acquisitions of firms in related industries $_{(t-2)}$	Thomson SDC
6.	Unrelated: Number of acquisitions of firms in unrelated industries $_{(t-2)}$	Thomson SDC
7.	Firm age: Firm age (2009-year of inception)	Company Website, GEN Guides to Biotech Companies-1996
8.	Firm size: Natural logarithm of total assets	Compustat
9.	R&D intensity: R&D expenses $_{(t-2)}$/total sales $_{(t-1)}$	Compustat
10.	Targeted: Number of times taken over $_{(t-1)}$	Compustat
11.	Knowledge stock: Patent numbers in last 5 years calculated assuming 15% annual depreciation and an 8% growth backward in times	PATSTAT
12.	Financial Leverage (debt/equity) $_{(t-2)}$	Compustat

Notes: Variables 1 and 2 are for the latent construct 'KNW'; Variables 3, 4, 5, 6, & 10 are for latent construct 'INV'; and Variables 7, 8, 9, & 12 are for the latent

Appendix II

Structure of International Patent Classification (IPC) codes and differences among them at various levels

Let us consider some patents and few of their IPC codes of Amgen Inc.

Appendix-IIa

Firm	Patent	Filed Year	IPCs
Amgen	US7687533	2007	A61P19/02
	US7667008	2007	A01K67/027
	US7705132	2007	A61K39/395
	US7572934	2008	A61K31/155 A61K31/192 C07C59/68

Appendix-IIb

Level	Comparison
Section	**A**61K31/155 and **C**07C59/68
Class	**A61**K31/155 and **A01**K67/027
Subclass	**A61K**31/155 and **A61P**19/02
Group	**A61K31**/155 and **A61K39**/395
Subgroup	**A61K31/155** and **A61K31/192**

Notes: Each of the levels defines the technology in hierarchical way. The above tables show how technology varies at different levels.

Table 1a
Descriptive Statistics for the firms engaged in R&D related alliances and acquisitions during 1989-2009

Variables	Obs	Mean	Std. Dev.	Min	Max
Depth	1830	0.912	1.834	0	23.5
Breadth	1885	0.204	0.337	0	1
Merger (dummy)	1885	0.217	0.412	0	1
Related	1885	0.135	0.472	0	8
Unrelated	1885	0.050	0.268	0	4
Targeted	1884	0.166	0.468	0	4
Alliance	1883	1.850	2.835	0	23
R&D Intensity	1254	35.348	288.207	0	7326.190
Leverage	1466	0.316	7.393	-117.328	186.768
Firm age	1885	21.995	4.704	8	48
Firm size	1472	4.227	1.722	-3.381	10.453

Notes: The depth and breadth have been calculated from 14909 patents filed during 1985-2009 in the USPTO and EPO by 202 firms engaged in human therapeutics (*in-vitro and in-vivo*).
We considered only that M&As, where the firms are acquirers. The 'related' firms refer to those that belong to SIC codes 2833-2836, i.e. those are engaged only in biopharmaceutical activities. The 'unrelated' acquisitions include over-the-counter or generic drugs, medical and consumer devices, manufacturing facilities and organic and inorganic chemical research firms.

Table 1b
Number of strategic alliances and M&As during year 1989-2009

	Min	Max		Min	Max
Strategic alliances	1	23	*Technology-based acquisitions*	1	8
Number of alliances with universities	0	9	*Number of related acquisition*	0	8
Number of alliances with competitors	0	19	*Number of unrelated acquisition*	0	4

Notes: The minimum and maximum values are yearly basis. Alliances means when the sample firms plays either R&D firms or clients or both. Acquisitions refer to the cases when the sample firms acquire other firms. M&As data is taken from Thomson's SDC and strategic alliances data is from Recombinant Capital.

Table 2: Standardized residual correlation

Variables	1	2	3	4	5	6	7	8	9	10	SMC	KMO
1.Depth	0										0.057	0.881
2.Breadth	-0.075	0									0.130	0.760
3.Merger (dummy)	0.016	0.001	0								0.424	0.643
4.Related	0.001	0.019	0.091	0							0.402	0.668
5.Unrelated	-0.019	-0.007	0.081	-0.063	0						0.152	0.584
6.Targeted	0.031	0.012	0.021	-0.016	-0.012	0					0.056	0.752
7.Alliance	-0.021	0.014	0.002	-0.015	-0.010	0.022	0				0.288	0.707
8.R&D Intensity	-0.006	-0.002	-0.004	0.003	0.000	0.001	-0.014	0			0.008	0.810
9.Leverage	0.014	0.013	-0.011	0.006	0.010	0.001	0.008	0.006	0		0.003	0.538
10.Firm age	-0.014	0.005	-0.008	0.004	0.007	0.048	-0.005	0.004	-0.005	0	0.078	0.822
11.Firm size	-0.022	-0.066	-0.018	0.038	0.016	-0.016	0.087	0.008	0.001	0.014	0.398	0.676

