When Do Scientists Become Entrepreneurs? The Social Structural Antecedents of Commercial Activity in the Academic Life Sciences[1]

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The authors examine the conditions prompting university-employed life scientists to become entrepreneurs, defined to occur when a scientist (1) founds a biotechnology company, or (2) joins the scientific advisory board of a new biotechnology firm. This study draws on theories of social influence, socialization, and status dynamics to examine how proximity to colleagues in commercial science influences individuals' propensity to transition to entrepreneurship. To expose the mechanisms at work, this study also assesses how proximity effects change over time as for-profit science diffuses through the academy. Using adjusted proportional hazards models to analyze case-cohort data, the authors find evidence that the orientation toward commercial science of individuals' colleagues and coauthors, as well as a number of other workplace attributes, significantly influences scientists' hazards of transitioning to for-profit science.

INTRODUCTION

What factors lead individuals to challenge customary standards of professional behavior, and to eventually revise an occupational community's perception of appropriate conduct? How do individual characteristics,

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work contexts, and occupation-wide developments influence individuals' decisions to undertake new forms of professional activity? We empirically explore these questions in an examination of academic scientists' decisions to participate in for-profit, entrepreneurial ventures.

The academic disciplines in the life sciences are the setting for our empirical analysis. Since the 1970s, many university life scientists have sought to capitalize on their research by starting or affiliating with private biomedical firms. Although academic scientists' early efforts to commercialize university discoveries were met with consternation in the scientific community, the eventual diffusion of commercial activity in academe has, in the minds of many, broadened the acceptable role of the university scientist to incorporate taking part in for-profit science (Etzkowitz 1989; Owen-Smith and Powell 2001). By dint of its prevalence, the designation "academic entrepreneur" has now achieved taken-for-granted status in the scientific community. Thus, whereas in the early years of biotechnology the scientists who participated in private ventures risked the disapproval of their peers, those who do so today typically act without concern for adverse professional consequence.

The evolution of entrepreneurial activity in the scientific community offers a compelling context for empirical investigation of social structural effects on professional conduct. In addition to the fact that the now-permeable boundary between academe and industry is an economically important interface along which to examine the determinants of professional behavior, significant change in the scientific community's perception of the legitimacy of commercial endeavors during the past 30 years (Etzkowitz 1989, 1998) presents both a phenomenon to be explained and an opportunity to illuminate social mechanisms. In this article, we concentrate on four determinants of individual faculty members' transitions to commercial science: socialization in graduate school, peer influence exerted across social network ties, spatial clustering of transitions driven by the presence of proentrepreneurship colleagues in scientists' workplaces, and differential access to the social resources that facilitate entrepreneurial behavior. In an effort to reveal underlying mechanisms, we also examine how measures of social proximity interact with other characteristics of scientists' work contexts and the broader institutional en-

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vironment to affect jointly the likelihood that a scientist becomes an entrepreneur.

In our models of the transition to academic entrepreneurship, it will prove difficult to tease apart opportunity-based factors from the attitudinal influences of socially proximate or visible peers. Relationships among members of a professional community constitute thick pipes: they direct the flow of everything from task-relevant information to advice, gossip, opinions, and referrals. In archival data, this degree of multiplexity obfuscates the specific social mechanisms that generate observed network effects. In the case we examine, the clean identification of social mechanisms is particularly challenging because of the specific pattern of adoption observed in the data. We will show that commercial science began within and diffused across the stratum of elite scientists. As a result, opportunity tied to position in the upper echelon of academic science and attitudinal influences traced through the particular structure of relations that connected academic entrepreneurs to their peers often imply similar empirical relationships. At the level of operative social mechanisms, the coincidence of these implications renders some of the findings overdetermined. We can identify structural effects, but we cannot always pinpoint precise mechanisms.

Although the analyses do not always cleanly isolate mechanisms, we believe that they do underscore a number of pathways of peer influence. The data also reveal an interesting interplay between opportunity-side factors and social context as twin determinants of commercial activity in academic science. Specifically, during the time in which academic entrepreneurship tested the boundary of legitimacy, it was also the case that only prominent scientists at prestigious universities were able to attract the resources to establish new firms. The substantial resource acquisition hurdles for entrepreneurial activity in this period effectively restricted opportunities to a very select group of the profession, the members of which possessed the stellar scientific credentials to capture the interest of third-party investors. In turn, the fact that early adopters were among the most admired members of the scientific community undoubtedly contributed to the diffusion of commercial activity. Over time, when opportunities gradually trickled down to less prominent individuals, the boundaries of generally accepted professional behavior within the academic community had expanded to include commercial initiatives as justifiable undertakings. Thus, conceptions of appropriate role behavior appear to have been endogenously related to the decisions of highly distinguished scientists to become entrepreneurs.

This study offers a number of other intriguing findings. We find strong evidence of the socially and spatially localized spread of commercial science. Scientists were more likely to become entrepreneurs when they worked in departments where colleagues had previously made the transition, particularly when the individuals who had become commercialists were prestigious scientists. Individuals with coauthors who had become entrepreneurs were also more likely to transition, especially when their coauthors occupied central positions in networks in the commercial sector. Ph.D.-holding scientists employed in medical schools, where acceptance of commercial science occurred sooner, were more likely to become entrepreneurs, but the gap in the transition rates between medical school faculty and other academic scientists fell over time as the scientific community's assessment of commercial activity became more positive. Descriptively, we also show that the profile of academic entrepreneurs relative to representative members of the profession shifted over time: while academic entrepreneurship has always been the province of distinguished scientists, the gap in professional standing between participants and nonparticipants has diminished over time as entrepreneurship has gained social acceptance in the scientific community.

The outline of the article is as follows. After describing the scientific community's historical ambivalence about privatizing research and a subsequent shift in its view toward accepting commercial activity, we formulate predictions linking socialization and social influences to scientists' propensities to become academic entrepreneurs (i.e., to found or join the scientific advisory board of a new biotechnology firm). We then describe the archival data we have collected to test the predictions, which are detailed career histories of 6,000 academic scientists. We also describe the estimator we utilize and the covariates in the regressions. Finally, we present the findings and the conclusion.

BACKGROUND: SCIENTIFIC NORMS AND THE EVOLUTION OF ACADEMIC ENTREPRENEURSHIP

In the late 1960s and early 1970s—the time of the seminal scientific developments that laid the groundwork for the development of commercial biotechnology—the scientific community was deeply skeptical of a blurring of the border between academe and commerce. This skepticism was anchored in widely accepted beliefs about the appropriate role behaviors of academic scientists, which in turn were rooted in conceptions of the norms of science.

In his classic statement of the normative structure of science, Merton (1968) described four norms that together constituted the ethos of science: universalism, communism, disinterestedness, and organized skepticism. In addition to codifying archetypical norms, early work in the sociology of science considered the accompanying social institutions, including the priority-based credit system for recognizing scientific contributors, which reinforced the norms. As in the emerging literature on social control in the professions, the early view was that scientists formed a self-regulating community. Governance in the profession was accomplished by socializing aspiring scientists during graduate training programs. The norms of science were reinforced by example and by an institutionalized reward system, while noncompliance was deterred by the threat of social sanctions (Parsons 1951; Hagstrom 1965; Storer 1966).

The fact that the incentive and control systems in science in fact fail to produce full compliance with the norms became a dominant theme in the literature during the 1960s and after (e.g., Merton 1963; Mulkay and Williams 1971; Cole and Cole 1973; Mitroff 1974; Latour and Woolgar 1979). Describing the "painful contrast" between the conduct prescribed by the norms and scientists' actual behavior, Merton (1963) documented scientists' often acrimonious disputes over priority in discovery and sometimes ambivalent desire for recognition as evidence of conflicts between the norms and incentive systems of science. Mitroff (1974) also took aim at the notion that scientists can be accurately portrayed as disinterested participants in the research process. He found that scientists were partisan, emotionally committed advocates of particular theories and hypotheses, rather than objective, disinterested arbiters of theory and evidence. Following Merton's (1963) lead, the subsequent decade of research in the sociology of science documented myriad discrepancies between scientists' actual behavior and the idealistic account of conduct implied by the original formulation of the norms.

Despite the fact that the norms were known to lack descriptive accuracy, when a few university faculty members began to form companies to commercialize breakthroughs in the biological sciences, the standards embodied in the Mertonian norms were invoked to challenge the appropriateness of academic entrepreneurship. In particular, the norm of communality, which holds that scientific advances are the rightful property of the scientific community writ large, provided ballast to those who opposed the privatization of academic science.[2] Consider, for instance, Derek Bok's remarks on the normative and institutional risks of university

[2] In Merton's (1968, pp. 610–11, emphasis added) frequently quoted description of the norm of communality, he was unambiguous in his view of the irreconcilability of privatizing scientific findings and the scientific norms. He wrote, "The substantive findings of science are . . . assigned to the community. . . . The scientist's claims to 'his' intellectual 'property' is limited to that of recognition and esteem. . . . *Secrecy* is the antithesis of this norm; full and open communication its enactment." Specifically addressing the issue of the legitimacy of claims to property rights on scientific discoveries, Merton wrote, "The communism of the scientific ethos is incompatible with the definition of technology as 'private property' in a capitalistic economy."

technology commercialization, which echoed widely espoused views within the scientific community and were emblematic of the discourse on the subject during the time. He wrote, "Commercial motives can introduce a . . . threatening form of *secrecy*. In order to maintain a competitive lead that could be worth large sums of money, scientists who engage in business may be tempted to *withhold information* until their discoveries can be further developed to a patentable state" (Bok 1982, p. 150, emphasis added). Further commenting on the incentive changes raised by the prospect of substantial income from academic entrepreneurship, he observed, "With stakes this size, the nature and direction of academic science could be transmuted into something quite unlike the *disinterested* search for knowledge that has long been thought to animate university professors. . . . [T]echnology transfer is disturbing not only because it could alter the practice of science in the university but also because it *threatens the central values and ideals of academic science*" (Bok 1982, p. 142, emphasis added).

Overtones of the norms of science infuse the rhetoric in Bok's discussion of the risks of technology transfer. Commercializing university science, Bok reasoned, would undermine communal ownership of scientific discoveries. In addition, financial rewards from private-sector successes might dwarf priority-based recognition as an incentive to do research, thus compromising one of the central institutions of science and potentially decoupling the reward system from the reinforcement of the scientific norms. Although Bok wrote at a time when there was already ample evidence of scientists' routine departures from the prescriptions of the norms of science, the fact that the norms had been institutionalized as ideals led naturally to their being summoned to defend the status quo against the encroachment of commercial interests in academic science.

Bok's skeptical view of academic entrepreneurship was common at the time of his writing. Two examples of the scientific community's stance toward privatizing scientific findings in the 1970s are particularly revealing, because they concern the very two seminal discoveries credited with launching the biotechnology industry: Cohen et al.'s (1973) technique for joining and replicating (recombining) DNA (rDNA) and Kohler and Milstein's (1975) development of monoclonal antibody technology, an achievement that was later recognized with a Nobel Prize. Stanley Cohen, a molecular biologist at Stanford University's medical school, eventually authorized the university to patent rDNA, but only after succumbing to the (reportedly) vigorous urgings of Niels Riemers, Stanford's aggressive head of technology transfer (Hughes 2001).[3] For their part, Kohler and

[3] According to Hughes's (2001) account of the controversy surrounding the decision to patent rDNA, Cohen chose to donate his personal entitlement to one-third of Stan-

Milstein considered it inappropriate to seek property rights for their technique (Rai 1999).[4] Thus, at the time of the scientific breakthroughs that paved the way to commercial biotechnology, directly profiting from research findings was frowned upon in the academic community.

