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Angaben zur Veröffentlichung / Publication details:

Zidorn, Wilfried, and Marcus Wagner. 2013. "The effect of alliances on innovation patterns: an analysis of the biotechnology industry." *Industrial and Corporate Change* 22 (6): 1497–1524. https://doi.org/10.1093/icc/dts042.

The effect of alliances on innovation patterns: an analysis of the biotechnology industry

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The purpose of this article is to show the effect of different types of alliances on the innovation patterns of successful firms in the biotechnology industry. Using a new approach to measuring changes in innovation patterns across technology classes, the results show that alliances are formed to specialize in a certain research field, rather than to enter a completely new market. The importance of this effect declines as the equity involvement of the partners in the alliance project increases.

JEL classification: O32, O34.

1. Introduction

In the past two decades, strategic alliances have become an increasingly important form of collaboration complementing traditional types such as Mergers and Acquisitions (M&A) (Hagedoorn, 2002). These alliances are defined as "...co-operative agreements in which two or more separate organizations team up in order to share reciprocal inputs while maintaining their own corporate identities" (De Man and Duysters, 2005: 1377) and range from loose and relational R&D partnerships to

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equity joint ventures (JVs; Contractor and Lorange, 2002).[1] Scholars find several rationales for firms to engage in alliances such as reducing costs and risk, financing and developing capital intensive projects, pooling complementary skills, and monitoring technological opportunities in new markets (Hamel, 1991; Hagedoorn, 1993; Powell *et al.*, 1996; Mowery *et al.*, 1998). Despite these complementary and expansionist rationales for firms to collaborate, only Rothaermel and Deeds (2004) show that alliances are used to enhance specialization in newly discovered technologies. Analyzing a sample of biotechnology firms, they argue that once a technology is explored, it has to be exploited. Exploitation, especially in the biotechnology industry, is a time-consuming process (DiMasi, 2001), which often requires financial and technological support garnered through alliances. As a result, biotechnology firms form alliances to specialize and to advance a technology to turn it to a marketable and Food and Drug Administration–approved product. This article seeks to support the finding of Rothaermel and Deeds (2004) and illustrate how alliances influence a firm's innovation pattern.

Furthermore, this study concentrates on how that influence is affected when firms commit equity to an alliance project. The literature suggests that firms reassess their motivation to collaborate when equity involvement in the alliance project increases. For instance, an attractive rationale for a firm to collaborate through equity JVs might be the pursuit of economies of scale, obtaining access to new markets and technologies, or investing in foreign projects in countries with different national circumstances, such as easier access to local resources (Narula and Hagedoorn, 1999). Furthermore, while non-equity alliances tend to operate in the short to medium term, equity alliances last, at least in theory, forever (Contractor and Lorange, 2002). To date, no study has analyzed whether these changing conditions for equity alliances have an effect on a biotechnology firm's innovation pattern. To analyze this relationship and thus to fill the gap in the literature, this article addresses the following research question: How do different types of inter-firm alliances influence a firm's innovation pattern?

To answer this research question, the current research has analyzed the 20 leading biotechnology firms (MedAdNews, 2004). The first part of the article briefly reviews the literature on the relationship between alliances and innovation, and develops the theoretical background for deriving testable hypotheses. The second part introduces the data and variables that are used for the analysis. After presenting and discussing the results, conclusions are drawn, and potential areas for future research proposed.

[1]This paper distinguishes between three types of alliances: Strategic alliances, such as marketing or purchasing alliances, strategic equity alliances, such as equity agreements or JV, and technology alliances.

2. Literature review

In this section, the literature on the rationales underlying business alliances and the influence of alliances on the innovation of a firm is reviewed. This study distinguishes between equity alliances and such collaborative agreements that do not involve equity commitment. These concepts and definitions are important to understand the effect of alliances on innovation and further serve to build the argument for the development of the hypotheses.

2.1 Alliances

The distinctive forms and operational methods of organizations and the resulting variety of partnership agreements have given rise to several reasons for inter-firm collaboration. For instance, working together helps firms to acquire complementary resources, which may turn an innovative project into a commercial success (Teece, 1986). Collaboration also potentially enables firms to screen markets for environmental changes and opportunities (Duysters and de Man, 2003), encourages the transfer of codified and tacit knowledge (Faems *et al.*, 2005), and spreads the costs for R&D (Hagedoorn, 2002). However, examining differences across sectors more closely, technology-related motives matter most, especially for inter-firm collaboration in high-technology industries (Hagedoorn, 1993). Innovative start-ups often possess new technology, but lack financial resources; this is especially the case in the biotechnology industry where new products have to pass several expensive clinical testing stages before being approved for sale (Van de Vrande *et al.*, 2009). Start-ups often collaborate with incumbent firms that are less innovative (Gilsing *et al.*, 2008) and face difficulties entering new markets, or exploring new technologies, often owing to multi-layered hierarchies and time-consuming process development. Both types of firms can compensate for their respective shortcomings through allying, which accelerates the R&D process and increases innovation output.[2]

There are several forms of agreements that are used to develop an alliance between firms, ranging from loose relational agreements to different types of licensing, to marketing and supply-chain relationships, to equity JVs (Gulati and Singh, 1998). Contractor and Lorange (2002) classify these types of alliances according to their expected longevity. Alliances that are planned for the shortest time span are relational contracts, such as training or learning alliances, and may last only a couple of years. Medium-term contractual relationships, such as licensing, involve significant technology transfers between partners and last an average of 5 years. Supply-chain relationships are usually claimed to have a medium to long life span. Finally, JVs are expected, in theory at least, to last forever (Contractor and Lorange, 2002).

[2]For an overview of the literature on R&D related motivations for cooperation, see Miotti and Sachwald (2003).

2.2 *Effect of alliances on innovation*

De Man and Duysters (2005) review the leading scientific articles that investigate the relationship between alliances and innovation in several sectors, including the semiconductor, chemistry, biotechnology, engineering, and information technology industries. The majority of the articles reviewed find alliances to have a positive effect on innovation, mainly for two reasons. First, firms with more experience in managing an alliance are more likely to increase their innovative output after allying. Second, firms with overlapping knowledge stocks (i.e. similar patent portfolios) outperform alliances in areas where the partners' knowledge is more distinct. Of 40 reviewed articles, 7 find a neutral effect of alliances on innovation. First, while alliances that involve equity such as JVs encourage firms to innovate, loose collaborations such as licensing have a neutral effect on innovation. That is to say, alliance partners need to establish a close relationship to effectively promote innovation, which is more likely for alliances with higher levels of equity involvement (Van de Vrande *et al.*, 2009). Second, the alliance network of a firm needs to be effectively formed, and the optimal number of alliance partners needs to be determined. For instance, alliance networks in dense industries where all partners are directly connected to each other do not increase the innovativeness of firms. Third, although government funded research alliances seem to decrease the costs of innovation, most studies that analyze government-related alliances or collaborations between universities and firms find a neutral or slightly positive influence on innovation. Of the 40 articles reviewed, 4 find a negative effect of alliances on innovation. The rationales for these findings include ineffective alliance networks, very specific alliance situations, and cost-saving objectives. Overall, the effect of alliances on innovation is somewhat equivocal.

