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Exploiting technological opportunities: the timing of collaborations☆

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Abstract

High-technology companies that discover new technological opportunities face two critical decisions: whether and when to collaborate in exploiting these opportunities. Prior research has examined factors such as transaction costs that determine whether firms decide to collaborate. In this study, we aim to understand *when* firms collaborate in exploiting opportunities. To this end we study the history of 86 biopharmaceutical product-development projects. We find that factors that reduce articulation and appropriation uncertainties in these projects—patent protection, high R&D intensity of the discoverer, partners' prior collaboration experience, and support infrastructures in the industry—can speed up collaboration. Interestingly, project-specific factors do not seem to affect timing.

Keywords: Technological opportunities; Product innovation; Collaboration

1. Introduction

This study examines how high-technology companies exploit technological opportunities. More specifically, we study how two characteristics of technological opportunities—the short window of opportunity and the different perceptions about the value of the opportunity among firms (Schumpeter, 1934; Arrow, 1962; Shane and Venkataraman, 2000)—both promote and prolong the exploitation of such opportunities through technological collaboration.[2] The study is based on the history of 86 biopharmaceutical opportunities developed in 1976–1992.

The first key characteristic of technological opportunities is that they are often temporary: the party that discovers an opportunity needs to exploit the opportunity quickly before the information reaches others in the field, or before the opportunity is replaced with a technologically more advanced one, i.e. before the window of opportunity closes. Prior literature has shown that those that discover opportunities often lack the necessary resources for fast exploitation.

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[2] We use the common definition of technological collaborations: they are voluntarily initiated cooperative agreements between firms that involve exchange, sharing or codevelopment of technology (e.g. Gulati, 1995). We do not include joint ventures nor licensing or co-licensing agreements in our sample of collaborations.

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However, collaborations can provide an efficient way to access additional or complementary resources that can speed up the exploitation (e.g. Teece, 1986; Arora and Gambardella, 1990).

The second characteristic of technological opportunities that the discoverer of an opportunity has a different perception of its true value than others (Kirzner, 1973), makes it hard to collaborate, however. Such information asymmetries may make it difficult to protect unique insights about the opportunity, and difficult for potential partners to evaluate the benefits of collaboration. In this study, we examine factors that can mitigate this information asymmetry and help firms find collaborative partners in time to exploit technological opportunities.

The empirical setting of this study is the biotechnology industry. Since the mid-1970s, several hundred R&D-intensive firms have entered the industry to pursue biotechnology opportunities. Established pharmaceutical companies have also been involved, for example through entering into technological collaborations with the new firms. The purpose of these collaborations is often to further exploit the technological opportunity previously discovered by the new biotechnology firm. An interesting feature of such collaborations is that there is a lot of variation in how they are set up: in whether they are used at all, and if they are, at what stage of the project development. Our study examines when during the project development a discoverer of the technological opportunity (i.e. a new biotechnology firm) and a partner (i.e. a pharmaceutical firm) collaborate in exploiting the technological opportunity.

Our empirical results from biopharmaceutical product opportunity development show that new biotechnology firms differ in the timing of their collaborations with pharmaceutical firms. We find that R&D-intensive biotechnology firms that have applied for a patent in the project or that have prior R&D collaboration experience, collaborate sooner. The establishment of industry support infrastructures such as state biotechnology centers, and the increasing intellectual property protection in the biotechnology industry also accelerate collaboration. On the other hand, characteristics of the project do not seem to affect the timing of collaborations (c.f. Oxley, 1997).

The contributions of the study are three-fold. First, the paper contributes to the entrepreneurship[3] literature by providing new knowledge about how technological opportunities are exploited. While many empirical entrepreneurship studies have focused on the discovery phase (e.g. Shane, 2000), exploitation has received much less attention. As Dosi (1988, p. 1160) points out, identifying the opportunity is only a necessary but not a sufficient condition for its actual exploitation. Second, we investigate a relatively new question of how firms time their R&D collaborations to exploit technological opportunities. Lerner and Merges (1998) examined how the allocation of control rights was related to project's stage of development, but we know of no other longitudinal work that has examined how R&D collaboration is related to time. Third, in answering the question of when firms collaborate, we provide new evidence that the government initiatives to support entrepreneurial activities in the biotechnology field have actually been effective. State biotechnology centers and stronger patent protection have accelerated exploitation of biopharmaceutical opportunities.

2. Conceptual development

Right timing of opportunity exploitation is important for high-technology firms. While the entrepreneur, by definition, discovers the opportunity before others (Hayek, 1945; Kirzner, 1973), this opportunity window usually lasts only a short time. Opportunities may become less lucrative as other firms realize the potential of the new discovery and start exploiting this realization. Alternatively, competitors may promote parallel technological paths that lead to discoveries that can become substitutes. More recent technological advances may also replace the original opportunity if it is not acted upon quickly. Thus, in high-technology industries where windows of opportunity close quickly, obtaining early access to know-how or resources that enable fast exploitation can make the difference between finishing first and

[3] We use Shane and Venkataraman's (2000) definition of entrepreneurship as the discovery and exploitation of profitable opportunities.

dropping out altogether (Reinganum, 1989; Eisenhardt and Schoonhoven, 1996).

Prior research has shown that discoverers of technological opportunities can access resources for exploitation most effectively through collaboration (e.g. Mitchell and Singh, 1996). Companies that collaborate early can secure access to vital external resources. Collaborating early can also free the discoverer's own resources for other uses (Mosakowski, 1991). Despite the benefits, however, early collaboration can also be problematic. Tacitness of knowledge is high in the early stages of technological opportunity exploitation, that is, early in the research and development project, and decreases as the knowledge is developed (von Hippel, 1988). Such tacitness makes collaborations difficult for two reasons. First, tacitness limits the company's ability to *articulate* the knowledge of the opportunity for efficient transmission and reception (Teece, 1981; Tyler and Steensma, 1995). Thus, the value of tacit knowledge often appears ambiguous to outsiders. This information asymmetry increases uncertainty and therefore transaction costs (Reed and DeFillippi, 1990). Second, from the opportunity discoverer's perspective, tacitness can make the knowledge vulnerable for *appropriation* by others. Know-how that is not yet articulated can be difficult to protect (Arrow, 1962; Demsetz, 1991). The knowledge appropriability argument is especially important in the case of the opportunity discoverers we examine in this study, since the core asset of these companies is the tacit knowledge they are developing.

