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When Do Alliance Partners Become Attractive Targets?

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Abstract

Technology acquisition motive is a very important determinant of firm acquisition. Acquisitions enable firms to: 1) reduce the lead-time for obtaining the desired new technology; 2) to capture the complementary tacit resources settled behind the new development; 3) and to utilize fully the accumulated knowledge possessed by the acquired firm. Our paper differs from yet complements this literature that models acquisition and alliances as essentially options to acquire partner firm assets and suggest that both mechanisms have to be considered related and, thus, worthy of study collectively. To test our hypotheses, we selected a sample of 316 biotech firms (283 US and 33 EU) from the Bioscan database, involved in 2,359 technology licensing agreements and 77 acquisition, spanning a period of 15 years.

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When Do Alliance Partners Become Attractive Targets? Mobilizing Patent Portfolio and Relational Resources

INTRODUCTION

Technology acquisition motive is a very important determinant of firm acquisition. Acquisitions enable firms to: 1) reduce the lead-time for obtaining the desired new technology; 2) to capture the complementary tacit resources settled behind the new development; 3) and to utilize fully the accumulated knowledge possessed by the acquired firm (Capron et al., 1998). In addition, the acquisition allow to simply replicate firms internal routines (Nelson and Winter, 1982), to reproduce local 'organizing principles' (Kogut, 1991), and to tap into existing external local networks (Jaffee, Trachtenberg, and Henderson, 1993). This is why, given the firm-specific nature and uncertain imitability of capabilities (Lippman and Rumelt, 1982), acquisition remains often a dominant choice (Chen and Zeng, 1996) compared to strategic alliances. Previous studies conceive acquisition as a substitute mechanism of strategic alliances (Wang and Zajac, 2007) and consequently, the analysis of attractive partners is separated from the rest.

Our paper differs from yet complements this literature that models acquisition and alliances as essentially options to acquire partner firm assets and suggest that both mechanisms have to be considered related and, thus, worthy of study collectively. In other words, we think that prior alliances can be used to identify the attractive acquisition targets under certain conditions. Accordingly, the paper addresses the following research question: *Under what do conditions alliance partners become attractive acquisition targets?* To test our hypotheses, we selected a sample of 316 biotech firms (283 US and 33 EU) from the Bioscan database, involved in 2,359 technology licensing agreements and 77 acquisition, spanning a period of 15 years.

We establish three primary findings: (i) *The higher the degree of partners' diversity within technology licensing agreements, the higher the probability to become an acquisition target;* (ii) *The higher the degree of patenting activity, the higher the probability to become an acquisition target;* (iii) *The higher the degree of interconnectivity, the higher is the probability of acquisition.*

THEORY AND HYPOTHESES

Acquisition and alliances: substitute or complement?

Several factors can favour a firm strategy based on acquisition. Thorough acquisitions firms can reduce the risk of wrong selection, and subsequent difficulties in knowledge integration (Hennart, 1988). Although acquisitions can be riddled with organizational inertia (Barkema and Vermeulen, 1998), they are a better mechanism to fully absorb the knowledge produced with external partner and to solve the issue of alliance instability and litigation on property rights (Inkpen and Beamish, 1997). In fact, information asymmetry and opportunism can inhibit market-mediated resource transactions (Williamson, 1975), and the cost of using the market increases as resources become more firm-specific and complex (Chi, 1994). This explains why, in the last decade, the biotech industry has been witness of a large flow of acquisitions, both between pharma and bio, and among the same segment of the biotech firms. A question immediately rises. Are alliances becoming an incomplete mechanism for knowledge exploration and exploitation? Licensing and R&D agreements are becoming so complex that partners are forced to opt for a full possession of the knowledge assets through acquisition in order to properly use the new scientific knowledge created by the innovative DBFs. However, blind acquisitions are risky and hazardous, because there is always a certain degree of information incompleteness, regarding the acquired firm. In this setting, we think that the acquiring firms can explore by allying whether partners can create new value when their resources are pooled. In other words, our idea is to use alliances as a screening tactic for acquisitions. The idea of using alliances as a screening tactic for acquisitions is established in the literature (e.g., Balakrishnan and Koza, 1993; Nanda and Williamson, 1995). This paper contributes to the strategy literature by explaining the conditions when a technology-based firms become an attractive target. Accordingly, we believe that when alliance partners turn into acquisition targets, costs are minimized and screening is optimized. This leads us to propose:

H 1: The higher the number of firm's strategic alliances, the higher the probability to become an acquisition target.

Is partner diversity in firm's alliance portfolio a prerequisite of acquisition?