2.3 *Equity and non-equity alliances*

Ineffective alliance networks often lead to a project failing owing to the high transaction costs of alliances. These costs are determined *ex ante* by high persuading and negotiating costs and *ex post* by high monitoring and coordination costs (Hennart, 1988; Langlois, 1992). A typical transaction cost for allies is opportunistic behavior (Williamson, 1975) that may result from each partner's effort to maximize its profits. However, with an increase in the partner's dependency on the alliance, especially through equity ownership, firms have fewer incentives to act opportunistically (Pisano and Teece, 1989), which may result in better alliance management and improved communication between partners. Collaborative agreements that involve the creation or transformation of equity ownership are defined as equity alliances. These alliances are either partial acquisitions and ownership of the partner firm through direct investments, or JVs, which are new and jointly owned entities of the allying firms (Das and Teng, 1996). Non-equity alliances, however, do not involve the creation or transformation of any type of equity ownership. These alliances are

considered to be arms-length relationships (Gulati, 1995), which may be reversed at low cost. Common non-equity alliances are different forms of licensing, joint R&D projects, marketing and supply-chain relationships, technology exchange agreements, and learning alliances.

Dyadic approaches to alliancing and its effects such as those shown by Hoang and Rothaermel (2005) or Wang and Zajac (2007) indicate that higher levels of resource complementary for two firms make it more likely that these firms choose an alliance. This suggests an implicit fit that has also been used to explain that several studies find essentially identical results at the firm and dyadic levels (e.g. Stuart, 1998). The implicit fit between the alliance partners determines net benefits, and thus alliancing likelihood and therefore characteristics of one partner are implicitly embodied in the other and vice versa, based on the cost–benefit considerations of each party. Also, the dyadic view cannot be applied with multi-partite alliances which are often the case in the biotech industry, whereas firm-level analysis still can be. Finally it has been suggested that in the case of binary dependent variables (as used in this article), dyadic approaches are, in principle, not necessary (Mizruchi and Marquis, 2006), which is why we ultimately opted for a firm-level analysis in the remainder of the article.

3. Development of hypotheses

Significant numbers of biotechnology firms have been established since the mid-1970s. With a major breakthrough within this field "...scientists discovered how to manipulate the genetic structure of cells to induce them to produce specific proteins" (Pisano, 1997: 12). The past three decades have witnessed a proliferation of biotechnology firms, which has led to fierce competition. This is partly caused by the high economic value of biotechnology solutions and application integration, which has attracted attention from several industries (Nesta and Saviotti, 2006). The environmental industry, the chemical industry (which works with bio-based materials and bioprocess engineering), the agriculture industry, the food and medical engineering industries, and most importantly for this article, the pharmaceutical industry have developed an interest in this emerging technology (Powell *et al.*, 1996). The increasing demands of those customer industries has led to a strong need for rapid product development that has further increased interest (Deeds and Hill, 1996) as well as patent races among the biotechnology firms (Gilbert and Newbery, 1982). The resulting "winner-takes-all" attitude of the industry and the need for quick market responses have divided the industry into several market segments. One explanation might be that firms that have developed core competencies in small market segments may react faster to market demand than firms that put their focus on the wider biotechnology industry. Over the past three decades, the biotechnology industry has

grown rapidly, and the increasing number of biotechnology firms has led to fierce competition in even the smallest industry segments.

Rothaermel and Deeds (2004) find that after the successful discovery of a new technology, it has to be developed and advanced. The development of a product in the biotechnology industry takes 12 years on average and requires expenditure of more than 800 million US dollars (USD; DiMasi *et al.*, 2003). Within those 12 years, a drug has to pass several clinical testing stages before it is approved by the Food and Drug Administration and can enter a market (Van de Vrande *et al.*, 2009). On the one hand, the biotechnology firm becomes an expert in a specific technology field through specialization and by implementing ongoing product improvements during this time. On the other hand, the drug has to be developed for more than a decade before the firm can realize product-specific sales. Furthermore, the process can fail at any stage, leaving the firm with nothing but expenditure. Young biotechnology firms, in particular, do not have sufficient internal resources to bear the high associated costs and risk. Therefore, during this time of specialization and development, a biotechnology firm will engage in several alliances, which leads to the following hypothesis:

> *H1: The more alliances a biotechnology firm forms in a given year, the higher its subsequent technology specialization.*

Van de Vrande *et al.* (2009) find that in environments marked by high degrees of uncertainty, cooperation with non-equity alliances are more attractive than allying through equity alliances, making it the preferred mode of governance.[3] Casciaro (2003) analyzes different types of uncertainties and their effects on the optimal alliance governance choice. He finds that firms are more likely to choose non-equity alliances over equity alliances when the task at hand contains many contingencies and levels of strategic uncertainty are high. While equity alliances tend to be complex to control, and take longer to establish and dissolve (Harrigan, 1988), non-equity alliances are reversible at low cost, and thus initial investments may largely be recovered if the joint project fails. Therefore, a firm seeking an equity alliance must manage and mitigate uncertainty, especially about partners. However, mitigating uncertainty is a time-consuming process for firms. The first step is to cooperate with partners operating in similar areas of knowledge through loose non-equity (learning) alliances, which have low levels of equity involvement. Once they have set up relationship and communication channels, firms may better evaluate the likelihood of successful joint projects. As a result, there will be less uncertainty about whether an alliance that involves more equity will be successful or not. These alliances are usually follow-up partnerships. The resulting superior connection between the allying partners, their better established communication channels

[3]Uncertainty about alliance success is highest for firms that (1) operate in distinctive knowledge areas and (2) have no pre-existing relationship with each other.

(De Man and Duysters, 2005), and the mutual trust stemming from the previous relationship allow firms to explore fields that differ more from their core research areas.

The consequences of project failure are more severe for alliances that involve equity, which causes firms to commit more resource and social capital to such alliances. Greater competencies within the alliance enable faster evaluations and assessments (Deeds and Rothaermel, 2003), which allow firms to research beyond their core technology specialization.

