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University alliances and firm exploratory innovation: Evidence from therapeutic product development

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ABSTRACT

This paper investigates the relationship between university alliances and firm exploratory innovation in the context of therapeutic product development. We build on organizational learning theory to elucidate that the use of university alliances is more positively associated with firm exploratory rather than exploitative innovation output. Moreover, we argue that the breadth of a firm's technological expertise strengthens the benefits of university alliances in the development of exploratory innovation output. Our empirical analysis is based on a panel dataset of 220 US therapeutic biotechnology firms from 2003 to 2010. Our findings support the contention that university alliances are differentially related to exploratory and exploitative innovation outcomes, and further indicate that firm technological breadth positively moderates the relationship between university alliances and firm exploratory innovation.

1. Introduction

Instead of relying solely on internal scientific research, firms in technology-intensive sectors increasingly embrace university collaborations to support their corporate R&D efforts (Arora et al., 2018; Fabrizio, 2009; Frølund et al., 2018; Hemmert et al., 2014; Perkmann and Salter, 2012; Simeth and Raffo, 2013; Walsh et al., 2016; Wirsich et al., 2016; Zucker et al., 2002). University alliances represent an important channel for firms to tap into scientific knowledge exchange networks and gain privileged access to early-stage scientific discoveries, promising university research and tacit knowledge (Belderbos et al., 2016; Bercovitz and Feldman, 2007; Stuart et al., 2007). Although engaging in collaborations with academics might entail selective revealing of firm proprietary knowledge (Alexy et al., 2013), allying with universities has been linked to significant innovation-related benefits for firms such as enhanced scientific productivity (Simeth and Raffo, 2013) and the development of high-impact inventions (e.g., Fabrizio, 2009; Fleming and Sorenson, 2004; George et al., 2002; Walsh et al., 2016; Zucker et al., 2002). Nonetheless, such innovation-related gains are contextually specific or contingent on firm attributes such as firm internal resources, scientific capabilities, and absorptive capacity, among others (Bruneel et al., 2016; Fabrizio, 2009; Hess and Rothaermel, 2011; Soh and Subramanian, 2014; Wirsich et al., 2016). Hence, despite the consensus in the literature that university alliances induce knowledge sourcing opportunities for firms, more systematic investigation needs to assess the contingent nature of the relationship between university alliances and firm innovation outcomes.

To address this research gap, we examine how embracing university alliances may be differentially related to firm exploratory and exploitative innovation output in therapeutic product development. Whereas exploitative innovations build on firms' existing knowledge and experience, exploratory innovations entail R&D moves into new fields where firms' existing knowledge and experience do not suffice (Arts and Fleming, 2018; March 1991; Rosenkopf and Almeida, 2003). We integrate insights from organisational learning theory (e.g., March 1991) and past scholarly work on university-industry collaborations (e.g. Soh and Subramanian, 2014; Stuart et al., 2007) to argue that university alliances are more positively associated with firm exploratory innovations than with firm exploitative innovations. Furthermore, we conjecture that the positive relationship between university alliances and firm exploratory innovations is stronger when firms have research capabilities across a greater technological breadth. We focus on the breadth of firm technological expertise as a moderator because this firm attribute has been found to facilitate knowledge exchange and learning processes across organizational borders (Zhang et al., 2007; Zhang and Baden-Fuller, 2010).

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Our empirical analysis is based on a novel and comprehensive panel dataset of 220 US therapeutic biotechnology firms over the period 2003–2010, and 1323 firm-year observations. This is an appropriate research setting as drug development projects in human therapeutics often build on university research, and university-industry alliances are commonplace in this industry (e.g., McMillan et al., 2000; Stuart et al., 2007). Our results from estimating negative binomial models with random effects provide empirical support for our hypotheses.

The contribution of this study to the literature is threefold. First, it highlights that firms' involvement in university alliances is more positively associated with firm exploratory rather than exploitative innovation output in therapeutic product development. Whereas prior work has largely focused on the relationship between university alliances and firm overall innovation performance (e.g., Fabrizio, 2009; George et al., 2002), our study underscores that such relationship is contingent on the type of innovations firms pursue. Second, our study is novel in identifying the moderating role of firm technological breadth in the examined relationship, suggesting that firms with expertise in diverse technological domains can capture greater benefits from university alliances for their exploratory R&D endeavours. In doing so, we add to the growing body of empirical work that takes a contingent approach to study the effects of university-industry collaborations on firm innovative performance (Bruneel et al., 2016; Fabrizio, 2009; Hess and Rothaermel, 2011; Soh and Subramanian, 2014; Wirsich et al., 2016). Finally, we contribute empirically to the exploration-exploitation literature. Whereas prior empirical research has mostly used patent data or survey data to differentiate between exploratory and exploitative innovation outputs (e.g., Benner and Tushman, 2002; Gilsing et al., 2008; Guan and Liu, 2016; Jansen et al., 2006; Phelps, 2010), we use data on drug development projects for this purpose.

2. Theoretical background and hypotheses

The organization of firm innovation entails a trade-off between *exploration* of knowledge and ideas that are new to the firm and *exploitation* of a firm's existing knowledge and expertise (March 1991; Levinthal and March 1993). Whereas exploratory innovation is linked to experimentation, distant search, and variation from a firm's core knowledge and capabilities, exploitative innovation is associated with local search, refinement and extension of a firm's existing knowledge and competences (Alexiev et al., 2010; Benner and Tushman, 2015; Bercovitz and Feldman, 2007; Guan and Liu, 2016; March 1991). Keeping the right balance between exploratory and exploitative innovation within a firm represents a major challenge as these two innovation types impose conflicting demands on a firm's organisational design and resources (Lavie et al., 2010).