Researchers have demonstrated that product development reduces both of the above-mentioned articulation and appropriation uncertainties that make early collaborations difficult (e.g. Garud and Nayyar, 1994). von Hippel (1994) explains this process as deliberate unsticking, or know-how codification, whereby tacit knowledge is converted to more explicit and defendable forms such as formulas and blueprints. Thus, one way to reduce tacitness is to wait until the project is more developed.

However, resource-poor opportunity discoverers cannot often wait for the project to be further developed. As discussed above, many opportunities are time sensitive. Unless resources can be accessed quickly, the opportunity may vanish or become considerably less attractive. Thus, in this study, we examine factors that make it possible for opportunity discoverers to speed up exploitation, i.e. to collaborate earlier during their product-development projects.

3. Hypotheses

In the following hypotheses, we propose that internal R&D activities (H1a, H1b), collaboration experience (H2a, H2b), and industry infrastructure development (H3a, H3b) reduce the above-mentioned articulation and appropriation uncertainties, and accelerate timing of collaborations. We use the term *entrepreneurial firm* for the firm that has discovered a technological opportunity and is trying to exploit that opportunity through collaboration. *Timing of collaboration* is defined as the stage in the product-development project during which the collaboration between the entrepreneurial firm and a partner begins.

3.1. Internal R&D activities

In Hypothesis 1, we propose that entrepreneurial firms can use their internal R&D activities to reduce articulation and appropriation uncertainties related to opportunity exploitation. First, at the project level, entrepreneurial firms can codify the tacit knowledge that describes the technological opportunity through patenting it, and thus accelerate collaboration. Second, at the firm level, R&D-intensive entrepreneurial firms can leverage their existing R&D resources and expertise to collaborate early in product development. We discuss both of these mechanisms below.

In Hypothesis 1a, we propose that the entrepreneurial firm can accelerate collaboration by applying for a patent for the product idea. Since each patent, by definition, includes a detailed explanation of a novel and valuable solution to a technical problem (Walker, 1995), applying for a patent in the project indicates that the entrepreneurial firm has articulated the project's potential usefulness and commercial viability. Projects that have put together a patent application thus entail much lower articulation uncertainty about the opportunity's potential value than projects that have not yet done so. This reduction in uncertainty is important in early stages of the project when the knowledge of the opportunity would otherwise be tacit. Moreover, patenting also protects the

firm's tacit ideas against opportunistic partners—the applicant first to file an application will be awarded the patent, and will gain the right to exclude others from making or using the invention (Walker, 1995). Thus, we expect that patenting decreases appropriation uncertainty in the project. We propose:

Hypothesis 1a. The earlier the entrepreneurial firm has filed a patent application for a product idea, the earlier the timing of technological collaboration in the product-development life cycle.

In Hypothesis 1b, we propose that research-intensive entrepreneurial firms are more likely to enter collaborations early in product development, for two reasons. First, in organizations that spend a relatively high amount of their resources on R&D, research and development activities gain leverage and become one of the organization's core areas (e.g. Thompson, 1967). Consequently, these organizations are more likely to devote the necessary resources and experience to protect, i.e. to buffer the core, from environmental disruptions. As a result, we propose that appropriation uncertainty for opportunities discovered by R&D-intensive organizations is lower than for organizations that spend relatively fewer resources on R&D. Second, we expect that R&D-intensive firms are more efficient in articulating their ideas in non-tacit forms since they are likely to have more opportunities to practice articulation—for example, through "selling" new ideas to other functional areas of the firm—than firms that emphasize R&D less. High R&D intensity is thus likely to reduce articulation uncertainty, and enable firms to collaborate sooner. In contrast, we propose that firms with low R&D intensity are more likely to collaborate later. These mechanisms lead us to the following hypothesis:

Hypothesis 1b. The higher the R&D intensity of the entrepreneurial firm, the earlier the timing of technological collaboration in the product-development life cycle.

3.2. Collaboration experience

In Hypothesis 2, we propose that the entrepreneurial firm's prior technological collaboration experience is likely to increase its ability to collaborate early in product development. Direct experience between the collaborating partners often helps reduce the articulation uncertainty surrounding tacit knowledge transactions. Below we also argue that in the absence of, or in addition to, such direct experience, partners can use entrepreneurial firm's previous technological collaboration behavior in the industry to reduce articulation and appropriation uncertainty in the current project (see also Gulati, 1999).

In Hypothesis 2a, we propose that mutual prior collaborations between the partners increase the likelihood of entering future collaborations early. First, prior mutual collaborations increase the partners' knowledge of one another's operating procedures (Balakrishnan and Koza, 1993) and increase the amount of similar knowledge that the partners share (Mowery et al., 1998). Since the new ideas that the partners introduce are often similar to those they have developed in the past (Nelson and Winter, 1982), overlapping knowledge and experience bases will help in future absorption of each other's new ideas (Cohen and Levinthal, 1990). Moreover, Dosi (1988, p.113) argues that collaborators who have a common experience are good at sharing tacit knowledge. Thus, subsequent mutual projects between the partners are likely to involve lower articulation uncertainty even at early stages of development.