To further develop the argumentation supporting the second hypothesis, the financial motivation of the allying partners has to be mentioned. Engaging in a strategic alliance is justified only if collaborative gains at least compensate for the costs of undertaking the alliance (Singh, 1997). Strategic equity alliances, however, require higher investments than their non-equity counterparts. To compensate for previous expenditure, joint projects with equity involvement have to be more profitable. Scholars find that innovative performance levels are higher when firms are engaged in explorative alliances (Nooteboom *et al.*, 2007), which result in more novel and radical technologies (Singh, 1997). These particular technologies are more likely to yield higher profits, which may be captured by firms that engage in strategic equity alliances because that enables them to pursue more explorative research. This leads to the following hypothesis:

> *H2: The positive effect of alliances on technology specialization diminishes when equity involvement of the partners increases.*

4. Empirical setting

4.1 Biotechnology industry and sample selection

The hypotheses are tested on the population of successful firms in the biotechnology. This industry is characterized through numerous and complex collaborative agreements and a high tendency to patent new technologies. Arundel and Kabla (1998) find that innovators within this industry apply for a patent for 74% of their innovations, whereas only 15% of all product or process innovations are patented within the basic metal industry.[4] Furthermore, the biotechnology industry is representative for a high-technology industry setting, where R&D and knowledge are considered to be of highest importance (Khilji *et al.*, 2006). A further benefit in regard to answer the aforementioned research question is that measuring patenting activity among firms within the same industry is clearly more informative than data on patenting across industries or countries (Basberg, 1984). Additionally, a focus on one industry helps to control for industry effects, such as scale economies or new technologies,

[4]This is followed by industries such as chemicals with 51% and machinery with 54% (Arundel and Kabla, 1998).

which have been shown to influence results in a complex manner that is difficult to control in multi-industry samples (Pangarkar, 2003). The original sample contains the 20 largest firms of the biotechnology industry for the period from 1984 to 2007 and their 8602 alliances based on 448 observations (MedAdNews, 2004). These firms operate in the North America, Europe, and Asia-Pacific and have alliance partners from all over the world. A filter is applied on the full sample that excludes firms with minor patenting activity. Testing technology-related hypotheses requires sufficient technological activity (Van Vianen *et al.*, 1990). Therefore, firms that hold less than 15 patents in the entire time span are excluded from the sample.[5] Furthermore, full financial information of some firms is not available for all years. Therefore, to meet the requirements for a lagged analysis, observations are included so that all firms have time series without year gaps. This reduces the sample to 18 firms with 4203 alliances during the period 1984–2007, which corresponds to 246 observations. This implies a sample selection that precludes conclusions on unsuccessful firms in the industry, nor on large pharmaceutical firms. However, the different business models and nationalities and the high total R&D expenditures of the firms in the sample that represent 82% of biopharmaceutical R&D expenditures should permit to generalize the findings mentioned later in the text safely to the biotechnology industry as a whole and also to other high-technology industries and contexts.

4.2 Measures, variables, and descriptive analysis

To test the hypotheses proposed earlier in the text, a number of variables are developed. Table 1 shows the variable definitions.

The following section describes important measures to determine a firm's technological portfolio (i.e. its technological competency). Coombs and Bierly (2006) report on the different direct and indirect measurement methods. Direct methods may include R&D expenses and patent counts or a combination of the two, or patent citations or absorptive capacity. Indirect measurement may be made by way of the ratio of a firm's scientists to coauthored scientific articles so as to determine the technology portfolio of a firm. In the literature, patent-related measurement methods are commonly used and are used in this study as well.

Patent count–based indicators are often used to assess a firm's technological capability. Using the International Patent Classification (IPC), patents can be accumulated into different classes, which approximate well to a firm's patent portfolio. Data from patent offices is globally available, and portfolios may be constructed for long time spans, revealing firm-specific technological resources and capabilities (Silverman, 1999). Studies that focus on determinants of innovation often use patent citations as a measurement. When an invention builds on previously patented technology, the applicant has to highlight the connection to former patents through a

[5]This excludes the outliers MGI Pharma (4 patents) and Celgene (14 patents) from the sample.

Table 1 Variable definitions

Variable name	Variable description	Data source
Dependent variable		
Technology specialization	Dichotomous variable that describes the change of the patenting behavior of firm *i* from period *t* to period $t+1$. Takes 1 if a firm *i* specializes within a certain technology field and 0 if it patents in new technology classes	USPTO
Independent variables		
Strategic and equity alliances	Sum of strategic and equity alliances in $t-1$	RECAP
Non-equity strategic alliances	Sum of strategic and non-equity alliances in $t-1$	RECAP
Technology alliances	Sum of technology alliances in $t-1$	RECAP
Control variables		
Tobin's Q	Market to book value in *t*	COMPUSTAT COMPUSTAT Global CRSP
Sales (log)	Logarithm of sales of a firm in *t*	COMPUSTAT COMPUSTAT Global CRSP
IPC growth	Growth of patents per IPC classes from period *t* to period $t+1$ of firm *i*	USPTO
M&A	Number of M&As in $t-1$	RECAP
HDI	Index to measure the concentration of a firm's patent portfolio	USPTO
Patent Stock (log)	Logarithm of accumulated (depreciated) number of patents a firm has gathered from the beginning to the time of observation	USPTO
Experience	Number of years since the Initial Public Offering (IPO) of the focal firm	Firm profiles
Time trend	Ascending integer values where each indicates the current year of observation ($1984=5$; $2007=28$)	Sample dataset
Asia	Dummy variable set to 1 if the headquarter is in Asia (default = US firms)	Firm profiles
Europe	Dummy variable set to 1 if the headquarter is in Europe (default = US firms)	Firm profiles

citation. This procedure implies that patents that are cited more often have the tendency to be more important in terms of economic and technological value and create higher innovation. Nevertheless, this analysis uses patent counts as base data. Whether patents have economic value is of minor importance to this study, as current innovation patterns, rather than a firm's innovation output, are its focus. Furthermore, patent counts are an immediate measurement of research activities (whereas patent citations evolve over time). Therefore the class (or subclass)[6] overlap of annual patent portfolios is used to represent the technological change (TC), as is detailed in the following section.

4.2.1 Technological change

To determine the TC of the 20 biotechnological firms, longitudinal patent data from the United States Patent and Trademark Office (USPTO) are used.[7] It contains 10,970 granted patents from 1980 to 2007. Several studies use the revealed technology advantage index to measure technology diversification (e.g. Patel and Pavitt, 1994; Malerba and Montobbio, 2003; Quintana-García and Benavides-Velasco, 2008). This index describes the relative comparative advantage of a firm in a certain technology field and is often used to compare the diversification of technology of different nations. Several studies that operate on the firm level base their measurement for technology specialization on the Herfindahl index (e.g. Garcia-Vega, 2006; Leten et al., 2007). Other studies use an approach to measuring technological diversification that is introduced by Jaffe (1986), in which a modified Herfindahl concentration index is used to measure the technological diversification between two alliance partners (e.g. Ejermo, 2005; Sampson, 2007; Grimpe and Hussinger, 2008). Following his approach, this study measures the annual changes in patent behavior within one firm. Hence, technology portfolios of each firm are generated, containing the distribution of granted patents among IPC classes. A firm's technology portfolio in each period is captured by a vector F_{it}, with F'_{it} being the transposed vector of F_{it}, and the period and the observed firm are indicated by t and i, respectively. Therefore, a firm's TC from year t to the subsequent year $t+1$ is measured as follows:

$$TC_{it} = \frac{F_{it}F'_{it+1}}{\sqrt{\left[\left(F_{it}F'_{it}\right)\left(F_{it+1}F'_{it+1}\right)\right]}}$$

The values can range from 0 to 1, where 1 indicates no change of the technology portfolio from one period to another and 0 stands for patents that are assigned to

[6]Only patent applications for patents granted are used, since they are most likely to represent successful research of the biotechnology firms of interest. Following the convention, patents are assigned to the application year.