In this study, exploratory innovation is defined from the viewpoint of the firm and refers to a product development project in areas that are new to the firm. The existing literature underscores two important characteristics of exploratory innovation –its recombinant nature and uncertainty of success– that further differentiate it from exploitative innovation (Cui et al., 2019; March 1991). Thus, exploratory innovation entails a recombination of cross-boundary knowledge and a shift away from an organization's existing knowledge base, skills, and problem-solving approaches, which is risky and uncertain in terms of success rate (Bierly et al., 2009; Lavie et al., 2010; March 1991; Rosenkopf and Nerkar, 2001).

Despite this fundamental distinction between exploratory and exploitative innovations, prior research on how firms use university alliances in support of their innovation processes has largely focused on firm overall innovation performance (e.g., Fabrizio, 2009; George et al., 2002). In the section below, we argue that university alliances are differentially related to exploratory and exploitative innovation outcomes.

2.1. University alliances and exploratory innovation

In this paper, university alliances refer to firms' collaborative agreements with academic institutions for sourcing upstream knowledge (e.g., Hess and Rothaermel, 2011). University alliances provide firms with exposure to early-stage scientific discoveries and tacitly held university research (Belderbos et al., 2016; Stuart et al., 2007; Zucker et al., 2002), novel problem-solving approaches (Bercovitz and Feldman, 2007; Du et al., 2014), and access to academic knowledge exchange networks (Wang and Shapira, 2012). A fundamental challenge in a firm's engagement with universities lies in the conflicting institutional norms governing public and private knowledge (Bruneel et al., 2010: Simeth and Raffo, 2013). Whereas university scientists follow the norms of open science and are keen to disseminate information within the scientific community to gain priority, firms may wish to appropriate the information for private gains (Dasgupta and David, 1994; Perkmann and Walsh, 2007). Given these challenges involved in university alliances, it is important for firms to understand the circumstances, under which university alliances are more (or less) beneficial.

We contend that engagement in university alliances is more beneficial for firms' innovation efforts oriented towards exploration rather than exploitation. First, university alliances have proven an effective conduit for learning across organisational boundaries (Bercovitz and Feldman, 2007; Liebeskind et al., 1996; Rosenkopf and Nerkar, 2001). By being such a conduit, university alliances support firms in embarking on learning trajectories that are more in line with exploratory innovation than with exploitative innovation. University research environments generally provide more space for autonomy and freedom for researchers to recombine knowledge from disparate fields, explore novel lines of research and contest established research approaches (Dasgupta and David, 1994; Du et al., 2014). Moreover, the research environment of university scientists is organized along a very different institutional logic based on norms of open science and academic incentive system than the research environment of firm scientists (Belderbos et al., 2016; Dasgupta and David, 1994; Perkmann and Walsh, 2007). This all is conducive to yielding novel, non-routine problem-solving approaches for firms that are more associated with exploratory than exploitative innovation. Thus, since university alliances may help partner firms overcome the tendency of local search and building on a firm's existing knowledge in the R&D process (Ahuja and Lampert, 2001; Rosenkopf and Almeida, 2003; Rosenkopf and Nerkar 2001), we expect a stronger positive association between university alliances and firm exploratory innovations rather than firm exploitative innovations.

In addition, university alliances can help firms mitigate the risks and uncertainties in the early stages of the R&D process that are associated with exploration (Banerjee and Siebert, 2017). Specifically, studies highlight how university alliances provide partner firms with a lower risk alternative to internal R&D (Veugelers and Cassiman, 2005) that is also cheaper (George et al., 2002). Drawing on basic science in the context of engagement with scientific communities allows firms to be more focused and structured in the distant search processes underlying the exploratory innovation and better cope with the inherent uncertainty associated with it (Fabrizio, 2009; Fleming and Sorenson, 2004). Indeed, past work has demonstrated that employing the so-called *scientific search mode* guides firms' search efforts in new and complex problem-solving contexts and facilitates the development of innovations with a higher degree of novelty (Fleming and Sorenson, 2004; Köhler et al., 2012). Also, firms can benefit from the standing and reputation their university partners have in the scientific community (Wang and Shapira, 2012), and gain advice and legitimacy for their exploratory R&D (Alexiev et al., 2010).

Taken together, the above arguments give rise to the following hypothesis:

Hypothesis 1. University alliances are more positively associated with firm exploratory innovation output than with firm exploitative

innovation output.

2.2. The moderating role of technological breadth

Firms learn in a path-dependent way (Levinthal and March 1993; March 1991; Mowery et al., 1996) and certain attributes of a firm's current knowledge base such as *firm technological breadth* may influence the learning benefits the firm derives from university alliances (Zhang and Baden-Fuller, 2010). In this study, we follow prior work (Zhang et al., 2007; Zhang and Baden-Fuller, 2010), and define firm technological breadth as the range of technological areas a firm has expertise in. We argue that the positive relationship between university alliances and firm exploratory innovations is stronger for firms that are active in a broader set of technological domains.

