The Impact of Founder Professional Education Background on the Adoption of Open Science by For-Profit Biotechnology Firms

ABSTRACT

This paper investigates the effect of founder professional education background on the adoption of the open-science technology management strategy by a sample of 512 young biotechnology firms. One major finding of the paper is that after controlling for founder prior work experience and other organizational and environmental factors, biotechnology firms with proportionally more Ph.D.-holding entrepreneurs on the founding team have higher probability to adopt open science. A second note-worthy finding is that founder professional education background can mitigate the constraint of organizational environment on strategy. While a crowded technological niche provides a more challenging environment for firms to implement open science due to higher scooping risks, the deterring effect of such a high-risk environment is smaller among firms founded by proportionally more Ph.D.-holding entrepreneurs. I also found that the link between entrepreneurial professional education background and open science is stronger in a less favorable institutional environment for open science. The finding is consistent with and complements the growing body of work emphasizing the importance of entrepreneurial background in developing knowledge about new venture strategy and structure. It suggests that demographic changes in educational background of entrepreneurs in an organizational field may bring exogenous shocks to and shift the strategic trend in an organizational field. The implications for management innovations in an organizational field are discussed.

I. Introduction

When a new organization is founded, what explains its adoption of one particular structure, strategy or practice over another? One school of explanation points to the constraint of organizational founding environment (e.g., Stinchecombe, 1965, Kimberly, 1975, Boeker, 1988, Romanelli, 1989). Others emphasize the role of external stakeholders such as venture capital firms (Hellman and Puri, 2002; Suchman, 2006). On the other hand, in a panel study of 170 California Silicon Valley high-technology startups, Baron and colleagues observed that "Founders of technology companies embrace quite distinct 'organizational blueprints'" and that there are "clear differences in models or blueprints even between firms competing in the same particular industry niche and claiming to pursue similar business strategies" (Baron, Burton and Hannan, 1999, p.3).

To explain such variations, scholars turned to factors associated with individual entrepreneurs. The existing evidence suggests that founders' backgrounds may have profound influence on the choice of early organizational structure, strategy and management practices. For example, Burton (2001) examined entrepreneurs' employment histories and observed that founders who were more experienced and previously exposed to alternative organizing models were more likely to adopt initial strategies that deviated from industry norms. Simons and Roberts showed that founders with pre-founding industry experience in a different location from where they started their firms were more likely to adopt locally novel organizational forms (Simons and Roberts, 2008). The founder imprinting literature (Baron, Burton and Hannan, 1996, 1999; Baron, Hannan and Burton, 1999, 2001; Burton and Beckman, 2007; Beckman and Burton, 2008) further suggests that founders not only shape early organizational models, they also have long-lasting influence on subsequent organizational structure, strategy and practices. Given what we know about the impact of founder background on early and later stage organizational structure and strategy, we cannot afford ignoring the influence of individual entrepreneurs as it may result in systematic underestimation of the variation in organizational models in a given field (Burton, 2001).

Prior investigation of founder background, however, has focused only on entrepreneurs' prior work experience (Burton, Sørensen and Beckman, 2002; Shane and Khurana, 2003; Higgins, 2005; Beckman, 2006; Sorensen, 2007; an exception is Boeker, 1988). Another founder background factor, entrepreneurs' education, also may have significant impact on founders' view of organizations but has been largely ignored so far. Though education is one of the most widely studied background variable in the entrepreneurship literature, the attention has been primarily on the relationship between education and entrepreneurial entry and outcome (in the form of individual earnings in self-employment or longevity of the startup firm (e.g., Carroll and Mosakowski, 1987; Evans and Leighton, 1989; Bates, 1990; Brüderl, Preisendörfer and Ziegler 1992; Lazear, 2005; Kim, Aldrich and Keister, 2006). Very often, education is only highlighted as part of the human capital that can boost the entrepreneurial entry rate and post-entry success.

However, entrepreneurs' educational background maybe a key factor to understand the emergence of innovations in an organizational field. The history of Google provides a salient example. When Larry Page and Sergey Brin, developed the prototype of the Google search engine during their Ph.D. training at Stanford, they approached several dominant Internet firms in the field to sell their technology. Alta Vista turned them down because it didn't want to use a search engine technology developed outside of the firm. Yahoo was reported not interested in the technology because it was eager to build Yahoo webpage into a portal on which web surfers stay and spend more time. A search engine that promised to quickly render useful information ran contrary to that goal. At the core of the issue, Page and Brin differed significantly with incumbent Internet firms on the value of the search engine technology. While most incumbent players viewed search engine as a commodity, Page and Brin, influenced more by their advisors and colleagues at Stanford, didn't buy into the popular belief at the time. They saw great value in a high-quality search engine and huge potential demand for it. Eventually, out of passion for their own visions and disappointment with incumbent firms, the two Ph.D. students became entrepreneurs and founded the company Google (Vise and Malseed, 2005).

There is a vast body of sociological and management literature that emphasizes the imprinting experience of professional education. First, individuals learn specialized knowledge during the process of professional education. As research in organizational demography has suggested, the expert knowledge and skills may constrain an individual's future information processing patterns and serve as a cognitive map for his evaluation of organizational strategies and practices (Hambrick and Mason, 1984; Wiersema and Bantel, 1992).

Second, professional education is also a process during which an individual internalizes core values of a profession. As Larson noted, a primary goal of professional training is to produce "effectively socialized average members…who recognize a profession's hierarchy and, implicitly, the criteria of success on which it is founded" (1977). The sociological literature of profession has shown how professional education shapes individual values and actions in organizational settings (e.g., Kornhauser, 1962; Miller, 1967). Thus, knowing what knowledge, values and ideologies a potential entrepreneur has internalized during his education will help us understand his preferences among competing organizational strategies and practices.

Third, educational background could influence the choice of organizational strategies and practices by shaping a potential entrepreneur's network of contacts. Marquis's (2003) research on network imprinting has shown that early social and physical conditions at the formation phase of a network affect how the network is structured even long after the initial conditions have disappeared. Empirical evidence on the effect of managers' business school education suggests that managers rely on the contacts developed from when they were educated at their business schools as sources of business information, based on which strategies are evaluated and formulated (Haunschild et al., 1999; Rider, 2008). Having information on the educational background of an entrepreneur offers us a window to observe his or her social interactions and how such interactions may shape his or her visions for a new firm.

Despite its importance, empirical evidence that relates entrepreneurial professional education background to early organizational structure, strategy and practices remains scanty. Organizational demography, particularly the research on top management teams (TMT), probably is the closest to answer this question, but its focus is more on the team dynamics determined by the distributional property of education among TMT members. In addition, most of the studies in this area draw from mature organizations and are cross-sectional (e.g., Kimberly and Evanisko, 1981; Bantel and Jackson, 1989; Wiersema and Bantel, 1992), a research design that does not render clean identification of the managerial educational background effect (see Hambrick, 2007, for a review of the identification problems in TMT research).

This paper seeks to empirically test the existence of an entrepreneurial professional education background effect on early-stage organizational strategy, after controlling for individual, organizational and environmental confounders. Focusing on organizational founders and startup firms to a large extent mitigates the selection problems in the identification of the founder educational background effect. In addition, I examine in this paper conditions that may modify the entrepreneurial professional education background effect. Specifically, I investigate how entrepreneurial educational background effect interacts with organizational environment in shaping early organizational strategy. For these purposes, I study a sample of 512 for-profit biotechnology firms in the U.S. and analyze how founders' educational background, internal organizational factors, and firms' institutional and technological environment jointly determine whether a firm will adopt open science—a policy that allows a firm's research personnel to do basic science research and publish the results in academic journals.

One major finding of the paper is that after controlling for founder prior work experience and other organizational and environmental factors, biotechnology firms with proportionally more Ph.D.-holding entrepreneurs on the founding team have higher probability to adopt open science. A second note-worthy finding is that founder professional education background can mitigate the constraint of organizational environment on strategy. While a crowded technological niche provides a more challenging environment for firms to implement open science due to higher scooping risks, the deterring effect of such a high-risk environment is smaller among firms founded by proportionally more Ph.D.-holding entrepreneurs. I also found that the link between entrepreneurial professional education background and the adoption of open science is stronger in a less favorable institutional environment for open science.

The finding of this study adds to entrepreneurship literature by establishing the influence of founder education on the choice of new venture strategies. More importantly, it provides evidence that emphasizes the role of entrepreneur background in shaping organizational structure and strategy. Such a finding compliments the growing body of work that argues for entrepreneurial agency over environmental determinism (Burton, 2001; Burton, Sorensen, Beckman, 2002; Shane and Khurana, 2003; Sine, Haveman and Tolbert, 2005; Johnson, 2007). In the context of high tech entrepreneurship, how a new venture is organized is not solely determined by its structural or institutional conditions, nor by its external stakeholders such as venture capital firms. Entrepreneurs draw from their educational background (or employment history as shown in the other studies) to form their unique visions for a firm, based on which a new venture's structure and strategy is built. In addition, my research speaks to the literature of university-industry interactions. Most studies on university-industry relationships focus on how commercial norms of the industry may contaminate the academic culture and productivity in universities. This study provides evidence in the reverse direction and show that the influence can be mutual between the two sectors.

II. Open Science as a Corporate Strategy

Traditionally, *open science* refers to the way in which knowledge generated at universities and non-profit research organizations is disseminated (David 1998). A distinctive set of norms and institutions has been developed in academia to govern scientists' behaviors and support open science. For example, intellectual findings are viewed as belonging to the scientific community, and rewards in the form of peer recognition is directed to those who first communicate the scientific discoveries to the public (Merton 1957). Firms in the private sector also engage in research and knowledge generation, though it is well understood that for-profit firms employ very different models of knowledge creation and dissemination from academic institutions. For example, firms tend to avoid investing in basic science research, as the economic returns of knowledge generated from basic research are difficult to appropriate (Nelson, 1959; Rosenberg, 1990). In addition, firms have strong concerns regarding the protection of intellectual property. Protective mechanisms such as patents and trade secrets are routinely employed to ensure that breakthroughs are first exploited by the firms that have invested in the discovery process (Dasgupta and David, 1994).