Following hypothesis 1, alliance activity allows partners to assess whether partners can be an attractive acquisition target in terms of resources. One of the most valuable resources that the acquiring firm can mobilize is the target's alliance portfolio. An alliance portfolio, also known as an ego-centric firm network, can be defined as a firm's entire collection of direct partnerships (Das and Teng, 2002). A number of studies have shown that having a portfolio of alliances can increase firm performance (Stuart, Hoang, and Hybels, 1999; Baum, Calabrese and Silverman, 2000).

From a alliance portfolio perspective, partner selection does not refer to choosing the "right" partner, at transaction-level, but requires paying attention to the structure of alliance portfolio in order to avoid lock-in effects or declining outcome that impact negatively firm patenting activity. Our idea is that the formation of an alliance portfolio will benefit from a certain degree of partners' diversity, defined as dissimilarities of partners in terms of resources, bargaining power differences, geographical distance, and position in the network's social structure. In turn, this impact positively in the likelihood to become an acquisition target. Another important element is the "social structure" of the Technology Licensing Agreements network. Are firms positioned in a central key role better off in term of probability to be acquired? This lead us to propose:

H2: The higher the degree of partners' diversity within technology licensing agreements, the higher the probability to become an acquisition target.

H3: The higher the degree of interconnectivity, the higher is the probability of acquisition.

Is patenting activity a key signal for acquisition?

Another key resource that the acquiring firm can mobilize is target' patent portfolio. From a resource-based view, a patent portfolio represents a valuable resource that, to the extent to which it impedes similar "inventing around" patents and do not infringe other existing patents, affect positively firm profitability. Besides the protection function, patent portfolio has come to have a broader strategic function in terms of signaling firm's knowledge quality to potential investors (Ndofor and Levitas, 2004); blocking competitors and prevent their innovation (Shapiro, 2001; Graevenitza, Wagnera, and Harhoffa, 2010); increasing bargaining power in negotiations (Ziedonis, 2004); and licensing out rights on patented technologies to further their development and commercialization. Overall, possessing a "strong" patent portfolio enables firm to innovate with a certain degree of freedom and strengthen their bargaining power. This lead us to propose:

H4: The higher the degree of patenting activity, the higher the probability to become an acquisition target.

METHODS

The data to test the hypotheses proposed here are found in a sample of DBFs listed in BioScan that have realized at least an agreement. We limited the sampling of our firms to 316 biotech firms, 283 U.S. firms and 33 E.U. firms located in Italy, France, Denmark, and Sweden. We covered the period 1973-2006. These firms are new biotechnology firms engaged in the research, development, and commercialization of therapeutics. This process yielded a sample of 767 biotechnology firms and 4695 alliance agreements (3282 deriving from the U.S. sample and 1413 from the E.U. sample). In the next step, we obtained each firm's alliance history. BioScan lists detailed qualitative information about each of the firms' alliances, such as the focal firm's partners, the month and year when the alliance was established, and what area of the industry value chain it covers (research, drug discovery, development, clinical trials, FDA regulatory process, marketing, and sales). All agreements were codified based on their content using the following schema: 1=funding (105), 2=research (1145), 3=development (1031), 4=technology transfer (100), 5=licensing (1214), 6=marketing & communication (557), 7=distribution (244), 8=production (222), 9=services &equipments (76). We also collected information regarding the companies with which the "BioScan firms" have reached the agreement (size of the firm, age, and sector of activity). Thus, we scanned the websites of about 2000 firms. We re-classified the sectors of activity of our companies and biotech organizations, dividing our sample into 4 sub-sectors: biotech, pharmaceutical, others (biomedical, health and servicing, chemical sector, applied engineering, and so on), and PROs, public research organisations. Data presented here, to simplify the analysis, have been aggregated into three sub-sectors: bio, pharma, and others. We classified the type of agreement and the type of organization that signed the agreements with our 767 biotech firms (pharma: 868, biotech: 1648, PRO: 675, and firms belonging to other sectors: 433). We paid particular attention to the definition of the biotech sector. We include here all the companies that have developed biotech technologies and that can be characterized as a DBF. Thus, we did not follow the official Standard Industrial Classification SIC criterion that often includes some biotech companies in the pharmaceutical sector. In the BioScan records analysed, some important data regarding the characteristics of the firms were incomplete. After a troublesome work of correction and revision, we gathered all the missing information through Internet searching, using the company websites. Extensive effort was required to ascertain the necessary information to run our econometric tests such us patent information using Q-pat database, M&A information using medtTRACK database, size of the firm, age, location, ownership, history and information about the firm products. Only in few cases we were obliged to exclude from our analysis some companies or the agreements for which we did not have sufficient information to classify them.