Second, prior collaborations, especially if they are still on-going, are likely to decrease appropriation uncertainty in the project. Gulati (1995) and Kogut (1989) showed that if parties to a collaboration are already involved in other collaborations together, the payoffs to opportunism in the current collaboration—such as stealing tacit knowledge—are lower because the continued gains in all of the other collaborations would be at risk. Similar knowledge bases between partners are also likely to help in co-aligning the partners' interests and perhaps make it less likely that project knowledge is used to purposes not in both partners' interest. Prior collaboration partners are thus less likely than firms that have never collaborated together to have problems with appropriation uncertainty. Thus, we propose:

Hypothesis 2a. The more collaboration experience the entrepreneurial firm has with the collaboration partner, the earlier the timing of technological collaboration in the product-development life cycle.

In Hypothesis 2b, we propose that in place of direct experience, a record of past collaboration activity can be used to mitigate articulation and appropriation uncertainties. First, potential partners can use the entrepreneurial firm's collaboration history to draw inferences about articulation uncertainty in the current project (Davidson and McFetridge, 1984; Podolny, 1994). Entrepreneurial firm that has previous R&D collaboration experience has gained experience in articulating its R&D ideas to an extrafirm audience—for example, the firm has successfully articulated ideas to previous partners that have decided to collaborate with this firm—which in turn is likely to increase the firm's ability to communicate its ideas effectively in the present collaboration.

Second, prior technological collaboration experience can also prevent appropriation of the entrepreneurial firm's tacit knowledge. As a firm gains collaboration experience a set of informal routines emerges to protect tacit knowledge related to opportunities: rules about what procedures must be followed to protect knowledge, who is eligible to make decisions, and what information must and must not be provided for potential partners (Powell and Brantley, 1992). Similar to the intrafirm routines described by Nelson and Winter (1982), entrepreneurial firms can use these collaboration appropriation routines they have derived from similar transactions to protect tacit know-how in the current project. We expect these routines to reduce appropriation uncertainty, and make the entrepreneurial firms more likely to collaborate early when the know-how is tacit. We therefore hypothesize the following:

Hypothesis 2b. The more technological collaboration experience the entrepreneurial firm has, the earlier the timing of technological collaboration in the product-development life cycle.

3.3. Industry development

So far, we have examined four complementary explanations for early collaboration: patenting, high R&D intensity, repeated collaborations, and prior R&D collaboration experience. However, these hypotheses do not fully explain how entrepreneurial start-up companies that, by definition, often lack extensive experience in R&D or in interfirm collaboration, can exploit technological opportunities through early collaboration. One approach to answering this question is to examine how factors external to the entrepreneurial firm could enhance such early exploitation.

In Hypotheses 3a and 3b, we examine how industry-level factors affect collaboration timing. We propose that various institutional structures such as specialized suppliers, industry associations, state agencies, and legal structures reduce the uncertainty of tacit transactions, and enable project knowledge to be transferred earlier in the development process. As discussed in more detail below, evolution of these industry-level institutional structures is proposed to decrease both the articulation and the appropriation uncertainty in development projects.

First, the emergence of a technical community in an industry will build a common pool of technological knowledge that will facilitate articulation of even the most tacit research ideas. This common pool of knowledge will reduce the information asymmetry between the entrepreneurial firm and its partner. As the industry matures, companies also gain access to a more developed set of complementary services, such as specialized technological consulting firms, that further facilitate the articulation of tacit know-how. Second, industry maturity can reduce the appropriation of tacit knowledge as rules and regularities develop within the industry to provide protection for tacit knowledge. Patent protection is an example.

In the biotechnology industry, we identify two types of major industry-level factors that reduce both the appropriation and articulation uncertainties. We propose that the intellectual property protection milestone of the Diamond versus Chakrabarty decision in 1980 that ensured patentability for biotechnology ideas (H3a), and the increase in the number of state biotechnology centers (H3b) accelerate collaboration timing. This leads us to propose the following hypotheses:

Hypothesis 3a. The more mature the industry, as measured through the increase in the intellectual property protection, the earlier the timing of technological collaborations in the product-development life cycle.

Hypothesis 3b. The more mature the industry, as measured through the increase in the number of state biotechnology centers, the earlier the timing of tech-

nological collaborations in the product-development life cycle.

In summary, this study examines when entrepreneurial companies collaborate during product development. We hypothesize that firms that have applied for a patent in the project (H1a), have high R&D intensity (H1b), mutual collaboration experience with a partner (H2a), or prior R&D collaboration experience in general (H2b), collaborate earlier. The timing of collaboration is also proposed to accelerate with the strengthening of the institutional support infrastructure in the industry (H3a, H3b).

4. Research context and methods

4.1. Research context

Biotechnology industry is an especially appropriate setting for the study for several reasons. First, opportunity discoverers in the industry often need to collaborate with others to exploit opportunities. In the early phases of the biotechnology industry, the technological opportunities created by the biopharmaceutical scientific discoveries were, to a large extent, recognized by the entrepreneurial firms in the industry, i.e. by the new biotechnology firms. However, these firms often lacked resources to exploit the opportunities. The industry thus provides an interesting setting to study whether and when the new biotechnology firms used collaborations to exploit these opportunities. Second, several authors have shown that knowledge in biotechnology is tacit (Pisano, 1989), and that collaborators need to take specific measures to ensure its transfer (Pisano and Mang, 1993). Biotechnology is thus a good setting to examine how entrepreneurial firms can overcome tacitness of knowledge to exploit opportunities through collaboration.

Biopharmaceutical drug development consists of three phases (Pisano and Mang, 1992). In the first phase, a technological or scientific opportunity in the form of a molecule inside the human body with either known or unknown therapeutic effects is discovered. In the second phase, the exploitation of the opportunity ensues by inducing bacteria, yeast or some other type of cell to synthesize the molecule in a test tube. If this can be done, information about the molecule, its structure, various versions, likely behavior, and promise as a drug is acquired. Third, experiments to learn more about the molecule's behavior in animals, and about its safety and efficacy in various doses in humans are conducted. In this study, we focus on examining the factors that determine at which stage of this process firms use collaborations.