However, in sectors where firms draw heavily from public research, it has been noted that for-profit firms are increasingly adopting research and publication policies that, to some extent, resemble those in the public sector. This trend of convergence is particularly notable in the life sciences industry (Gambardella, 1992, Cockburn and Henderson, 1996; Lim, 2004). Figure 1 shows the proportion of biotech firms founded by a calendar year that have started publishing in ISI-indexed scientific journals by age five. Overall, there is an increasing proportion of biotech firms that allow staff to publish research findings. Among all firms founded by 2000, the end of my observation period, approximately 60% of the firms in my dataset had adopted the open-science strategy by age five.[1]

---- INSERT FIGURE 1 ABOUT HERE ----

Scholars have identified some strategic benefits associated with a policy of allowing and encouraging corporate research staff to engage in some basic research and publish in scientific journals. For example, Henderson and Cockburn (1994) found that pharmaceutical firms rewarded scientific staff based on their standing in the hierarchy of public-sector science for the purpose of developing capabilities of absorbing advances in public research. Basic science knowledge may serve as a map for more effective technological development and knowledge diffusion (Fleming and Sorenson, 2004; Sorenson and Singh, 2007). Assuming university-affiliated scientists prefer research projects that will lead to publications, adoption of open science could also help firms attract high-quality recruits (Stern 2004) and academic collaborators. Finally, though not yet empirically confirmed, game theorists suggest that publication of discoveries may be used by firms engaging in a patent race to establish a higher standard of prior art and to prevent competitors from being granted the patent rights to a particular invention (Lichtman, Baker and Kraus, 2000; Parchomovsky, 2000).[2]

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[1] Adoption of firms by age five is graphed in Figure 1 because this study focuses on early organizational strategy. If I were to include firm adoption of open science (measured by one or more publications in research journals) at any age, the percentage of adopters reaches approximately 80% as of 2000.

[2] The U.S. patent system is based on a first-to-invent rule and uses prior art as a reference point against which new patent applications are evaluated. Since all new patents must meet the standard of non-trivial innovation over the prior art, publishing research advances could raise the standard of prior art and effectively set the bar higher for competitors seeking to patent a similar technology.

Despite the strategic benefits, there is the fundamental tension faced by for-profit firms between using open science to advance its technology and protecting proprietary innovations. First, while pharmaceutical firms have been found benefiting from absorbing knowledge produced by academic institutions (Henderson and Cockburn, 1994), Gittelman and Kogut's (2003) study of biotech firms produces opposing evidence that questions the extent to which biotech firms can successfully translate knowledge absorbed from public science into commercially viable technologies. Second, even in today's environment, when an open science strategy has been more widely adopted by life sciences firms, several biotech entrepreneurs and senior executives told this author during interviews that they treated the matter of research staff publications very carefully for fear of inadvertently leaking crucial information to competitors. Most of the executives in my interview reported that their firms routinely screen employee manuscripts and allow only a fraction of the proposed manuscripts to be published. Many had experiences of being told by the screening committee not to present a paper even though it had already been accepted by a highly regarded academic conference. According to one interviewee, "the perception that there is more flexibility in today's life sciences firms to work on and publish basic science research is not accurate…you'd be surprised how much restriction firms impose to protect their IP".

In reality, even if a firm carefully screens the manuscripts that staff members wish to submit for publication, this is not a bullet-proof way to prevent competitors from scooping. The more a firm allows its staff to publish, the more risk it entails. Though systematic data on scooping are lacking, disputes of this nature arise routinely among firms in technology-intensive sectors. For example, in 1984 researchers at Cistron Biotechnology submitted a paper to the *Nature* magazine that contained the gene sequence of an Interleukin-1 beta immune system protein. Steven Gillis, then head of the research department at Immunex, was one of the reviewers. He allegedly copied the sequence data and used it in Immunex's own patent application (Kokmen, 1996). After a three-year lawsuit, Cistron won a $21 million settlement in 1996. The case, nonetheless, highlighted the tension between adopting a practice that is designed primarily for public sector research and the need of for-profit firms to protect intellectual property rights, which is always present in firms that employ an open-science strategy.

Scooping risks are most significant for new firms. This is because unlike their more established competitors, new firms do not have dedicated legal departments and the necessary financial means to battle a competitor that behaves as Immunex did (Lerner, 1995). Because of the trade-offs involved, it is not always easy for entrepreneurs to assess the merit of this strategy or to determine how much restriction they should impose when executing the strategy. Though publications help signal the quality of the knowledge generated by a new venture to its external stakeholders, there is noise in such signals. Unlike patenting proprietary knowledge in exchange for the legal protection of a period of monopoly use of that knowledge, firms publishing discoveries in scientific journals cede control of the knowledge to any competitor capable of understanding and using it.

To summarize, when open science was transplanted from academia to the industry, it is no longer the academic open science in its original sense. Firms utilize it for strategic reasons but also worry about its risks. At least in biotech, it coexists with traditional technology strategies such as patenting and trade secrets. Indeed, it is up for debate whether open science adopted by industrial biotech firms studied in this paper is truly "open" or not and it is not the goal of this paper to assess the degree of "openness". At a minimum, it is fair to claim that open science is a unconventional strategy for managing an industrial firm's technology. It is chosen because the ambiguity and uncertainty related to this practice makes it a suitable target for examining factors that shape the propensity of a firm to adopt it. In addition, in the biotech industry, research and development is a salient aspect of early organizational building. Because most biotech firms do not have any products or revenues at the founding stage, research-and-development-related strategies are at the core of organizational survival in this industry.

III. Founder Professional Education Background and Open Science

In the introduction section, I have summarized general sociological and management theories regarding the role of professional training in shaping corporate decisions. In this section, I focus more specifically on the context of my study—the biotechnology industry. The findings of the study, however, are generalizable beyond biotech (see the discussion section for more on this point).

Does biotech founders' educational background affect the adoption of open science at the firms they have created? In the context of the biotech industry, a significant proportion of entrepreneurs have received graduate training. Among the 1,090 biotech entrepreneurs studied in my data, 540 (49.5 percent) of founders have a Ph.D., 149 (13.7 percent) hold an M.D. and the rest report other types of degrees. Compared to entrepreneurs with other types of education, a Ph.D.-holding entrepreneur has spent a significant portion of his or her life doing basic science research. In a typical doctoral program in the U.S., a student spends only two years on course work and the rest of his training time participating in the knowledge generation and dissemination process. Because of the length and intensity of most Ph.D. programs in the U.S., I treat Ph.D.-holding founders as being subject to a more intensive professional education which can potentially influence their perceptions of open science, in comparison to founders holding other types of degrees. Thus, the question more directly related to the setting of this study is: are firms founded by Ph.D.-holding entrepreneurs more likely to adopt open science?

There are four reasons for which we might expect that a Ph.D.-holding entrepreneur develops a more favorable perception of open science. One reason has to do with their exposure to the norms of science during their doctoral training. In Merton's classic description of the ethos of science (1957), one core norm is communism, which prescribes that findings generated by a scientist belongs to the scientific community and require full and open communication with the entire community. The idea of full and timely disclosure of substantial scientific findings is woven into much of the Ph.D. training process, and reinforced by the priority-based incentive system in academia. However, a significant body of sociological literature in the 1960s and 1970s produced evidence that challenges the accuracy of the Mertonian description of the normative structure of science (e.g., Merton, 1963; Mulkay and Williams, 1971; Cole and Cole, 1973; Latour and Woolgar, 1979). More recent evidence by Blumenthal and his colleagues (1997) has also shown that faculty members will deviate from the norm of timely disclosure of scientific findings when commercial interest is at stake. Thus, although Ph.D.-holding entrepreneurs may have more exposure than their non-Ph.D.-holding counterparts to the scientific norms of open communication, it is questionable to what extent Ph.D.-holding entrepreneurs will commit to them and whether their commitment lasts till the time of venture creation, especially when the incentives are at odds with the professional norms (Wallace, 1995). Given the controversial evidences, I expect the commitment effect to be existent, but far from being the sole driver behind Ph.D.-holding entrepreneurs' preference for open science.

A second reason for expecting a favorable perception of open science among Ph.D.-holding entrepreneurs is their more science-oriented cognitive structure developed from their doctoral training. Studies have shown that the deployment of different cognitive models may affect a wide range of organizational outcomes including trajectory of technological development (Garud and Rappa, 1994), direction of corporate strategies (Barr, Stimpert and Huff, 1992) and corporate reaction to technological disruptions (Tripsas and Gavetti, 2000; Kaplan, Murray and Henderson, 2003). The basic premise is that cognitive structure or mental models developed on the basis of historical precedents affects the ways in which a manager processes information when making organizational decisions. As outlined in section II, there are tradeoffs associated with open science: while there are risks of losing control of proprietary knowledge, the practice also carries the benefits of boosting a firm's absorptive capacity and attracting scientific talents and university collaborators. When open science is new in the field, whether or not an organizational founder sees more of the benefits or disadvantages may be related to the prior education and work experience of the founder. The doctoral training experience may influence an entrepreneur by allowing him to see more of the benefits of open science. For example, given the knowledge and skills, he may appreciate more of the contribution of public-domain knowledge to a firm's technology development and thus be more likely to emphasize the absorptive-capacity-boosting side of open science. Coming from a doctoral background, an entrepreneur is also more likely to understand the preferences of an average scientist and thus see open science as an excellent tool for attracting scientific talents to work for or collaborate with his firm. Thus, during organizational founding, a Ph.D.-holding entrepreneur is more likely than entrepreneurs who have received other types of degrees to form a positive evaluation of the open science strategy and see it as conducive to doing top-quality corporate research.

Professional training is also about assimilating trainees into the professional hierarchy and socializing them into believing in the status hierarchy of the profession. Thus, a Ph.D.-trained entrepreneur might prefer open science out of status aspirations. Status order within a profession is positively related to the level of abstraction of knowledge (Abbott, 1988). Though a Ph.D.-trained high-tech entrepreneur is supposed to focus more on developing commercially viable technologies, being able to publish basic science research in academic journals allows him to maintain, to some degree, a respectable status within the larger scientific community. In fact, many scientist-turned biotech entrepreneurs maintain affiliations with academic institutions, not only for keeping abreast of the latest scientific development, but also for maintaining certain standing in academia. An open-science strategy is instrumental for achieving both of these purposes.

Finally, assuming strong inertia in scientist-entrepreneurs' networks (Marquis, 2003; Mauer and Ebers, 2006), a Ph.D.-holding entrepreneur's network at the stage of firm founding will be rich in two types of contacts. One will be people who are sharing similar Ph.D. training experiences, e.g., graduating from the same program or school. By the time of venture creation, many of these contacts will be working in academia. Such a network is effective in reinforcing any preexisting preference for open-science in a Ph.D.-holding entrepreneur. Given the homophily tendency, a second type of contacts will be those who are also Ph.D.-trained and now founding or managing their own startups. Assuming that open-science as a novel corporate strategy is more likely to emerge among one of the scientist-turned entrepreneurs, information regarding the open-science strategy (e.g., how to implement it and what benefits are associated with the strategy) is more likely to be circulating within such networks of scientist entrepreneurs. Thus, a Ph.D.-holding entrepreneur is more likely than an entrepreneur who hails from another type of educational background (e.g., MBA) to learn about open-science, particularly when it is still new to the industry. Based on reasons related to commitment to professional values, cognitive structure, status aspirations and network patterns, I expect that

Hypothesis 1*: Firms with a higher proportion of Ph.D.s on the founding team are more likely to adopt an open science strategy.*

In the process of venture creation, many factors other than founders' visions can drive a new firm's strategy. Whether or not an entrepreneur's vision for a start-up can be realized is often the negotiated outcome between the entrepreneur and their environment (Johnson, 2007). How does a founder's educational background interact with a firm's founding environment in determining early organizational strategy? Two types of environment are often examined to explain the variations in organizational strategies—technological and institutional. The technological environment limits the choice of organizational strategy to those that boost the new venture's operational efficiency. As described in section II, when deciding on a technology strategy, a key concern of for-profit firms is appropriability – the extent to which a firm can protect its intellectual property from being imitated by its competitors. This is a particularly important dimension of a biotech firm's technological environment, as most biotech firms have no product at the time of founding, and new ventures are often built on the mere promise of a discovery. When scooping risks are high and protection of intellectual property is difficult, a firm is operating in a high-risk environment with regard to the open-science strategy.