[7]Granted patent applications of subsidiaries are added to the patent portfolio of the parent firm.

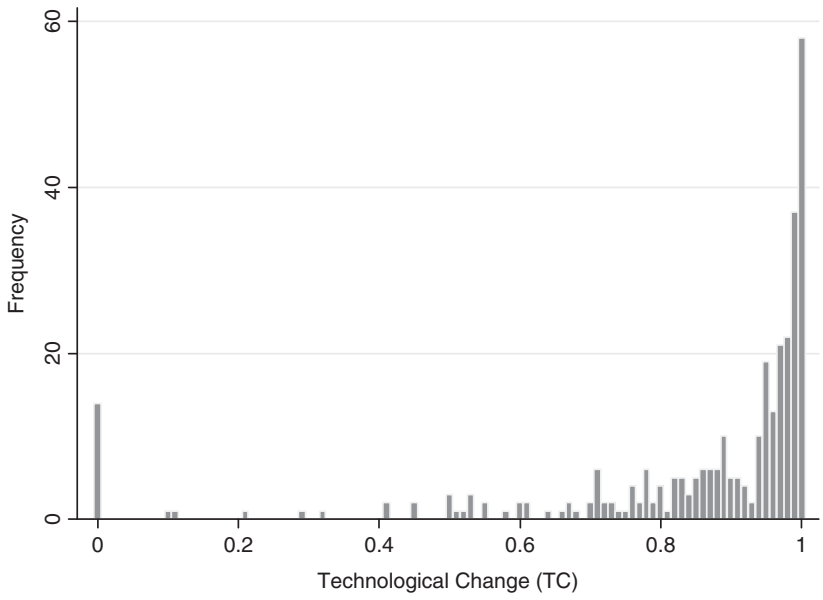

Figure 1 Histogram of technological change.

entirely different technology classes in the subsequent period. In other words, if the patenting behavior of firm i in period t is equal to the patenting behavior of the same firm i in the period $t+1$, the level of TC reaches a value of 1, and if it is completely different (in terms of IPC classes), the level reaches a value of 0. The distribution of the TC measure is illustrated in Figure 1.

4.2.2 Dependent variable

Two steps are necessary to develop the dependent variable *Technology Specialization*. First, following the convention in previous literature on patents (e.g. Mowery et al., 2001; Trajtenberg, 2001), a 3-year moving average of the TC measure is created. Second, the median of this adjusted TC measure (0.93) is applied to create a binary variable.[8] As graphically illustrated in Figure 1, the TC measure shows a left skewed distribution. On the one hand, the biotechnology firms of interest have a tendency to patent technology in period $t+1$ that is similar to the technology patented in period t. On the other hand, some observations have a TC value of 0, which represents firms

[8]The relatively high median value of 0.93 is not too surprising, as too much diversification of research (i.e. lower values of the TC measure) negatively influences technological performance (Leten *et al.*, 2007). Results (available on request) do not change qualitatively when using the median of the TC measure for only the subsequent period (0.95) to create the binary dependent variable.

that patent technologies in new IPC classes in period $t+1$. The TC measure is concentrating at the extreme values, which motivates the creation of a binary variable. Thus, firms that specialize in their core technology areas are separated from firms that enter into differing areas. If the value is above the median, firms are expected to have a more coherent patent portfolio from one year to another, which is indicated by 1. Stronger deviation from a firm's core technology areas as represented by TC values below the median is indicated by 0. Here, firms are expected to research technology areas that differ from their core technology areas.

4.2.3 Independent variables

The current research uses data from RECAP to measure the effect of alliances on the dependent variable. The data contains longitudinal information about events in the cooperation of biotechnological firms, from 1980 to 2008. This database allows the isolation of three types of alliances. Firstly, the variable *Non-Equity Strategic Alliances* describes all alliances that are partly strategic but do not include any type of equity alliance.[9] Secondly, the variable *Strategic and Equity Alliances* contains all types of agreements of non-equity strategic alliances, combined with strategic equity alliances, that is, equity agreements and JV agreements. Finally, the variable *Technology Alliances* describes all technology- and research-motivated collaborative agreements, where merely the development of technology is the definitional criterion.[10] All three types of alliances are included in separate models as independent variables.

4.2.4 Control variables

Financial data have been gathered using Worldscope, Thomson Financial, the merged database of COMPUSTAT and CRSP, and COMPUSTAT Global. Tobin's Q is used to control for the effect of efficient resource usage. *Firm size* is measured through the variable *Sales (log)*, which is the logarithm of total firm sales. Large firms are more likely to benefit from economies of scale by more effectively processing R&D resources, which in turn increase a firm's technological activity (e.g. Griliches, 1990; Leten *et al.*, 2007). Effects of global changes in a firm's patent behavior are measured by the variable *IPC growth*, which is the growth of patents per IPC class by year. It is used to determine the firm-specific diversification in its patenting behavior. To generate the *M&A* variable, information that is provided in RECAP about M&A in the previous year is analyzed, which is important because of increasingly open

[9]Asset purchase, Co-Development, Collaboration, Cross-License, Development, Distribution, Marketing, Research (according to the terms' glossary of the RECAP database).

[10]Co-Development, Collaboration, Development, Research, Asset Purchase (according to the terms' glossary of the RECAP database).

innovation processes (Wagner, 2011).[11] Whenever a firm of interest has faced an M&A-related event, it is counted. This enables the study to control for the M&A activity of a focal firm by year. The variable *HDI* represents the Herfindahl index and is used to control for the annually changing concentration levels within the technology classes (i.e. IPC classes) of a firm's patent portfolio. Furthermore, changes in a firm's knowledge base are controlled by the variable *Patent Stock (log)*. In line with extant literature, the knowledge represented by these patents is depreciated by 15% each year (Hall, 1990; Ernst, 1998). The variable *Experience* is based on the years since the foundation of the focal firms and helps to further address firm heterogeneity. In line with extant studies to control for time-related effects, the variable *Time Trend* is created by using ascending integer values each indicating the current year of observation (e.g. Stock et al., 2001; Rothaermel and Hill, 2005; Acs et al., 2009). A dummy variable is included that states where the firm is headquartered geographically because firms that are headquartered in different countries may have different patenting patterns. According to the Triad concept of the world economy, the firm may be headquartered in the United States, Asia, or Europe (Ohmae, 1985).