Against this backcloth, the scientific community has experienced a significant change of views, as university faculty have come to accept, and, in many institutions, to endorse faculty participation in for-profit companies. This trend is documented in a series of papers by Etzkowitz (1989, 1994, 1998, 2001), which report findings from interviews with scientists from three time periods (early 1980s, mid-1980s, and early 1990s). These studies depicted the shifts in scientists' attitudes toward commercial involvement, which have evolved from opposition to acquiescence to acceptance. Indeed, Etzkowitz has argued that, ultimately, a revision in the scientific norms has taken place, which has brought into consonance the high incidence of for-profit science in academe and the scientific community's perceptions of appropriate standards for conduct.[5] For example, one of the scientists Etzkowitz interviewed opined, "The norms of science which traditionally condemn profit-making motives are beginning to change to allow for . . . entrepreneurship" (Etzkowitz 1998, p. 824). Another scientist observed, "When I first came here the thought of a professor trying to make money was anathema . . . really bad form. That changed when biotech happened" (Etzkowitz 1998, p. 829). Based on interviews

ford's licensing royalties on the technology to the university. Since the three rDNA patents accrued more than $250 million in licensing fees before the final one expired in 1997, Cohen's share of the licensing royalties would have amounted to tens of millions of dollars. Herbert Boyer, on the faculty of the University of California, San Francisco (UCSF) medical school, at first refused to relinquish his personal share of patent royalties. However, after UCSF began a campuswide investigation of industrial research, and Boyer experienced the "personal hostility" (Hughes 2001, p. 558) of many of his colleagues, he acquiesced to strong pressure from colleagues, and he, too, eventually renounced his claim to a share of the patent royalties.

[4] Reflecting the common opposition to commercial life science in the post-WWI era, a number of universities had put into place policies that explicitly forbade filing for biomedical patents. For example, in 1934 the President and Fellows of Harvard University enacted a rule, still in effect in the 1970s, that "no patents primarily concerned with therapeutics or public health may be taken out by any member of the university, except with the consent of the President and Fellows; nor will such patents be taken out by the university itself except for dedication to the public" (Palmer 1948).

[5] There were a number of exogenous events that led to an increase in commercial activity in academe. A detailed discussion of these is beyond the scope of this article, but in brief, three important catalysts were the Reagan administration's decision to substantially curtail the amount of federal funding available to finance university research, which spurred universities to seek funds from industry; the passage of the Patent and Trademark Amendment Act (commonly known as the Bayh Dole Act), which encouraged universities to seek intellectual property protection for federally funded research; and the capital market's enthusiastic reception of Genentech and other first-generation biotechnology companies.

with Australian scientists, Slaughter and Leslie (1997, p. 184) likewise concluded, "Faculty, professional officers, and administrators were reshaping their epistemology of science to accommodate professional interactions with the market."[6] Indeed, Krimsky (1987) and Etzkowitz (1989) have reported the emergence of procommercial locutions, such as "*limited* secrecy" and "the extension of knowledge through commercialization of research," which have become part of the vernacular of academic science. Many of these expressions do more than just convey acceptance of commercial activity—they present normative justifications for academic entrepreneurship.

HYPOTHESES: SOCIAL AND ORGANIZATIONAL INFLUENCES ON ACADEMIC ENTREPRENEURSHIP

To recapitulate the argument to this point, accounts of the emergence of for-profit science in academe note significant early opposition that gave way to eventual acceptance. In the early years of biotechnology, university scientists contemplating commercialization would have given considerable thought to the potential critical reactions of their colleagues. Moreover, the novelty of academic entrepreneurship at this time meant that there would have been uncertainty about its ramifications. The existence of normative opposition and the lack of information about this new practice are conditions that surely would have prompted scientists to look to socially comparable individuals in their effort to form a judgment about the behavior (e.g., Katz and Lazarsfeld 1955; Coleman, Katz, and Menzel 1957; Burt 1987; Van den Bulte and Lilien 2001). In addition, for those who developed a latent interest in commercial science, the early academic entrepreneurs would have been important sources of contacts and referrals. Our hypotheses thus address what we anticipate to be the most likely social structural determinants of scientists' likelihood of becoming entrepreneurs.

Employment Context Effects on the Transition to Entrepreneurial Science

Accepted standards of professional behavior frequently vary across work situations (Becker et al. 1961). In the context we examine, universities

[6] Owen-Smith and Powell (2001) portrayed a more balkanized cohabitation of attitudes in current-day life sciences departments, in which "new-school" faculty members actively patent and advise biotechnology firms, and "old-school" faculty abide by the traditional scientific norms. These authors have detected a fundamental shift toward commercializing research findings, but note that there are still prominent holdouts who disapprove, sometimes vehemently, of the practice of academic entrepreneurship.

have demonstrated considerable heterogeneity in their stance toward entrepreneurial science (cf. Krimsky 1987; Louis et al. 1989). Even today, Kenney and Goe's (2004) comparative study of the cultures at the University of California, Berkeley and at Stanford University found that the values at Stanford are much more supportive of faculty participation in private ventures. We thus anticipate that work context will influence the likelihood that a scientist becomes an entrepreneur. Specifically, there are reasons to anticipate that a faculty member's transition to entrepreneurial science is more facile in universities that have previously spawned academic entrepreneurs. Several mechanisms could be marshaled to support such a claim. Perhaps the most prosaic consideration is encapsulated in the adage that it is easier to follow a path than to break one. When a colleague across the hall has transitioned to commercial science, he is able to provide advice on practical matters, including how to navigate the university's technology transfer office. He may also offer introductions to resource holders in the commercial sector, or assume the role of angel investor to support a firm started by a colleague (Etzkowitz 1998; Shane and Stuart 2002).

In addition to providing convenient access to advice, the presence of academic entrepreneurs is likely to influence scientists' attitudes about for-profit science. Consider, for instance, Nathanson and Becker's (1981) study of obstetricians' decisions to perform abortions after *Roe v. Wade*. This practice resembles the one we examine insofar as its legitimacy was contested in the community of practicing physicians. Nathanson and Becker showed that even socially conservative physicians sometimes provided abortion services, but only when they worked in medical offices dominated by liberal obstetricians—a finding demonstrating both the situational dependence of standards of professional conduct and the role of workplace social influences on the formation of beliefs about the appropriateness of controversial practices.

We hypothesize that physical proximity to adopters of commercial science will influence scientists' attitudes toward the practice. Asch's (1951) classic and much replicated study established the reluctance of individuals to stand against the opinion of a group, even when no sanctions are imposed for deviating from the group's consensus. Asch found, however, that the presence of just a small number of dissenters from the majority view greatly facilitated nonconforming behavior. In the context we study, for a scientist who is enticed by the commercial sector but is apprehensive about the reaction of peers, the company of just one or a few academic entrepreneurs may allay concerns about the social repercussions of his or her action. Moreover, spatial proximity to academic entrepreneurs facilitates the formation of a reference group that condones the activity. Strategically abridging one's set of comparators to select into a group of likeminded people follows from Festinger's (1954) social comparison theory, which proposed that individuals delete from their comparison sets those who espouse views that markedly diverge from their own. Thus, the option of joining a reference group supportive of commercializing research findings should facilitate a would-be academic entrepreneur's transition to commercial science. We therefore predict

HYPOTHESIS 1.—Scientists are more likely to transition to the entrepreneurial role when they are affiliated with institutions that employ other scientists who have participated in commercial science.

Assuming support for hypothesis 1, how can we distinguish among the factors that might cause within-university clustering of entrepreneurial transitions?[7] To target the social influence of peers as a partial explanation for why scientists more frequently enter the private sector when they work in universities that employ other academic entrepreneurs, we consider a number of qualifications to hypothesis 1. We focus on patterns in the data that may isolate peer influence from other potential causes of the posited relationship.

First, we can exploit the fact that Ph.D. scientists in academia are employed in one of two very different organizational contexts: faculties of sciences or medical schools. Among the many differences between these two employment contexts, we expect that medical school faculty would have been less apprehensive about participating in commercial ventures than faculty in science departments outside of a professional school (Hughes 2001). University science departments typically value basic research, whereas medical schools house both scientific research labs and facilities for the delivery of clinical care. In addition, medical schools have long engaged in applied research, such as clinical trials of pharmaceuticals. For these reasons, Ph.D. scientists working in medical schools may have been more comfortable working at the intersection of academic and commercial science. It follows that the propriety of engaging in entrepreneurial science would have been accepted by peers in medical schools, and therefore that the risk of running aground of group norms would be lower there than in university science departments.

One implication of this argument is that the incidence of academic entrepreneurship will be higher for life science faculty members in medical

[7] In addition to there being other plausible explanations for the predicted association, hypothesis 1 raises issues of econometric identification. Two allied concerns will need to be addressed: omitted variable bias and endogeneity. For instance, to identify work context effects, we must guard against the possibility that scientists who aspire to commercialize their research seek positions in universities that have spawned many commercial scientists, and thus that the results merely reflect assortative matching along the dimension of procommercial values. We defer further discussion of these issues to a later section.

schools than in university science departments. More important for gaining empirical traction on the social mechanisms that drive the transition to entrepreneurship, if working in close spatial proximity to scientists who have previously engaged in the commercial sphere does in fact serve to ease a would-be entrepreneur's concerns about the reactions of his or her colleagues, then we would expect to observe

HYPOTHESIS 2.—The effect of prior local adopters on scientists' rate of transition to entrepreneurship will have been weaker in medical schools than it was in university science departments.

We capitalize on the ethnographic accounts of the growing acceptance of commercial science to derive two corollaries that should be supported if previous transitions to commercial science in a work context do in fact ease future transitions by reducing the potential social discord in the work group. To the extent that acceptance of entrepreneurial science has grown in the academic community at large as the practice has diffused, the strength of the effect of a local, proentrepreneurship work context should decline with time. We should therefore observe

HYPOTHESIS 3.—The effect of prior local adopters on scientists' rate of transition to commercial science will decline as academic entrepreneurship gains acceptance in the scientific community.

This expectation reflects the fact that even work settings comprising individuals who opposed entrepreneurial science will not have escaped the broader normative realignment of the scientific community. The same logic applies to the difference in individual transition rates between Ph.D. scientists in medical schools and those on the faculties of arts and sciences (FAS) departments. We anticipate

HYPOTHESIS 4.—As faculty members in arts and sciences departments come to accept entrepreneurship as a legitimate professional activity, the difference in the rates of transition to academic entrepreneurship between scientists in medical schools and those in departments of arts and sciences will decline.