Model Specifications
Descriptive statistics and correlations are presented in Table 1 and Table 2. They show that independent variables are weakly correlated with one another. Consequently, the risk of multicollinearity does not appear to be very relevant. However, Table 1 shows that some independent variables, particular among the types of agreement, are correlated with one another. Consequently, multicollinearity diagnostics were examined. We explicitly assessed potential multicollinearity in all models and found that the variance inflation factors were well below the suggested cut-off point of 10 (Kleinbaum et al., 1988) with the exception of model 8 (Tables 2 and 3), where we have two independent variables slightly beyond the threshold of 10 (bio agreements and national agreements).

The dependent variable, passive M&A is a dichotomic variable taking on discrete non-negative integer values and assumes zero value if the company has not been acquired or merged by any other firm and, instead, takes the value one if the firm has been acquired or merged, so a Logit or Porbit specification is recommended. We applied the following specification of a Logistic regression model to test our hypotheses:

$$p = \frac{\exp(Z)}{1 + \exp(Z)}$$

where p is the proportion of occurrences, Z=β_0+β_1 x_1+⋯+β_k x_kand x_1…x_k are the explanatory variables. The inverse relation of equation is:

$$Z = ln\left(\frac{p}{1-p}\right)$$

that is, the natural logarithm of the odd ratio, known as the Logit (Shariff et al, 2009). In other words, the Logit regression model expresses the log outcome rate as a linear function of a set of predictors (Christensen, 1997). To obtain consistent and robust standard errors that are corrected for over-dispersion, we employed a general linear model (GLM) estimation technique using R 2.14.1 (Gourieroux et al., 1984).

Variables

Dependent variable
We used passive merger and acquisition(M&A) as a proxy of the firms' capability to grow and finance: We found that the M&A indicator, which, as known, represents one of the most reliable information on the growth performance of the firm, is also the indicator connected with the higher stability and coherence of the regression model. The informative source for the M&A data was the MedTRACK archive. MedTRACK is the most comprehensive database of private and public biomedical companies. Business development and financial professionals use MedTRACK to glean pipeline, financial, competitive products, deals, mechanism of action, partnering, M&A data and patent information on biomedical companies, and products worldwide.We included here all passive M&A registered in the period 2005-2011.

Independent variables

Number of agreements ('total agreements'): This variable is an indicator of the portfolio strategies pursued by biotech firms. Entering into an agreement enables DBFs to increase their innovation capability and to commercialise property rights stemming from research. BioScan deduced the number of agreements. As known, this represents the most important information collected by the database, which also registers the date of the alliance, the content of the alliance, and the name and the location of the partner involved. Information on the type of agreements was codified into 9 categories related to the innovative stage of the value chain (from finance-R&D up to marketing) and by the type of organisation involved. Thus, we categorised the agreements as bio-bio, bio-pharma, bio-PRO, and bio-other sectors.
We also distinguished the agreement in relation to the localisation of the partner. *Local agreements*: licensing agreements with partners located in the same state*; national agreements*: licensing agreements with partners located in the same nation (U.S. for American firms and EU for European firms); and *international agreements*: agreements with partners located outside the national borders. The variable 'time to the first agreement' indicates the time lag existing from the foundation of the firm to the date of the first agreement signed by the organisation. This variable shows the propensity to build early research alliances. In other words, it configures a particular attitude of the firm to open its boundaries through searching for novel alliances.
We used, also, 4 proxies linked to the firms' innovative capability: the number of family patents ("family patents") and the number of products ("total products"), which are further separated into products already commercialised ("product on the market") and products related to different stages of development and still inserted in the innovation pipeline

("pipeline product"). We found that the patent indicator, which, as known, represents the most reliable information on the innovative performance of the firm. The informative source for the patent data was the Q-pat archive. We included here all patents registered in the period 1995-2010. Information on products on the market and in the pipeline was collected by reading the BioScan archive and transforming the descriptive notes included for each firm into cardinal numbers.
In this research, we studied the alliances network of the biotech firms, especially the structure and evolution of the community network, to better understand the dynamic of this kind of network, so we used some centrality measures to understand how the firm's position in the network influence the probability of a merger or an acquisition.
We used the following measure: the first measure is the hub score. The hub score of a node, k, equals the total number of other nodes to which it is connected. The next measure is betweenness. Betweenness is a centrality measure of a node within a network. Nodes that occur on many shortest paths between other nodes have higher betweenness than those that do not.
The last measure is closeness. Closeness is also a centrality measure of a node within a network. Nodes that are "shallow" to the other nodes (that is, those that tend to have short geodesic distances to other nodes within the network) have higher closeness. Closeness is preferred in centrality analysis to mean shortest-path length, as it gives higher values to more central nodes, and so is usually positively associated with other measures such as degree.
Betweenness and closeness are also the common measures for centrality analysis.
Betweenness is a measure to describe the importance of the node in the network according to shortest path, and closeness is a measure to describe how close the node is to other nodes.
The similarity index was constructed starting from 140 areas of expertice (areas) in the biotech industry contained in Bioscan database and mapping the similarities of the biotech firm a_i and the firm b_i with which it has made a deal. The index is 0 if there are no similar areas of business and grows with increasing the similar area. The formula is the following:

$$similarity\ index_{a_i} = \frac{\Sigma\left(areas_{a_i} \cap areas_{b_i}\right)}{\Sigma\left(areas_{a_i} \cup areas_{b_i}\right)} = \frac{\Sigma similarities_{a \cap b}}{\Sigma\left(areas_{a_i} \cup areas_{b_i}\right)}$$

We also controlled whether an acquired company has made an alliance before the acquisition with the acquiring firm ("Alliances before M&A", no=0, yes=1).
Finally, we included in the model some dichotomous variables to explain with whom the biotech firms have made an M&A (m&a with another biotech firm, m&a with a pharmaceutical firm and m&a with other type of firm) and if the acquisition was cross border or not.

Control variables
We incorporated control variables that may influence the innovative firms' performance in entering agreements. We controlled for firm ownership (public or private), age, firm size (size is proxied by the number of employees) and region (US or Europe). This information refers to the latest available data published on the firm's website or to the data reported in the BioScan archive.

Estimation model
We ran a logit analysis on the data collected, dividing the analysis into eight models. We controlled the goodness of the models using the Akaike information criterion (AIC) and the pseudo R squared index (R squared). The results of the analysis are in the Table 3.

RESULTS

Our sample of DBF firms covers the most important consolidated biotech firms of the sector: 283 US biotech and 33 European firms; for this reason the average size is quite striking: about 500 employees per firm (the largest organization declared 20,000 employees). Our sample refers to a population of firms which occupies 153,200 labour units among scientists and workers. The average biotech company in our sample had entered 6.2 technology agreements, called here "development agreement" (table 1). Technology agreements with biotech firms are nearly double than agreements with pharma. National agreements are nearly double than international agreements, which, on the other side, are double than local agreements. Data on patents show an average number of 151.8 registered patents per firm. The firms analysed have on average 4.5 products in pipeline and 10.1 products on the market. In the period considered on the total sample of 316 firms 77 were acquired (we called this modality "passive acquisitions"). In 23 cases, the acquirer firm was an international organisation. 34 firms were acquired by other biotech firms while 33 by other pharma firms and 10 from firms or organisations belonging to other sectors.

In table 3 we reported the principal models (eight) used to test our hypotheses, from model 1 which mainly deals with the control variables to model 8, which includes nearly all important independent variables. Considering the main results of our estimations, there is to observe that all our hypotheses, even if with different degrees of significance, are confirmed.

Firstly, both the number of agreements (which is clearly a proxy of the intensity with which firms do recur to R&D alliances in order to develop their new knowledge), but overall the number of patents (which is a proxy of the technological intensity existing in firms) are positively and significantly associated with the decision of acquisition. Thus, hypothesis 1 and 4 are fully confirmed. In our data the technological intensity of the firms appears from the point of view of the degrees of significance even more important than the variable "number of agreements". When firms decide to expand their business they target the more innovative biotech, thus those which can exhibit the best significant patent portfolio. Looking at model 4, we can further comment our results: acquiring firms are more attracted by biotech firms with exclusive relationships with pharma firms, or by alliances with firms belonging to other sectors. In contrast, the sign is negative, and the value less significant, for firms with exclusive alliances with other biotech firms, and for firms with exclusive agreements with PRO (Public research Institution). Firms which have extended their alliance strategy to include some international agreements result to be are more attracting by buyers than firms with national or local agreements (model 3). Our results confirms, in this sense, some issues discussed by the international business literature which sees the acquisition of foreign firms as one of the main modality for firms to become international.