Notes: The table shows the raw and standardized residuals of the observed correlation with respect to the fitted correlation matrix. SMC is the squared multiple correlations between each variable and all other variables. KMO reports the Kaiser-Meyer-Olkin measure of sampling adequacy. It varies between 0 and 1. Higher the KMO value of variables, better the variables to be used in factor analysis.

Table 3a: Goodness of fit

	Acquisition		Acceptable threshold level
	Related	Unrelated	
Comparative Fit Index (CFI)	0.975	0.959	>0.95
Tucker-Lewis Index (TLI)	0.948	0.957	>0.95[a]
Standardized Root Mean Squared (SRMR)	0.037	0.033	<0.08[b]
Root Mean Squared Error of Approximation (RMSEA)	0.047	0.037	<0.05[b]
χ^2	114.034	93.06	Insignificant p-value
Degree of freedom	33	26	

Notes: This indicates overall fit of the model. χ^2: p<0.05 (significant at 5% level). $\left(\frac{\chi^2}{d_f}\right)$ should be between two and five (Joreskog & Sorbom 1993). [a] Sharma et al. (2005) [b] Hu and Bentler (Hu & Bentler 1998; Hu & Bentler 1999)

Table 3b: Structural Model- Factor loadings

Relationships	Standardized Coefficient (Related)	CR[a]	Standardized Coefficient (Unrelated)	CR[a]
Involvement -> Innovation	-0.732	-16.16	-0.629	-9.39
	(0.045)		(0.067)	
Innovation -> Knowledge	0.288	7.86	0.310	6.91
	(0.037)		(0.045)	

Notes: CR[a] is the critical ratio (equivalent to z-statistics) to test that statistical significance. Standard errors are in parentheses. All coefficients are statistically significant at 0.1% level.

Table 3c: Measurement Model- Factor loadings

Latent Variables	Involvement (INV)	CR[a]	Innovation (INN)	CR[a]	Knowledge (KNW)	CR[a]
Panel A						
Merger (dummy)	0.451	13.14				
Related Acquisition (2-yr lag)	0.626	17.01				
Targeted (2-yr lag)	0.326	8.78				
R&D intensity (2-yr lag)			0.085[b]	1.93		
Alliance (2-yr lag)			-0.731	-24.69		
Firm size			-0.804	-30.67		
Firm age			-0.227	-6.84		
Leverage (2-yr lag)			-0.422[b]	-0.66		
Depth					0.733	12.49
Breadth					0.426[b]	1.41
Construct reliability	0.461		0.552		0.512	
Variance extracted	23.38%		28.35%		35.93%	
Panel B						
Merger (dummy)	0.603	10.36				
Unrelated Acquisition (2-yr lag)	0.521	5.49				
Targeted (2-yr lag)	0.251	6.32				
R&D intensity (2-yr lag)			0.081	8.52		
Alliance (2-yr lag)			-0.560	-20.85		
Firm size			-0.841	-25.95		
Firm age			-0.203	-6.09		
Leverage (2-yr lag)			-0.619[b]	-0.58		
Depth					0.341	11.94
Breadth					0.822	9.12
Construct reliability	0.451		0.564		0.543	
Variance extracted	23.27%		29.04%		41.18%	

Notes: Maximum likelihood estimation. To avoid endogeneity problem we have taken 2-year lag for the independent variables. Factor loadings with critical ratio (CR[a]) are shown. Panel A is for related and Panel B is for unrelated acquisitions. All coefficients are statistically significant at 0.1% level. Factor loadings with superscript (b) are not statistically significant at any traditional levels.