As a final extension of hypothesis 1, we consider the possibility that peers occupying prominent social positions have a particularly strong effect on within-work-group contagion. Models of social influence have considered the process by which the (weighted) opinions of socially relevant alters mold a given individual's attitudes (e.g., Coleman 1964, chap. 11; Marsden and Laumann 1984; Burt 1987; Galaskiewicz and Burt 1991; Ibarra and Andrews 1993; Marsden and Friedkin 1993; Friedkin 1998). The positional characteristic most robustly associated with the strength of influence of an alter's views on the attitudes of a focal actor is the alter's prestige. For example, Podolny and Stuart (1995) showed that inventions were most likely to diffuse when they had been previously adopted by high-status organizations. We thus postulate that the previous transitions of high-prestige co-workers will have a stronger effect on the likelihood that colleagues will become entrepreneurs in the future. Specifically,

HYPOTHESIS 5.—Scientists are more likely to transition to the entrepreneurial role when they are affiliated with universities that employ high-status scientists who have previously made the transition.[8]

Imprinting and the Sustenance of the Norms of Science

Norms are transmitted through socialization of newcomers to the principles held by those who are influential within a group. Merton and Rossi (1957) described anticipatory socialization as the process by which an individual acquires the values and orientations of those in statuses he or she aspires to enter. In science, graduate education programs are a central locus for the conduction of professional norms (Hagstrom 1965). Although formal education is just one of the avenues through which norms are transmitted, its consequence for internalization may be salient because it occurs at the incipient stage of professional development.

Dating back to Durkheim, analysts of belief systems have argued that the constraint on the beliefs of a group's members is an increasing function of the degree of consensus of views within the group (cf. Martin 2002). This proposition dovetails with evidence from the experimental studies showing the forceful influence of a group's consensus on an individual's (un)willingness to waver from the majority view. This leads us to expect that Ph.D. candidates who are trained in university departments in which the traditional norms represent the consensus view are less likely to participate in commercial science later in their careers. By contrast,

HYPOTHESIS 6.—Life scientists who were trained in universities with proentrepreneurship faculty members are more likely to transition to commercial science later in their careers.

Social Network Effects in the Transition to Entrepreneurial Science

Physical proximity alone makes it likely that colleagues within a workplace interact on a regular basis (cf. Festinger, Schachter, and Back 1950). We have thus assumed the existence of ties among individuals employed in the life science departments of the same university. At a minimum, the

[8] It is also likely that highly prestigious scientists who have become entrepreneurs would have extensive contacts and significant influence in the commercial sphere. Thus, while these individuals are likely to be opinion leaders in their departments, they may also facilitate co-worker transitions because they are best positioned to refer their colleagues to useful contacts in the private sector. In other words, hypothesis 5 could be derived from either a social influence or resource access logic.

actions of co-workers are likely to be known to a focal scientist. We now briefly move beyond the proximate work contexts of scientists to consider the influence of the relationships of scientists that span university boundaries. Specifically, we rely on the evolving coauthorship network in the biological sciences to trace some of the connections comprising the biomedical field's invisible college (de Solla Price 1963; Moody 2004, for a recent illustration in sociology).

Most of the predictions we have offered about work context effects could be extended with little revision to an analysis of coauthorship relations. Thus, we could reason analogously to formulate predictions akin to hypotheses 1, 2, 3, and 5, but that would address the role of attitudinal influences in coauthor rather than workplace-based social networks.[9] For instance, along the lines of our justification for hypothesis 1, a scientist that coauthors with academic entrepreneurs has ready access to a reference group supportive of commercializing research. While it is likely that scientists' attitudes are shaped by the views of their coauthors, we assume in addition that coauthors are often friends, and, moreover, that they are knowledgeable of opportunities in their fields of specialization. Therefore, information, referrals, and other types of opportunity-related resources are likely to flow through the coauthorship network. Coauthoring with commercial scientists thus yields the type of social capital benefits described in Burt (1992) and elsewhere: access to information about opportunities in the commercial sector and referrals to the individuals and organizations that possess the resources consumed in new venture formation. For reasons of both attitudinal influence and resource access, we expect

Hypothesis 7.—Scientists who have previously coauthored research with academic entrepreneurs are more likely to transition to commercial science.

If we are correct in supposing that resource-based factors account for much of the effect of coauthorship ties on the transition rate, we should find that the identity of a focal scientist's entrepreneurial coauthors is important (cf. Lin, Ensel, and Vaughn 1981; Stuart, Hoang, and Hybels 1999). In particular, ties to academic entrepreneurs who occupy central

[9] In the empirical analysis, we have placed the primary emphasis on co-workers because individual scientists likely have less discretion in choosing their co-workers than they do in selecting their coauthors. Therefore, there is greater risk that compatibility of values drives the formation of coauthoring relations, leading to the emergence of cliques among pro- and anticommercialization scientists in the network. In other words, assortative matching along homogeneity of values may explain the formation of coauthorship ties, rather than the network structure influencing the formation of attitudes about commercial science. As we discuss below, however, we can use the temporality (and other) features of the data to try to distinguish these alternatives.

positions in the *private sector* should have a greater influence on a yet-to-transition scientist than do relationships with peripheral commercial scientists. We therefore offer a final prediction:

HYPOTHESIS 8.—Coauthorship ties with scientists who have high centrality in the commercial sector will have a particularly large effect on the transition rate.

A Caveat about Social Mechanisms

How certain are we about the social mechanisms that may underlie the hypothesized relationships? On one hand, we know from the empirical literature on university-industry relations and from the controversies surrounding early commercialization efforts that in the formative years of biotechnology, academic entrepreneurship defied generally held assumptions about appropriate professional conduct. The process of moving from a period of widespread opposition of this practice to one in which academic entrepreneurship has become commonplace clearly entailed a significant change of views within the profession. On the other hand, we know from research on the formation and development of technology-based companies that access to resources is central to the entrepreneurial process. Scientists who lacked the ability to attract resources and lend status to their private-sector endeavors would not have progressed far along the path toward entrepreneurship.

We believe that the relational structure of the scientific community was integral both to the process of opinion formation and change and to the parceling out of commercial opportunities. Thus, resource exchange and social influence were co-occurring and sometimes commingled processes that were fundamentally shaped by the social structure of the scientific community. In formulating the argument, we have simply attempted to organize the development of the hypotheses according to the social mechanisms we consider most likely to imply particular relationships, and we have sought to specify a few contingencies that provide empirical purchase on mechanisms. Although we hope to be able to partially isolate these two processes, in most cases we can only establish that one, the other, or both types of effects exist in the data.

METHODS AND DATA

Because we can identify almost every individual who has earned a Ph.D. from a U.S. university, we have knowledge of the population from which academic entrepreneurs in the life sciences hail. Moreover, using information recorded in scientific journal articles, it is possible to construct relatively detailed career histories for academic scientists. Therefore, we were able to draw a probability sample of doctoral degree holders in the life sciences and track members' work histories. We combine these data with information on university scientists who have ventured into commercial science to analyze rates of transition to the role of entrepreneur.

Case-Cohort Design

The data set we have created has a case-cohort design. Advanced by epidemiologists to study rare diseases (Prentice 1986; Self and Prentice 1988), case-cohort designs are useful when events are infrequent in a population, rendering it costly to draw a random sample with enough information for inference. Case-cohort sampling entails drawing a random sample, or a "subcohort," from a defined population. This random sample forms the comparison set for the "cases" (events), which can include all instances of an event in the population.[10]

To construct the data set, we first obtained information about all *Ph.D.-holding* founders and scientific advisors from *every* biotech firm that has *ever* filed an IPO prospectus (form S1 or SB2) with the U.S. Securities and Exchange Commission (SEC). We were, however, unable to acquire systematic data about founders and advisors of still-private companies, or of those that failed prior to going public. This limitation has two consequences: first, we significantly undercount the actual number of academic entrepreneurs; second, we are working with a selected sample of companies. Because the firms in our sample were judged by some to be appealing financial investments and so were able to sell shares to the public, we can assume that the firms in the database are relatively successful compared to the average start-up biotechnology company.

A total of 533 U.S.-headquartered biotech firms have filed papers to go public between 1972, when the first biotechnology firm went public, and January 2002. We retrieved SEC filings for these companies to obtain biographical sketches of founders and scientific advisors.[11] In this analysis, we retained only those individuals who (1) held a Ph.D. degree from a U.S. university, (2) were in the employ of a U.S.-based university or research institution, and (3) were under the (assumed) age of 65 when they

[10] Social scientists have also developed methods that entail oversampling events relative to their frequency in a population. For instance, applications of choice-based sampling (e.g., Manski and Lerman 1977) often oversample choices.

[11] For companies that filed papers to go public after 1995, IPO prospectuses are conveniently available in the SEC's EDGAR database (http://www.sec.gov/edgar.shtml). We acquired the remaining S-1 forms at the SEC's reading room in Washington, D.C. Not every S-1 provided detailed information about founders and advisors; we were only able to obtain this information for approximately 70% of the companies.

founded or began advising the biotech company.[12] We have identified 190 academic founders of biotechnology companies and 727 members of scientific advisory boards (SABs).[13] The transitions to commercial science of these 917 university faculty members are the events we analyze.

To create a comparison group, we drew a random sample of 13,564 doctorate degree holders from the UMI Proquest Dissertation database, which contains the vast majority of doctoral degree recipients from U.S. universities. The random sample was constructed to mirror the distribution of academic disciplines (e.g., microbiology, biochemistry, etc.) and degree grant years in the group of commercial scientists identified in SEC filings. Thus, the sample is stratified by scientific discipline and Ph.D. year to correspond to the distributions of these attributes in the group of academic entrepreneurs. The members of the random sample were then tracked forward from the time they obtained their degrees.

Published statistics suggest that less than 50% of individuals with newly issued Ph.D.'s in the life sciences are able to find employment in academia. To identify who in the random sample remained in academia, we relied on publication histories created from ISI's Web of Science database. We have retrieved all publications for each of the 13,564 scientists in the random sample and the 917 scientists in the event population. Based on publication histories, we eliminated about 60% of the random sample because of the fact that these individuals never published under an academic affiliation, which we assume indicates that they did not obtain academic appointments.[14] After we deleted exits, the final data set con-

[12] We do not actually know scientists' ages, except in the case of company founders and some scientific advisors. We assume that scientists were issued Ph.D.'s at the age of 30 and remain in the risk set for a 35-year period, or until they have exited academia if attrition occurs earlier. The findings are quite robust to relatively minor changes in these assumptions. For instance, starting the clock at the time (Ph.D. year + two or three) to allow for a postdoctoral fellowship does not change the results in any meaningful way.

[13] The precise obligations of members of SABs vary by company, but at a minimum, they are expected to attend board meetings and be available to provide confidential advice to company personnel on scientific matters. SAB members are typically compensated with annual stock grants. They also frequently maintain active consulting arrangements with the company. For more detail, see our companion paper (Ding et al. 2005).

[14] Because promotion in most academic institutions is based on publications, we also assume that people who have had prolonged periods without publishing have exited academia. Specifically, scientists are treated as exiting after a five-year period with no publications. In addition, we have deleted scientists whose tenure in academia is shorter than five years to ensure that the subcohort does not include individuals who failed to obtain an academic appointment after holding one or two postdoctoral fellowships. One limitation of the ISI data is that it only provides information about authors' affiliations for post-1972 publications. In cases for which pre-1973 affiliations were unavailable from other sources, we used an individual's 1973 affiliation for the years

tained 5,120 scientists in the randomly drawn subcohort. With a total of 917 individuals experiencing events, the ratio of matched sample members to individuals experiencing events is over 5:1. It has been demonstrated that a cohort-to-case ratio of 5:1 (or higher) results in little loss of efficiency in model estimation (Breslow et al. 1983; Self and Prentice 1988).