I expect that firms with proportionally more Ph.D.-trained founders react less to the risks in the technological environment than those with less Ph.D. representation. Though far from conclusive, there is some documented evidence that suggests resilience in professional education effect, even in an environment that is contradicting to professional ideals. For example, Riegal (1958) and Kornhauser's (1962) studies of Ph.D. scientists working for industrial firms show that in situations where professional values are in conflict with corporate goals, professionals still show considerable commitment to the values they have internalized during their graduate training. In health care, concern over loss of professional autonomy were cited as one of the reasons for physicians' reluctance to participate in health maintenance organizations during the early proliferation of HMOs (Kralewski, et al., 1987; Rosenbach, et al., 1988; Ku and Fisher, 1990). Stern's (2004) more recent study of the salary distribution of life scientists suggests that scientists are willing to take a pay cut for employment by a company that implements a research and publication policy consistent with their professional values. These findings suggest that there is a possibility that Ph.D.-scientists-turned-biotech entrepreneurs are less sensitive to the risks in the technological environment than entrepreneurs who have not been through the intensive professionalization process.

***Hypothesis* 2a:** *The negative effect of a high-appropriability-risk technological environment on the adoption of an open-science strategy is smaller in firms with more Ph.D. founder representation.*

When there are uncertainties regarding the benefits of a specific strategy, organizational adoption often follows a social contagion process (Coleman, et al., 1957; Burt, 1987; Mizruchi, 1990; Davis, 1991; Haveman, 1993). In the biotech context, firms occupying similar competitive positions in the industry are likely to recruit from the same talent pool, attempt to engage the same set of star university professors as collaborators, or search for similar sources of funding. When a competitor starts practicing open science and benefiting in the form of better recruits or collaboration with university scientists, firms that fall behind risk losing to the early adopters. In addition, adoption of open science by competitors increases the legitimacy of the practice (Burt, 1987). Mimicking competitors thus might increase the legitimacy of the new firm and boost its survival chances. Given such benefits, adoption of the open science a strategy is a relatively easy decision when the strategy has been widely diffused or adopted by a majority of firms in the industry (Abrahamson and Rosenkopf, 1993), at which point it doesn't take a Ph.D.-trained entrepreneur to appreciate the value of open science. The social pressure alone can push firms to adopt it. This suggests

Hypothesis 2b: *The effect of Ph.D. representation on a founding team on the adoption of the open-science strategy is weaker when the strategy has been more widely adopted.*

IV. Data, Method and Variables

IV.1 Data

My data include all dedicated biotechnology firms headquartered in the U.S. that have ever filed IPO prospectuses (Form S-1, SB-2, or S18) with the U.S. Securities and Exchange Commission. These firms are identified based on information from industry directories and in the "business" section of firms' prospectuses. I used three primary sources to identify biotechnology firms: the Compustat database, the Bioscan Directory, and the Recombinant Capital database. A total of 512 biotechnology firms founded between 1969 and 2000 have filed IPO prospectuses. Information coded from these filings includes: (i) biographical sketches of founders,[3] scientific advisors, and senior executives (e.g., name, gender, age,

[3] There is no specific requirement with regard to reporting firm founders by the SEC. However, founders can be identified from the prospectuses if, at the time of IPO, they serve as executive officers or scientific advisors, are principal shareholders of the firm, or hold important intellectual properties on which the firm relies. About 70% of

highest degree obtained and recent jobs held); (ii) firm founding year (i.e., year of incorporation), core technology field and mode of creation (i.e., independently created versus corporate spin-off); and (iii) financial data up to five years prior to the IPO prospectus filing date.

One limitation of the data is that, due to the lack of any systematic historical data on private firms, only information about biotechnology firms that have filed IPO prospectuses in the U.S. was gathered. As a consequence of this sampling method, I am working with a selected sample. It is likely that the firms in this database are relatively successful compared to the average startup firm in the biotechnology sector. However, this should not be a serious concern given that the outcome variable of this study is firms' strategic choices, rather than performance, which is more sensitive to the exclusion of private firms. In addition, the impact of firm founders on organizational strategy tends to be stronger in smaller organizations, as bureaucracy is less established in these firms and founders are less constrained by bureaucratic procedures. This implies that my test of founder educational background effect is a more conservative one.

I obtained firms' publication records from ISI's Web of Science database. In order to minimize problems caused by corporate name changes, I tracked all previous company names using several business information databases (e.g., One Source, Informagen Biotech and Pharmaceutical Company Directory, and Thomson Financial Database). A total of 35,318 research articles had been published by 442 firms by 2002. In addition, I also retrieved publication records for firms' founders and scientific executives prior to their joining the firm.

I used Recombinant Capital's clinical trial database to construct variables of organizational environments. Recombinant Capital (Recap) tracks over 3,400 therapeutic products that have been in the clinical trial process since 1978. Each record contains information on the product developer, target disease area, underlying technology, and time when the product enters each stage of the clinical trial process. The data are used to categorize biotech firms based on their core technology areas and to construct the firms' niche density and competitive influence variables.

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the founders in my data can be identified from the IPO prospectuses documents. I identified the remaining via search over the Internet (e.g., the Bioscan and Informagen directories).

IV.2 Models

I use three different estimators to model founder adoption of open science. In prior studies of diffusion of corporate strategies and practices, organizational adoption is often modeled as a dichotomous choice. I follow this tradition and use a logit model to estimate a firm's probability of adopting open science conditioning on the founder professional education as well as control variables for other individual, organizational and environmental factors. Since I cannot directly date when a firm formally or informally adopts the open science policy, I rely on the outcome of adoption—a firm's published papers in scientific journals (more description of the dependent variable is in the next section). In the logit, a firm is considered to have adopted open science if it has one or more publications in scientific journals.

This traditional model of adoption, though straight-forward, might be problematic in the context of biotech industry. First, there might be miscellaneous reasons for a biotech firm to have a research publication even though it doesn't have a policy of endorsing open science. For example, a paper might be reported as a firm's publication because of an address change of a recently graduated employee—in such a case, the published paper says nothing about the firm's policy. Second, a simple dichotomous measure might not capture the full picture of how open science is carried out in a firm. The core issue for a firm is not only announcing a policy to its staff but, more importantly, deciding the extent to which it will support the policy. These include decisions whether to encourage staff to devote a portion of their time to basic science research not closely related to the firm's immediate technological goal, whether to set up incentives for staff to engage in scientific publications, whether to use publications and reputation in the public science sector as part of staff performance measures, or how much restriction to impose when censoring researchers' publication requests. All of the above reveal the level of commitment that a firm has to open science and will be reflected in a firm's publication output.

For the above reasons, I also rely on a count of a firm's research publications as indicators of adoption. I use a quasi-maximum-likelihood (QML) Poisson model. A significant portion of the firms in my sample has zero publication count (see Figure 3). As a result, my data display both over-dispersion and excess zeros. Because the Poisson model is in the linear exponential family, the coefficient estimates remain consistent as long as the mean of the dependent variable is correctly specified. Further, in a QML Poisson, "robust" standard errors are consistent even if the underlying data generating process is not Poisson (Gourieroux et al. 1984). QML Poisson is preferred because it imposes little structure on the underlying data distribution and in general is a more conservative estimate of the coefficients due to the larger standard errors. In addition to QML Poisson, I include a zero-inflated negative binomial (ZINB) estimator. ZINB incorporates a switch function that estimates the latent propensity for a firm to be in the zero publication group and then estimates the positive outcome with the latent propensity accounted for in its likelihood function.

IV.3 Variables

Dependent Variables

In the logit estimations, my dependent variable is an indicator whether a firm had, by the fifth year after it was founded, adopted open science by starting to publish research articles in ISI-indexed scientific journals. In the QML Poisson and ZINB estimations, my dependent variables are the count of a firm's research papers by its age five. Preliminary analysis of the timing of biotech firms' publication activity shows that most firms that eventually publish research begin publishing within the first few years of their founding. Figure 2 tracks, among all firms that have one or more papers during the window of my observation, the proportion that begin publishing by a specific firm age. The adoption rate rises sharply during the early years in firms' life cycles and begins to slow down after five years from inception, at which point 65 percent of the firms (that eventually will publish) have already started publishing. The choice of a 5-year window also allows for the time needed to set up corporate research functions and for possible publication lag due to editorial processes. At the same time, the gap between founding and adoption is also short enough that I can reliably assess the role played by organizational founders. Sensitivity analysis conducted using a 4 or 6-year observation window indicates that the results are not sensitive to the cutoff age. Figure 3 reports the distribution of firms across publication level by age five. The distribution is skewed: 42% of the firms in the data have zero publications, 33% publish between 1 and 5 papers, while 25% publish between 6 and 90 papers.

---- INSERT FIGURE 2 AND 3 ABOUT HERE ----

Founder Background Variables

I computed the proportion of a firm's founders who have received Ph.D. training as indicator of founder professional education background.[4] I expect firms with a higher percentage of Ph.D. founders will be more likely to have higher propensity of pursuing open science. I also control in all models for founders' prior work experiences. I computed the proportion of each firm's founders who have worked for a pro-open-science employer. Most founders listed their prior work experience (particularly the more recent experience) in the bio-sketch in S1. In the case that such information is not in S1, I used the Internet to search for a founder's background information. The pro-open-science ex-employers include academic institutions and firms that have published, in ISI-indexed journals, five or more papers (the average publication count of the biotech firms in my data during the first five years since firm inception).[5] I computed the percentage of such entrepreneurs in a firm's founding team to measure the level of influence coming from founders with pro-open-science work experience.

Organizational Environment Variables

I construct a niche crowding measure for the appropriability risk in an organization's technological environment. To the extent that two firms compete in the same technological niche, they pursue similar knowledge and it would be easier for them to scoop technological advances from each other. Appropriability risk is thus associated with the characteristics of a firm's technological niche: in

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[4] In unreported robustness check analysis, I ran the same set of regressions, replacing the percentage of Ph.D. founders with the count of Ph.D. founders in a firm's founding team. The only meaningful difference between the two sets of models is that when using the count variable, the Ph.D. founder-institutional environment interaction effect becomes weaker. These results are available upon request.