Secondly, diversity in firm's alliance portfolio come out to be an important prerequisite of acquisition. We study partner diversity through the so-called "similarity index" (model 5), in which for each alliance, we confront the product setting of the firms (this data was extracted by the BIOSCAN archive and elaborated by us building a technological tree in which we re-classified the biotech products into various three digit sectors). Extremely important, the sign is negative, and the value of the coefficient highly significant. The existence of technological complementarity in alliances improves the attractiveness of the firm and increases the probability to be acquired. This leads to suggest that DBFs require a more complex alliances portfolio, with firms bearing a differentiated set of complementary knowledge and experience. In line with this reasoning, we can bring also other elements linked to the relational structure of the firm, deriving from the network analysis of the whole structure of technological alliances pertaining to our database (1,828 development agreements), presented in model 6. The acquisition of a biotech firms appears to be highly correlated to its centrality, both measured with the closeness and the betweenness score. Developing their acquiring strategy, firms target actors which show a "hub" position in their alliance network, and that allow them to enter into multiple technological and knowledge flows. Therefore, hypothesis 2 and 3 are confirmed.

Third, and perhaps surprisingly, the existence of a previous alliance between the target and the acquiring firm did not come out as a significant element, which pushes toward further integration. In this context, within the biotech sectors, bio-pharma (or bio-bio) alliances cannot be considered antecedents to the acquisition. Even if blind acquisitions are risky, and hazardous, because the existence of information incompleteness, regarding the acquired firm, setting an alliance ex-ante, by an "acquiring firm", did not emerged as the first "best strategy" implemented to test and evaluate the technological capability of the partner. On the contrary, acquiring firms appear to be more interested in targeting highly innovative (patenting) firms, or/and firms with a large number of alliances, placed in a central position (centrality) with their alliances technological partners.

But *who is acquiring who* in the biotech sector? Despite numerically the number of acquisitions by pharma firms and biotech firms scores nearly the same, the variable *m&a/pharma* (which means acquisition of DBF by pharma scores in our data positively and extremely significant (model 7). One deals with an important element of industry restructuring and concentration that deserves further analyses.

References

Aghion P., Tirole J. 1994. The management of innovation. The Quarterly Journal of Economics 109: 1185-1209.

Amburgey, T.L., Dacin, T., Singh, J.V. 1996. Learning races, patent races, and capital races: Strategic interaction and embeddedness within organizational fields, in J.A.C. Baum and J. Dutton (eds.), The Embeddedness of Strategy, JAI Press, Greenwich, CT, 303-322.

Anand, B., & Khanna, T. 2000. Do firms learn to create value? The case of alliances. Strategic Management Journal, 21: 295-315.

Arora, A. Fosfuri, A. Gambardella, A. 2001. Markets for Technology: The Economics of Innovations and Corporate Strategy, MIT Press, Cambridge.

Beckman, C. M., Haunschild, P., & Phillips, D. 2004. Friends or strangers? Firm-specific uncertainty, market uncertainty, and network partner selection. Organization Science, 15: 259–275.

Dollinger MJ, Golden PA, Saxton T. 1997. The effect of reputation on the decision to joint venture. Strategic Management Journal, 18(2): 127–140.

Grossman S, Hart O. 1986. The costs and benefits of ownership: A theory of vertical and lateral integration. Journal of Political Economy 94: 691-719.

Hart O, Moore J. 1988. Incomplete contracts and renegotiation. Econometrica 56(4): 755-785.

Hart O. 1995. Firms contracts and financial structure. Clarendon Press: Oxford, UK

Hitt, M. A., Dacin, M. T., Levitas, E., Arregle, J.L., & Borza, A. 2000. Partner selection in emerging and developed market contexts: Resource-based and organizational learning perspectives. Academy of Management Journal, 43: 448–467.

Hoang, H. Rothaermel, F. 2005. The Effect Of General And Partner-Specific Alliance Experience On Joint R&D Project Performance, Academy of Management Journal, Vol. 48, No. 2, 332–345.

Katz, M.L., Shapiro, C. 1985. On the Licensing of Innovations, RAND Journal of Economics, vol. 16, n.4, 504-520

Kollmer, H. Dowling, M. 2004. Licensing as a commercialisation strategy for new technology-based firms, Research Policy 33:1141–1151.

Lambe, C.J., Spekman, R.E., Hunt, S.H. 2002; Alliance competence, resources, and alliance success: Conceptualization, measurement, and initial test, Journal of the Academy of Marketing Science, 30:2, 141-158.

Li, D. Eden, L. Hitt, M. and Ireland, R.D., 2008. Friends, Acquaintances, Or Strangers? Partner Selection In R&D Alliances, Academy of Management Journal, Vol. 51, No. 2, 315–334.

Liebeskind, J., Oliver, A., Zucker, L., Brewer, M., 1996. Social networks, learning, and flexibility: sourcing scientific knowledge in new biotechnology firms. Organization Science 3, 783–831.

Mahoney, J.T., Pandian, J.R. 1991.The Resource-Based Within the Conversation of Strategic Management. Strategic Management Journal, 12 (Winter Special Issue 1991): 95-117.