4.2.5 Descriptive analysis

To further explore the data in support of the multivariate analysis, Table 2 presents an overview of the sample, which describes the important characteristics of the firms of interest. In the sample, Amgen has the highest average annual sales (3.7 billion USD), whereas Regeneron Pharma has the lowest (45.6 million USD). As illustrated, not only are the firms that are bigger in terms of average sales reporting high levels of cooperation, but also are smaller firms.

The total number of patents of each firm does not reveal a pattern when sorted by total sales. In other words, there is no relationship between the size of the firm and the number of patents it applies for, from a descriptive perspective. Initial insights into technology specialization are indicated by the different IPC classes. Each patent is assigned to one of eight sections, 129 classes, and 635 subclasses. The first three (or four) IPC digits—breaking the categories down to the IPC classes (subclasses)—are the most pertinent to this study.[12] Most firms patent in four to five different IPC sections and six different IPC classes.[13] Firms with average sales below 300 million USD have less diversified patent portfolios, as they concentrate on a smaller number of IPC sections and classes. With some exceptions (Medimmune, Actelion, and

[11]Acquisition is defined as an event where "the Client Company acquires legal control (greater than 50%) of the R&D Company, including both assets and liabilities," and merger is defined as an event where the "legal control (50%+) of two entities passes to a third party from which the business of the two will be conducted on a ongoing basis" (according to the terms' glossary of the RECAP database).

[12]Sub-classes are additionally used to test whether the statistical analysis is robust.

[13]The highest level of diversification is found for Chiron, with 21 different IPC classes.

Table 2 Sample overview

Firm	Years	Average sales (in million USD)	M&A and alliances						Granted patents				Average Technological Change	SIC HDI[b]	SIC overlap[c]
			Total	M&A	Equity	Strategic[a] (equity)	Strategic	Technological	Total	Sections (of maximum 8)	Classes (of maximum 129)	Subclasses (of maximum 635)			
Amgen Inc	25	3669.03	1214	1.2%	5.7%	21.4%	17.0%	17.0%	1399	4	6	15	0.93	0.55	21.8%
Genentech Inc	18	2473.67	573	0.2%	4.0%	18.5%	14.7%	19.5%	1896	4	14	35	0.88	0.56	36.2%
Merck Serono SA	5	1997.20	157	0.6%	3.8%	17.2%	14.0%	21.7%	45	3	5	9	0.80	0.86	68.8%
Genzyme Corp	12	1573.52	729	3.4%	8.8%	20.6%	15.2%	18.5%	711	6	17	31	0.97	0.46	44.9%
CSL Ltd	13	1227.35	170	1.8%	5.3%	19.4%	15.9%	23.5%	58	5	10	24	0.81	0.84	27.1%
Life Technologies Corp	9	793.07	321	7.5%	8.4%	19.6%	18.7%	20.2%	387	3	5	8	0.89	0.72	16.7%
Gilead Sciences Inc	17	745.11	343	2.6%	8.2%	18.4%	12.8%	13.4%	356	4	10	31	0.88	0.91	33.3%
Medimmune Inc	12	616.21	315	1.0%	5.7%	19.7%	14.9%	20.0%	268	3	4	6	0.98	0.67	32.2%
Chiron Corp	23	600.24	1004	1.5%	6.7%	21.1%	15.9%	16.2%	1793	5	11	15	0.91	0.55	20.9%
Cephalon Inc	16	469.42	384	1.8%	3.9%	14.3%	12.2%	14.8%	282	5	21	47	0.95	0.73	34.5%
Millennium Pharmaceuticals	6	467.93	8	12.5%	12.5%	25.0%	25.0%	25.0%	35	5	17	34	0.65	0.80	71.7%
Actelion Ltd	6	420.25	44	4.5%	4.5%	11.4%	11.4%	20.5%	23	2	2	4	0.89	0.88	50.0%
Genencor International Inc	5	356.48	81	0.0%	2.5%	24.7%	22.2%	24.7%	400	6	19	44	0.89	0.72	0.0%
Nabi Biopharmaceuticals	12	195.94	79	2.5%	2.5%	10.1%	10.1%	13.9%	38	2	3	8	0.94	0.90	20.0%
Imclone Systems Inc	17	131.70	107	0.0%	3.7%	22.4%	18.7%	11.2%	97	4	6	15	0.89	0.63	25.0%
QLT Inc	13	98.00	224	2.2%	6.7%	16.1%	11.6%	12.9%	76	2	6	12	0.95	0.92	50.0%
Biogen Inc	20	66.35	499	0.0%	3.2%	18.2%	15.0%	15.0%	435	5	11	23	0.94	0.74	16.2%
Regeneron Pharmaceuticals	17	45.58	130	0.0%	8.5%	20.8%	12.3%	17.7%	271	4	8	14	0.93	0.83	39.3%
Average	13.67	885.95	354.56	2.0%	6.0%	19.0%	15.0%	18.0%	476.11	4.00	9.72	20.83	0.89	0.74	34.0%
Maximum	25.00	3669.03	1214.00	13.0%	13.0%	25.0%	25.0%	25.0%	1896.00	6.00	21.00	47.00	0.98	0.92	72.0%
Minimum	5.00	45.58	8.00	0.0%	2.0%	10.0%	10.0%	11.0%	23.00	2.00	2.00	4.00	0.65	0.46	0.0%

[a]These strategic alliances contain all alliances that are defined as strategic alliances [Asset purchase, Co-Development, Cross-License, Development, Distribution, Marketing, Research (according to the terms' glossary of the RECAP database)] and are also some alliance types that involve equity (i.e. equity agreements and joint ventures).

[b]Concentration measurement for the Standard Industry Classification (SIC) classes of the alliance partners.

[c]Relative SIC classes overlap between the focal firms and alliance partners.

Table 3 Descriptive statistics and correlation matrix

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	VIF
1. Technology specialization	0.60	0.49															
2. Non-equity strategic alliances	3.93	4.33	0.24*														18.1
3. Strategic and equity alliances	5.04	5.36	0.24*	0.97*													16.8
4. Technology alliances	4.29	5.03	0.29*	0.90*	0.88*												6.57
5. Tobin's Q	4.09	5.67	0.22*	0.05	0.05	0.01											1.26
6. Sales (log)	5.14	2.28	0.14*	0.41*	0.38*	0.51*	−0.11										3.56
7. IPC growth	−0.11	1.26	0.03	0.10	0.06	0.11	−0.01	0.06									1.24
8. M&A	0.45	1.01	0.07	0.29*	0.27*	0.34*	−0.09	0.33*	0.07								1.24
9. HDI	0.40	0.23	−0.26*	0.20*	0.20*	0.19*	−0.16*	0.19*	−0.26*	0.16*							2.01
10. Patent stock (log)	4.19	1.45	0.26*	0.51*	0.50*	0.55*	0.14*	0.60*	0.13*	0.30*	0.43*						4.14
11. Experience	15.02	7.57	0.32*	0.20*	0.16*	0.29*	0.11	0.51*	0.08	0.18*	−0.10	0.43*					3.01
12. Time trend	19.19	6.40	0.21*	0.08	0.03	0.22*	−0.08	0.62*	0.11	0.25*	−0.14*	0.39*	0.61*				2.69
13. Asia	0.05	0.22	−0.22*	−0.10	−0.11	−0.06	−0.15*	0.16*	0.02	−0.05	−0.09	−0.22*	−0.25*	0.10			1.87
14. Europe	0.04	0.21	−0.07	−0.09	−0.11	−0.04	−0.10	0.11	−0.09	−0.06	−0.10	−0.25*	−0.12	0.17	−0.05		1.69
15. United States	0.90	0.30	0.21*	0.14*	0.16*	0.07	0.18*	−0.20*	0.05	0.08	0.14*	0.34*	0.27*	−0.20*	−0.72*	−0.66*	3.29

$N = 246$.