Firms with a broader technological expertise are exposed to more diverse knowledge domains, and when interacting with university partners are more likely to find new, previously untried knowledge combinations (Katila and Ahuja, 2002; Mannucci and Yong, 2018; Soh and Subramanian, 2014). Such firms likely have a stronger absorptive capacity, and more effectively screen, assimilate, and integrate external knowledge, sourced through university-industry alliances (Cohen and Levinthal, 1990). This is because absorptive capabilities are to an important extent specific to a particular knowledge domain (Huang and Jong, 2019). Thus, the broader the firm technological expertise, the higher the likelihood that incoming scientific knowledge relates to some parts of firm existing knowledge base (Ahuja and Lampert, 2001; Cohen and Levinthal, 1990; Zhang et al., 2007). Bridging knowledge elements across borders and domains creates opportunities for knowledge brokerage (Hargadon and Sutton, 1997), experimentation with novel ideas (Miller et al., 2007; Rosenkopf and Nerkar, 2001), and the creation of new knowledge combinations, associations, and analogies (Ahuja and Lampert, 2001; Cassiman et al., 2008; Fleming, 2001; Galunic and Rodan, 1998). Accordingly, we expect firm technological breadth to be a positive moderator of the relationship between university alliances and firm exploratory innovation outputs.

Moreover, we expect firms with broader technological expertise to realize stronger synergies in R&D partnerships with universities (Mindruta, 2013; Pisano, 2006). Firms generally use university alliances to gain access to specialized scientific knowledge at early stages of development (Belderbos et al., 2016; Bercovitz and Feldman, 2007; Bstieler et al., 2015; Stuart et al., 2007; Veugelers and Cassiman, 2005). As firms expand their technological breadth, they are better positioned to exploit these complementarities between their internal knowledge base and the specialized external scientific knowledge, sourced through university alliances, in their exploratory R&D efforts (Mindruta, 2013; Soh and Subramanian, 2014).

Thus, our second hypothesis is as follows:

Hypothesis 2. University alliances are more positively associated with firm exploratory innovation output as firm technological breadth increases.

3. Method

3.1. Data and sample

The research setting for this study is the human therapeutics subsector of the US biotechnology industry. New product development in human therapeutics is a protracted and expensive process (Powell et al., 1996); it relies on a highly complex knowledge base and dense collaborative networks of academic and commercial organizations (Jong, 2006; Liebeskind et al., 1996; Whittington et al., 2009). Moreover, it is subject to extensive regulatory requirements (Rothaermel and Deeds, 2004). Firms involved in human therapeutics are especially science-intensive (McMillan et al., 2000; Stuart et al., 2007), and provide an ideal setting to study the dynamics of university-industry collaborations and new drug discovery and development (Hoang and Rothaermel, 2010). Also, focusing on this specific segment of the US biotechnology industry allows us to construct a more homogeneous sample and control for industry idiosyncrasies (Rothaermel and Deeds, 2004; Whittington et al., 2009).

We focus in our empirical analysis on publicly traded and independently operated US therapeutic biotechnology firms that are active in early stages of therapeutic product development. To construct our sample, we used the following criteria. First, we matched the names of the US biotechnology firms that initiated at least one therapeutic R&D project at a preclinical stage during the period 2003–2010 according to the Pharmaprojects database with the active publicly traded biotechnology companies listed in Datastream database. Next, consistent with past research (Kehoe and Tzabbar, 2015; Whittington et al., 2009), we drew on Lexis Nexis Corporate Affiliations database and excluded all firms that were not independent entities (e.g., subsidiaries, joint ventures) or were founded before 1973. This procedure yielded a sample of 220 therapeutic biotechnology firms.

We retrieved information on these firms from a variety of data sources. We used Pharmaprojects database to collect detailed information on each firm's drug development pipeline, including stages of development and therapeutic categories for each drug candidate. Pharmaprojects is a comprehensive database tracking clinical trials in the global biopharma industry from the earliest stage of a drug's development through to discontinuation or launch and has been widely used in scholarly work (Aggarwal and Hsu, 2014; Hess and Rothaermel, 2011; Sosa, 2011). Further, we drew on Scopus database to collect bibliographic information for all the scientific papers published by the firms from our sample in indexed academic journals. To gather data on the firms' patent portfolios and the technological classes in which each firm applies for patents, we used United States Patent and Trademark Office (USPTO) database. Next, we used Recombinant Capital (Recap) database to collect data on alliances with universities and firms. As recognized in past research (Hoang and Rothaermel, 2010; Schilling, 2009), Recap is one of the most comprehensive data sources tracking alliance activity in the biotechnology industry between organizations of any type, including firms, universities, government laboratories, etc. Finally, we used Datastream database to obtain financial information for firms, such as R&D expenditure, total assets, etc.

Our final sample consists of 220 US-based therapeutic biotechnology companies and our econometric analyses are based on an unbalanced panel dataset consisting of 1323 firm-year observations over the period 2003–2010.

3.2. Measures

3.2.1. Dependent variable

The dependent variable in this study is firm innovation output. We measure this variable as an annual count of new drug candidates that enter preclinical testing. This measure of innovation output is consistent with measures used by others in the empirical context of therapeutic product development (e.g., Aggarwal and Hsu, 2014; Bierly and Charkrabarti, 1996; Hess and Rothaermel, 2011; Jong and Slavova, 2014; Sosa, 2011). As the therapeutic development process is so costly, risky, and protracted over time, traditional measures of R&D success such as sales or even products on the market are problematic. Accordingly, industry practitioners and observers use alternative proxies for R&D performance and value creation, with the progression of projects along the different stages of the preclinical and clinical testing trajectory being the most widely used. Firms realize a significant amount of value during the clinical trials process, well before any product hits the market. For example, in its acquisition of Pharmasset that was announced at the end of 2011, Gilead Sciences in essence paid US$ 11 billion for a hepatitis C drug that was in clinical trials phase 2 of the drug development path (Grocer, 2011).