Statistical Method

Each academic scientist is treated as being at risk of engaging in commercial science the later of: (1) the time he or she is issued a Ph.D. degree, or (2) the year 1961, when the first biotechnology company was created.[15] All individuals who have yet to engage in commercial science are right-censored at the earlier of (1) January 2002, (2) the assumed age of 65, or (3) the assumed time of exiting academia through a long period of publication dormancy. Because of our substantive interest, we do not model repeated entries to commercial science, even though they occur frequently in the data. Once an individual is observed to have founded or joined the advisory board of a biotech company, a "founding" or "SAB membership" event is coded to occur in the year the company is founded, and the individual is removed from the risk set. Thus, the 917 events we study are first-time transitions.

Although founding a company and joining an SAB are disproportionate events in terms of the implied time commitment, two considerations prompted us to pool the events in the analysis. First, a scientist who engages in either activity reveals that he or she has determined that commercializing science is an acceptable dimension of professional conduct (or reveals the scientist's willingness to suppress his or her opposition for a counterbalancing gain). Second, in unreported, competing risks models, we have found that the determinants of the two events are quite similar. Because the conclusions we would draw do not change substantively, we have chosen to report a single set of models.

To obtain consistent estimates, it is necessary to modify the proportional hazards estimator to accommodate the case-cohort sampling design. Specifically, let $Z_i(t)$ denote a vector of covariates for individual i at time t. Individual i's hazard can be written

$$\lambda_i[t;\ Z_i(t)] = \lambda_0(t) r_i(t), \tag{1}$$

between Ph.D. grant and 1972. Fortunately, pre-1972 episodes constitute an insignificant percentage of the employment spells in the overall database.

[15] The vast majority of biotechnology firm foundings took place after Genentech was established in 1976. If we assume scientists were not at risk of transitioning until 1976 and thus delay starting the analysis until that year, the reported findings do not change, reflecting the fact that most of the information in the database is in the post-1976 era.

where

$$r_i(t) = \exp[\beta' Z_i(t)] \tag{2}$$

gives the ith individual's risk score at time t, β is a vector of regression parameters, and $\lambda_0(t)$ is an unspecified baseline hazard function.

Estimation of β typically is based on the partial likelihood

$$\prod_t \frac{Y_i(t)\exp[\beta' Z_i(t)]}{\sum_{k=1}^{n} Y_k(t)\exp[\beta' Z_k(t)]}, \tag{3}$$

where $Y_i(t)$ indicates whether individual i experiences an event at t, and $Y_k(t)$ indicates whether person k is at risk at t. Equation (3), however, produces biased estimates if applied to case-cohort data. The bias occurs because including all events in a population and a randomly drawn subcohort causes the relative frequency of events in the case-cohort data set to exceed the proportion of events in the actual population. In turn, the contribution of the "failure" cases (events) to the likelihood function is overrepresented.

To address this problem, biostatisticians have proposed a pseudo-likelihood estimator. Using S to denote membership in the subcohort, the pseudo-likelihood can be written:

$$\prod_t \frac{Y_i(t)\exp[\beta' Z_i(t)]}{Y_i(t)w_i(t)\exp[\beta' Z_i(t)] + \sum_{k\neq i, k\in S} Y_k(t)w_k(t)\exp[\beta' Z_k(t)]}, \tag{4}$$

where the $w_i(t)$ and $w_k(t)$ are weights assigned to each observation in the risk set, and all other terms are defined above. The numerator of the pseudo-likelihood (eq. [4]) is identical to that of the partial likelihood (eq. [3]). The first term in the denominator of equation (4) represents the contribution of the failure cases to the likelihood, and the second term represents the contribution of the randomly drawn subcohort members in the risk set at time t. We use the weighting scheme proposed by Barlow (1994).[16] In it, the case weights for all individuals who experience an event at time t, the $w_i(t)$, are always "1." The weights on the members of the subcohort who are still at risk by time t, the $w_k(t)$, are $1/p_k$, where p_k is the probability that member k of the subcohort was selected for the random sample. Individuals who are not in the random-draw subcohort receive no weight in the pseudo-likelihood function until the time they experience an event (Barlow et al. 1999).

[16] A few different weighting schemes (Prentice 1986; Self and Prentice 1988) and variance estimators have been proposed (Prentice 1986; Therneau and Li 1999) to fit Cox models to case-cohort data. Simulation studies using the different weights and variance estimators have yielded consistent results, particularly when the size of the control sample is large, as it is in our case.

The basic idea of the pseudo-likelihood in equation (4) is to compensate for the oversampling of events by weighting each term in the pseudo-likelihood by the inverse of the *ex ante* probability that the corresponding observation is included in the sample. Thus, subcohort weights augment the contribution of each of the observations in the random draw so that the proportion of events in the constructed case-cohort sample resembles the proportion of events in the population overall (or any true random sample thereof). To accomplish this in the data we analyze, for each individual k in a given scientific discipline and degree-year strata, we compute p_k as the proportion of the total population (all Ph.D.'s issued in that discipline in that year) included in the random draw.[17] With case weights added, a jackknife robust variance estimator based on the estimated effect of deleting each observation from the analysis is used to obtain unbiased standard errors.

Finally, there is one limitation of the Cox model that merits comment. Information on some of the covariates and on the timing of scientists' participation in commercial ventures is available only to the year. Thus, data on events are known only in discrete time. The consequence of our imprecise knowledge of the timing of events is that there are a number of tied events in the data. In the regressions, tied events are handled using Breslow's (1974) approximation method, which has been shown to be reliable as long as the ratio of events to observations at risk is small in

[17] We also experimented with a variant of Barlow's (1994) weight to account for possible sample selection bias caused by the fact that there is attrition from the random draw of Ph.D. holders (13,564 individuals) to the sample of scientists with verifiable academic appointments (5,120 individuals). Specifically, as above, p_k is the proportion of each discipline and degree-year strata that is included in the random draw. If all observations were included from the random draw from the UMI database (i.e., if all Ph.D. degree recipients obtained academic appointments), p_k would be the true weight. However, attrition exists because many of the random sample members fail to find academic positions. Because we possess basic information about all individuals who earn Ph.D. degrees, we can exploit the weighting scheme to adjust for selective entry into the academic profession, conditional on completing a Ph.D. program. Specifically, we know that Ph.D.'s from highly ranked programs are more likely to secure academic positions. Using the limited information available from the UMI database for the subcohort members, we estimated a probit model yielding the predicted probability that person k is selected into the 5,120-person sample as a function of degree year and prestige of the Ph.D.-granting institution. We label this probability γ_k. The probit model indicates that graduates from highly ranked universities are most likely to secure academic positions, thus entering the final, matched sample. With this predicted probability, the conditional probability $p(\text{cond})_k$ is then the product of p_k and γ_k. Since the weight $w_k(t)$ applied to each member k is the inverse of his or her probability of reaching the final matched sample, including γ_k augments the leverage of the matched sample members who are most likely to attrite from the data set. We report results from the standard weighting scheme, however, because the selection-adjusted estimates differed only slightly.

all time intervals (Petersen 1991). This ratio is very low in our data set. As a robustness check, we will also report results from a discrete-time hazard model.

Variable Definitions

We rely on several data sources to create covariates at the individual, network, and university levels. Unless otherwise stated, all variables are time changing and updated at the beginning of each calendar year. The appendix provides brief descriptions of the sources we consulted to construct the variables.

Individual-level covariates.—Past research has found that scientists' human capital influences participation in biotech ventures (Audretsch and Stephan 1996; Zucker, Darby, and Brewer 1998; Khurana and Shane 2001). We generated three measures of human capital. First, utilizing data from the Web of Science, we created annually updated cumulative publication counts. Second, using the NBER patent database, we constructed a time-changing indicator of whether an individual has ever been listed as an inventor on a patent. University scientists who appear as inventors on patents presumably have more opportunities to enter the private sector than do scientists without patents. Third, based on affiliations reported on scientists' papers, we tracked over time the number of job changes of each scientist in the data set. Although some job changes are caused by failure to obtain promotions, individuals with many changes of position have had frequent employment offers and are therefore assumed to be highly regarded in the profession.

Work context covariates.—We included three university-level control variables in the regressions. First, there has been a surge in universities' efforts to commercialize science. One indicator of the local intensity of this effort is whether or not a university has created a formal technology transfer office (TTO). These offices perform tasks such as applying for patents on faculty research, which are then assigned to (legally owned by) the university. We obtained the founding dates for all university TTOs from the Association of University Technology Managers (2001) annual surveys. A time-changing "TTO" dummy variable indicates whether a scientist's employer has an active TTO.

Sine, Shane, and Di Gregorio (2003) found that prestigious universities spawn a high percentage of the university-originated start-up companies. To account for the prestige of a scientist's employer and degree-granting university, we collected Gourman Report rankings for all institutions in our data set. The Gourman rankings were issued for the first time in 1980, so we assigned universities their original rating for all years prior to 1980. Because continuous rank proved uninformative in the regressions, we collapsed the scale and dummy coded universities according to whether they are in the top 20.

Many of the hypotheses concern the effects of working in close proximity to colleagues who had previously made the transition to participate in commercial science. Co-worker transitions are operationalized as an endogenous count of past events within employing institutions: we sum the number of academic entrepreneurs in our data set from previous years in a focal scientist's university.[18] In the regressions, this "co-worker transitions" variable is updated annually and included to examine hypotheses 1, 3, and 5.

To identify employment in a medical school, we created an indicator variable for whether a scientist's primary affiliation is with a professional school. In addition, we constructed a second count of co-worker transitions, this time limited to the university "division" that employs the focal scientist. Specifically, we counted only past events within the medical school if a scientist's primary affiliation is with a medical school and events in university sciences departments if the scientist is in the FAS. We expect within-division co-worker transitions to matter less for individuals employed in professional schools than they do for those in the FAS.

To test hypothesis 3, we interacted the number of past co-worker transitions with a period effect—a dummy variable coded as "1" if the year is prior to 1990.[19] We anticipate that the effect of co-worker transitions will decline in the aggregate level of academic entrepreneurship, and thus that co-worker transitions will have a stronger effect in the early period. Similarly, we interacted the period effect with the medical school dummy to test hypothesis 4. In this case too, we expect that the positive effect of employment in a medical school will be stronger in the early period.

Hypothesis 5 postulates a higher hazard of commercialization among scientists employed at universities where colleagues who have previously

[18] To construct the endogenous count of academic entrepreneurs at each university (and other related covariates), we included all of the 315 founders and 1,555 SAB members appearing in SEC filings and employed in U.S. universities at the time firms were founded. The discrepancy between this total and the 917 events in the regression analysis is that the larger number includes medical doctors and those with Ph.D.'s from non-U.S. universities. We excluded these individuals from the analysis because we lack comprehensive information on the populations from which they draw, so we are unable to construct valid subcohorts for these two groups.