*$P < 0.05$.

Genzyme), higher average sales increase the patent portfolios' level of diversification. Furthermore, firms with moderate and high levels of TC have significant more collaborative agreements than firms with relative low levels.

Further descriptive statistics and the correlation matrix are provided in Table 3. The dependent variable *Technology Specialization* has a mean of 0.60. The independent variables representing firm-specific cooperation activity are highly correlated in the data set (with the lowest correlation level of $r = 0.88$), which is not too surprising because they contain partly overlapping allying events. During the later analysis, these variables are estimated separately to avoid issues of multi-collinearity.[14] Therefore, each of these variables is estimated by means of a separate model. The average firm has a *Tobin's Q* value more than 1, representing a higher market than book value. The variable *IPC growth* shows a negative value with −0.11, which implies that the average number of IPC classes slightly decreases over time, from a descriptive perspective, indicating a trend toward lower diversification of technology. Furthermore, the average firm is engaged in 0.45 M&A-related events per year. *HDI* of the patents within the IPC classes shows a mean of 0.4, which points to a high patenting concentration in certain IPC classes. The country dummies indicate that most firms (90%) have their headquarters in the United States.

5. Results

This section describes the relationship of the independent and control variables with the dependent variable. To test the hypotheses, four models are estimated with a random-effects[15] logistic regression model, and their results are illustrated in Table 4.

The estimation is based on 246 observations, which represent unbalanced panel data on 18 biotechnology firms.[16] The models are estimated with a binary dependent variable, which makes interpretation and especially comparison of the results more difficult. In contrast to linear regression models, the coefficients of the logistic regression may not be readily interpreted as marginal effects. Therefore, the sample average of the marginal effects and the marginal effects evaluated at the mean of the regressors are computed and are presented in Table 4. Model 0 is a baseline model, which takes the effects of the control variables into account. Significant effects for *IPC growth*, *HDI*, and *Patent stock (log)* on the dependent variable are found. The

[14]A linear regression model has been used to estimate the variance inflation factor (VIF) for all models and is presented in Table 3. The moderate VIF values indicate no issues of multi-collinearity.

[15]The magnitude and direction of the results do not change when applying a fixed-effects specification as shown in Table A1. However, the Hausman test shows that in all instances, random-effects model is to be preferred.

[16]Celgene Corp. and MGI Pharma Inc. have been removed from the data set owing to the limited quality of the financial data available for them.

Table 4 Effect of alliances on technology specialization of successful biotechnology firms

	Model 0			Model 1			Model 2			Model 3		
		MEM	AME		MEM	AME		MEM	AME		MEM	AME
Independent variables												
Strategic and equity alliances				0.11 (0.05)**	0.026 (0.01)**	0.018 (0.01)**						
Non-equity strategic alliances							0.15 (0.06)**	0.033 (0.01)**	0.023 (0.01)***			
Technology alliance										0.17 (0.06)***	0.038 (0.01)***	0.027 (0.01)***
Control variables												
Tobin's Q	0.10 (0.07)	0.02 (0.01)	0.02 (0.01)	0.10 (0.07)	0.02 (0.01)	0.02 (0.01)	0.10 (0.07)	0.02 (0.01)	0.02 (0.01)	0.09 (0.07)	0.02 (0.01)	0.01 (0.01)
Sales (log)	−0.15 (0.16)	−0.03 (0.04)	−0.02 (0.03)	−0.20 (0.16)	−0.05 (0.04)	−0.03 (0.02)	−0.20 (0.16)	−0.05 (0.04)	−0.03 (0.02)	−0.21 (0.16)	−0.05 (0.03)	−0.03 (0.02)
IPC growth	−0.31 (0.14)**	−0.07 (0.03)**	−0.05 (0.02)**	−0.32 (0.15)**	−0.07 (0.03)**	−0.05 (0.02)**	−0.33 (0.15)**	−0.07 (0.03)**	−0.05 (0.02)**	−0.35 (0.15)**	−0.08 (0.03)**	−0.05 (0.02)**
M&A	0.11 (0.20)	0.02 (0.04)	0.02 (0.03)	0.05 (0.20)	0.01 (0.05)	0.01 (0.03)	0.04 (0.21)	0.01 (0.05)	0.01 (0.03)	−0.02 (0.21)	−0.01 (0.05)	0.00 (0.03)
HDI	−5.02 (1.09)***	−1.14 (0.26)***	−0.83 (0.15)***	−4.84 (1.09)***	−1.09 (0.25)***	−0.76 (0.15)***	−4.91 (1.09)***	−1.10 (0.25)***	−0.78 (0.14)***	−4.99 (1.09)***	−1.11 (0.25)***	−0.78 (0.14)***
Patent stock (log)	0.80 (0.26)***	0.18 (0.06)***	0.13 (0.04)***	0.63 (0.26)**	0.14 (0.06)**	0.10 (0.04)**	0.64 (0.26)**	0.14 (0.06)**	0.10 (0.04)**	0.61 (0.26)**	0.14 (0.06)**	0.10 (0.04)**
Experience	0.06 (0.05)	0.01 (0.01)	0.01 (0.01)	0.06 (0.05)	0.01 (0.01)	0.01 (0.01)	0.05 (0.05)	0.01 (0.01)	0.01 (0.01)	0.05 (0.05)	0.01 (0.01)	0.01 (0.01)
Time trend	−0.004 (0.06)	−0.001 (0.01)	−0.001 (0.01)	0.03 (0.06)	0.01 (0.01)	0.00 (0.01)	0.02 (0.06)	0.01 (0.01)	0.00 (0.01)	0.02 (0.05)	0.00 (0.01)	0.00 (0.01)
Asia	−0.98 (1.42)	−0.24 (0.35)	−0.17 (0.24)	−1.06 (1.42)	−0.26 (0.34)	−0.17 (0.23)	−1.10 (1.43)	−0.27 (0.34)	−0.18 (0.23)	−1.32 (1.36)	−0.32 (0.31)	−0.21 (0.21)
Europe	0.48 (1.19)	0.10 (0.23)	0.08 (0.18)	0.32 (1.18)	0.07 (0.24)	0.05 (0.18)	0.28 (1.19)	0.06 (0.24)	0.04 (0.18)	0.03 (1.16)	0.01 (0.26)	0.01 (0.18)
Constant	−1.17 (0.79)			−1.33 (0.81)			−1.23 (0.80)			−0.89 (0.79)		
Observations (groups)		246 (18)			246 (18)			246 (18)			246 (18)	
Pseudo R^2		0.27			0.29			0.29			0.31	
Log Likelihood		−122.7699			−119.5934			−119.2971			−117.3326	
Wald χ^2 (*df*)		45.96 (10)***			47.28 (11)***			47.33 (11)***			48.39 (11)***	

MEM, marginal effects at mean; AME, average marginal effects.