4.2. Method

To model the timing of technological collaborations in biopharmaceutical projects we estimated a Heckman selection model (Heckman, 1976; Greene, 2000). The Heckman method is frequently used in situations where one dependent variable (in our case the timing of collaborations) is only observed when the second dependent variable (in our case likelihood of collaborations) is positive (see also Gompers et al., 1998). Two equations are estimated. The first one is the likelihood that firms decide to collaborate in product development in a given time period. The second equation is used to estimate the timing of this collaboration in the product's development cycle. Whereas estimating two separate regressions—and estimating timing by using only data for projects that involved a collaboration—would produce inconsistent estimates of the variables, Heckman selection model provides consistent estimates that generalize the timing results to the larger sample.

Since the collaboration data in the study are right-censored, but the probit estimation used in the basic Heckman model does not take censoring into account, we use Lee's (1983) generalization of the Heckman model to estimate the results. In this generalization, the first equation estimates the *likelihood* of collaboration with an event history model. A semiparametric Cox model is used (Cox, 1972). The advantage of using Cox model is that it accounts for right-censoring in the data, and that we do not have to make parametric assumptions about the form of the duration dependence in the hazard rate. We then use predicted probabilities from the Cox model to generate a sample correction variable lambda:

$$\lambda_{it} = \frac{\phi[\Phi^{-1}(F_i(t))]}{1 - F_i(t)}$$

where $F_i(t)$ is the cumulative hazard function for project i at time t, ϕ is the standard normal density

function, and Φ^{-1} the inverse of the standard normal distribution function (Lee, 1983). This λ_{it} is then included as a control in a second-stage OLS regression model to predict collaboration *timing* among projects that will be developed together with a partner.

To control for firm effects, we use a robust estimation procedure in the likelihood equation (Lin and Wei, 1989), and OLS fixed effects model in the timing equation. The fixed effects model offers a conservative test of the hypotheses because only the variation within a firm across time is used to estimate the regression coefficients, and across-firm variation is eliminated (Judge et al., 1985). For example, through fixed effects we can control for differences in R&D capabilities between firms.

5. Data and variables

5.1. Biopharmaceutical development project data

To examine collaboration decisions, we collected data on biotechnology-based product-development projects. We used the Pharmaceutical Manufacturers' Association definition of biotechnology drugs as vaccines, human therapeutics and in vivo diagnostic products. The study was restricted to these areas to hold constant the underlying technology and clinical requirements for all sample projects (see also Pisano, 1990). To ensure that our research examined agreements over comparable levels of tacit knowledge, we focused only on the first technological collaboration in each project.

After a comprehensive search of public documents such as SEC reports, analyst reports and industry-specific journals and reports (e.g. *Genetic Engineering News*, *Pharmaprojects*, *Bioscan* directories, and the Actions Database published by The North Carolina Biotechnology Institute), we were able to access data on 98 projects that were developed in new biotechnology firms in 1976–1992. Of the 12 projects that could not be included, 2 turned out to be projects originally developed by an outside firm, and the remaining 10 projects could not be included since the control variable data for the 6 companies developing them was not publicly available, reducing the final sample size to 86 projects.

A list of technological collaborations in each project was compiled by identifying all collaborations between the biotechnology company and pharmaceutical companies in this project. Collaborations that did not include R&D (pure production, distribution and marketing collaborations, for example) were excluded from the sample, as were collaborations where the primary objective was capital investment. Using news stories and company reports to corroborate our initial descriptions of the collaborations, we were careful to exclude all collaborations where one of the parties gave monetary contributions, for example, but did not participate in research activities. Of our 86 development projects, 68 were developed together with another company during our observation period, and the remaining 18 were developed internally without any R&D collaboration.

We observed the independent variables of the study monthly for each project from the project's start until an agreement was reached or the observation period ended (at the end of 1992). There were 24 biotechnology firms and 4922 project-month observations in the final sample. Independent variables were lagged by 1 month for monthly data, and by 1 year for the data that was available yearly. We estimated the models using the *Stata* statistical package.

5.2. Variables

5.2.1. Dependent variables

Since we used a generalized Heckman model, there were two dependent variables in the study, *Collaboration likelihood* for the likelihood model and *Collaboration timing* for the main regression model (for testing Hypotheses 1–3). *Collaboration likelihood* is coded as a 0–1 dummy variable that records whether a project involves a technological collaboration. The dependent variable in the second model is *Collaboration timing*, the time period that the biotechnology company spends developing the project prior to technological collaboration. Since determining the exact starting date of a research project is often difficult, and this date is often not publicly available, we follow Pisano and Mang's (1993) and Lerner and Merges' (1998) methodology for operationalizing timing through FDA approval dates. These authors used the date of the FDA approval for initiating human clinical trials, that is, the project's Investigational New Drug

(IND) status, as a consistent benchmark of the status of the development project.

Interview and survey evidence on drug development indicates that the development time of new biotechnology products is 11 years on average, and that it takes about 7 years after the Investigational New Drug date to introduce the biopharmaceutical to the market (e.g. Pisano and Mang, 1992; F-D-C Reports, 1996; Outlook, 2001). Thus, we approximate that biotechnology projects are initiated about 4 years before the IND date, and set the first year of observation in each project at 4 years before this date. The first observation month could not, however, be earlier than the date at which the biotechnology firm was established. The later in the research project's development cycle the collaboration occurred relative to the IND date, the higher the *Collaboration timing* value (see also Lerner and Merges, 1998).