Porter, M 1996. Competitive Advantage, Agglomeration Economies, and Regional Policy, International Regional Science Review, 19, 1&2, 85-94.

Porter, M. 1990. The comparative advantage of nations, New York: Free Press

Rothaermel F.T., Deeds, D.L. 2004, Exploration and exploitation alliances in biotechnology: a system of new product development, Strategic Management Journal, 25:201-221.

Rothaermel, F. T. 2001. Incumbent's advantage through exploiting complementary assets via interfirm cooperation. Strategic Management Journal, 22: 687-699.

Rothaermel, F.T., Boeker, W., 2008. Old technology meets new technology: Complementarities, similarities, and Alliance formation , Strategic Management Journal, 29: 47–77.

Schilling M., 2008. Understanding the alliance data, Strategic Management Journal, 30, 233-260.

Shan, W., Walker, G., & Kogut, B. 1994. Interfirm cooperation and startup innovation in the biotechnology industry. Strategic Management Journal, 15: 387- 394.

Stan, X. L. & Rowley, T. J. 2002. Inertia and evaluation mechanism in interorganizational partner selection: Syndicate formation among U.S. investments banks. Academy of Management Journal, 45(6): 1104-1119.

Stuart, T. E., Hoang, H., & Hybels, R. C. 1999. Interorganizational endorsements and the performance of entrepreneurial ventures. Administrative Science Quarterly, 44: 315-349.

Teece, D. 1986. Profiting from Technological Innovation: Implications for Integration, Collaboration, Licensing, and Public Policy,Research Policy, 15: 285-305

Teece, DJ. 1992. Competition, cooperation, and innovation: organizational arrangements for regimes of rapid technological progress. Journal of Economic Behavior and Organization 18(1): 1–25.

Wuyts, S. Geyskens, I. 2005. The Formation of Buyer-Supplier Relationships: Detailed Contract Drafting and Close Partner Selection, Journal of Marketing, 69 (4), 103-17.

Tab. 1 Descriptives

	Variables	Mean	St. Dev.	Min	Max	Sum	Sample
1	*family patents*	151.810	346.778	0	2535	47972	316
2	*total products*	14.611	66.779	0	1007	4617	316
3	*pipeline products*	4.497	5.117	0	50	1421	316
4	*produts on the market*	10.114	66.263	0	1000	3196	316
5	*total agreements*	7.465	7.347	1	68	2359	316
6	*passive m&a (yes=1)*	0.244	0.430	0	1	77	316
7	*alliance before m&a (yes1)*	0.038	0.191	0	1	12	316
8	*agreements w/bio*	3.392	4.540	0	47	1072	316
9	*agreements w/pharma*	1.994	2.764	0	20	630	316
10	*agreements w/PRO*	0.013	0.178	0	3	4	316
11	*agreements w/other*	0.892	1.556	0	10	282	316
12	*local agreements*	1.136	2.036	0	19	359	316
13	*national agreements*	4.123	4.742	0	37	1303	316
14	*international agreements*	2.206	2.902	0	22	697	316
15	*development agreements*	5.785	6.251	0	52	1828	316
16	*marketing agreements*	1.693	2.328	0	16	535	316
17	*m&a w/bio (yes=1)*	0.108	0.310	0	1	34	316
18	*m&a w/pharma (yes=1)*	0.104	0.306	0	1	33	316
19	*m&a w/other (yes=1)*	0.028	0.167	0	1	10	316
20	*local m&a (yes=1)*	0.171	0.377	0	1	54	316
21	*international m&a (yes=1)*	0.070	0.255	0	1	23	316
22	*size*	484.810	1702.997	1	20000	153200	316
23	*age*	17.699	8.960	5	40	5593	316
24	*history*	1991.851	7.265	1980	2004	629425	316
25	*ownership (public=1)*	0.513	0.501	0	1	162	316
26	*region (US=1)*	0.896	0.306	0	1	283	316
27	similarity_index	0.338657	0.434872	0	2.969	107.02	316
28	Kleinberg_hub_score	0.093654	0.157052	0	1	29.595	316
29	betweenness score	251.5506	967.1227	0	10278	79490	316
30	closeness score	0.011893	0.003925	0	0.014	3.7582	316

Tab. 2 Correlations Model (316 observations)