Further, our empirical approach entails differentiating between

exploratory and exploitative innovation output. In this study, exploratory innovation output is operationalized as the number of new drug candidates at a pre-clinical stage of development in therapeutic areas that are new to the firm. To create these measures, we examined the distribution of each firm's drug development projects across different therapeutic categories, identified in Pharmaprojects database. Pharmaprojects uses more than 200 therapeutic categories to classify drug candidates according to the disease areas for which they are being developed. Examples of such therapeutic categories include: Anticancer, other; Anticancer, immunological; Antiviral, other; Anti-inflammatory; Cardiovascular; Monoclonal antibody, other; Antidiabetic, among others. We consider a new drug candidate in a given year as exploratory innovation if it is classified in a therapeutic category, in which the focal firm did not have any drug candidates in the pipeline in the previous five years. Specifically, we measured exploratory innovation output as the number of new preclinical trials in therapeutic categories in which firms did not have experience in the previous five years. We operationalized exploitative innovation output as the number of new preclinical trials in therapeutic categories in which the firms had previous drug candidates under development over the preceding five years.

3.2.2. Independent variables

Our main predictor in the estimated models – *university alliances*– is measured as the number of cooperative agreements with universities. Consistent with past work (George et al., 2002; Soh and Subramanian, 2014), we used Recap database to identify such agreements. Specifically, Recap provides information about the agreements formed by biotechnology firms, including the alliance type, the type of alliance partner (e.g., university, firm), and the date of alliance formation. Following Stuart et al. (2007), we counted the total number of cooperative agreements with universities for each firm from our sample in years t, t-1, and t-2. The use of a moving window of three years allows us to attenuate annual fluctuations and captures more accurately a firm's propensity to form alliances with universities.

3.2.3. Moderator variables

With the variable *technological breadth,* we gauge the range of technological areas a firm has expertise in. For that purpose, we used the three-digit patent classifications listed on each firm's patent, provided by USPTO. Consistent with prior work (George et al., 2008; Kotha et al., 2011; Zhang et al., 2007; Zhang and Baden-Fuller, 2010), we measured *technological breadth* as the number of different three-digit technology classes in which the focal firm has patents in years t, t-1, and t-2.

3.2.4. Control variables

We include several controls in the estimations of our models.

Alliances with firms. We include the number of alliances with firms each biotech firm from the sample has formed in the previous three years to account for alternative sources of external knowledge. Indeed, prior research has recognized cooperative agreements with commercial partners to be an important channel for knowledge transfer (Grant and Baden-Fuller, 2004).

Patents. We account for firm knowledge stock by counting the number of patents each firm has applied for at the USPTO for a moving window of three years (George et al., 2008; Kotha et al., 2011).

Pipeline. We control for a firm's experience in the development of new therapeutic products by including the number of therapeutic products in the firm's pipeline over the prior three-year period.

Discontinued drugs in development. We include the number of discontinued drugs in development for a moving window of three years to account for the possibility that past failure might influence subsequent new product development endeavours (Hu et al., 2017).

Publications. We control for the number of firm publications in scientific journals for a moving window of 3 years as prior work has used this variable as a proxy for the scientific capabilities of corporate researchers (e.g., Deeds et al., 2000; Gittelman, 2007).

R&D expenditure. Because R&D spending likely affects a firm's knowledge base and innovation capabilities (Cohen and Levinthal, 1990), we control for R&D expenditure in mil$ over a moving window of three years.

Firm size. We control for firm size, operationalized as a logarithm of firm total assets because larger firms likely enjoy economies of scale and scope (Soh and Subramanian, 2014).

Firm age. We control for firm age, and proxy this as the difference between the current year and the company's founding year, as past work suggests that firm age might shape firms' commitments towards explorative or exploitative activities (e.g., Ardito et al., 2019).

We use year fixed effects to control for possible time specific effects that affect the whole biotechnology industry, such as market conditions or the general economic environment.

We adopt a lagged specification and use a 1-year lag between the observation of our independent and control variables on the one hand and the observation of our dependent variable on the other hand. This allows some time to capture the hypothesized learning effects and helps mitigate endogeneity and reverse causality concerns.

3.3. Statistical method

The dependent variable in our different model specifications is a count variable (annual count of new drug candidates that enter preclinical testing). While Poisson regression is appropriate to model count data, the variance of the dependent variable exceeds its mean, suggesting that over-dispersion might be a concern (Hausman et al., 1984). Therefore, we follow Cameron and Trivedi (1998) and use negative binomial regressions to estimate our models. Next, we consider including firm effects to address potential firm specific unobserved heterogeneity (Dushnitsky and Lenox, 2005). We performed Hausman specification tests, and the results suggest that the use of random effects models is appropriate. Therefore, we adopt random effects negative binomial regressions to test our hypotheses. To assess the sensitivity of our results we additionally performed fixed effects negative binomial estimations. The main results remained robust.