5.2.2. Independent variables

Patent application. In Hypothesis 1a, we proposed that the more articulated the opportunity, the earlier the collaboration. Patent application is a good measure of the project's articulation status in our study since the patenting propensity in the biotechnology industry is high. Prior work has also shown that patents correlate highly with other indicators that describe the extent of the firm's R&D activities (Comanor and Scherer, 1969; Trajtenberg, 1989). *Patent application* variable is coded as 1 if the entrepreneurial firm has filed a patent application on the focal development project prior to time $t-1$. Patent data were obtained from the US Patent and Trademark Office, company documents and news stories.

R&D intensity. Following Cohen and Levinthal (1990) and Helfat (1994), we use the biotechnology firm's R&D intensity to proxy for the intensity of the firm's total R&D inputs to the innovation process. High R&D intensity was hypothesized to promote early collaboration (H1b). To obtain R&D intensity for each sample company yearly, the firm's R&D expenditure was divided by its number of employees.

Prior collaborations with partner. To test for the effects of repeated collaborations with the partner (H2a), *Prior collaborations* variable was formed to represent the number of the entrepreneurial firm's prior collaborations with the focal partner. Collaboration data for each firm were obtained from Predicasts, company reports, and from the Biotechnology Actions Database.

R&D collaboration experience. To test for the effects of the previous technological collaboration experience, *R&D collaboration experience* variable measures the cumulative number of the entrepreneurial firm's R&D collaborations within the biopharmaceutical industry. This experience is hypothesized to accelerate collaboration timing (H2b). Monthly collaboration data for each firm were obtained from Predicasts, company reports, and from the Biotechnology Actions Database.

Intellectual property protection. *Pre-1980* and *Post-1986* variables distinguish the two major institutional events in the biotechnology subfield (1980–1986 is the omitted category). In 1980, the Supreme Court, in the Diamond versus Chakrabarty case, determined that genetically engineered organisms could be patented under US patent code. In 1986, the regulation of certain research and commercialization activities involving biotechnology was formalized by the Office of Science and Technology Policy (OSTP) into a *Coordinated Framework for the Regulation of Biotechnology* (Glass, 1991). The OSTP outlined how multiple federal agencies with overlapping jurisdictions relating to biotechnology would coordinate their activities. These milestones are especially important given our sample, tacit know-how collaborations, and the need for entrepreneurial companies to protect their technological insights. As discussed previously, we expect collaborations to occur earlier in the development process following changes in these industry-level factors (H3a).

Support infrastructure. State biotechnology centers have grown to be an important aspect of the US biotechnology public infrastructure. These centers are state government, university, or non-profit making organizations that work to strengthen commercial biotechnology within a specific geographic region. Most of the new biotechnology firms formed for pharmaceutical research have received either financial or research support from biotechnology centers. In fact, more than one in six of the entrepreneurial biotechnology firms owe all or part of their origins to the biotechnology centers (Dibner, 1991; Directory of Biotechnology Centers, 1995). We measure the *Support infrastructure* variable as the number of biotechnology centers in the US at time $t-1$, and

expect that the increasing number of these centers will accelerate collaboration (H3b). These data were collected from Biotechnology Center Directories.

5.2.3. Control variables

Several control variables were incorporated in both the likelihood and the timing equations. Some of the above-discussed independent variables that predict timing are included in the likelihood equation as controls. Below we discuss some additional controls that are included in the equations. The selection of this set of control variables is based on prior empirical work in transaction cost economics that has shown that these variables are important determinants of transaction decisions (see Shelanski and Klein, 1995 for a summary).

CEO background. Since the decision of whether and when to collaborate is usually sought after, orchestrated, and negotiated at the highest levels of the company organization (Eisenhardt and Schoonhoven, 1996), and the CEO's prior experience from a particular industry—exposure to industry-specific problems and solutions, for example—can affect his or her strategic decisions (Gunz and Jalland, 1996; Brockmann and Simmonds, 1997), a CEO background control was included. Since the collaborations in our sample focus on agreements between a biotechnology firm and a pharmaceutical firm, the previous pharmaceutical experience of the CEO, or the lack of it, is especially relevant. For example, we would expect that CEO's prior pharmaceutical experience will enable early collaboration through reduced articulation uncertainty in the project. We include three types of controls: whether the biotechnology firm CEO has experience in the pharmaceutical industry (*Pharma CEO*), in the venture capital field (*Venture CEO*), or has a university background (*University CEO*). For example, the dummy variable *Pharma CEO* is defined as 1 for entrepreneurial firms whose CEO at time $t-1$ has had previous work experience in the pharmaceutical industry. These data were obtained from the SEC reports and Who's Who in America, and updated in case of CEO turnover.

Cash. To control for the possibility that the need for external capital accelerated some collaboration decisions (Arora and Gambardella, 1990), a variable measuring the cash position of the biotechnology firm was included. *Cash* is an asset-based measure, including inflation-adjusted cash and marketable securities at the end of each financial period. Although a cash flow variable would have been preferable for controlling for the cash position of firms, these data were not available. For the period that the start-up biotech companies in the sample were private, IPO documents of the companies were searched to locate the cash measures. In these documents, only the asset-based cash measure was available.

R&D expenditure. We use the firm's yearly, inflation-adjusted *R&D expenditure* (M$) to proxy for the entrepreneurial firm's total internal R&D inputs to the innovation process. High R&D investment is likely to postpone collaborations, and to decrease the likelihood of collaborating (Teece, 1986).