Results of a random-effects logistic regression model.

Standard errors in parentheses.

*$P<0.1$, **$P<0.05$, ***$P<0.01$ (two-sided tests).

growth in IPC classes shows a negative effect at a 5% significance level. The growth in the number of IPC classes from period t to period $t-1$ tends to have negative effect on the dependent variable. Firms that have technological activities in many fields are likely to have patents in diverse IPC classes. Hence, those firms do not specialize on a certain technological opportunity. The variable *HDI* shows a negative effect at a 10% significance level. This variable controls for changes in concentration levels from period t to period $t-1$ and shows that firms that concentrate their research activities on many IPC classes have lower levels of technology specialization than firms that focus on a small number of IPC classes. *Patent stock (log)* shows a positive influence on the dependent variable at a 10% level and points out that a higher patent stock positively influences levels of a focal firm's technology specialization in subsequent periods. These effects do not change in terms of sign and significance when further variables are added. Adding the independent variable *Strategic and Equity Alliances*, as described in Model 1, increases the fit of the model and shows a positive effect on the dependent variable *Technology Specialization* at a significance level of 5%. Furthermore, the control variables do not significantly change when adding the independent variable *Strategic and Equity Alliances* to the baseline model, as in Model 1.

Furthermore, Model 2 shows a positive influence of the variable *Non-Equity Strategic Alliances* on *Technology Specialization*. This effect is somewhat bigger (0.15) than the influence of strategic alliances combined with equity alliances (0.11) and is significant at a 5% level. Furthermore, the same control variables as in Model 1 show a significant effect on the dependent variable.

Finally, the influence of the variable *Technology Alliances* in Model 3 has a positive influence on *Technological Specialization*. This effect with a coefficient of 0.17 (1% significance level) has a stronger effect on the dependent variable than the variables *Strategic and Equity Alliances* (0.11) and *Non-Equity Strategic Alliances* (0.15). The control variables show similar estimation results to the two previous models, which further supports the stability of the results.

The marginal effects for the alliance variables of the logistic regression models indicate that the estimated effects of the different types of alliances in Models 1–3 differ significantly from each other.

In summary, H1 that proposes a positive effect of cooperation on a firm's technological specialization is fully supported through the types of alliances in Models 1–3. This indicates that a biotechnology firm that collaborates to a considerable degree is more likely to possess coherent and stable subsequent research activities than a biotechnology firm with low collaboration activities. H2 assumes a diminishing influence of higher levels of equity involvement within a collaborative agreement on technological specialization, and is also supported. Technology alliances characterized by an independent and loose cooperation structure compared with the collaboration types of interest have a higher positive effect on technological specialization than the other two types of alliances tested.

6. Discussion

The more alliances a firm forms during a certain year, the higher the probability that the firm's historic patterns of patent applications will match the post-deal patent applications. That is to say, more cooperative agreements lead to research activities in focused knowledge areas. These results indicate that cooperative firms in the biotechnology industry pursue rather specialized and focused research, more than they do diversified research. This result is consistent with the characteristics and motivations of the biotechnology industry. A key to success for firms in high-technology industries is the rate of new product development (Deeds and Hill, 1996). The highly competitive nature of the biotechnology industry dictates that new discoveries have to be protected immediately, which can cause patent races (Gilbert and Newbery, 1982). This "winner-takes-all" attitude of the industry demands accelerated research. To address this need and to gain a first mover advantage within the industry, cooperation is used as a management tool to accelerate a firm's own R&D processes through scale economies, and to complement resources to discover new products based on existing technologies rather than on explorative and entirely new technologies. Additionally, this increasing number of patents makes a biotechnology firm more attractive for investors (e.g. pharmaceutical companies). Owing to long clinical testing process of drugs, the enormous corresponding costs (Schmidt and Calantone, 2002), and the involved technological complexity (Talay *et al.*, 2009), even experienced and successful biotechnology firms need financial and technological support through partners. However, these partners only invest in and develop technologies that are to some extent promising where first mover advantages can be captured. Therefore, it is rational for biotechnology firms to further exploit technologies (e.g. drugs) that have been successful in the past, and which are more likely to be prosperous in the future. Continuous development and a consistent flow of new products are important for high levels of firm performance (Artz *et al.*, 2010).

The results show that firms that engage in many strategic and equity alliances tend to have less technology specialization. That is to say, a joint project that involves equity, such as a JV, leads to the focal biotechnology firm's subsequent research activities moving into more distinctive knowledge areas. In fact, the effect of strategic equity alliances on technological specialization remains positive, but has a diminishing influence compared with the general influence of strategic alliances. One explanation for this discrepancy could be in the different pre-requisites management uses as decision base before entering one of the two types of alliance. The propensity to engage in equity alliances is greater when there is a great deal of uncertainty about the project outcome (Folta, 1998). Levels of uncertainty are highest for firms (i) that operate in distinctive knowledge areas and (ii) that have no pre-existing relationships to each other (De Man and Duysters, 2005). Yet, firms that would like to cooperate through equity alliances have to minimize uncertainty, which is a time-consuming process. The first step is to cooperate with partners operating in similar areas of

knowledge through loose non-equity (learning) alliances, which have low levels of equity involvement. After setting up relationship and communication channels, firms may better evaluate the likelihood of successful joint projects. As a result, there will be less uncertainty about whether an alliance that involves more equity will be successful or not. The resulting superior connection between the allying partners and the better communication owing to the previous relationship allows them to explore fields that differ slightly from their core research (De Man and Duysters, 2005).

To engage in a strategic alliance is only justified if the collaborative gains at least compensate the cost of undertaking the alliance (Singh, 1997). Therefore, another explanation for the aforementioned diminishing effect may be found in the fact that strategic equity alliances demand larger investments than their non-equity counterparts. Hence, these projects have to yield higher returns to compensate the greater efforts and resources that are put into them. Scholars find that innovative performance is stronger when firms are engaged in explorative alliances (Nooteboom *et al.*, 2007), which result in novel technologies (Singh, 1997). That is to say, alliances that focus on explorative technology research are more likely to yield higher profits. Therefore, to capture these higher returns that are needed to compensate the higher initial investments for equity alliances, firms have to promote more explorative and experimental research.