	Variables	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*20*	*21*	*22*	*23*	*24*	*25*	*26*	*27*	*28*	*29*	*30*
1	*passive m&a (yes=1)*	1,000																													
2	*family patents*	0,064	1,000																												
3	*total products*	-0,028	0,048	1,000																											
4	*pipeline products*	-0,080	0,245	0,139	1,000																										
5	*produts on the market*	-0,022	0,029	0,997	0,063	1,000																									
6	*total agreements*	0,073	0,371	0,019	0,214	0,003	1,000																								
7	*alliance before m&a (yes1)*	0,350	0,156	-0,008	0,013	-0,009	0,175	1,000																							
8	*agreements w/bio*	0,070	0,376	0,054	0,179	0,040	0,849	0,231	1,000																						
9	*agreements w/pharma*	0,068	0,280	-0,014	0,122	-0,024	0,626	0,036	0,351	1,000																					
10	*agreements w/PRO*	-0,035	-0,006	-0,031	0,148	-0,043	0,389	-0,030	0,077	-0,020	1,000																				
11	*agreements w/other*	0,073	0,168	0,006	0,046	0,002	0,538	0,131	0,350	0,188	0,122	1,000																			
12	*local agreements*	0,002	0,236	0,029	0,148	0,018	0,572	0,133	0,564	0,157	0,321	0,287	1,000																		
13	*national agreements*	0,068	0,337	-0,026	0,234	-0,044	0,862	0,089	0,704	0,575	0,364	0,443	0,260	1,000																	
14	*international agreements*	0,072	0,223	0,070	0,055	0,067	0,721	0,203	0,604	0,536	0,166	0,439	0,323	0,367	1,000																
15	*development agreements*	0,061	0,363	-0,008	0,223	-0,025	0,954	0,161	0,794	0,623	0,445	0,405	0,565	0,847	0,636	1,000															
16	*marketing agreements*	0,062	0,188	0,079	0,063	0,075	0,551	0,119	0,506	0,324	0,024	0,514	0,269	0,409	0,539	0,305	1,000														
17	similarity index	0,040	0,334	0,024	0,234	0,006	0,615	0,213	0,556	0,452	0,144	0,261	0,283	0,620	0,346	0,616	0,291	1,000													
18	Kleinberg hub score	0,084	0,286	0,018	0,164	0,005	0,525	0,150	0,396	0,671	-0,016	0,154	0,213	0,538	0,301	0,546	0,191	0,651	1,000												
19	betweenness index	0,082	0,364	0,016	0,216	-0,001	0,505	0,292	0,583	0,193	0,090	0,204	0,402	0,439	0,279	0,499	0,259	0,539	0,421	1,000											
20	closeness index	-0,083	0,056	-0,004	0,094	-0,011	0,186	0,036	0,150	0,205	0,047	0,003	0,082	0,195	0,094	0,218	-0,024	0,162	0,262	0,117	1,000										
21	*m&a w/bio (yes=1)*	0,612	-0,030	-0,029	-0,072	-0,024	-0,053	0,305	-0,030	-0,055	-0,062	0,031	-0,033	-0,063	-0,007	-0,058	-0,011	-0,078	-0,062	-0,074	-0,093	1,000									
22	*m&a w/pharma (yes=1)*	0,602	0,142	-0,016	0,024	-0,018	0,149	0,203	0,119	0,162	0,012	0,050	0,064	0,127	0,126	0,149	0,067	0,176	0,167	0,207	-0,004	-0,119	1,000								
23	*m&a w/other (yes=1)*	0,302	-0,042	0,010	-0,125	0,020	0,005	-0,034	0,023	-0,020	-0,021	0,024	-0,040	0,056	-0,052	-0,015	0,055	-0,071	0,035	-0,027	-0,039	-0,059	-0,058	1,000							
24	*local m&a (yes=1)*	0,800	-0,050	-0,025	-0,069	-0,020	0,008	0,218	-0,017	0,028	-0,032	0,086	-0,055	0,031	0,008	-0,001	0,024	-0,056	-0,016	-0,042	-0,054	0,521	0,422	0,276	1,000						
25	*international m&a (yes=1)*	0,482	0,165	-0,009	-0,024	-0,007	0,122	0,271	0,149	0,082	-0,006	0,003	0,092	0,077	0,118	0,115	0,074	0,156	0,172	0,204	-0,029	0,226	0,394	0,103	-0,124	1,000					
26	size	-0,015	0,428	0,132	0,267	0,113	0,312	0,093	0,367	0,046	0,086	0,190	0,343	0,230	0,174	0,273	0,259	0,220	0,106	0,366	0,039	-0,045	0,018	0,016	-0,030	0,022	1,000				
27	age	0,051	0,224	0,203	0,134	0,194	0,110	0,049	0,085	0,016	0,051	0,164	0,031	0,080	0,126	0,034	0,264	0,071	0,003	0,066	0,017	-0,015	0,021	0,125	0,049	0,016	0,312	1,000			
28	history	-0,051	-0,216	-0,187	-0,165	-0,176	-0,170	-0,074	-0,131	-0,046	-0,079	-0,220	-0,070	-0,130	-0,170	-0,084	-0,311	-0,119	-0,022	-0,080	-0,046	0,023	-0,034	-0,115	-0,045	-0,022	-0,314	-0,948	1,000		
29	*ownership (public=1)*	0,126	0,155	-0,008	0,260	-0,028	0,220	0,061	0,129	0,239	0,071	0,128	0,012	0,259	0,124	0,205	0,152	0,171	0,183	0,085	0,079	0,032	0,105	0,053	0,106	0,043	0,153	0,289	-0,307	1,000	
30	*region (US=1)*	0,122	0,085	0,045	0,039	0,042	0,048	0,068	0,034	0,067	-0,039	0,070	-0,054	0,129	-0,051	0,018	0,106	0,049	0,101	0,051	-0,019	0,085	0,049	0,058	0,100	0,053	0,050	0,115	-0,147	0,226	1,000