[5] The pro-open-science prior employment experience at academic institutions in this measure is restricted to employment as faculty member or postdoctoral researcher at an academic institution. Stuart and Ding (2006) randomly sampled over 10,000 life sciences Ph.D.s and followed their career history based on the affiliation information revealed in their published papers. In their sample, only about one half of holders of a doctorate degree in the life sciences end up getting a faculty position in universities while the rest works for industrial firms, with or without some post-doctoral experience. Indeed, the boundary between education and work experience can be fuzzy, particularly for post-doctoral training. Luckily, the percentage of entrepreneurs transitioned directly from post-doctoral status is small in my data. Any ambiguity around host to interpret post-doctoral training is not likely to drive significant changes in the results.

crowded, densely populated niches, the risk of being scooped is higher, as there are more potential imitators.[6] Such an environment poses more challenge for the adoption of open science.[7]

The crowding measure requires a meaningful way to divide the technological space in the biotech industry into different areas. For this purpose I used the dataset on clinical trials tracked by RECAP, in which companies' products in the clinical trial process are each identified with one (or, in a few cases, more) primary technological area(s). There are a total of 34 technological areas in RECAP's classification. I measured niche crowding for each firm as the number of other firms competing in the firm's main technological niche at the time of founding. There are several points to note about this measure. (1) For a firm with more than one technology area, I used the one in which the firm has the most number of clinical trials as its main technological niche. (2) I used data on firms' clinical trials up to the fifth year after the founding date to determine a firm's primary technology area. By the fifth year there is more information available about where a firm's primary niche is.[8] (3) The density count includes not only the 512 public

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[6] There is a slight difference between crowding in the context of scooping risks and that used in conventional organizational ecology research. When ecology scholars discussed crowding, it was often related to the carrying capacity of a niche. This way of operationalizing crowding takes into account the resource constraint of environment, and is more suitable for explaining outcomes such as organizational performance and survival. In this paper, however, the crowding concept is used to capture the likelihood that a firm's knowledge can be leaked to competitors. Thus, crowding is measured by the number of potential imitators a focal firm faces rather than the rate of saturation in a niche.

[7] I also have computed a more fine-grained, patent-citation-overlap based measure for technology crowding. The measure is similar to that in Podolny, Stuart and Hannan's (1996) study of semi-conductor patents. I first compare a focal firm's patents and those of another existing firm in terms of the overlap in the citations made by these patents. A patent citation overlap index is generated for each pair of firms in existence by the year a focal firm was founded and the mean citation overlap is taken across all pairs of firms. However, I did not end up using this measure in my models because a significant number of firms do not have patent applications during my observational window and this measure cannot adequately capture the true level of crowding in a firm's niche.

[8] Because it is very rare that firms have developed products that reach clinical trial stage at early ages, adjustment has to be made regarding when firms start operating in a technological area. Assuming that a firm should have developed substantial expertise in an area when it has a product in the clinical trial process, I extended the starting time for each clinical trial backward for 5 years (or to the time of firm founding, whichever is later). For example, Humulin, the rDNA-based human insulin product jointly developed by Genentech and Eli Lilly, entered pre-clinical stage in 1978. I extended the record backwards for 2 years in this case, since Genentech was founded in 1976. As a result, Genentech would have one clinical trial record using recombinant-DNA technology since time of founding instead of zero records. This method effectively reduces data loss due to firms' lack of clinical trial products during early ages. In addition, I assume firms would not usually discard their technological expertise. Thus, once a firm enters a technological area in a given year (*i.e.*, has a product that enters clinical trial in that year), I treat the firm as remaining in that area until disbanding or 2002, the last year of observation.

biotech firms in my dataset, but also the pharmaceutical and private biotechnology firms in the U.S. and abroad (the dataset includes a total of 3,728 biotech and pharmaceutical firms, public and private). The inclusion of these firms yields a more accurate measure of the scooping risks as firms, large or small, stand ready to benefit from the knowledge disclosed by a focal firm. It is expected that the density of a firm's primary technological niche has a negative effect on publication propensity.

I have also constructed a measure for the isomorphic pressure in a firm's institutional environment. In explaining the mimetic mechanism, DiMaggio and Powell (1983) pointed out that we should not assume firms automatically imitate each other, particularly when it is related to core technologies of an organization. They suggested that firms are more likely to select their imitation targets based on how relevant the targets are to themselves, either through having direct ties with the targets (e.g., interlocking directors) or through occupying similar positions in the competitive landscape (i.e., structural equivalence). Because open science as a strategy does not involve a lot of tacit knowledge transfer between firms (a situation where influence through direct ties is more important), I constructed a structural-equivalence-based measure of the pressure for adopting open science in an organization's institutional environment. Following previous research (Burt, 1987; Bothner, 2003), for each firm *i* at time *t*, the influence from other firms in the industry is:

$$CP_i = \sum_{j=1,\, j\neq i}^{J} w_{ij} P_j \qquad (1)$$

where P_j is an indicator variable that is coded 1 if competitor *j* has, by firm *i*'s founding year, already started publishing, and w_{ij} is a weight applied to each P_j. Each competitor *j*'s influence on focal firm *i* is represented by w_{ij}, which captures the degree of similarity between *i* and *j* in the competitive landscape—or in network terms, the structural equivalence between *i* and *j*. To compute the weight I relied on firms' technological areas based on the primary technologies underlying their products already in the clinical trial process. Firms develop their core capabilities in technological areas in which they have generated products that reach the clinical trial stage. In these areas, firms closely monitor their rivals and thus are more susceptible to competitive influence. Therefore, for two firms *i* and *j*, I measured their similarity to each other by comparing their product allocation in each of these 34 technological areas. Specifically,

$$d_{ij} = \sqrt{\sum_{k=1}^{34}\left(\frac{n_{ik}}{\sum_k n_{ik}} - \frac{n_{jk}}{\sum_k n_{jk}}\right)^2} \qquad (2)$$

where n_{ik} and n_{jk} are firms *i's* and *j*'s counts of clinical trial cases in technological area *k*, and $n_{ik}/\Sigma_k n_{ik}$ and $n_{jk}/\Sigma_k n_{jk}$ are the proportions of *i's* and *j*'s clinical trial cases in that area by the fifth year after firm inception. Essentially, this is a Euclidean distance measure based on differences in firms' shares of clinical trial products in each of the technological sectors. Next, the Euclidean distance is converted into a structural proximity weight w_{ij} using:

$$w_{ij} = \frac{\max(d_i) - d_{ij}}{\sum_j [\max(d_i) - d_{ij}]} \qquad (3)$$

w_{ij} is then applied to the influence of all rival firms in eq. (2) to generate the covariate CP, which will be used in the regression to estimate the institutional pressure created by a firm's similarly positioned rivals. I expect this measure to have a positive effect on the probability that a firm will adopt open science.

Control Variables

A strong alternative explanation is that the observed effects could be driven by unobserved heterogeneity across technology subfields. For example, Ph.D.-holding entrepreneurs may be more likely to sort themselves into subfields where capabilities to understand basic science knowledge are crucial, and corporate strategy is more oriented towards open science. Indeed, there are significant heterogeneities across the technological subfields in which biotech firms engage their research. Some involve more basic research (e.g., genomics and bioinformatics), which is more frequently published in academic journals, while others deal with more applied knowledge, which does not commonly get published in academic journals. To control for such heterogeneity, I included a series of technology field dummies in the models. Specifically, I first coded a firm's technological area based on the category in which it has the biggest share of its products in the clinical trial process according to the RECAP data. For firms that do not have any product covered by the clinical trial database, I relied on the information about their core business and technologies disclosed in their IPO documents. I tried to map the core technology information in the prospectus as close as possible to the 34-technology-field classification used in the RECAP clinical trial data. These fields were then grouped into eight primary technology areas. Table 1 reports the distribution of biotech firms across these areas as well as the percentage of founders with a Ph.D. degree in an area. The area with the highest concentration of Ph.D.-holding entrepreneurs is genomics and bioinformatics, a relatively new area in biotech that focuses on exploiting genomics information to expedite drug discovery processes. The lowest concentration is among firms researching on growth, blood and hematopoietic factors.

---- INSERT TABLE 1 ABOUT HERE ----

Firms' research performance can be affected by the structure of their networks (Maurer and Ebers, 2006; Stuart, Ozdemir and Ding, 2007). Previous studies have reported a high degree of correlation between firms' publication count and their collaboration with academic researchers (Cockburn and Henderson, 1996;1998). Because academically affiliated researchers tend to prefer projects that can lead to publication (as part of academic reputation building), it is possible that firms are willing to relax the disclosure rule to some extent in order to attract top-quality researchers to collaborate on projects. To control for the influence of firms' academic collaborators, I used the Biotech Alliances data available from RECAP, in which a total of 11,000 alliance agreements have been tracked and analyzed since 1978. For each biotechnology firm in my data, I computed the total number of alliance projects it had started with academic institutions by the fifth year following its inception. I expect this measure to have a positive effect on a firm's likelihood to engage in publishing its research.

I have constructed six variables measuring firms' research capabilities. First, I counted the total number of research papers published by a firm's founders by the year of firm inception. This is to account for the possibility that the firm's publication count is driven up primarily by the founders' ability to publish. Second, the founding team size was also measured to control for the possibility that large founding teams secure more resources for the firm. Third, I computed the total number of research papers published by a firm's chief scientific officer before he or she joined the firm, and I used this count as a proxy of the quality of the firm's research personnel. As with the founder publication measure, this number is fixed at the year before the scientific officer started working for the focal firm. I also included in the models a dummy variable indicating a firm has formed a scientific advisory board and the count of publications by the most productive member of a firm's SAB. These two measures are to account for the possibility that a firm with a SAB of star scientists can attract research staff who are good at publishing papers. Lastly, I counted the total number of patents held by a firm by age five. The patent count serves as a baseline indicator of a firm's research activities.

A firm's research output is often proportional to financial resources. I obtained, from IPO prospectuses and Compustat, five financial measures: (i) the total amount that a firm spent on research and development (R&D) between age three and five, (ii) total assets, (iii) net sales, (iv) net income, and (v) total amount of invested capital. Financials at firm age one and two were not used because of substantial missing data. For age three to five, there were still 25% of firms with no data, in which case imputation was applied using the AMELIA multiple imputation program (King *et al.* 2001). I expect an increase in these resource and capability control variables will boost a firm's publication count.

I also controlled for how firms are created by including a dummy variable indicating whether a firm is established as a corporate spin-off. Spin-offs pose some difficulty in estimating the effect of firms' intrinsic propensity to adopt open science. It is possible that the parent firm has a strong influence on its spun-off subsidiary. Moreover, the early-stage managers of a spin-off often come from the parent and are likely to follow the rules, routines, and management styles of the parent firm (Phillips, 2002; Chatterji, 2006). Therefore, spin-off firms may have different sources of cultural influences from independently formed ones. A total of 89 firms are corporate spin-offs, according to information revealed in their IPO prospectuses.

Finally, a series of five-year-period dummies were included in the models to control for any unobserved factors arising from the specific historical periods in which a firm was created.