[19] The date (1990) was chosen because it bisects the period of active entrepreneurship in the data set, which ranges from 1978 to 2002. As we describe in the results section, the findings are not at all sensitive to changes in the definition of the period. Thus, although the cut point is arbitrary and does not fully capture the nuance of year-to-year changes in attitudes about commercialization, the basic results hold across a range of period definitions.

made the transition to commercial science have high prestige in the academic community. To measure the prestige of colleagues who have transitioned, we computed the predicted number of journal article citations received by each scientist in our data set, again updating this quantity each year. The Web of Science database supplied total citation counts for each published article at the time we retrieved the data (2002). However, we wish to know the total number of citations each article had received up to any given year, which would make it possible to compute scientists' annually updated, cumulative citation counts. To approximate this quantity, we distributed each *paper's* total citation count in 2002 back through time, assuming that citations arrive according to an exponential distribution with hazard rate (i.e., inverse mean) equal to 0.1.[20] This enables us to compute scientists' predicted, annual citation counts, based on the known total number of citations received by each paper in 2002. We then weighted the transition of each co-worker by his or her total citation count at the time of entering the commercial sector. Finally, for each scientist at risk of becoming an academic entrepreneur, we created the average citation count across all peers who had previously transitioned to commercial science while working in that scientist's university.

The sixth hypothesis forecasts that the climate in place during scientists' doctoral training will have a lasting effect on the hazard of transitioning to commercial science. We test this prediction with two variables. First, we included an indicator for whether a scientist received a Ph.D. from a university that had an operational TTO prior to the time that the degree was granted. Second, we created a quantity analogous to the "co-worker transitions" variable for each scientist's Ph.D.-granting institution. This variable is a count of the number of academic entrepreneurs spawned by an individual's Ph.D.-granting institution *prior* to the time that the focal scientist received his or her degree. These two variables do not change over time—their values are fixed at the time that an individual received a Ph.D.

Coauthorship network covariates.—The 301,501 papers written by the scientists in our sample were used to construct egocentric coauthorship networks. We included two variables to test hypothesis 7, which states that scientists who have coauthored with academic entrepreneurs are themselves more likely to become commercial scientists. First, we counted the number of scientists-turned-entrepreneurs with whom a focal scientist

[20] The bibliometric literature suggests that citations accumulate according to an exponential distribution (Redner 1998), and this is true of the typical paper in our database. We identified the specific parameter, 0.1, by manually coding 50 randomly selected papers in each of three publication years: 1970, 1980, and 1990, and then choosing the parameter that yielded the best fit to the actual time path of citations to these randomly chosen papers.

has one or more joint papers. We counted only coauthors that (1) had transitioned to commercial science prior to the current year, and (2) had never been employed by the same university as the focal scientist (to avoid confounding the coauthorship network measure with the co-worker transitions variable described above). Second, we summed the number of patents on which a focal scientist's coauthors are listed as inventors, again updating this quantity each year as coauthors are added and as coauthors from the past were granted patents. We anticipate that both of these variables will accelerate the hazard of becoming an academic entrepreneur.

Hypothesis 8 postulates acceleration in the transition rate for scientists who had coauthors that were central in the commercial sector. Many of the academic entrepreneurs in our database founded or advised just a single company, but some were very well networked in the private sector. An example is Leroy Hood of the California Institute of Technology, who has cofounded 11 companies, including Amgen, one of the most successful biotechnology firms. As a proxy for the level of information available about commercial sector opportunities in a scientist's coauthorship network, we identified the most active academic entrepreneur among each scientist's coauthors and included in the regressions a count of number of companies with which that individual is affiliated. To illustrate, consider the case of W. R. Gray. He wrote a series of papers with Hood, the first of which was published in the early 1960s. Each time Hood founded or advised a company and Gray remained in the risk set, the realization of the "event count of the most central coauthor" variable for Gray would be incremented by one.

"Commercializability" covariates.—One might worry that many of the covariates formulated to test the hypotheses simply serve to distinguish scientists by unobserved type, rather than to act directly on the transition to entrepreneurship. For instance, suppose that universities with faculty members who have commercialized their work are prone to recruit new faculty members who do commercially oriented research. If this were the case, the co-worker transitions variable may matter just because it is correlated with an otherwise unmeasured difference among scientists in the commercial potential of their research. In short, omitted variable bias relating to the type of research conducted by scientists may drive some of the results.

To address this concern, we computed two variables to control for differences in the research foci of scientists. First, academic life scientists frequently conduct collaborative research projects with for-profit firms. For each scientist in the data, we included in the regressions the total number of coauthors at for-profit firms with which the scientist has joint publications. Under the assumption that papers with scientists in industry are more likely to have commercial applicability, this variable is included to capture the degree to which scientists' research is readily commercializable.[21]

To further control for the commercializability of scientists' research foci, we generated a second, proximity-to-commercial-science covariate based on the actual stock of research of each scientist. Intuitively, this measure entails using the publications of scientists who have already become entrepreneurs before a given year to define the benchmark for commercializable research at that time. We can then compare the content of the research of each at-risk scientist to this benchmark to generate a research commercializability score for each person-year. Specifically, we define:

$$CP_{it} = \sum_{j=1}^{k} w_{jt} \left(\frac{n_{ijt}}{\sum_{j=1}^{k} n_{ijt}} \right), \tag{5}$$

where

$$w_{jt} = \frac{\sum_{i=1}^{m} (n_{ijt} / \sum_{j=1}^{k'} n_{ijt})}{n_{jt}^{0}} \tag{6}$$

and $i = 1, \ldots, m$ indexes the academic entrepreneurs in the data set, $j = 1, \ldots, k'$ the scientific keywords appearing in the titles of the journal articles published by scientists who have become academic entrepreneurs before t, and n_{jt}^{0} is the number of times each keyword j has appeared in the research papers published by still-at-risk scientists before t.[22]

To compute CP_{it}, we first created an $m \times k'$ row-normalized matrix for year t, with each already-transitioned commercial scientist listed on a row, and each of the keywords used to describe his or her papers listed on a column. The ijth cell in the matrix, $n_{ijt}/\Sigma_j(n_{ijt})$, is defined to be the proportion of commercial scientist i's total research output that is devoted to keyword j. We then take the column sums from this matrix, which form a $1 \times k'$ vector of weights corresponding to keywords that are large

[21] Clearly, one could consider an academic scientist's number of coauthors in industry to be a network-based measure of access to information and other resources related to commercial-sector opportunities. The limitation of this variable as a test of hypothesis 8 is that it likely confounds the nature of a scientist's research with characteristics of his or her network. Thus, we treat "number of private-sector coauthors" as a control variable.

[22] We relied on title words in journal articles instead of journal- or author-assigned keywords because the Web of Science database did not begin to include keyword descriptors until 1992. However, the titles of biomedical research papers typically indicate the research area and the methodology used in the paper. We find high overlap between title words and keywords in the papers for which both are available.

to the extent that a keyword j has been used frequently to describe articles written by scientists who had become academic entrepreneurs before t.

Next, we collected all papers published by the scientists in our data set who had *not* entered commercial science by year t and computed the frequency that each keyword j has appeared in the titles of these scientists' papers. We labeled this frequency n^0_{jt}. The raw weight for a keyword j, represented in the numerator of equation (6), was deflated by n^0_{jt}. The deflated weights, w_{jt}, can be understood simply: they correspond to keywords and are large for keywords that have appeared with *disproportionate frequency* as descriptors of papers written by commercial scientists. Finally, for each individual i in the data set who is at risk of transitioning to commercial science, we produced a list of the keywords in the individual's papers published in all time periods before t, calculated the proportion of the total represented by each keyword j, applied the appropriate keyword weight w_{jt}, and summed over keywords to produce a composite score. The resulting variable, CP_{it}, is large to the degree that the keywords in the titles of a focal scientist's papers have appeared disproportionately in the titles of academic scientists who have previously made the transition to for-profit science. This research-output-based similarity score is entered in the regressions to control for the commercializability of scientists' areas of specialization.

Controlling for time.—Finally, the regressions include year dummy variables to control for time-changing factors, ranging from macroeconomic conditions to the scientific community's reconciliation of the roles of faculty member and entrepreneur. It is well documented that omitted factors that increase over time and are positively associated with adopting a practice may produce spurious evidence of contagion in a network (Strang and Tuma 1993; Van den Bulte and Lilien 2001). Entering year dummies into the regressions will remove this confound.

RESULTS

Table 1 lists, in descending order, the 10 universities that have spawned the greatest number of academic entrepreneurs. With Harvard University, Stanford University, MIT, Yale University, and Columbia University all making the list, it is apparent that commercial activity has been quite concentrated in prestigious institutions.

In light of the institutional loci of academic entrepreneurship, it should be unsurprising that highly accomplished scientists were the most likely to transition to commercial science. The univariate statistics reported in table 2 underscore this point. The table compares the human capital covariates for the scientists in our data at five different cross sections of

TABLE 1
Top Ten Commercial Life Sciences Universities, 1971–2002

	Founders	Scientific Advisors	Total
Harvard University	25	159	184
University of California, San Diego	34	83	117
Stanford University	21	67	88
University of California, San Francisco	12	74	86
University of Washington	8	47	55
Massachusetts Institute of Technology	16	37	53
Johns Hopkins University	7	32	39
Yale University	6	31	37
Columbia University	4	32	36
Cornell University	3	28	31

Note.—Total number of university-employed biotechnology company principals employed by the 10 universities that spawned the greatest number of academic founders of and advisors to life science companies.

professional tenure (5 through 25 years since an individual earned his or her Ph.D.), broken out by whether or not a scientist had become an academic entrepreneur at any point in his or her career. For instance, if a scientist founded a company in his or her nineteenth year in academia, that scientist's realizations on each of the covariates contributed to the averages listed in the "Founder or SAB" column for all of the cross sections in the table (until he or she was removed from the risk set in experience year 19). The mean values in the table show that those who became commercial scientists published more papers than scientists in the matched sample: at each tenure cross section, the publication count for academic entrepreneurs was approximately 1.7 times that of scientists who never transitioned to commercial science. Similarly, founder and SAB scientists were listed on more patents and changed jobs more often than matched sample members. Likewise, a higher percentage of the founder and SAB scientists were employed in top-20 universities.

The descriptive statistics in table 2 compare academic entrepreneurs to members of the random sample at selected intervals of professional *tenure*. Figure 1, by contrast, demonstrates how the profile of scientists who transitioned to entrepreneurship changed over *calendar time*. This figure plots three ratios: the average number of journal article publications of individuals who became entrepreneurs in period t relative to the average publication counts of members of the matched sample in that period, the average number of journal article citations of entrepreneurs relative to members of the matched sample, and the average number of last-authored publications of entrepreneurs relative to members of the matched

TABLE 2

MEAN VALUES OF HUMAN CAPITAL COVARIATES AT FIVE PROFESSIONAL TENURE CROSS SECTIONS, BY SUBSAMPLE MEMBERSHIP

	Fifth Year		Tenth Year		Fifteenth Year		Twentieth Year		Twenty-fifth Year	
	Founder or SAB	Match	Founder or SAB	Match	Founder or SAB	Match	Founder or SAB	Match	Founder or SAB	Match
Cumulative publication count	7.032	4.257	20.172	11.781	37.154	21.245	56.064	32.195	75.874	44.713
Cumulative patent count	.154	.062	.368	.165	.557	.308	.838	.503	.969	.657
Number of jobs held	1.334	1.144	1.505	1.388	1.610	1.502	1.636	1.557	1.660	1.556
Employer prestige	.426	.261	.405	.226	.391	.208	.440	.201	.450	.198
N	868	5,026	728	3,671	539	2,832	327	2,181	191	1,482

NOTE.—Reports mean values for scientists' human capital variables, computed at five different levels of professional tenure (5, 10, 15, 20, and 25 years since Ph.D.), and broken out by whether or not a scientist has *ever* founded or joined the SAB of a biotechnology company. Scientists who became academic entrepreneurs at any point in their careers contribute to the means in the "Founder or SAB" columns; means for scientists whose employment spells terminate in censoring are reported in the "Match" columns.