Knowledge specificity. As might be expected, knowledge related to particular biopharmaceutical projects varies in specificity. Since more specific projects are more difficult to transfer interfirm (see also Jensen and Meckling, 1992), we control for the *Knowledge specificity* of each development project. In this paper, we use the project's targeted protein to operationalize specificity. Three types of host cells are commonly used for biopharmaceutical production: bacteria, yeast, and mammalian cells. The choice of the host cell is determined by the targeted protein. During the observation period of this study the mammalian process was widely considered the least well understood (Hofmann, 1992; Pringle, 1992), that is, closer to the frontiers of scientific understanding. It was a recent development, involving specific knowledge that was known to fewer people, and difficult to transfer to other uses (Hofmann, 1992; Pringle, 1992). For example, most mammalian cells function only in certain types of complex cell-specific environments (Lewis, 1987), and delicate mammalian techniques are often characterized as more art than science. On the other hand, bacteria and yeasts have been used in fermentation since Stone Age, and biotechnological innovation has improved these processes since the 1930s (Sharp, 1985). Thus, we expect projects that involve specific mammalian knowledge to be less likely to involve a collaboration, or to involve a collaboration at a later stage in the product-development project. *Knowledge specificity* is coded as a dummy variable that equals 1 if the project involved mammalian knowledge. We also include an interaction between *Knowledge specificity* and *R&D expenditure* as

Table 1
Descriptive statistics and correlations

		Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Patent application	0.08	0.26															
2	R&D intensity	54.51	27.79	−0.13*														
3	Prior collaborations with partner	0.21	0.41	−0.02	−0.08													
4	R&D collaboration experience	2.43	2.68	−0.06*	0.08*	0.26*												
5	Pre-1980	0.10	0.30	−0.07*	0.03*	−0.19	−0.18*											
6	Post-1986	0.34	0.47	−0.08*	0.14*	0.05	0.30*	−0.24*										
7	Support infrastructure	6.71	4.87	0.13*	−0.22*	0.19	0.20*	−0.40*	0.01									
8	Pharma CEO	0.47	0.50	−0.03*	0.32*	0.02	−0.16*	−0.14*	0.10*	0.01								
9	University CEO	0.18	0.39	0.12*	−0.28*	−0.10	−0.12*	−0.01	0.03*	0.02	−0.44*							
10	Venture CEO	0.14	0.35	−0.12*	0.00	−0.01	0.30*	0.37*	−0.17*	−0.14*	−0.38*	−0.19*						
11	Cash	48.01	77.68	0.00	0.13*	0.25	0.47*	−0.12*	0.37*	−0.04*	0.12*	−0.09*	0.02					
12	R&D expenditure	17.17	26.95	−0.10*	0.35*	0.16	0.53*	−0.12*	0.37*	−0.07*	0.13*	−0.18*	0.20*	0.82*				
13	Knowledge specificity	0.51	0.50	−0.12*	0.14*	−0.10	−0.08*	−0.29*	0.24*	0.14*	0.25*	−0.12*	−0.31*	−0.17*	−0.13*			
14	Number of competitors	285.03	122.91	−0.04*	0.05*	0.13	0.38*	−0.49*	0.85*	0.31*	0.14*	0.04*	−0.28*	0.41*	0.39*	0.32*		
15	Pharma biopatents	50.50	53.50	−0.04	−0.39*	−0.20	−0.04	0.20	0.21	−0.03	−0.13	0.07	−0.02	−0.19	−0.27*	0.05	0.16	
16	Collaboration likelihood	0.01	0.11	0.07*	−0.01		0.00	0.01	−0.02	0.02	0.01	0.01	−0.02	−0.02	−0.03*	−0.04*	−0.02	
17	Collaboration timing	3.20	3.02	0.21	0.03	0.17	0.33	−0.08	0.53*	0.04	0.20	−0.35*	0.13	0.55*	0.51*	0.10	0.54*	−0.03

Bivariate correlations.
* $P < 0.05$.

a predictor of collaboration likelihood, since it seems likely that highly specific knowledge requires a higher R&D investment from the firm. Thus, high levels of R&D could help in the transfer of specific projects.

Number of competitors. We also control for the level of market competition in the biotechnology industry. We expect that the pharmaceutical firms have less need to strike a collaboration early to secure first-mover advantages with a particular biotechnology partner, if several other alternative partners exist (Williamson, 1975; Pisano, 1990). Similarly, since the new biotechnology firms have more opportunities for learning from their peers as the number of biotechnology firms increases, there may be less need for early collaboration, suggesting that later collaboration is more common as the number of competitors increases. *Number of competitors* is measured as the number of new biotechnology firms present in the industry each year.

Pharma biopatents. A count of biotechnology patents for each pharmaceutical partner is included in the timing equation to control for the biotechnology research capabilities of pharmaceutical partners. Such capabilities may matter, since prior research has shown that familiarity reduces the time needed to absorb new knowledge (e.g. Oxley, 1997; Katila, 2002), and can thus speed up collaboration. Biotechnology experience of the pharmaceutical partner was measured as the number of biotechnology patents the pharmaceutical firm had applied for during 2 years prior to collaboration. We use US Patent and Trademark Office definition of biotechnology-specific patent classes to compile a list of biotechnology patents for these firms. See Table 1 for descriptive statistics of all variables.

6. Results

Table 2 reports the results of the empirical tests. Five of our six hypotheses were supported. Model 1 in Table 2 includes the event history model explaining collaboration likelihood, and Model 2 presents estimates from the fixed effects OLS model that explains timing of collaboration, including Lee's (1983) correction for sample selection bias. Model 2 thus reports the results of the hypothesis testing. *Collaboration likelihood* is used as the dependent variable in the first model. *Collaboration timing* is the dependent variable in the second model. The log likelihood and R^2 estimates for each model are given at the bottom of the table. Venture CEO drops out of the timing model (Model 2) since fixed effects models cannot include time-invariant covariates. Model 3 includes sensitivity tests.

In Hypothesis 1a, we proposed that patent protection would encourage firms to transact early in the product-development life cycle. Model 2 in Table 2 includes the test for this hypothesis. Although the coefficient for *Patent application* is negative, as expected, it does not reach significance. Thus, Hypothesis 1a is not significantly supported. We return to this unexpected result in Section 7. In Hypothesis 1b, we proposed that high *R&D intensity* would reduce *Collaboration timing*. This prediction is borne out: *R&D intensity* has a negative sign in Model 2 and this relationship is significant. Firms that invest heavily in searching for technological opportunities also have early access to resources for opportunity exploitation.