V. Results

Table 2 and 3 report variable descriptive statistics and the covariance matrix. Table 4 presents results from the logit, QML Poisson and ZINB regressions of firms' open-science adoption within the first five years after inception.

---- INSERT TABLES 2-4 ABOUT HERE ----

Models 1-3 report the baseline estimates with only the control variables. Out of the fourteen control variables, it is not surprising that alliance count with universities, publication count of the scientific executives both have consistent and positive effect on the likelihood of a firm's adoption of open science across all three model specifications. Large founding teams also increase the adoption propensity. This may have to do with the fact that the pairing of business experts with scientific experts is more often observed in founding teams with two or more entrepreneurs. The positive relationship between patent and publication is also consistent with previous findings (Gambardella, 1992), indicating that most firms rely on both patenting and publication in knowledge development. Financial resources seem to affect the count of publications rather than the probability to publish, but the impact is small in magnitude. For each additional million dollars a firm spends on R&D, its publication count increases by merely 1% in the PQML specification and 3% in the ZINB specification. Similar effects are found for a firm's net income. These results are not surprising given that firms are expected to devote more of their financial resources to generating patents than publications. Spinoff firms also seem to have high number of publications than independently formed ones. With all the other controls in the model, there is evidence that a founder's prior work experience still has a strong influence on a firm's technology management strategy. Both the logit and PQML models report positive and significant effects of the percentage of founders in a founding team with publishing ex-employers. One percent increase in founders with some pro-open-science work experience almost doubles the probability that the firm will adopt open science (=exp[0.657] in column 1) and increases a firm's publication count by 78% (=exp[0.577] in column 2).

Model 2 tests my hypotheses 1 on founder Ph.D. educational background effect. I included the variable that measures the percent of Ph.D. scientists on a founding team to test this hypothesis. Like the "founder prior work experience" variable, this variable exerts a strong impact on the likelihood of adoption. With an additional percent of Ph.D. scientists on a founding team, a firm's adoption rate is 2.4 times the original (=exp[0.862] in column 4). An additional percent of Ph.D. scientists on a founding team increases a firm's publication count by about two times (=exp[0.828] in column 5 and =exp[0.676] in column 6).

The significant effect of Ph.D. founder representation in the models lends support to my H1 regarding the impact of founder professional education background on a firm's likelihood to adopt the open science strategy. Note that while founder prior work experience effect is strong in model 1, its magnitude drops and its effect is no longer significant, after educational background is included in the estimation. The correlation of the "percent Ph.D. founders" and "percent founder with pro-open-science ex-employer" is 0.348, hence multi-collinearity is not a major concern between the two variables.

Hypotheses 2a and 2b are about patterns of interactions between founder educational background and organizational founding environment. H2a postulates that firms founded by Ph.D.-trained entrepreneurs react less to high-appropriability-risk environment for open science. Models 7-9 include two additional variables, a firm's technology niche density (D) to measure the risks in a firm's technology environment for open science, and the interaction term between proportion of Ph.D. entrepreneurs on a founding team and a firm's technology niche density. The unreported main effect of the technology niche density (D) is negative and significant when included alone in the logit, QML Poisson and the count portion of the ZINB model. The interaction effect is positive and significant, suggesting that Ph.D.-holding founders are modifying the impact a challenging technology environment for open science. Figure 4 illustrates the moderating effect of founder educational background on an organization's technological environment, based on the results in column 7. Three lines were drawn in figure 4 that represent the change in a firm's adoption propensity (i.e., there is one or more publications by a firm) as technology crowding intensifies (which indicates that the technological environment turns less favorable for open science) for three different types of firms—those with zero, 50 percent or 100 percent Ph.D.s on the founding team. When a firm's founding team does not include any Ph.D.-trained scientist (the solid line), it reacts negatively to the unfavorable technological environment. Its likelihood to adopt open science falls most precipitously among the three lines as technology crowding increases and scooping risk intensifies. Firms' reactions to unfavorable technology environments decrease with higher representation of Ph.D.-trained scientists on the founding team. For example, when a firm's technological niche density increases from 1 to 50, the adoption rate of firms with zero Ph.D.-trained entrepreneurs decreases by 33 percent (=exp[-0.008*50]), while adoption rate of firms founded by 50% Ph.D.-trained entrepreneurs decreases by only 16 percent (=exp[(-0.008+0.009*0.5)*50]). In contrast, when firms are founded by all Ph.D-trained scientists, the reaction is even a slight increase in the adoption rate (=exp[(-0.008+0.009*1)*50]). It seems that in a technological environment unfavorable for open science, having more founders with a Ph.D. training helps mitigate the negative impact of the environment. The consistent results across all three models lend support to my hypothesis 2a regarding the pattern of interaction between founder educational background and an organization's technology environment.

In models 10-12, I added the variable of influence of competitors (CP) that measures the isomorphic pressure from a firm's institutional environment. I also included the interaction term of this variable with founder educational background. Without the interaction term included, the main effect of CP is positive and significant on a firm's probability to publish and publication count. In the reported models, the interaction effects are negative and significant in the logit and QML Poisson models, though not significant in the ZINB model. I illustrate the finding of column 10 with Figure 5, which draws the effect of founder educational background on the probability that a firm adopts open science in three types of institutional environments—relatively unfavorable (i.e., competitor adoption index is at the 25th percentile point), neutral (50th percentile point) and favorable (75th percentile point). In the figure, we see that when the institutional environment is relatively unfavorable (solid line), founder educational background plays a strong role in a firm's adoption of open science—the propensity of adoption rises most steeply among the three scenarios. In contrast, the slope for founder educational background effect on the rate of adoption is much more gentle when more competitors have adopted open science and the institutional environment becomes more favorable (top broken line). A similar pattern is found for the results from the QML Poisson model. Despite the insignificant result from the ZINB model, the overall evidence based on the other two model specifications seem to support my hypothesis 2b.

---- INSERT FIGURES 4 and 5----

Issues of Selection

The issue with many of the TMT studies of demographic background effect using mature organizations is the difficulty in teasing out the selection problems (Hambrick, 2007). For example, the

TMT theory might posit that managers with abundant technical expertise invest heavily in R&D. However, the observed relationship between managerial background and corporate R&D strategy could be driven by the fact that technically sophisticated managers are more likely drawn to heavy-R&D-investment firms. Alternatively, it could be driven by the fact that firms that wish to implement a heavy-R&D-investment strategy select technically sophisticated managers into top management roles because of a perceived match between corporate strategy and managerial capabilities.

Studying entrepreneurial educational background and startup organizational strategy to some extent helps mitigate these issues. The first type of selection problem described above is lessoned because the organization does not exist until its founder has created it. However, selection in my data might still occur when scientist-turned entrepreneurs sort themselves into technology areas that clearly benefit from a strategy like open science. If this happens, my observed relationship between founder professional education background and open science only reflects the matching of entrepreneurial capability to implement open science and the industrial sector that can let this capability be realized, rather than the intentional influence of the entrepreneurs. I have dealt with this form of selection issue by including technology area fixed effects in most of the models, which help control for unobserved heterogeneity across technology areas.

A second form of selection in my data could take place when a firm's external stakeholders (e.g., VC firms) decide to support firms founded by Ph.D. entrepreneurs who wish to adopt open science, out of a belief that the combination of Ph.D.-trained entrepreneur and open science will enhance a startup firm's performance. If this is true, then my finding about the influence of Ph.D. founder professional training merely reflects the higher survival chances of firms showing such a combination (i.e., Ph.D.-trained founders and open science) than firms showing other combinations (e.g., firms founded by Ph.D.-trained entrepreneurs that did not adopt open science, or firms founded by non-Ph.D.-trained entrepreneurs that have adopted open science). If this form of selection exists in my data, it is more likely to occur when open science is more widely diffused and its strategic advantages better understood, in which case external stakeholders have more confidence in supporting Ph.D.-trained entrepreneurs, whom they believe can execute the open science strategy well. Thus, if my finding is driven by this form of selection, we should observe stronger relationship between professional education background and open science when institutional environment is more favorable. However, the interaction between "percent Ph.D. founders" and "influence of competitors" in model 7 turns out negative and significant, suggesting that that the link between founder educational background and firm adoption of open science is actually weaker when open science has become more institutionalized. As a result, I do not expect the selection by external stakeholders to be a serious problem in my models.

There might be another form of selection taking place in the industry context I am investigating. I found in my analysis that the relationship between Ph.D. founder representation and firm publication is stronger in adverse organizational environment and I attributed it to the strong influence of Ph.D. entrepreneurs in reducing environmental determinism. An alternative explanation may be that during the early stage of the biotech industry, it was primarily academicians with a Ph.D. degree who populated the biotech startup firms. Non-Ph.D. entrepreneurs only successfully entered the industry during the later stage of the industry. First of all, inclusion of a series of period dummy variables in the model helps to minimize the possibility my results are driven by this form of selection. Second, I report the mean firm founding year for each of the technology areas in my data in the last column of Table 1. The difference in mean founding year of firms in the technology areas is modest. Genomics and bioinformatics is the only area that is markedly different from the rest of the areas in mean firm founding year. This is also an area with the highest representation of Ph.D. entrepreneurs. This area, however, emerged during the more recent period in the biotech history.

VI. Conclusion and Discussion

This paper addresses the question whether entrepreneurial professional education background affects early organizational strategies at newly-created ventures. I sampled 512 U.S. biotech firms and analyzed the adoption of the open-science strategy, which is traditionally found in academia and has been gradually diffused among for-profit, technology-intensive firms. The results lend support that founders' professional education is a significant source from which entrepreneurs draw to develop their visions of a startup and it influences the choice of organizational strategy. In the biotech context, I found that firms created by entrepreneurs who have received Ph.D. training were much more likely to adopt open science than those created by entrepreneurs with other types of educational background. This effect holds even after I have carefully controlled for possible confounding factors. Moreover, founder educational background may counter-balance the effect of organizational environment. When a biotech firm has more Ph.D.-trained founders, it is less deterred by a high-risk technological environment for open science. Finally, when examining founder educational background effect in different institutional environments, I found a stronger effect of founder educational background when the open science strategy is not yet widely diffused.

Among the findings, the most important to note is the identification of the effect of founder professional education background on organizational strategy. Studying startup firms helps to mitigate the problem caused by managers selectively joining firms with a strategy matching their demographic background, an issue that has plagued many of the cross-sectional studies of managerial demographic effect on strategic change in mature organizations. I also used technology-area fixed effects in the estimations to tease out the selection problem caused by entrepreneurs who chose to found firms in technology areas that allow them to emphasize their particular educational background. In addition, the interaction pattern between founder educational background and organizations' institutional environments reassures me that selection by external organizational stakeholders of a certain combination of founder educational background and organizational strategy is not a serious concern in my data.