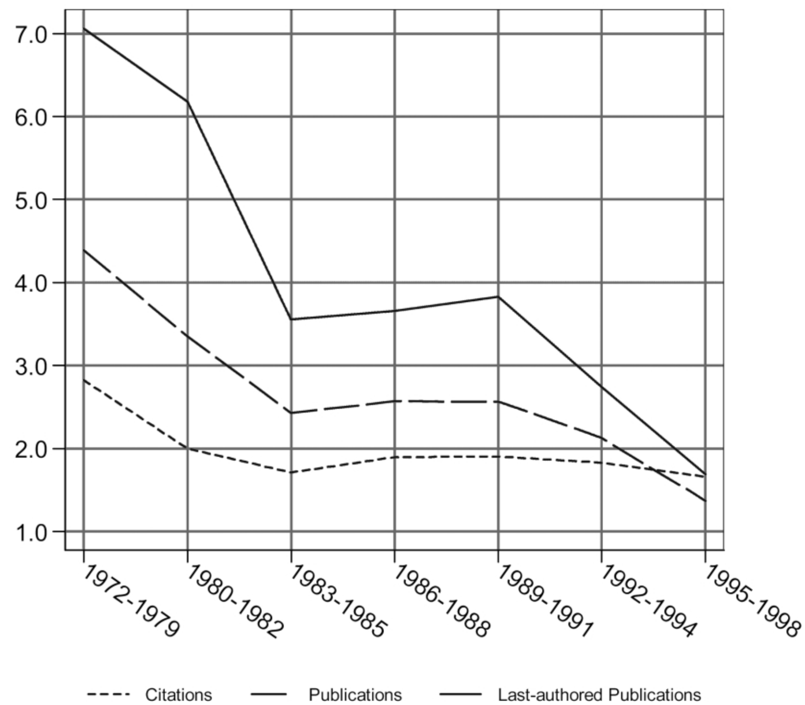

FIG. 1.—Ratios of mean prestige measures, academic entrepreneurs to matched scientists

sample.[23] Thus, a value of one on the *y*-axis would indicate that the scientists who became entrepreneurs in a given period were equivalent in prestige to the representative scientists in the random cohort; values above one manifest a positive status gap between entrepreneurs and typical scientists. Figure 1 clearly demonstrates two points: at all times, academic entrepreneurs have been distinguished scientists, but over time, participation in private ventures shows evidence of democratizing: there is a clear, downward trend in all of the ratios. This suggests that academic entrepreneurship increasingly began to be pursued by less prestigious members of the profession. The figure illustrates a precipitous drop in all three ratios throughout the 1970s and early 1980s, a relatively constant status gap throughout the late 1980s, and evidence of another gradual decline in the relative prominence of academic entrepreneurs throughout

[23] In the life sciences, the author listed last on an article is typically the scientist who runs the laboratory in which the research was conducted. Thus, last authorship is a measure of prominence.

much of the 1990s. We discuss the implications of this trend in the concluding section of the article.

Multivariate regressions are presented in table 3. The three measures of scientists' human capital—the publication count, patent dummy, and number of job changes—are strong, positive predictors of the hazard of transitioning to commercial science. Specifically, having received a patent in the past increases a scientist's hazard of transitioning by a factor of 2.4 (= exp [0.889]). Better-published scientists also have higher transition rates. Although the effect may seem small—an additional paper results in a 1.01 times increase in the hazard—note from table 2 that the typical life scientist publishes frequently.[24] Finally, frequent job changers are also more likely to engage in commercial science, a fact that likely results for two reasons: scientists who have changed jobs a number of times may be talented in ways not captured by the other covariates, and scientists who have worked in multiple institutions probably have extensive networks that lead to opportunities for entrepreneurial science. Consistent with the findings of past studies and the descriptive statistics, the regressions show that accomplished scientists were appreciably more likely to become academic entrepreneurs.

Model 1 also includes university-level variables. The results indicate that scientists in top 20 universities are almost three times more likely to engage in commercial-sector science. The prestige of a scientist's Ph.D.-granting institution also has a lasting influence on the hazard of becoming an academic entrepreneur: individuals with degrees from top 20 departments entered the commercial sector at 1.6 times the rate of those who graduated from lower-status programs. Finally, the dummy variable denoting that a scientist's employer has an active TTO has a positive effect.

As we have noted, it is quite likely that scientists differ in terms of the commercial value of their research. To control for this, we have included in model 1 the two covariates constructed to capture differences in the commercial potential of scientists' research. The first is the number of researchers in industry with whom a scientist has collaborated; the second is his or her commercial proximity score. Both variables have significant, positive effects on the hazard.

In model 2 we add the total number of colleagues at a focal scientist's university who had previously become entrepreneurs. As anticipated in hypothesis 1, co-worker transitions have a positive effect on the hazard: each additional commercial science entrant multiplies the hazard that colleagues at his or her university will become entrepreneurs by a factor

[24] The right tail of the publication distribution is long. One individual in the data set, Thomas Starzl, widely known as the father of transplantation research, has authored more than 1,500 journal articles.

TABLE 3
Case-Cohort-Adjusted Cox Regressions of Transition to Commercial Science

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Control variables:									
Human capital:									
Cumulative publication count (lagged)	.011	.011	.010	.010	.010	.010	.010	.009	.009
	(.001)***	(.001)***	(.001)***	(.001)***	(.001)***	(.001)***	(.001)***	(.001)***	(.001)***
Ever patented dummy (lagged)	.889	.877	.891	.898	.893	.893	.898	.833	.831
	(.145)***	(.145)***	(.147)***	(.144)***	(.147)***	(.146)***	(.146)***	(.147)***	(.142)***
Number of jobs held	.723	.717	.675	.688	.685	.675	.678	.658	.650
	(.082)***	(.084)***	(.082)***	(.084)***	(.084)***	(.087)***	(.087)***	(.090)***	(.087)***
University-level controls									
Employer prestige (=1 if in top 20)	1.014	.757	.739	.740	.786	.567	.493	.498	.525
	(.130)***	(.139)***	(.142)***	(.138)***	(.139)***	(.136)***	(.139)***	(.137)***	(.135)***
Ph.D. university prestige (=1 if in top 20)	.478	.486	.490	.488	.495	.468	.475	.445	.450
	(.127)***	(.126)***	(.127)***	(.124)***	(.125)***	(.125)***	(.134)***	(.132)***	(.128)***
Employer has TTO	.259	.222	.175	.100	.133	.102	.067	.038	−.004
	(.125)**	(.127)*	(.134)	(.129)	(.130)	(.127)	(.127)	(.124)	(.122)
Research commercial proximity:									
Number of private-sector coauthors (lagged)	.014	.015	.015	.015	.016	.015	.015	.010	.008
	(.006)**	(.006)**	(.006)**	(.006)**	(.006)***	(.006)**	(.006)**	(.007)	(.007)
Keyword commercial proximity score × 100	.196	.187	.190	.180	.181	.174	.179	.176	.181
	(.027)***	(.027)***	(.027)***	(.026)***	(.026)***	(.027)***	(.027)***	(.028)***	(.028)***

Work context effects:								
Count of co-worker transitions at employing university (lagged)	.010		.007	.009	.006	.006	.004	.003
	(.001)***		(.002)***	(.002)***	(.002)***	(.002)***	(.002)**	(.002)*
Count of co-worker transitions within division (lagged)		.059						
		(.012)***						
Employed at medical school		.786	.524	.464	.573	.505	.453	.445
		(.134)***	(.122)***	(.125)***	(.121)***	(.120)***	(.122)***	(.120)***
Count of co-worker transitions within division (lagged) × employed at medical school		−.054						
		(.012)***						
Count of co-worker transitions at employing university (lagged) × period dummy (=1 if prior to 1990)			.011			.010	.011	.010
			(.003)***			(.003)***	(.003)***	(.003)***
Employed at medical school × period dummy (=1 if prior to 1990)				.249		.202	.249	.254
				(.089)***		(.092)**	(.095)***	(.094)***
Prestige of co-workers who have transitioned / 100					.015	.015	.014	.014
					(.002)***	(.003)***	(.003)***	(.003)***
Socialization effects:								
Ph.D.-granting university has TTO						−.054	−.039	−.037
						(.167)	(.165)	(.160)
Count of prior faculty transitions at Ph.D. university						.002	.004	.005
						(.005)	(.005)	(.005)

TABLE 3 (*Continued*)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Network effects:									
Cumulative count of academic entrepreneur coauthors (lagged)								.493	.296
								(.088)***	(.096)***
Coauthor cumulative patent count									.019
									(.007)***
Event count of the most central academic entrepreneur coauthor ...									.495
									(.057)***
Log pseudo-likelihood	−9,723.05	−9,693.18	−9,646.9	−9,655.30	−9,635.92	−9,635.92	−9,622.56	−9,585.01	−9,527.18
LR test		59.74	152.10	135.49	131.21	174.25	200.97	276.07	391.75
df		1	3	3	3	3	7	8	10

NOTE.—Time at risk = 103,572; number of subjects = 6,037; number of events = 917. All models control for calendar year dummies. Robust SEs in parentheses.
* $P < .1$.
** $P < .05$.
*** $P < .01$.

of 1.01. This effect may also seem small, but recall from table 1 that a few universities have experienced more than 100 faculty transitions, and that this effect is net of a number of other university-level controls. Indeed, including the covariate has one substantive consequence for the other coefficients: it attenuates the effect of "university has a TTO." This likely occurs because the co-worker transitions variable is a more nuanced measure of the commercial activity in the life sciences taking place at the employers in our data.

A number of different mechanisms could account for the co-worker transitions effect. Among them is the possibility we accentuated in the development of the predictions: particularly in the early period of the data when most academic scientists considered commercial activity to be illegitimate, the presence of local adopters may have favorably predisposed a would-be academic entrepreneur to go forward with the transition. By affording their colleagues easy access to a reference group of procommercial faculty members and influencing their views of the compatibility of the roles of academic scientist and entrepreneur, the presence of commercial scientists would have facilitated subsequent peer transitions.

Hypotheses 2 to 4 refine the first prediction in an effort to single out this type of mechanism. We introduced three new variables in model 3 to test hypothesis 2. First, we replaced the university-level event count with a "count of co-worker transitions within divisions." We also included an "employed at medical school" dummy and a multiplicative term between it and the within-division co-worker transitions. The medical school dummy has a positive coefficient, indicating that Ph.D. research scientists in medical schools were more likely to become commercialists than their counterparts in university science departments. With human capital and commercial proximity controls included, the relatively higher incidence of entrepreneurial transitions in medical schools is consistent with the argument that local norms were relatively more accepting of commercial activity in these work settings. Moreover, in support of hypothesis 2, the effect of within-division co-worker transitions on the hazard of becoming an entrepreneur is considerably stronger in science departments than in medical schools. Comparing the coefficient on the co-worker transitions covariate to the one on the interaction term, we can see that the net effect of an additional co-worker transition is positive in both medical schools and university science departments. However, the change in the hazard caused by each additional entrant to commercial science is significantly smaller in medical schools than it is in university departments (the estimated effect is 1.06 [$= \exp(.059)$] in university departments, versus 1.005 [$= \exp(0.059 - 0.054)$] in medical schools). This contingency may exist because, as we have argued, social influences were stronger in academic departments than in professional schools because of the difference in acceptance of entrepreneurial activity across the two work contexts.