Hypothesis 2a proposed that prior collaborations with a partner would accelerate current collaboration, and indeed, the negative coefficient of *Prior collaborations with partner* in Model 2 supports this hypothesis. Collaborations with familiar partners are struck earlier in the development process. Relatedly, in Hypothesis 2b we proposed that entrepreneurial firm's prior technological collaboration experience also accelerates collaboration. Since the coefficient for *R&D collaboration experience* is negative and significant at the $P = 0.1$ level in Model 2, the results provide some evidence that R&D collaboration experience speeds up rather than slows down access to resources through collaboration.

Model 2 in Table 2 includes the test for Hypothesis 3 as well. This hypothesis predicted that industry maturity, i.e. the evolution of the intellectual property protection laws and support infrastructure in biotechnology, would lead firms to engage in collaboration earlier in the product-development project. The estimated positive coefficient for *Pre-1980* and the negative coefficient for *Post-1986* provide support for Hypothesis 3a: industry-level measures to increase intellectual property protection indeed seem to have facilitated tacit know-how transactions. The coefficient for *Support infrastructure* (Hypothesis 3b) is similarly negative and significant, showing that state biotechnology centers have been effective in helping

Table 2
Generalized Heckman selection model predicting *Collaboration likelihood*$_{it}$ and *Collaboration timing*$_{it}$

	Model 1 Collaboration likelihood	Model 2 Collaboration timing	Model 3 Collaboration timing
Intercept		−0.13 (3.76)	−0.52 (4.16)
Patent application	1.02*** (0.26)	−0.70 (1.19)	−0.73 (1.42)
R&D intensity	0.01 (0.01)	−0.11** (0.04)	−0.11* (0.04)
Prior collaborations with partner		−1.26* (0.61)	−1.20* (0.67)
R&D collaboration experience	0.22** (0.08)	−0.48† (0.29)	−0.49† (0.34)
Pre-1980	−0.06 (0.43)	2.71* (1.29)	2.63* (1.37)
Post-1986	0.63 (0.56)	−5.23* (2.26)	−5.39* (2.56)
Support infrastructure	0.03 (0.03)	−0.25* (0.10)	−0.25* (0.11)
Pharma CEO	0.81** (0.30)	−3.55* (1.33)	−3.56* (1.45)
University CEO	0.40 (0.46)	−4.79** (1.47)	−4.68** (1.55)
Venture CEO	0.12 (0.39)		
Cash	−0.01† (0.004)	−0.004 (0.02)	−0.003 (0.03)
R&D expenditure	−0.07* (0.03)	0.21* (0.09)	0.21* (0.10)
Knowledge specificity	−1.74** (0.58)	1.02 (1.19)	0.89 (1.64)
Knowledge specificity × R&D expenditure	0.06* (0.03)		
Number of competitors	−0.003 (0.003)	0.05*** (0.01)	0.05*** (0.01)
Pharma biopatents/100		−0.10 (0.71)	0.01 (0.81)
λ		1.11 (1.02)	1.20 (1.40)
Biotechnology capabilities			0.03 (0.10)
Non-R&D collaborations in project			0.18 (1.76)
The log likelihood	−183.30		
R^2		0.29	0.28

The table gives parameter estimates; standard errors are given in parentheses. The variable λ is an adjustment for sample selection as in Lee (1983). There are 4922 monthly observations. Two-tailed tests for controls, one-tailed tests for hypothesized variables.

† $P < 0.1$.
* $P < 0.05$.
** $P < 0.01$.
*** $P < 0.001$.

new biotechnology firms to access resources fast to exploit technological opportunities.

In general, the control variables exhibit the expected results. Like prior transaction cost studies, we find that more specific projects (*Knowledge specificity* in Model 1 in Table 2) are less likely to be developed together with a partner. However, building on this finding, we find a positive interaction of *Knowledge specificity* and *R&D expenditure* in Model 1. Firms that develop specific projects but also have large investments in R&D are more likely to collaborate. We also find, as we speculated earlier, that the increasing *Number of* biotechnology *competitors* delays collaboration. However, we do not find a significant effect of this variable on collaboration likelihood. Finally, it is interesting to note that the industry-level variables (*Pre-1980*, *Post-1986*, *Support infrastructure*) that strongly predict collaboration timing in Model 2 are not significant in Model 1; the decision on whether to collaborate is mainly determined by project and firm-level factors (see also Oxley, 1997 for the importance of project characteristics in determining likelihood of collaboration), whereas the timing decision is explained by firm and industry-level factors.

Sensitivity tests were also conducted to test the robustness of the findings. For example, to control for within-firm differences in entrepreneurial firms' biotechnology R&D capabilities over time, we included each sample company's citation-weighted biotechnology patents as an additional control (*Biotechnology capabilities*). The main source for this patent data collection was the US Patent and Trademark Office database. Who owns whom directories were used to create the patent portfolios for each firm.

We also included a control for prior non-R&D collaborations in each project (*Non-R&D collaborations in project*). This variable is proposed to affect the motivation of the parties to enter future collaborations in the project. The results from the timing model that include these additional controls strongly support the original findings, and are reported in Model 3 in Table 2.

To test for the sensitivity of the results to alternative samples, we estimated the models by excluding those technology collaborations that only focused on clinical trials, but had no other R&D objective. Prior research has described clinical trials as either a fairly routine process with a limited research component, or in contrast, as an integral part of the R&D process where new biological insights are discovered (see for example Azoulay, 2000). To take both of these possibilities into account, we ran the models both by including contracts that focus on clinical trials (original results in Table 2), and without them. Three projects involving clinical trials (120 monthly observations) were excluded in the latter case, and the results in both cases were substantively similar.