Moreover, the founder-environment interaction patterns in my study suggest that founders coming from certain education background may choose organizational strategies and practices that deviate from what's been considered appropriate in an organizational environment. The empirical evidence dovetails with extant work (e.g. Burton, 2001; Sine, Haveman and Tolbert, 2005) that emphasize the importance of entrepreneurial agency as mitigating forces of the technical and institutional environment at organizational founding.

This has important implications for understanding the emergence of novel organizational practices in a field. New organizations are important birthplaces of innovations. It is very often the possibility of carrying out a new idea or a new vision that attracts individuals into entrepreneurship. My study has shown that the effects of these new ideas and visions born out of entrepreneurs' educational background may have a powerful impact on organizations. Because education has shown a nontrivial effect in moderating both organizational technological and institutional environment, if we have the information on entrepreneurs' educational background, we may be able to identify sources of exogenous shocks that can potentially trigger institutional changes in an organizational field. In this case the influx of Ph.D.-trained scientist-entrepreneurs seems to have contributed significantly to the emergence and gradual diffusion of the non-conventional practice of open science in the biotech industry. Similar example can also be found in the case of the "Chicago Boys", a group of University-of-Chicago-trained economists who worked under the Pinochet regime and launched the first radical free market reform in Chili in the 1970's (Valdes, 1995).

This study also speaks to the literature on the exchanges between public and private sciences. While previous literature on the normative influence between the two sectors has focused on the importation of commercial norms into public science (Blumenthal et al. 1997; Agrawal and Henderson, 2002; Owen-Smith and Powell 2004; Krimsky 2003; Owen-Smith, 2005; Azoulay, Ding and Stuart, 2008), I look into possible influences in the opposite direction, *i.e.*, the importation of academic norms into private science. The extent of the influence of academic norms on the organization of private science is yet to be determined through more research. Nonetheless, this study illustrates that when exchanges take place between two sectors governed by different value systems, penetration of values and norms can go both ways. This is particularly true when there are significant personnel exchanges between the sectors, as in the history of the biotech industry. Certain aspects of academic norms have been transmitted to the biotech industry along with the influx of scientist-turned entrepreneurs.

One legitimate concern is how generalizable the arguments of this paper are. Biotechnology is a distinctive industry, and any claim to the contrary rests upon a shaky foundation. However, biotech is hardly the only industry that sees a significant increase in the number of firms founded by Ph.D.-trained entrepreneurs. Some emerging science-based industries appear to be witnessing increasing participation of entrepreneurs with advanced professional training. Consider, for example, the company Nanosys, a seven-year-old nanotechnology firm that filed an IPO prospectus in 2004. Nanosys has a research strategy that encourages staff to work with researchers at MIT, Harvard, University of California, and Columbia, and produce cutting-edge discoveries in the area of nanotechnology. On its founding team are scientific founders with Ph.D. trainings, many of whom were affiliated with universities such as Caltech, MIT, and UC-Berkeley. Like Nanosys, emerging companies in nanotechnology are often founded by entrepreneurs with Ph.D.-educational background. Though more research in other contexts is needed, I believe the core argument of this paper—that entrepreneurs with a particular professional education background may offset environmental constraints and introduce novel practices into an organizational field—applies to a number of different industrial settings.

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Table 1: Distribution of Biotech Firms across Technology Areas

Technology Areas	Number (percent) of Firms	Fraction of Founders with Ph.D.*	Mean Firm Founding Year
Synthetics and semi-synthetics	124 (24.2%)	48.7%	1989.3
Generics and other	101 (19.7%)	56.4%	1986.4
Monoclonals	100 (19.5%)	45.6%	1987.1
Drug delivery and vaccines	73 (14.3%)	41.8%	1988.6
Enzyme inhibitors, peptides, antisense and ribozymes, interferon and interleukins	40 (7.8%)	55.6%	1986.6
Recombinant DNA, Cell and Gene Therapy	34 (6.6%)	39.2%	1987.7
Genomics and bioinformatics	29 (5.7%)	66.7%	1993.8
Factors – Growth, Blood and Hematopoietic	11 (2.2%)	37.5%	1987.8

* The fraction is computed by dividing the number of Ph.D.-holding founders of firms in a technology area by the total number of founders with all degree backgrounds in the technology area.

Table 2: Descriptive Statistics

Variables	Mean	Standard deviation	min	max
Firm publication count by age five	5.643	11.854	0	90
Firm has one or more pub. by age five	0.594	0.492	0	1
Percent Ph.D. founders	0.505	0.410	0	1
Pct. founders with pro-open-science ex-employers	0.640	0.405	0	1
Technology niche density (D)	42.68	66.07	0	357
Competitive influence (CP)	0.700	0.614	0	6.244
Founding team size	2.111	1.276	1	9
Number of alliances with universities	1.186	2.048	0	16
Publication count of founders	9.346	35.34	0	285
Publication count of scientific VP	24.55	47.61	0	417
Firm has SAB	0.635	0.482	0	1
Maximum publication count among SAB members	70.15	116.6	0	1575
Number of patents applied	4.320	8.862	0	87
Firm is a corporate spin-off	0.164	0.371	0	1
R&D expenses (in million dollars)	7.619	14.30	0	157.7
Total assets (in million dollars)	26.95	55.13	0	936.8
Net sales (in million dollars)	5.024	11.18	0	120.9
Net income (in million dollars)	-7.281	12.35	-144.3	11.09
Total invested capital (in million dollars)	36.09	92.14	-3.158	1018.7
Firm founding year	1988.1	5.541	1969	2000
N		512		

Table 3 Covariance Matrix

	Firm pub. count	Firm pub dummy	Founding year	Founding team size	Num. of alliances	Pub count of VP	Firm has SAB	Max. SAB pub	Founder pub count	R&D expenses
Firm pub. count	1									
Firm pub dummy	0.394	1								
Founding year	0.161	0.207	1							
Founding team size	0.136	0.094	0.086	1						
Number of alliances	0.220	0.273	0.153	0.020	1					
Pub. count of VP	0.182	0.184	0.111	-0.015	0.185	1				
Firm has a SAB	0.054	0.116	0.098	-0.011	0.142	0.161	1			
Max. SAB pub	0.173	0.159	0.097	0.043	0.077	0.220	0.457	1		
Founder Pub. Count	0.021	0.058	0.014	0.254	0.091	0.068	-0.023	0.001	1	
R&D expenses	0.348	0.173	0.331	0.180	0.109	0.060	-0.042	0.057	-0.003	1
Spinoff	0.119	0.012	0.098	0.266	0.022	-0.028	-0.091	-0.050	-0.061	0.159
Num. of patents	0.318	0.179	0.099	0.036	0.046	0.049	0.006	0.166	-0.008	0.192
Total assets	0.189	0.193	0.246	0.123	0.077	0.046	0.023	0.067	-0.008	0.427
Net sales	0.195	0.135	0.096	0.023	-0.028	0.009	-0.071	0.001	-0.006	0.359
Net income	-0.147	-0.184	-0.387	-0.117	-0.113	-0.087	0.001	-0.062	0.010	-0.622
Total inv. capital	0.270	0.215	0.324	0.154	0.100	0.033	0.011	0.089	-0.015	0.662
% founders w/ open science ex-employer	0.100	0.181	0.120	-0.150	0.111	0.037	0.061	0.034	0.065	-0.017
% Ph.D. founders	0.167	0.207	0.132	-0.050	0.073	0.073	0.181	0.047	0.016	0.017
Tech. niche density	-0.075	-0.033	0.486	0.174	-0.005	0.015	0.049	0.046	0.058	0.169
Competitive influence	0.202	0.235	-0.103	-0.032	0.082	0.016	0.062	0.065	0.009	0.121

Table 3 Covariance Matrix (Continued)

	Spinoff	Num. of patents	Total assets	Net sales	Net income	Total inv. capital	% founder w/ open science ex-employer	% Ph.D. founders	Tech. niche density	Competitive influence
Spinoff	1									
Num. of patents	0.064	1								
Total assets	0.129	0.123	1							
Net sales	0.016	0.253	0.445	1						
Net income	-0.102	-0.129	-0.486	-0.317	1					
Total inv. capital	0.176	0.168	0.852	0.489	-0.616	1				
% founder w/ open science ex-employer	-0.268	0.066	0.052	-0.024	0.008	0.012	1			
% Ph.D. founders	-0.057	0.076	0.028	-0.036	-0.012	0.024	0.348	1		
Tech. niche density	0.050	-0.012	0.149	0.004	-0.270	0.163	-0.030	-0.031	1	
Competitive influence	0.021	0.152	0.119	0.244	-0.087	0.101	0.059	0.024	-0.070	1