The third hypothesis speculates that the influence of co-worker transitions at a scientist's university will attenuate as the practice of commercial science diffuses. To examine this, we included in model 4 an interaction between co-worker transitions and the "prior to 1990" period effect.[25] The positive coefficient on the interaction term supports our intuition. To illustrate magnitudes, consider the consequence of a change from 0 to 10 co-worker transitions at a scientist's employer before and after the year of 1990. The implied change in the multiplier of the hazard caused by increasing the co-worker transitions covariate before 1990 was 1.2 ($= \exp[0.007 \times 10 + 0.011 \times 10]$); after 1990, the multiplier reduces to 1.07 ($= \exp[0.007 \times 10]$).

The fourth hypothesis posits that the difference in the transition rate between academic departments and medical schools will decline as academic entrepreneurship diffuses. This prediction is tested in model 5 by including an interaction term between the "prior to 1990" dummy and the medical school indicator variable. In the years before 1990, Ph.D. scientists in medical schools became entrepreneurs at twice ($= \exp[0.464 + 0.249]$) the rate of faculty in university science departments, even after conditioning on the measures of research commercializability. However, after 1990, scientists in medical schools transitioned at 1.6 times ($= \exp[0.464]$) the rate of peers on faculties of arts and sciences. Thus, the difference in transition rates across work contexts persists throughout the entire analysis period, but as set forth in hypothesis 4, the gap between FAS and medical schools diminished substantially as participation in commercial science gained acceptance in the scientific community.

The results of the interactions between the time period and the two proxies of the predispositions of scientists' colleagues toward commercial work (i.e., "number of co-worker transitions" and "employed in a medical school") invite comparison to other studies of the diffusion of practices that became institutionalized. In their influential study of the spread of civil service reforms, Tolbert and Zucker (1983) found that measures of

[25] Similar results obtain if the period effect is specified to be "prior to" any year between the mid-1980s and the mid-1990s. In unreported regressions, we tested hypothesis 3 by including an interaction term between co-worker transitions and the sum across all universities of the number of academic founders and SAB members affiliated with the companies in our data set that were founded before the given year. We expected the effect of past local transitions to decline in the total number of profession-wide events. The coefficient on the interaction term was indeed negative and statistically significant. Testing the prediction this way, however, requires that we omit the calendar-year dummy variables, which is why we have run the interaction with a period effect in the reported models.

the instrumental benefits of formal organization affected cities' propensities to adopt civil service reforms, but only until the practice achieved taken-for-granted status (see also Dobbin and Sutton 1998). At that point, the legitimacy of the practice itself propelled subsequent adoptions. Although we have no compelling reason (or evidence) to believe that the practice of academic entrepreneurship diffused beyond the point that it was individually rational for participants, our results suggest that the degree of local contagion declined in the global spread of the practice. A plausible explanation for this is that workplaces gradually lost the ability to sustain views that markedly differed from those sweeping through the profession at large. In other words, not unlike Tolbert and Zucker's (1983) finding that the diffusion of a novel practice ultimately can be driven by its legitimacy, our results are consistent with the possibility that widespread acceptance of a once controversial behavior inhibits the ability of holdouts to resist its local adoption.

To test the fifth hypothesis, we included in model 6 the average prestige (the average of the citation counts) of the co-workers who have previously transitioned while working at scientists' universities. The argument that the transition of high-prestige co-workers may do the most to promote acceptance of commercial activity in a workplace finds support in the positive coefficient on the citation count of co-workers who have entered commercial science. The estimates show that a standard deviation increase ($=$ 18.9) in the citation count of co-workers who have become commercial scientists multiplies the hazard of at-risk scientists at the same university by a factor of 1.3 ($= \exp[0.015 \times 18.9]$).

We next examine whether the presence of procommercial faculty at individuals' Ph.D.-granting universities influenced the likelihood that graduates subsequently became entrepreneurs. We have included two new predictors in model 7 to explore this issue: whether a scientist's degree-granting institution had established a TTO prior to the scientist's graduation year, and the number of commercial scientists at the university, again predating the time that a focal scientist was issued a degree. Neither covariate has a statistically significant effect on the hazard of transitioning, after accounting for human capital and work-context-related factors. The "count of prior transitions at Ph.D. university" does have a positive, statistically significant effect in pared specifications, but the effect is not robust to the inclusion of the full covariate matrix.

The coauthorship network covariates are included in model 8. There is a large effect of relationships with scientists who have already become entrepreneurs: each additional commercial scientist in ego's collaboration network multiplies the hazard by a factor of 1.6 ($= \exp[0.493]$). In model 9, we have introduced two more covariates aimed at assessing the influence of coauthors' profiles. One covariate is the average number of patents held by ego's coauthors. The second is the number of companies ego's most commercially active coauthor has founded or advised prior to a given year.[26] Both of these covariates work as forecasted: the estimated coefficients are positive and statistically significant. Indeed, the "event count of the most central academic entrepreneur coauthor" has a particularly large effect—for each increment to the event count of ego's most commercially central coauthor, the hazard of ego's transition increases by a factor of 1.6.

The magnitude of the effect of the commercial sector centrality of coauthors raises the possibility that a small group of commercially active and academically productive scientists may help cultivate private-sector opportunities for colleagues who have yet to make the transition. For instance, the aforementioned Leroy Hood at the California Institute of Technology could be one such person. Prior to 2002, he had written 493 papers, accrued 943 coauthors throughout his career, and held formal affiliations with seven companies in our data set and four still-private firms. George Whitesides of Harvard University is another researcher with many contacts in academic and industry circles: he has had 613 coauthors on 578 papers and has founded or advised 11 companies. These individuals, or others with similar credentials, appear to be conduits to the commercial sphere, perhaps by providing introductions or access to other types of resources that enable colleagues to follow their footsteps to entrepreneurship.

Robustness Check: Social Influence or Endogenous Matching?

One potentially confounding factor is that job matching could produce some of the effects we attribute to network-based influence or referral processes. As we have mentioned, co-worker transitions at a university might increase the hazard because scientists who do commercially oriented research are more likely to match to jobs in universities that already employ procommercial scientists. We have attempted to exclude this possibility in the regressions by directly accounting for the commercial relevance of scientists' research. Our data allow us to take one additional step to rule out job matching.

Because the biotechnology industry did not flourish until the late 1970s, there is little risk that, prior to this time, life scientists and universities formed matches based on a correspondence of attitudes toward privatizing academic research. Thus, if we restrict the analysis to individuals who

[26] We have also entered this covariate as the mean number of commercial ventures of ego's coauthors, but a Bayesian information criterion (BIC) test favors the use of the maximum (the most central coauthor).

(1) earned their Ph.D.'s prior to the year that Genentech was founded (pre-1976 Ph.D.'s), and (2) remained with the same (1976) employer throughout the duration of our data set, we can reduce the concern that the findings are driven by a sorting process yielding a match between procommercial scientists and university departments.[27] We report this analysis in model 1 of table 4 (excluding the socialization proxies because they do not vary among early Ph.D.'s). Pre-1976 Ph.D.'s who remained in their positions account for about one-third of the total number of events. Although we lose two-thirds of the events, the results are similar in the restricted and full samples. Notably, co-worker transitions and most of the interaction effects remain statistically significant and operate in the expected direction. In fact, the only meaningful change in the results is for the coauthorship network effects, which are dominated by the commercial sector centrality covariate in the restricted sample.

We can undertake a similar robustness check for the coauthorship network effects. Here, the alternative we wish to exclude is that academic scientists who desire to enter the commercial sector proactively seek coauthors who already have established relationships in industry. Although it is not possible to rule out this possibility completely, we can again exploit the temporal dimension of the data to mitigate the concern. We do so in model 2 of table 4, in which we split the cumulative count of academic entrepreneurs in a scientist's coauthorship network into two components: relationships between ego and a coauthor that predated the time that the *coauthor* entered commercial science, and ties that were established after the coauthor had become an academic entrepreneur. If the latter quantity drives the results, the network effects indeed may be spurious, perhaps just reflecting the strategic behavior of scientists who wish to expand their networks to maximize their opportunities to become commercialists. In fact, we observe just the opposite pattern: the coefficient for the number of relationships formed *prior to* the time that coauthors had transitioned is more than twice the size of the coefficient for the number of coauthorship ties ego had formed with collaborators who had already entered commercial science.

Model 3 in table 4 reproduces the full regression, model 9 in table 3, but the parameters are obtained from a discrete-time hazard estimator. We report this regression to reassure the reader that the results are neither sensitive to the estimator we have chosen nor are contingent on the use

[27] We cannot completely rule out the possibility of job matching because the duration of the pre-1976 employment relation is endogenous (i.e., scientists who are well matched to their pre-1976 departments are more likely to remain in that position, rather than switch jobs). Nonetheless, finding similar coefficients after excluding job hoppers should bolster confidence in the results.

TABLE 4
ROBUSTNESS CHECKS OF REGRESSIONS OF TRANSITION TO COMMERCIAL SCIENCE

	Model 1: Adjusted Cox	Model 2: Adjusted Cox	Model 3: WESML
Control variables:			
Human capital:			
Cumulative publication count (lagged)	.008	.009	.006
	(.002)***	(.001)***	(.001)***
Ever patented dummy (lagged)	1.154	.843	.820
	(.224)***	(.146)***	(.134)***
Number of jobs held		.669	.528
		(.088)***	(.081)***
University-level controls:			
Employer prestige (=1 if in top 20)	.919	.492	.477
	(.228)***	(.138)***	(.137)***
Ph.D. university prestige (=1 if in top 20)	.188	.447	.496
	(.229)	(.132)***	(.113)***
Employer has TTO	−.033	.032	.002
	(.210)	(.124)	(.122)
Research commercial proximity:			
Number of private-sector coauthors (lagged)	−.009	.012	.006
	(.016)	(.007)*	(.008)
Keyword commercial proximity score × 100	.499	.177	.163
	(.098)***	(.028)***	(.028)***
Work context effects:			
Count of co-worker transitions at employing university (lagged)	.011	.005	.004
	(.005)**	(.002)**	(.002)**
Employed at medical school	.678	.444	.279
	(.303)**	(.122)***	(.121)**
Count of co-worker transitions at employing university (lagged) × period dummy (=1 if prior to 1990)	−.001	.011	.008
	(.007)	(.003)***	(.004)**
Employed at medical school × period dummy (=1 if prior to 1990)	.121	.247	.269
	(.234)	(.094)***	(.108)**
Prestige of co-workers who have transitioned/100	.011	.014	.012
	(.005)**	(.003)***	(.003)***
Socialization effects:			
Ph.D.-granting university has TTO		−.015	.015
		(.166)	(.145)
Count of prior faculty transitions at Ph.D. university		.004	.009

TABLE 4 (*Continued*)