4. Results

Table 1 presents descriptive statistics, including the means, standard deviations, minimum and maximum values, and a correlation matrix among the main variables used in the analysis. On average, a firm in our sample engages in 0.55 alliances with universities over a period of three years and introduces 1.04 new preclinical drug candidates each year. Variance inflation factors (VIFs) are used to assess the threat of multicollinearity. The maximum value of the VIFs associated with the predictors is 2.66. This suggests that multicollinearity is unlikely to be a concern in our analysis.

Table 2 reports the results from estimating random effects negative binomial models for new therapeutic product development projects. The dependent variable in Model 1 is innovation output. The random-effects negative binomial regressions show a non-significant effect of university research alliances on the annual count of new drug candidates that enter preclinical testing.

We further proceed with a more fine-grained analysis by differentiating between exploratory innovation output and exploitative innovation output. Hypothesis 1 predicts a stronger positive relationship between embracing cooperative agreements with universities and a firm's propensity to produce exploratory (rather than exploitative) innovations. To test Hypothesis 1, we follow a methodology used in past empirical studies (e.g., Bierly et al., 2009; Guan and Liu, 2016; Jansen et al., 2006), and re-estimate the specification in Model 1 separately for the firm's new drug candidates that are classified as exploratory innovations and exploitative innovations.

First, we ran the specification in Model 1, using as a dependent variable exploratory innovation output. The results are presented in

Table 1
Descriptive statistics and correlations.

		mean	st.dev.	min	max	1	2	3	4	5	6	7	8	9	10	11	12	13
1	**Innovation output, year t+1**	1.04	1.87	0	23	1.00												
2	**Exploratory innovation output, year t+1**	0.47	1.06	0	14	0.75	1.00											
3	**Exploitative innovation output, year t+1**	0.56	1.28	0	15	0.84	0.27	1.00										
4	**University alliances, years t, t-1, t-2**	0.55	1.10	0	12	0.12	0.11	0.08	1.00									
5	**Technological breadth, years t, t-1, t-2**	4.27	4.48	0	26	0.26	0.08	0.30	−0.04	1.00								
6	**Patents, years t, t-1, t-2**	9.67	19.08	0	176	0.24	0.10	0.27	0.02	0.69	1.00							
7	**Publications, years t, t-1, t-2**	13.72	25.09	0	282	0.30	0.11	0.35	0.12	0.54	0.66	1.00						
8	**Firm age (year t)**	12.62	6.14	1	29	0.01	−0.03	0.04	0.02	0.12	0.08	0.17	1.00					
9	**R&D expenditure in mil$, years t, t-1, t-2**	108.07	210.43	0	2475.58	0.17	0.06	0.20	0.09	0.45	0.52	0.61	0.14	1.00				
10	**Firm size, year t**	10.49	1.96	2.77	16.08	0.20	0.08	0.23	−0.001	0.54	0.43	0.49	0.18	0.56	1.00			
11	**Alliances with firms, years t, t-1, t-2**	2.06	2.47	0	23	0.18	0.10	0.19	0.35	0.22	0.21	0.40	0.04	0.40	0.37	1.00		
12	**Discontinued drugs in development, years t, t-1, t-2**	0.40	0.99	0	8	0.05	−0.02	0.09	0.04	0.13	0.14	0.28	0.04	0.12	0.12	0.11	1.00	
13	**Pipeline, years t, t-1, t-2**	7.49	7.45	0	55	0.40	0.14	0.46	0.21	0.41	0.43	0.54	0.14	0.39	0.38	0.30	0.32	1.00

Model 3. The beta coefficient of university alliances in Model 3 is positive and statistically significant ($\beta = 0.100$; p-value < 0.05). This indicates that there is a positive association between university collaborations and firms' propensity to create new drug candidates that are explorative in nature. Next, we ran the specification of Model 1, using as a dependent variable exploitative innovation output. The results are presented in Model 5. The beta coefficient of university alliances is not statistically significant in Model 5. Taken together, these findings indicate that university alliances are positively related to a firm's propensity to pursue exploratory innovations, whereas it is unrelated to firm exploitative innovations. This lends support to Hypothesis 1. We estimated the specifications in Models 1, 3, and 5 using fixed effects negative binomial regressions to check for the sensitivity of the results. The main results remain unchanged, and are presented in Models 7, 10, and 13, respectively.

Hypothesis 2 contends that firm technological breath is a positive moderator of the relationship between university alliances and firm exploratory innovation output. Testing for moderation is typically conducted using multiple regression by introducing the product of the predictor variable and the moderator variable into the regression equation when the main effects are controlled (Boyd et al., 2012; Li et al., 2019). We introduce the moderator variable and the interaction term in Models 2,4 and 6. The dependent variable in Model 2 is innovation output, and the random-effects negative binomial model reveals that the interaction term is not statistically significant. This result could be partially explained by the potential distinct effects university alliances exert on firm exploratory and exploitative innovations. To test Hypothesis 2, in Model 4, we introduce exploratory innovation output as a dependent variable and ran the regression specified in Model 2. In support of Hypothesis 2, the results in Model 4 show a positive and significant interaction term ($\beta = 0.022$; p-value < 0.05), providing evidence that the positive relationship between university alliances and firm exploratory innovations is stronger for firms with broader technological expertise. The results remain robust when estimating the specification in Model 4 using fixed effects negative binomial regressions. The results are presented in Model 11. To further analyse the results, we check whether the examined interaction effect is different for exploratory and exploitative innovation output. In Model 6, we use exploitative innovation output as a dependent variable and ran the regression specified in Model 2. The results show a negative and significant interaction term ($\beta = -0.019$; p-value < 0.05). When re-estimating Model 6 using negative binomial regression with firm fixed effects, the interaction term is negative but not significant. These results are shown in Model 14. Thus, our findings provide evidence that university alliances are more positively associated with firm exploratory innovation output for higher levels of firm technological breadth.