Table 4 Models of Firm Publication By Age Five

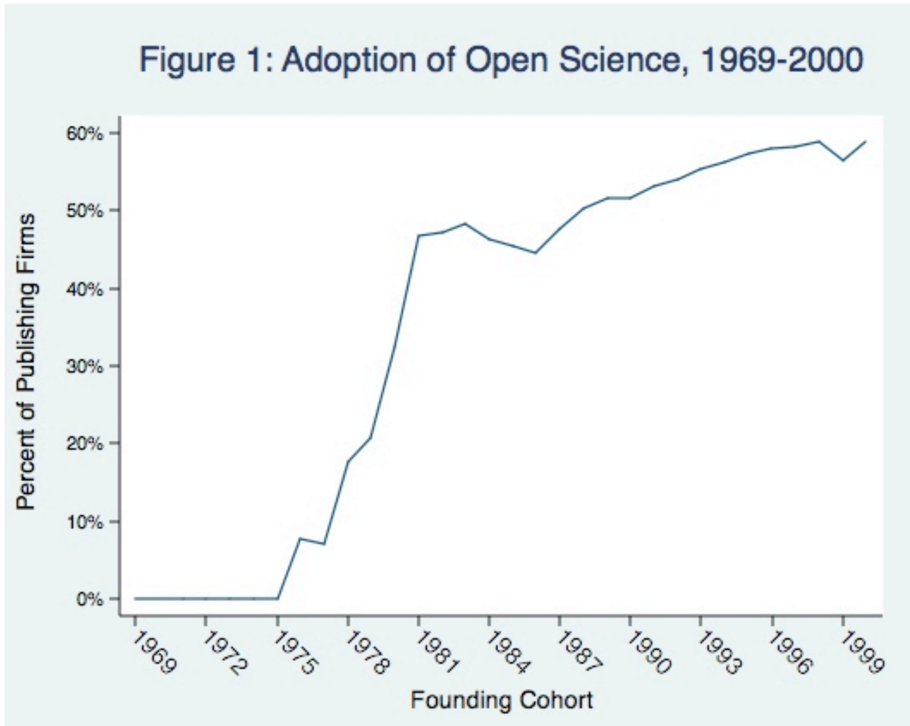
	(1)	(2)	(3a)	(3b)	(4)	(5)	(6a)	(6b)
	Logit	QML Poisson	ZINB		Logit	QML Poisson	ZINB	
			Count	Inflate			Count	Inflate
Firm Founding Year				-0.079				-0.074
				(0.060)				(0.066)
Founding Team Size	0.225	0.231	0.147	-0.262	0.258	0.251	0.145	-0.356
	(0.104)*	(0.066)**	(0.069)*	(0.271)	(0.106)*	(0.065)**	(0.066)*	(0.266)
Number of alliances with univ	0.264	0.103	0.101	-0.336	0.267	0.112	0.110	-0.362
	(0.080)**	(0.027)**	(0.033)**	(0.284)	(0.082)**	(0.024)**	(0.033)**	(0.356)
Pub count of scientific VP	0.007	0.005	0.004	-0.016	0.007	0.004	0.005	-0.015
	(0.003)*	(0.001)**	(0.001)**	(0.012)	(0.004)*	(0.001)**	(0.001)**	(0.011)
Firm has SAB	0.145	-0.061	-0.082	-0.465	0.029	-0.140	-0.223	-0.090
	(0.271)	(0.212)	(0.189)	(0.957)	(0.276)	(0.209)	(0.179)	(0.814)
Max. pub count among SAB members	0.001	0.001	0.0004	-0.007	0.001	0.001	0.001	-0.011
	(0.002)	(0.0004)**	(0.001)	(0.006)	(0.002)	(0.0004)**	(0.001)	(0.007)
Publication count of founders	0.0004	-0.001	-0.001	-0.004	0.0002	-0.002	-0.002	-0.003
	(0.003)	(0.002)	(0.002)	(0.013)	(0.003)	(0.002)	(0.002)	(0.012)
Number of patent applications	0.048	0.023	0.031	-0.864	0.051	0.020	0.028	-0.855
	(0.021)*	(0.006)**	(0.009)**	(0.373)*	(0.022)*	(0.006)**	(0.009)**	(0.295)**
Spinoff (Yes = 1)	0.283	0.861	0.521	0.526	0.284	0.893	0.456	0.300
	(0.357)	(0.280)**	(0.214)*	(0.786)	(0.358)	(0.281)**	(0.209)*	(0.789)
R&D expenses (mm$)	-0.010	0.010	0.030	0.045	-0.010	0.010	0.029	0.055
	(0.013)	(0.005)*	(0.012)**	(0.033)	(0.013)	(0.005)*	(0.011)**	(0.041)
Total assets (mm$)	0.018	-0.001	-0.006	0.019	0.019	-0.002	-0.006	0.020
	(0.009)*	(0.002)	(0.003)†	(0.018)	(0.009)*	(0.002)	(0.003)*	(0.019)
Net sales (mm$)	0.009	0.011	-0.002	-0.449	0.012	0.011	-0.0004	-0.550
	(0.018)	(0.006)†	(0.007)	(0.165)**	(0.018)	(0.007)	(0.007)	(0.200)**
Net income (mm$)	-0.007	0.014	0.031	0.089	-0.008	0.014	0.029	0.109
	(0.021)	(0.005)**	(0.010)**	(0.053)†	(0.021)	(0.005)**	(0.010)**	(0.068)
Total invested capital (mm$)	0.004	0.002	0.007	-0.007	0.004	0.002	0.007	-0.006
	(0.004)	(0.001)	(0.002)**	(0.009)	(0.004)	(0.001)	(0.002)**	(0.010)
Percent founders with publishing ex-employers	0.657	0.577	0.273	-1.338	0.401	0.260	0.075	-1.056
	(0.277)*	(0.265)*	(0.197)	(0.784)†	(0.292)	(0.261)	(0.200)	(0.746)
Percent founders with Ph.D.					0.862	0.828	0.676	-1.496
					(0.287)**	(0.209)**	(0.196)**	(1.000)
Founding Period Dummies	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Technology Area Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust Standard Errors	No	Yes	No	No	No	Yes	No	No
Log-Likelihood	-262.75	-2574.73	-1134.25		-258.18	-2478.47	-1123.17	
Wald χ^2	166.17	443.33	148.70		175.32	450.19	167.76	
Model d.f.	25	25	25		26	26	26	
Vuong statistics			5.44				5.22	
Number of zeros in dep. Var.			208				208	

(1) Number of Observations = 512; (2) Standard errors in parentheses unless otherwise explained; (3) † significant at 10%, * significant at 5%, ** significant at 10%.

Table 4 Models of Firm Publication By Age Five (Continued)

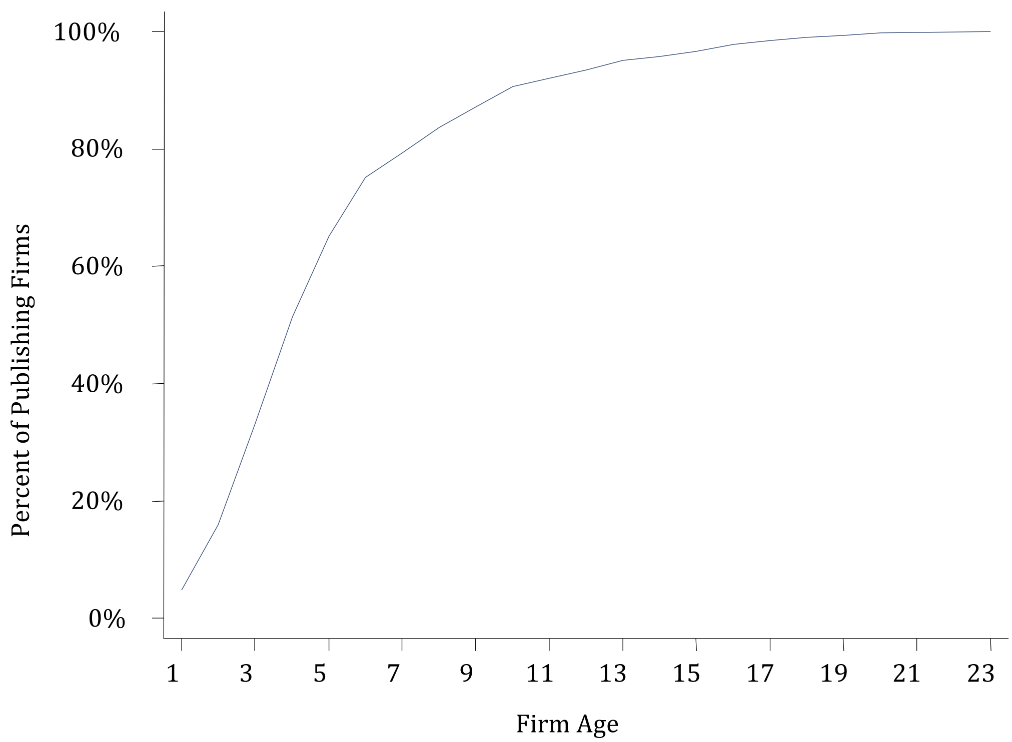
	(7)	(8)	(9a)	(9b)	(10)	(11)	(12a)	(12b)
	Logit	QML Poisson	ZINB Count	Inflate	Logit	QML Poisson	ZINB Count	Inflate
Firm Founding Year				-0.040				-0.117
				(0.085)				(0.055)*
Founding Team Size	0.278	0.254	0.171	-0.958	0.387	0.279	0.190	-0.255
	(0.108)*	(0.064)**	(0.062)**	(0.461)*	(0.119)**	(0.065)**	(0.060)**	(0.210)
Number of alliances with univ	0.266	0.104	0.140	-0.167	0.238	0.099	0.096	-0.100
	(0.082)**	(0.024)**	(0.035)**	(0.375)	(0.080)**	(0.024)**	(0.030)**	(0.139)
Pub count of scientific VP	0.006	0.004	0.004	-0.009	0.007	0.004	0.005	-0.001
	(0.003)†	(0.001)**	(0.002)**	(0.010)	(0.003)†	(0.001)**	(0.001)**	(0.005)
Firm has SAB	0.027	-0.185	-0.269	0.032	-0.001	-0.242	-0.254	-0.449
	(0.275)	(0.205)	(0.175)	(0.876)	(0.282)	(0.209)	(0.169)	(0.500)
Max. pub count among SAB	0.001	0.001	0.001	-0.003	0.001	0.001	0.001	-0.001
members	(0.002)	(0.0004)**	(0.001)*	(0.006)	(0.001)	(0.0004)**	(0.001)	(0.002)
Publication count of founders	0.0002	-0.001	0.0002	0.020	-0.00003	-0.001	-0.002	-0.010
	(0.003)	(0.002)	(0.002)	(0.012)	(0.004)	(0.002)	(0.002)	(0.009)
Number of patent applications	0.052	0.020	0.033	-2.110	0.039	0.019	0.020	-0.389
	(0.022)*	(0.006)**	(0.010)**	(0.956)*	(0.021)†	(0.006)**	(0.008)*	(0.139)**
Spinoff (Yes = 1)	0.348	0.792	0.292	-3.566	0.480	0.746	0.421	0.372
	(0.363)	(0.257)**	(0.204)	(1.627)*	(0.388)	(0.269)**	(0.198)*	(0.718)
R&D expenses (mm$)	-0.009	0.009	0.024	-0.020	-0.004	0.009	0.018	0.025
	(0.014)	(0.005)*	(0.010)*	(0.044)	(0.015)	(0.005)†	(0.009)*	(0.026)
Total assets (mm$)	0.021	-0.002	-0.001	0.204	0.022	-0.002	-0.005	-0.023
	(0.009)*	(0.002)	(0.003)	(0.092)*	(0.010)*	(0.002)	(0.003)*	(0.023)
Net sales (mm$)	0.006	0.008	0.005	-0.277	0.001	0.003	0.001	-0.010
	(0.018)	(0.007)	(0.009)	(0.125)*	(0.019)	(0.007)	(0.008)	(0.047)
Net income (mm$)	-0.010	0.011	0.023	0.665	-0.007	0.010	0.023	0.163
	(0.022)	(0.005)*	(0.010)*	(0.275)*	(0.022)	(0.005)*	(0.009)**	(0.083)*
Total invested capital (mm$)	0.004	0.002	0.003	-0.204	0.003	0.002	0.006	-0.007
	(0.004)	(0.001)	(0.001)†	(0.109)†	(0.004)	(0.001)	(0.002)**	(0.008)
Percent founders with	0.438	0.236	-0.002	-2.969	0.458	0.072	-0.088	-1.226
publishing ex-employers	(0.294)	(0.247)	(0.205)	(1.399)*	(0.308)	(0.258)	(0.197)	(0.622)*
Percent founders with Ph.D.	0.460	0.485	0.590	0.769	2.115	1.351	1.091	-0.920
	(0.351)	(0.272)†	(0.222)**	(1.228)	(0.542)**	(0.360)**	(0.301)**	(0.975)
Technology Niche Density (D)	-0.008	-0.011	-0.008	0.024	-0.004	-0.005	-0.004	0.004
	(0.004)*	(0.004)**	(0.002)**	(0.015)	(0.002)	(0.002)**	(0.001)**	(0.005)
D × Percent Founders with	0.009	0.008	0.007	-0.010				
Ph.D.	(0.005)†	(0.005)†	(0.003)*	(0.015)				
Influence of Competitors (CP)					2.326	0.626	0.431	-2.825
					(0.464)**	(0.206)**	(0.196)*	(0.886)**
CP × Percent Founders with					-1.935	-0.580	-0.300	1.637
Ph.D.					(0.678)**	(0.260)*	(0.266)	(1.238)
Founding Period Dummies	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Technology Area Dummies	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Robust Standard Errors	No	Yes	No	No	No	Yes	No	No
Log-Likelihood	-255.67	-2399.47	-1141.49		-237.73	-2354.03	-1108.94	
Wald χ^2	180.34	482.88	145.26		216.22	506.83	172.19	
Model d.f.	28	28	21		29	29	29	
Vuong statistics			5.12				5.23	
Number of zeros in dep. Var.			208				208	

(1) Number of Observations = 512; (2) Standard errors in parentheses unless otherwise explained; (3) † significant at 10%, * significant at 5%, ** significant at 10%. (4) Technology area dummies in model 9a are dropped due to convergence issues.