Technology alliances that are characterized by low levels of equity involvement show the highest positive effect on technological specialization. An explanation for this influence is that the biotechnology industry is very research driven. Evaluating the effect of technology alliances exclusively, disregarding for instance marketing and purchasing alliances, these alliances are the ones that should yield innovation. Therefore, biotechnology firms that engage in technology alliances are more likely to have more patents granted (Al-Laham *et al.*, 2011).

7. Conclusions

This article analyzes various types of alliances and their effect on innovation patterns in the biotechnology industry. Although most research describes how alliances influence innovation across a number of industries, little is known about its direct effects on the innovation patterns of biotechnology firms. This article seeks to close this gap by distinguishing different types of alliances and by using a new approach to quantify temporal technology dynamics. A set of hypotheses on the relationship between alliances and changes on the basis of the firm's technological portfolio is derived and then tested. It is shown that the higher the number of alliance deals, the higher the degree of research specialization that follows. This effect diminishes when the equity involvement of the firms in the alliance increases.

The empirical results show that firms in the biotechnology industry use alliances to perform focused research. A biotechnology firm that establishes a partnership through any kind of collaborative agreement throughout the year shows a higher subsequent technological specialization (year-on-year technology overlap). An explanation is found in the high-technology characteristics of the industry analyzed. Unlike most other industries, the biotechnology industry is characterized through frequent and immediate patenting. Once a firm patents a technology, competitors are legally prohibited from further developing that technology. Owing to this "winner-takes-all" attitude, alliances are used to accelerate R&D processes and to capture first-mover advantages. The results are similar for all types of alliances that are analyzed. However, the various types of alliances have differing effects on technological specialization. First, strategic alliances show a weaker effect when they are implemented through equity alliances (e.g. JVs). The reason for this is that strategic equity alliances are often follow-up investments, indicating pre-relational contracts between the partners, through a previous (learning) alliance, for example. These relationships allow the alliance partner more efficient and effective communication, which reduces misinterpretations. Therefore, uncertainty about the possible success of an alliance decreases and allows joint research projects in areas that deviate slightly from the actual line of business. Furthermore, investments in strategic equity alliances and levels of irreversibility are higher than those required by non-equity alliances. To compensate for the higher expenditure, expected returns have to be higher than would arise from strategic non-equity alliances. Explorative and experimental alliances that have a focus on the development of new technologies are characterized by higher innovation levels, and greater potential profits. Furthermore, technology alliances have the highest influence on technology specialization as strategic alliances with equity involvement. Technology alliances are core elements in the research-driven biotechnology industry. Therefore, they these alliances are used to accelerate research, which in turn may lead to the early filing of patents.

In conclusion, this article shows that the effect of alliances has effects different from the general effects revealed in the extant literature on firms in the biotechnology industry. While most literature states that firms try to acquire knowledge through cooperation to enter and explore new markets, firms in the biotechnology industry try to create a competitive advantage through cooperating by specializing within narrower knowledge areas. Furthermore, this study contributes by filling the gap in research about the effect of equity alliances on firm-specific research. While most alliance research has neglected the analysis of this effect thus far, this study has shown that firms that collaborate through equity alliances are more likely to engage in research that differs strongly from their core technology. However, this analysis has some limitations. This study is based almost entirely on one country. On the one hand, the most successful biotechnology firms are located in the United States, and thus the sample represents the parent population. On the other hand, country-specific characteristics could limit the generalizability of the results.

Therefore, the data should be extended by information drawn from biotechnology firms around the world. Furthermore, some firms of interest have not been public throughout their economic lifetime, making financial data unavailable. Therefore, survey research should be used to extend the database.

Whether partners compete on the product market or only relate to each other as concerns the technologies used, is an additional factor that could associate technology specialization (Cusmano, 2000). This could be either directly or indirectly by affecting observable alliance characteristics such as whether an alliance is equity based or not (Stiebale, 2010).[17] Unfortunately, this information is not directly available for this study. However, information about the SICs of the alliance partners is available, which can be taken as a proxy for product market competition. Furthermore, being classified as technology alliance makes technological overlap of partners less likely. When summing this up across years and comparing it with the percentage shares of technology (which are by definition non-equity) and equity alliances, it becomes clear from Table 2 that the associations are not straightforward. The highest correlation between alliance types and the overlap in SIC classes between focal firms and their alliance partners is found for equity alliances ($r = 0.47$), indicating that firms that compete on the product market rather cooperate through equity-based alliances. This could increase the stability of an alliance or reduce opportunistic behavior of partners. However, future research would be well advised to explore these interlinkages with more direct measures of technology relatedness and product market competition. Additionally, further research should concentrate on technological specialization in other industries to enable comparison across industries. Specifically, research should test whether the analyzed effects of alliances on technological specialization have similar effects in other high- and low-technology industries. Furthermore, the effect of alliances on innovation has to be analyzed in more detail by emphasizing the different economic value of explorative and exploitative alliances and on the previous relationships between the collaborating partners. All these extensions could ideally also be done using dyads as units of analysis to ascertain (as we expect) that no significant differences of the results exist compared with a firm-level analysis. Finally, future research could also combine the approach of this article with data on new product development in the biopharmaceutical industry.

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Appendix

Table A1 Fixed-effects regressions of alliances on technology specialization of successful biotechnology firms

	Model 0		Model 1		Model 2		Model 3	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Independent variables								
Strategic and equity alliances			0.11	0.05**				
Non-equity strategic alliances					0.14	0.07**		
Technology alliance							0.15	0.06**
Control variables								
Tobin's Q	0.10	0.07	0.11	0.08	0.11	0.08	0.10	0.08
Sales (log)	−0.37	0.18**	−0.41	0.19**	−0.40	0.19**	−0.41	0.19**
IPC growth	−0.27	0.15*	−0.29	0.15*	−0.30	0.16*	−0.31	0.15**
M&A	0.07	0.24	0.08	0.24	0.08	0.24	0.03	0.24
HDI	−4.00	1.22***	−3.94	1.23***	−3.99	1.23***	−3.99	1.24***
Patent stock	0.37	0.37	0.26	0.38	0.30	0.38	0.29	0.38
Experience	0.21	0.09**	0.22	0.09**	0.20	0.09**	0.19	0.09**
Observations (groups)	217 (15)		217 (15)		217 (15)		217 (15)	
Log likelihood	−82.9201		−80.7711		−80.5955		−79.6990	
Wald χ^2 (*df*)	55.24 (7)***		59.54 (8)***		59.89 (8)***		61.68 (8)***	

Coeff., coefficient; SE, Standard error.

Results of a fixed-effects conditional logistic regression model.

***$P<0.01$, **$P<0.05$, *$P<0.1$ (two-sided tests).