Because negative binominal models are non-linear models, the magnitude, sign, and significance of the interaction terms can vary across observations (Hoetker, 2007). Therefore, we follow past work (Yayavaram and Chen, 2015), and use a graphical analysis to provide a more nuanced interpretation of the interaction effects in Model 4. Fig. 1 plots the average marginal effects of university alliances for various values of firm technological breadth with 95% confidence intervals, when all other variables are kept at their mean values. The average marginal effects of university alliances are not statistically significant at very low levels of firm technological breadth, but they turn positive and are increasing for higher values of firm technological breadth. This provides support for the hypothesized positive interaction effect predicted in Hypothesis 2.

We performed additional analyses and robustness checks to assess the validity of our empirical findings. First, to assess how sensitive our results are to the reported negative binominal random-effects specification, we additionally performed more conservative fixed-effects negative binomial estimations, and the main results remain unchanged. Using firm fixed effects allows controlling for factors that differ across firms but that are relatively stable over time within firms, such as

Table 2
Results from negative binomial regressions.

	Innovation output, year t+1		Exploratory innovation output, year t+1		Exploitative innovation output, year t+1		Innovation output, year t+1			Exploratory innovation output, year t+1			Exploitative innovation output, year t+1		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
Technological breadth*University alliances		−0.004		0.022**		−0.019**		−0.003	−0.004		0.023*	0.021**		−0.013	−0.020**
		(0.007)		(0.009)		(0.009)		(0.009)	(0.007)		(0.012)	(0.009)		(0.010)	(0.009)
Technological breadth		0.042***		0.011		0.067***		0.039*	0.041***		0.022	0.010		0.047*	0.065***
		(0.013)		(0.018)		(0.017)		(0.021)	(0.013)		(0.028)	(0.018)		(0.026)	(0.017)
University alliances (years t, t-1, t-2)	0.033	0.066	0.100**	0.015	−0.015	0.106*	0.011	0.032	0.067	0.104*	0.006	0.017	−0.067	0.017	0.105*
	(0.035)	(0.047)	(0.042)	(0.061)	(0.046)	(0.059)	(0.050)	(0.067)	(0.047)	(0.060)	(0.085)	(0.061)	(0.065)	(0.087)	(0.059)
Patents (years t, t-1, t-2)	0.004*	−0.0001	0.002	0.001	0.005*	−0.001	0.006*	0.004	0.0001	0.004	0.001	0.001	0.006	0.004	−0.0003
	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.005)	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)
Publications (years t, t-1, t-2)	0.006***	0.006***	0.004	0.004	0.009***	0.009***	0.002	0.002	0.006***	0.003	0.003	0.004	0.001	0.001	0.009***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.005)	(0.003)	(0.004)	(0.004)	(0.003)
Firm age, year t	−0.018**	−0.020**	−0.013	−0.016	−0.023**	−0.025**	−0.019	−0.021	−0.020**	0.007	0.001	−0.016	−0.035	−0.035	−0.025**
	(0.008)	(0.008)	(0.010)	(0.010)	(0.012)	(0.011)	(0.023)	(0.023)	(0.008)	(0.026)	(0.026)	(0.010)	(0.037)	(0.037)	(0.011)
R&D expenditure in mil $ (years t, t-1, t-2)	−0.001**	−0.0004*	−0.0002	−0.0003	−0.001***	−0.001***	−0.0001	−6.58e-06	−0.0004*	−0.0001	−0.0002	−0.0003	−0.001	−0.0003	−0.001***
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0005)	(0.0003)	(0.0004)	(0.0004)	(0.0003)
Firm size, year t	0.080***	0.046	0.055	0.042	0.142***	0.085*	0.204***	0.182***	0.047	0.173**	0.156**	0.043	0.226***	0.197**	0.088*
	(0.031)	(0.032)	(0.038)	(0.040)	(0.044)	(0.045)	(0.057)	(0.058)	(0.032)	(0.070)	(0.071)	(0.040)	(0.086)	(0.088)	(0.045)
Alliances with firms (years t, t-1, t-2)	−0.005	−0.005	0.0004	−0.004	0.001	0.002	−0.001	−0.003	−0.004	−0.008	−0.011	−0.004	0.020	0.018	0.002
	(0.017)	(0.017)	(0.024)	(0.023)	(0.021)	(0.021)	(0.022)	(0.021)	(0.017)	(0.030)	(0.030)	(0.023)	(0.025)	(0.025)	(0.021)
Discontinued drugs in development (years t, t-1, t-2)	−0.066	−0.070*	−0.102*	−0.102*	−0.042	−0.044	−0.012	−0.016	−0.070*	0.006	−0.011	−0.102*	−0.003	−0.004	−0.044
	(0.041)	(0.041)	(0.059)	(0.059)	(0.049)	(0.048)	(0.049)	(0.049)	(0.041)	(0.073)	(0.073)	(0.059)	(0.056)	(0.056)	(0.048)
Pipeline (years t, t-1, t-2)	0.030***	0.029***	0.017**	0.016**	0.040***	0.039***	−0.029***	−0.032***	0.029***	−0.025*	−0.025**	0.016**	−0.024**	−0.027**	0.040***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)	(0.007)	(0.013)	(0.013)	(0.008)	(0.012)	(0.012)	(0.008)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−1.274***	−1.036***	−1.897***	−1.693***	−1.784***	−1.504***	−1.728**	−1.584**	−1.048***	−2.975***	−2.709***	−1.699***	−1.193	−1.139	−1.522***
	(0.341)	(0.345)	(0.435)	(0.447)	(0.495)	(0.491)	(0.681)	(0.689)	(0.345)	(0.784)	(0.792)	(0.446)	(1.115)	(1.136)	(0.492)
Number of observations	1323	1323	1323	1323	1323	1323	1273	1273	1323	1123	1123	1323	936	936	1323
Number of firms	220	220	220	220	220	220	205	205	220	178	178	220	149	149	220
Log likelihood	−1715.08	−1710.04	−1153.85	−1150.33	−1161.85	−1153.87	−1126.75	−1124.93	−1710.38	−697.94	−695.15	−1150.48	−692.60	−690.83	−1154.18
Chi squared	146.60	164.09	75.09	87.40	116.48	154.08	55.96	59.88	163.01	45.50	52.41	86.99	28.87	32.67	152.66