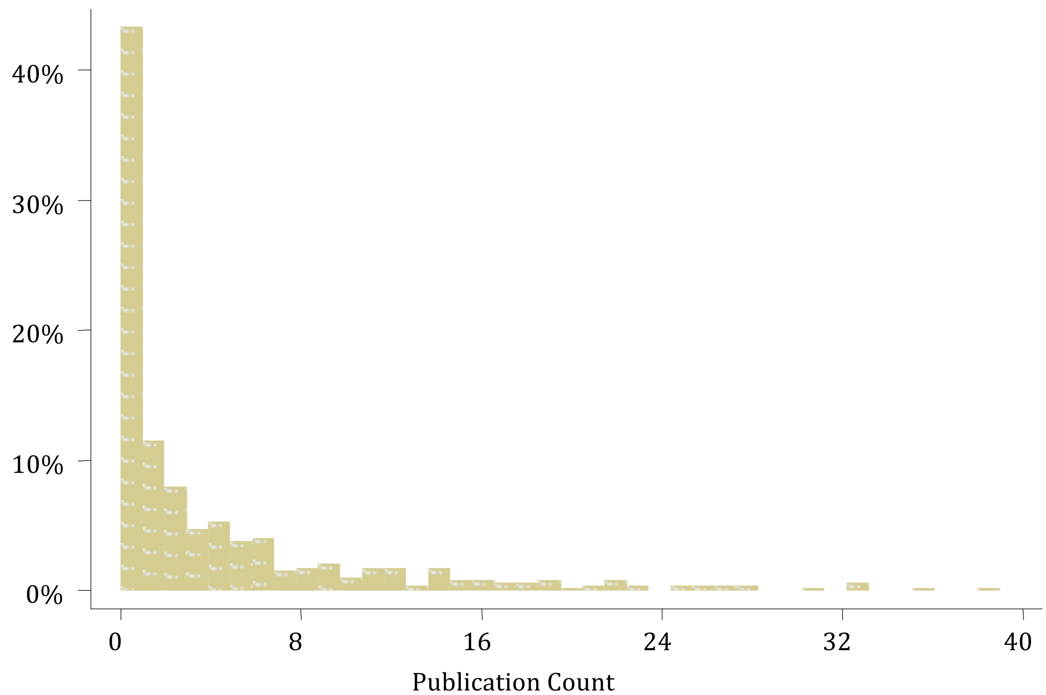
Legend: reports the proportion of all firms founded by a calendar year that has started publishing research in ISI-indexed journals by age five.

Figure 2: Time of First Publication among Publishing Firms



Legend: reports the proportion of firms, among all that have published one or more papers by the end of 2002, that has started publishing by a given firm age.

Figure 3: Distribution of Firm Publication Count



Legend: the distribution of firm publication count within the first five years after inception. 13 firms with over 40 publications are dropped for better representing the distribution of the data.

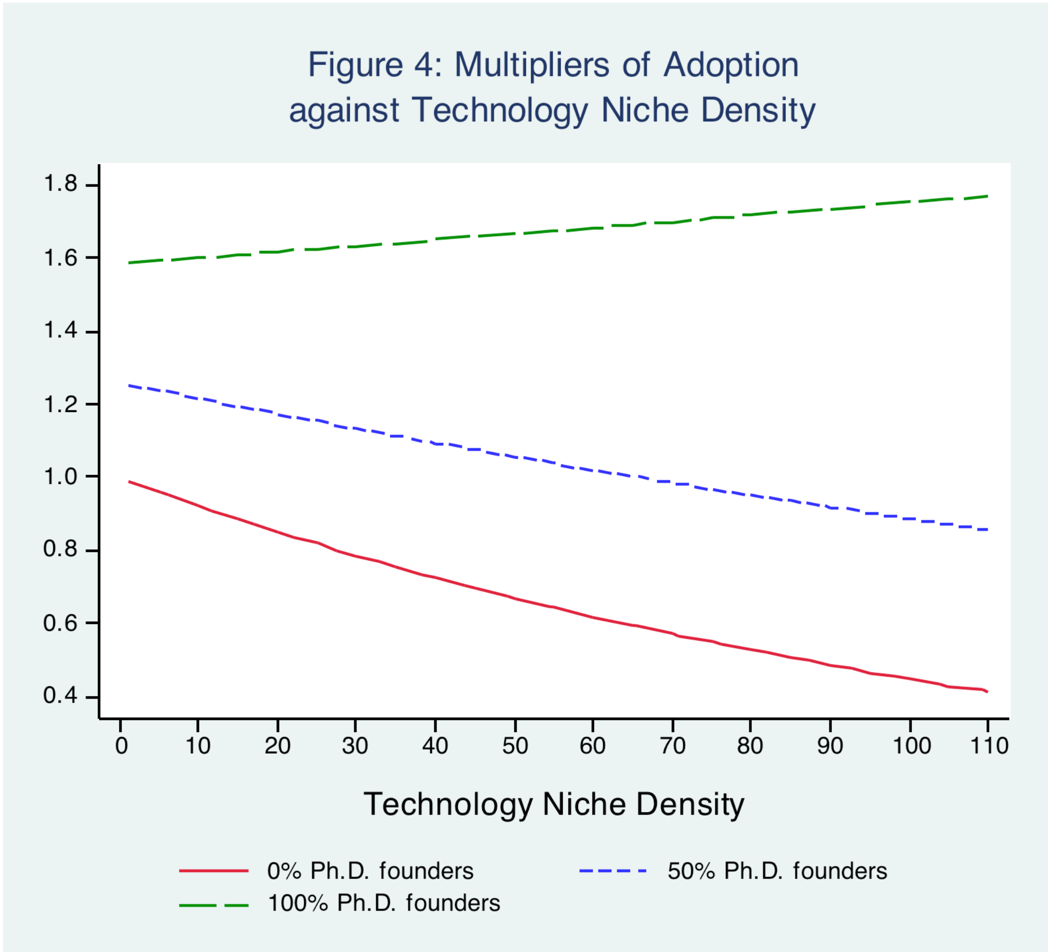


Figure 4: Multipliers of Adoption
against Technology Niche Density
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0
10
20
30
40
50
60
70
80
90
100
110
Technology Niche Density
0% Ph.D. founders
50% Ph.D. founders
100% Ph.D. founders

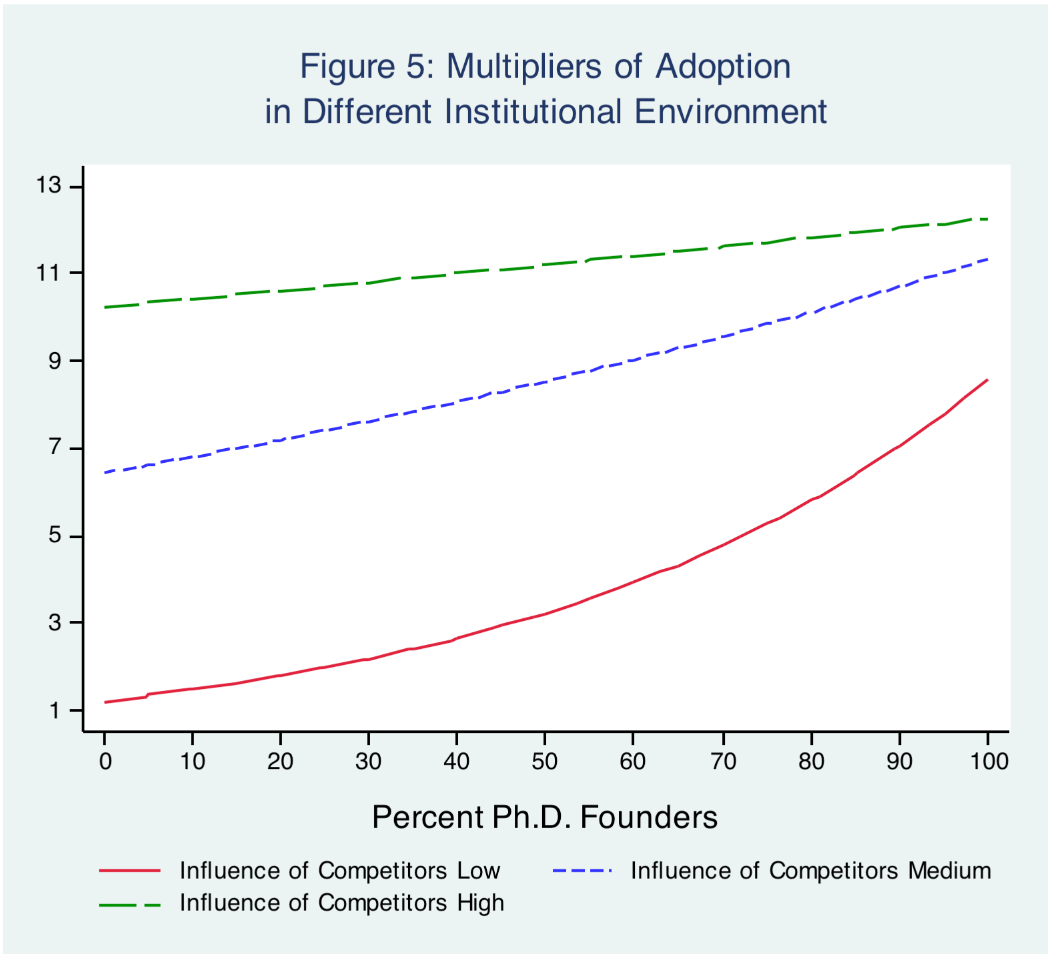


Figure 5: Multipliers of Adoption
in Different Institutional Environment
13
11
9
7
5
3
1
0
10
20
30
40
50
60
70
80
90
100
Percent Ph.D. Founders
Influence of Competitors Low
Influence of Competitors Medium
Influence of Competitors High