7. Discussion

7.1. Research contributions

Here we draw some connections between our study and related research. At a broad level, this study contributes to understanding the dynamics of collaboration behavior of new biotechnology firms. We showed that while often-mentioned sources of transaction costs such as knowledge specificity have a strong effect on whether biotechnology firms collaborate, institutional developments at the industry level along with firm-specific factors seem to better predict the timing of such collaborations.

From the entrepreneurship literature point of view, this study examines a relatively little-studied question of how firms gain timely access to resources they need for exploiting technological opportunities. The study also extends our understanding of how prior experience explains the success of entrepreneurial firms. We found that experience makes it easier for entrepreneurial companies not only to recognize (e.g. Shane, 2000) but also to exploit technological opportunities—in our sample, firms with prior collaboration experience, and CEOs with prior knowledge and experience of the pharmaceutical industry were more likely to engage in early exploitation of opportunities through collaboration. We also showed how industry-level evolution explained why entrepreneurial firms were able to exploit opportunities earlier than their predecessors in the industry.

From the transaction cost point of view, this study makes two main contributions. First, our findings build on prior transaction cost arguments to explain the timing of collaborations. Several studies have applied the transaction cost framework to evaluating the choice between the market and firm alternatives for organizing innovation. Tapon (1989), Pisano (1990), and Brockhoff (1992), for example, examined variations in the use of interfirm R&D agreements for the development of biotechnology-related drug products. These empirical studies showed that transaction hazards, such as small numbers bargaining problems, limit a pharmaceutical firm's ability to rely on external sources for research. Other authors (for example, Barley et al., 1992; Mang, 1998) have also indicated that the differences in the technological area of the project, or differences in the technological specialty of the firm, lead to differences in transaction behavior. Our findings from the event history models confirmed these results in the domain of biotechnology projects, and the findings from the timing models showed how these transaction cost factors both similarly and differently affect the timing of collaborations.

Second, this study increases our understanding of how transaction costs change with time. Although Williamson (1975, p. 10) argued that a transaction "choice ought not to be regarded as fixed" and that "the degree of uncertainty associated with the transaction in question may diminish" over time, Shelanski and Klein (1995) found that most empirical work on transaction cost economics has been cross-sectional. We address this gap by examining a longitudinal panel dataset. We include as variables the firms' own time-variant actions to reduce tacitness of know-how, as well as the industry-level institutions, rules, and regularities that change transactional uncertainty over time. And, our findings provide support for the dynamic nature of transaction costs.

Finally, the study has methodological contributions. The Heckman selection model is a comprehensive method for simultaneous examination of the likeli-

hood and timing models. These models have often been examined separately; whereas our study allows generalization of timing results to the larger sample. Moreover, our focus is explicitly on the R&D projects rather than dyads or firm-level collaborations.

7.2. Limitations and future work

The data does not confirm all of our expectations, however. We hypothesized that patent application would increase the likelihood of earlier transactions (Hypothesis 1a), but did not find strong support for the hypothesis. One reason for this finding may be that firms that have applied for a patent may have less time pressure to engage in collaborations, perhaps because the patent gives them an opportunity to exploit the opportunity in other ways, for example through licensing. More explanations for this result should be examined in future work.

The *CEO background* control variable had significant coefficients in both models, and deserves further attention. As expected, CEOs who have a pharmaceutical industry background are most likely to engage in technological collaborations with the pharmaceutical firms (Model 1 in Table 2). These CEOs along with, somewhat surprisingly, the CEOs who have university research backgrounds (but no pharmaceutical experience) are also the fastest collaborators. Additional research on university entrepreneurs is needed to examine why biotechnology firms managed by university CEOs collaborate early.

The measures used in this study are of course not without limitations. For example, the high patenting propensity in the biotechnology industry makes patents an especially appropriate measure for knowledge codification in this study, but this measure does not generalize to all other industries. Due to data constraints, the results of the study will also generalize best to public firms; how the results apply to private firms should be examined in future work. One possibility is that for private, less-established companies, industry-level factors are even more important predictors of timing than our results suggest. This will be an important issue for future research.

This study also leads to several other ideas for future work. Examining how the timing of collaborations affects entrepreneurial firm performance is one such. In the empirical context of this study, it would be interesting to evaluate how collaboration timing affects project success (for example the subsequent sales of the new drugs). Another interesting issue for future work is to study how firms differ in their ability to collaborate early. While we, in this study, used a fixed effects approach to control for unobserved firm heterogeneity to make sure our results reflect within-firm changes over time, an interesting question for future work is to examine how firms evolve to be different, and whether some firms develop capabilities for collaborating at a certain development stage. Another related idea for future work is to study how incumbent corporations manage collaboration (see also Powell and Brantley, 1992). Comparing the collaboration patterns of entrepreneurial companies to those of incumbent companies entering a new technological subfield could help us further explore the relationship between firm capabilities and opportunity exploitation. An experienced incumbent firm may, for example, be able to overcome the inherent constraints of the new technological subfield through its reputation and existing complementary capabilities.

While this study deals solely with US biotechnology firms and their domestic and foreign partners, the results have a broader relevance. In particular, the research should be applicable to other high-technology industries where opportunities come and go quickly, and few companies can act on them alone. The results of the study could be also used to plan industry-level infrastructure decisions in fast-moving high-technology industries to support collaboration and early access to resources.

Managers of entrepreneurial firms need to decide whether and when they engage in collaborations to exploit technological opportunities. In this study, we argued that the same characteristics that make such opportunities attractive—the window of opportunity to develop the idea before others catch up, and the asymmetry of information about the true value of the opportunity—also make it hard to find partners to quickly exploit these opportunities. We also provided evidence of the factors that mitigate these barriers to collaboration. We found that the firms' R&D and collaboration experience, and the institutional developments in the industry, can speed up collaborations on even tacit know-how.

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