Standard errors are in parentheses.
*p < 0.10; **p < 0.05; ***p < 0.01.

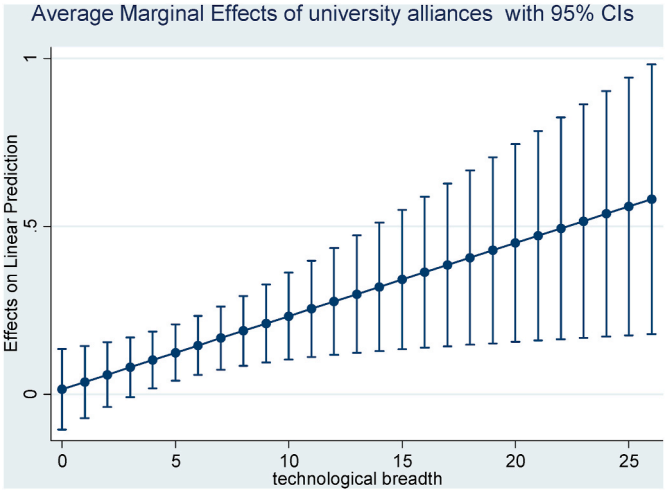

Fig. 1. Average marginal effects of university alliances with 95 percent confidence intervals for different values of firm technological breadth.

management know-how or organizational culture (e.g., Benner and Tushman, 2002). Specifically, we re-estimate the specifications in Models 1,3, and 5 using firm fixed effects instead of random effects and present the results in Models 7, 10, and 13, respectively. The beta coefficient of university alliances is positive and statistically significant in Model 10 (p-value < 0.1), but it is not statistically significant in Models 7 and 13. These findings lend support to our Hypothesis 1, predicting that university alliances are more positively associated with firm exploratory innovation output than with firm exploitative innovation output. Next, we ran the specifications in Models 2,4, and 6 using firm fixed effects instead of random effects and show the results in Models 8, 11, and 14, respectively. In support of our Hypothesis 2, the interaction between university alliances and technological breadth is positive and statistically significant (p-value <0.1) in Model 11, whereas it does not reach significance in Models 8 and 14. These findings support the contention that firm technological breath is a positive moderator of the relationship between university alliances and firm exploratory innovation output.

Second, to address issues of potential endogeneity and reverse causality, we incorporated a one-year time lag for the measure of our dependent variables, after measuring the independent and control variables in all the model specifications. This time lag helps rule out an alternative explanation that firms that pursue exploratory innovations are more likely to resort to university alliances.

Since the development of certain university alliances may improve the firm's technological breadth and vice versa, there is the potential concern that the independent variable university alliances and the moderator technological breadth may be partially confounded. Accordingly, we added a further robustness check to evaluate the effect of the exclusion of the patents co-developed with universities for the computation of the firm's technological breadth. To identify such patents, we searched in the assignee field in each patent for the following keywords (and abbreviations): university, univ, college, coll, institute, inst. We re-estimate the specifications in Models 2,4, and 6 using this alternative measure of technological breadth and present the results in Models 9, 12, and 15, respectively. The results remain robust.

Finally, universities might be more likely to form alliances with firms that collaborate with university scientists on academic publications. To address this concern, we include a control variable that measures the proportion of firm scientific journal publications that are co-authored with university scientists in the estimations of our Models 1–6. The main results remain unchanged.

5. Discussion and conclusion

Our paper investigates the relationship between firms' engaging in university alliances and innovation outcomes in the context of therapeutic product development. Combining insights from organizational learning theory and prior work on university-industry linkages, we develop a contingency-based model that views firms as active learners from academic partners rather than passive recipients of university-industry spill-overs. Specifically, our theoretical framework asserts that engaging in university alliances has a stronger positive relationship with firms' exploratory rather than exploitative innovation. Furthermore, it underscores the moderating role of firm technological breadth, suggesting that firms with expertise in diverse technological domains can capture greater benefits from university alliances for their exploratory R&D endeavours.