Tab. 3 Determinants of Passive M&A Estimates for a Logit Regression Model (316 observations

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8	
Variables	Coeff.	Std. Err	Coeff.	Std. Err	Coeff.	Std. Err	Coeff.	Std. Err	Coeff.	Std. Err	Coeff.	Std. Err	Coeff.	Std. Err	Coeff.	Std. Err
Intecept	-1.960 ***	0.802	-1.766 ***	0.809	-1.919 ***	0.803	-1.935 ***	0.811	-1.876 ***	0.844	-1.161 ***	0.915	-1.876 ***	0.764	-1.161 ***	0.915
Family Patents	0.011 ***	0.004	0.038 ***	0.004	0.072 **	0.001	0.014 **	0.043	0.021 ***	0.001	0.020 ***	0.001	0.027 ***	0.001	0.020 ***	0.001
Total products	-0.004	0.005			-0.004	0.005	-0.004	0.005	-0.003	0.005	-0.004	0.006	-0.005	0.005	-0.004	0.006
Products on the market			-0.088	0.035												
Pipeline products			-0.002	0.004												
Total agreements	0.002 **	0.019	0.006 **	0.020					0.007 ***	0.028	0.015 **	0.031	0.007 ***	0.026	0.015 **	0.031
Agreements with bio							-0.003 *	0.033								
Agreements with pharma							0.008 **	0.051								
Agreements with PRO							-0.057	0.068								
Agreements with otherfirms							0.073 **	0.089								
Local agreements					-0.051 *	0.072										
National agreements					-0.002 *	0.031										
International agreements					0.037 ***	0.049										
Size	0.236 **	0.111	0.282 ***	0.114	0.242 ***	0.112	0.233 ***	0.114	0.205 ***	0.118	0.230 ***	0.121	0.235 ***	0.115	0.230 ***	0.121
Age	-0.171 *	0.331	-0.239 *	0.335	-0.197 *	0.333	-0.171 *	0.339	-0.166	0.349	-0.170 *	0.359	-0.163	0.243	-0.170 *	0.359
Ownership (Public=1)	0.441 ***	0.292	0.583 ***	0.298	0.428 **	0.295	0.441 ***	0.297	0.514 **	0.312	0.504 ***	0.316	0.524 **	0.212	0.504 ***	0.316
region (Usa=1)	0.672 ***	0.191	0.053 ***	0.221	0.486 ***	0.148	0.453 **	0.322	0.182 **	0.255	0.125 **	0.258	0.122 **	0.273	0.125 **	0.258
Alliances before M&A									0.183 *	0.667	0.313 *	0.552	0.179 *	0.553	0.313 *	0.552
Similarity index									-0.576 **	0.491	-0.742 ***	0.537	-0.544 **	0.401	-0.742 ***	0.537
Hub score											0.705 **	1.253	0.611 **	1.233	0.705 **	1.253
Closeness score											0.021	0.029	0.022	0.020	0.021	0.029
Betweenness score											1.494 **	0.351	1.512 **	0.291	1.494 **	0.351
m&a w/bio (yes=1)													0.575 **	0.422		
m&a w/pharma (yes=1)													0.739 ***	0.215		
m&a w/other (yes=1)													0.454	0.092		
local m&a (yes=1)															0.826 ***	0.382
internationalm&a (yes=1)															0.219 *	0.205
AIC	353.83		348.4		357.0		358.46		324.45		324.22		323.5		331.32	
R Squared	0.314		0.296		0.301		0.288		0.293		0.286		0.271		0.301	

Signif. Codes: *p<0.1; **p<0.05;

***p<0.001