Table 4:

Sensitivity analysis: System-GMM dynamic panel-two-step robust estimates

Dependent variables	Depth	Breadth	Depth	Breadth
Merger (dummy)	-2.251***	0.056***	-2.162***	0.022***
	(-17.85)	-4.62	(-23.69)	(-3.99)
Targeted $_{(t-2)}$	-0.581***	-0.039	-0.230***	-0.025***
	(-7.20)	(-0.54)	(-5.28)	(-9.66)
Related acquisitions $_{(t-2)}$	0.338***	0.015*		
	(-5.59)	(-2.15)		
Unrelated acquisitions $_{(t-2)}$			-0.763***	0.064***
			(-13.48)	(-7.58)
Firm age	0.239***	-0.002	0.298***	-0.004*
	(-9.94)	(-1.07)	(-22.11)	(-2.40)
Firm size	0.621***	-0.052***	0.580***	-0.048***
	(-13.56)	(-12.37)	(-17.08)	(-10.56)
R&D intensity $_{(t-2)}$	-0.024***	0.029	-0.027***	-0.042**
	(-3.51)	(-0.35)	(-3.55)	(-3.15)
Leverage $_{(t-2)}$	0.066***	-0.039	0.079***	-0.081**
	(-30.99)	(-0.48)	(-40.41)	(-2.75)
Alliance $_{(t-2)}$	0.260***	-0.004	0.298***	0.006***
	(-10.59)	(-1.85)	(-19.25)	(-3.72)
Year effect	Yes	Yes	Yes	Yes
Intercept	-4.912***	0.471***	-5.713***	0.353***
	(-7.15)	(-8.67)	(-11.75)	(-7.82)
Observation	1158	1158	1158	1158
Arellano-Bond test for AR(1)-p	0.003	0.000	0.000	0.000
Arellano-Bond test for AR(2)-p	0.746	0.763	0.861	0.911
Hansen J-stat.-p	0.716	0.587	0.810	0.636
Diff-in-Hansen GMM instr.-p	0.984	0.320	0.615	0.986

Notes: Instruments for the level equations are number of alliances in last 5 years and sales growth. A maximum of two lags are used.

In all the models state of firms location and industry effects are included but not reported.

Hansen test statistics of over identifying restrictions, tests for correlation among residuals and instruments, are reported (p-values only). The validity of the additional moment conditions for the level equations is shown by difference Hansen tests. The p-values for the first and second order serial correlations AR(1) and AR(2) are shown. t-statistics are in parentheses. * denotes significance at the 5%, ** denotes significance at the 1% and *** denotes significance at the 0.1%.

Figure 1: Impact of related acquisitions on knowledge development
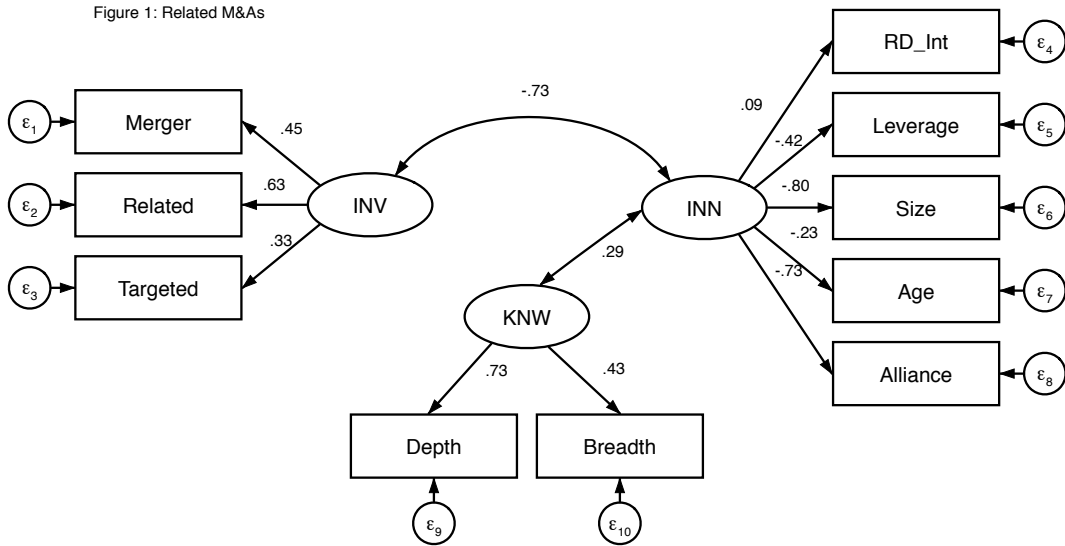

Figure 1: Related M&As

Figure 2: Impact of unrelated acquisitions on knowledge development

Figure 2: Unrelated M&As

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