By identifying novel boundary conditions of the widely-theorized positive relationship between university alliances and firm innovative performance, our study contributes to the literature on university-industry collaborations (Belderbos et al., 2016; George et al., 2002; Soh and Subramanian, 2014; Stuart et al., 2007). Recent research has elucidated that some firms might use university partnerships as a segue to next generations of technologies and knowhow, while others might use such partnerships as an extended 'workbench' for short-term, incremental problem solving (Frølund et al., 2018; Perkmann and Salter, 2012). Our findings are in line with the contention that technological newness can benefit from university-industry collaborations (e.g., Wirsich et al., 2016). Also, our results are consistent with past scholarly work on knowledge search strategies, suggesting that re-combinations of knowledge elements across organizational and technological boundaries often lead to innovations with a high degree of novelty (Ahuja and Lampert, 2001; Fleming, 2001; Galunic and Rodan, 1998; Rosenkopf and Nerkar, 2001). Our research brings greater clarity to the role university alliances play in inducing firms to engage in non-routine problem solving and embark on learning trajectories that are more in line with exploratory innovation rather than exploitative innovation. In doing so, it complements past research that has traditionally viewed university-industry alliances as a mechanism for knowledge transfer and spill-overs (Belderbos et al., 2016; Bercovitz and Feldman, 2007; Walsh et al., 2016; Zucker et al., 2002).

Our empirical results further suggest that when firms are active in a broader range of technological domains and at the same time collaborate with universities, their exploratory innovation output increases, but this is not the case for their exploitative innovation output. Our study adds to the on-going debate about the challenges and trade-offs firms face in managing knowledge across the realm of science and technology, and how these impact firm innovation (Alexy et al., 2013; Bruneel et al., 2016; Bstieler et al., 2015; Cassiman et al., 2008; Du et al., 2014; Simeth and Raffo, 2013; Soh and Subramanian, 2014). Specifically, it offers a more detailed understanding of how and under what conditions firms can harness the potential of university alliances to support their R&D efforts. By unveiling the role of firm technological breadth as an important moderator, our paper contributes to the growing body of work that takes a contingency approach to examine the impact of university alliances on firm innovative performance (Belderbos et al., 2016; George et al., 2002; Soh and Subramanian, 2014).

Finally, we contribute empirically to the exploration-exploitation literature. Our findings are in line with prior research illuminating different mechanisms at play when firms engage in exploratory versus exploitative R&D (Alexiev et al., 2010; Benner and Tushman, 2002; Jansen et al., 2006). Further, our study uses data on drug development projects to differentiate between exploratory and exploitative innovation outputs. In doing so, it adds to past empirical work that has traditionally drawn on patent data (e.g., Benner and Tushman, 2002; Gilsing et al., 2008; Guan and Liu, 2016; Phelps, 2010) or survey data (e.g., Jansen et al., 2006) to develop such measures.

Addressing some of the limitations of this study provides fruitful

avenues for future research. First, although the therapeutic biotechnology industry provides an ideal empirical setting for testing our conceptual model, it exhibits unique characteristics such as an unusually strong reliance on scientific knowledge and highly uncertain, long R&D lifecycles. Thus, future research will need to ascertain the level of generalizability of our results.

Second, this study sheds new light into the relationship between university alliances and firm innovative performance by pointing out the type of innovation output and firm technological breadth as important contingencies. To fully understand the examined relationship, however, future research should also explore additional contextual factors or firm attributes. For example, future studies may disentangle whether university alliances are complements or substitutes for other channels of scientific knowledge sourcing. These other channels include the adoption of R&D strategies that embrace certain rules and norms associated with open science, the pursuit of in-house fundamental scientific research, collaborating with academics on scientific publications, participating in scientific conferences and workshops, and hiring external scientists.

Next, future research may provide more granularity in the operationalization of the main variables used in our empirical analysis. For instance, the measure of the exploratory innovation based on counting the number of new drug candidates in therapeutic areas that are new to the firm has limitations. For example, this measure does not evaluate the extent to which a firm has produced therapeutic outputs that are far from or close to its core areas of expertise. Future research may develop an enhanced measure of exploratory innovation outputs, accounting for their distance from a firm's core expertise. Also, the measure of university alliances as the number of deals between biotech firms and universities has limitations, as it does not account for the type, size, and subject area of the agreement and characteristics of the university partner (such as ranking, prestige, etc.). Addressing these issues could provide a potential avenue for future research on university-industry collaborations.

Fourth, our study uses a unique longitudinal dataset based on secondary sources of information. Despite the advantages of this dataset in terms of improving the rigor of the econometric analysis and addressing potential reverse causality concerns (e.g., using time lags), caution about inferring causality should be observed. Future research could use alternative methodological approaches to provide a richer account of the mechanisms that are in play.

Concerning managerial-oriented insights, this study provides a more nuanced understanding of why tapping into university alliances may not be equally effective for firms when it comes to advancing their R&D goals. Our study informs managers about the conditions, under which firms may harness the potential of university alliances to support their R&D efforts. Specifically, our results highlight that engaging in university alliances can support firms in their efforts to produce exploratory innovations. What is more, firms might need to broaden their technological expertise to capture greater benefits from forging ties with universities. For firms that pursue exploitative innovations, however, our findings suggest that embracing university alliances might be a less successful strategy. This points out to hidden trade-offs managers should be aware of when reaching out for academic collaborations in attempts to improve their innovative performance.

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