	Model 1: Adjusted Cox	Model 2: Adjusted Cox	Model 3: WESML
		(.005)	(.006)
Network effects:			
Cumulative count of academic entrepreneur coauthors (lagged)	−.003		.273
	(.238)		(.097)***
Coauthor cumulative patent count	.025		.017
	(.015)		(.008)**
Event count of the most central academic entrepreneur coauthor	1.158		.433
	(.172)***		(.070)***
Cumulative count of academic entrepreneur coauthors (ties started after event)		.412	
		(.101)***	
Cumulative count of academic entrepreneur coauthors (ties started before event)		1.099	
		(.323)***	
Log pseudo-likelihood	−2,759.50	−9,579.03	−287.50
Time at risk	49,580	103,572	103,572
Number of subjects	3,294	6,037	6,037
Number of events	292	917	917

NOTE.—Model 1 uses the restricted sample of pre-1976 Ph.D.'s who remained with their 1976 employer throughout the data set. All models control for calendar year dummies; model 3 also controls for tenure-specific dummies. Robust SEs in parentheses.
* $P < .1$.
** $P < .05$.
*** $P < .01$.

of continuous-time models. Specifically, we employed the weighted exogenous sampling maximum likelihood (WESML) estimator proposed by Manski and Lerman (1977), which is a logistic regression model that incorporates weights to adjust for (in our case) the oversampling of events.[28] The model includes a set of (unreported) duration-specific

[28] Manski and Lerman (1977) show that the following weighted maximum-likelihood estimator produces consistent estimates in choice-based samples:

$$\ln L_w = w_1 \sum_{Y_i=1} \ln(\pi_i) + w_0 \sum_{Y_i=0} \ln(1-\pi_i)$$

$$= -\sum_{i=1}^{n} w_i \ln[1 + e^{(1-2y_i)x_i\beta}],$$

where $w_i = w_1 Y_i + w_0(1 - Y_i)$ and the weights are

$$w_1 = \frac{\text{the fraction of events in population}}{\text{the observed fraction of events in the sample}}$$

dummy variables to account for time dependence in the rate. Comparing the parameter estimates from the WESML logit in model 3 of table 4 to the identical specification using the adjusted Cox (table 3, model 9) indicates that the findings are fully robust to the choice of discrete- versus continuous-time methods.

CONCLUSIONS

Our findings show that faculty members were more likely to become entrepreneurs—to found or join advisory boards of for-profit biomedical firms—when they worked in university departments that employed other scientists who had previously ventured into the commercial sector. The effect of working with academic entrepreneurs was largest when those having commercialized their work were prestigious scientists, and it was attenuated for individuals in medical schools and after for-profit science had significantly diffused across the community of academic scientists. In addition, scientists with coauthors who had become academic entrepreneurs were more likely to transition to commercial science, particularly when their coauthors were well connected in industry and when the link was established prior to the time that the collaborator had established an affiliation with a private-sector firm. Either because they influenced colleagues' attitudes toward the acceptability of commercial activity or because they opened pathways for information exchange and introductions, entrepreneurial scientists significantly affected the likelihood that their collaborators and co-workers would embrace private-sector science.

Before returning to the central themes of this article, we wish to remark briefly on its general relevance to research on entrepreneurship. One of the perennial obstacles to empirical research on the transition to entrepreneurship is the difficulty of obtaining suitable data. Acquisition of appropriate data can be especially challenging if the researcher is interested in studying the formation of a particular type of organization, in which case entrepreneurial events may be sufficiently rare that even a large random sample would not contain enough information to support statistical inference. Compounding this problem, it is sometimes difficult even to specify the boundaries of the population—or risk set—of individuals who might reasonably be expected to become entrepreneurs of a particular type. The upshot of these difficulties is that much of the lit-

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and

$$w_0 = \frac{1 - \text{the fraction of events in population}}{1 - \text{the observed fraction of events in the sample}}.$$

erature on entrepreneurship can be aptly criticized for sampling on the dependent variable, or drawing conclusions from samples that only include principals of actual start-up companies (Carroll and Mosakowski 1987). The research design we have employed circumvents this problem. By limiting the focus to academic founders of biotechnology companies, we are able to identify the population of individuals who are "at risk" of becoming academic entrepreneurs. And by selecting all events, we escape the problem of small numbers. More generally, we believe that the use of case-cohort data structures should enable researchers to begin to assemble data sets that eschew the methodological shortcomings that have rendered inference questionable in many studies in the entrepreneurship literature.

We introduced the article with two questions. One asked, How do individual characteristics, work contexts, and occupation-wide developments influence individuals' decisions to embrace new forms of professional conduct? We are now prepared to offer a response, at least for the specific case of the spread of entrepreneurial activity in the academic life sciences. Our primary focus on social influence processes led us to locate individuals' work settings at center stage in the analysis—a focus ultimately justified by the evidence of within-workplace and within-network transmission. However, the regressions also underscore the role of individual-level opportunity in driving the transition to for-profit science. We examined two types of measures of opportunity: scientists' human capital stocks (e.g., publication totals and patents) and their social positions (e.g., the prestige of employers and degree-granting institutions). Across the board, the measures of human capital and social standing positively influenced the hazard of transitioning to entrepreneurship. Although a few measures of opportunity, notably patents and proximity to commercial science, are likely endogenously related to scientists' attitudes toward privatizing research, much of the explained variance in the decision to become an academic entrepreneur rests in interindividual differences in the chance to enter commercial science.

The finding that the most accomplished scientists were also most likely to become academic entrepreneurs is interesting when viewed in context of the literature on professional norms. Some have espoused the view that entrepreneurship *per se* is incompatible with professional standing (e.g., Goldstein [1984] and Nathanson and Becker [1981], for medical doctors). As an activity unbefitting a professional, entrepreneurship was often thought to be relegated to the low-prestige individuals that populate the fringe of a professional group. More generally, it is thought that intraprofessional status follows from public adherence to professional norms: insofar as strict compliance with group norms represents the basis of a claim to deference, those who comply with codes of professional ethics accrue status (see Abbott [1983] for theoretical exposition; Laumann and Heinz [1977] for evidence). Theoretical considerations and empirical studies supporting a positive association between prestige and conformity notwithstanding, our analysis seemingly uncovers the opposite relationship: at the time when the scientific community questioned the propriety of academic entrepreneurship, highly regarded scientists employed at prestigious universities were most likely to challenge the accepted standards of professional conduct.

We see two possible explanations for the fact that the most prominent members of the profession were the most likely to become academic entrepreneurs. The first and most likely explanation is opportunity, or more precisely, the lack thereof: to succeed in the private sector, an individual must have had the capacity to mobilize resources. Most science-based biomedical companies consume significant resources in their early stage and therefore require the financial support of third-party investors, such as venture capitalists. Because only elite scientists had the reputations to attract the interest of investors in the formative stages of the biotechnology industry, marginal members of the profession likely were unable to secure opportunities in the private sector. Thus, in the era in which the majority in the profession discouraged commercial involvement, it is quite possible that low-status members of the scientific community were both least committed to the ideals embodied in the Mertonian norms and most interested in entrepreneurial activity, but nonetheless did not transition to the private sector because they were unable to obtain the necessary, third-party support. Indeed, as we argue in a pair of companion papers (Ding et al. 2005, 2006), a lack of connections to members of the business community is likely to be a determining factor in female scientists' low rates of participation in academic entrepreneurship.

A different stream of the literature on social status and conformity suggests a second possibility. To the extent that status confers protection from social sanctions (Phillips and Zuckerman 2001), high-prestige scientists may have been the least deterred by the implicit threat of reputation loss when they became entrepreneurs. While conformity to group norms can be one basis for deference, in the case we examine, there is an independent dimension of status rooted in the significance of scholars' contributions to the corpus of scientific knowledge. To the extent that involvement with private sector firms was overlooked or forgiven for those who had most significantly advanced scientific understanding, one would expect to observe the highest incidence of entrepreneurship among the scientific elite.

Regardless of the reason for the positive correlation between scientific achievement and the propensity to commercialize research, the fact that many among the most prominent stratum of the profession have become entrepreneurs has done much to influence community-wide views of commercial science. This returns us to the other question we posed at the outset of the article: What factors lead to revision in an occupational community's perception of appropriate conduct? In the case of academic entrepreneurship, while many exogenous factors such as the decreasing availability of federal funding for universities played a role, the decisions of so many prominent faculty members at elite universities to start or affiliate with private companies hastened the acceptance of academic entrepreneurship in the scientific community. Indeed, we have found suggestive evidence of this dynamic: relative to those of ordinary professional standing, high-prestige scientists were considerably more likely to sway colleagues at their universities to participate in private-sector science. As well, we observe this dynamic in the sequence of scientists' transitions to the commercial sector: over time, there is clear evidence that academic entrepreneurship began to trickle down the scientific prestige hierarchy. Thus, while social structural conditions did shape the pattern of diffusion of entrepreneurial science, the selective adoption of academic entrepreneurship among the scientific elite shaped the institutional context in which the social influence process was unfolding. And as the practice of academic entrepreneurship diffused and gained acceptance, the consequences of local social influences diminished.

We have focused on conditions affecting the spread of academic entrepreneurship, but many interesting questions surround the consequences of the practice's diffusion. For instance, what are the implications of the increasing prevalence of academic entrepreneurship for the career dynamics of academic scientists? In the early period of our analysis, participation in for-profit ventures appears to have been restricted to the senior ranks of the profession, but by the late 1990s (unreported) plots of the transition rate show that young, often untenured scientists had begun to affiliate with for-profit firms. What is the influence of private-sector attachments on the advancement prospects of young life scientists? Do early work life affiliations with for-profit companies signal the emergence of new avenues for career paths in academic science? And how does involvement with for-profit firms amend the research agendas of academic scientists? These are just a few of the many questions that await the attention of sociologists interested in the intersection of science, technology, and careers.

APPENDIX

Data Sources

The SEC provided S-1 and SB-2 statements filed by biotechnology firms registering securities for sale to the public in an IPO. These forms differ only in that disclosure requirements are more modest for firms that qualify as small business (SB). In a few cases, firms filed IPO prospectuses but never actually went public, usually because stock market conditions deteriorated between when IPO papers were filed and the scheduled issue date. We used these prospectuses to collect biographical information on founders, board members, executives, and scientific advisors, as well as company founding dates, location, and financials. (See http://www.sec.gov/edgar.shtml.)

The UMI Proquest Digital Dissertations database contains more than 90% of the doctorate degrees granted in the United States since 1861. Name, degree-granting institution, date of degree completion, discipline of graduate, and, for later years (after 1993), identity of the thesis advisor, are available in the database. We draw the random (control) sample of Ph.D. scientists from the population of degree holders in the relevant disciplines listed in the UMI database. (See http://www.umi.com/.)

The ISI Web of Science is a detailed bibliometric database. Prior to 1973, the database contains only basic information about each paper, including authors, journal name, and paper title. After 1973 authors' affiliations, paper abstracts, keywords, and citations are available. We use the ISI database to compute publication counts for each scientist, identify scientists' employers, generate proximity scores between scientists based on keywords, and build the coauthorship network in the life sciences. (See http://isi0.isiknowledge.com/.)

The National Bureau of Economic Research (NBER) patent database contains all U.S. patents issued since the early 1970s. The fields we use are the patent application date (the date the patent application was submitted to the U.S. Patent Office), inventor names, and assignee names. Inventors are individual researchers (academic scientists for the patents we consider), and assignees are employers. We use these data to compute counts of numbers of patents issued to all individual members of our database. (See http://www.nber.org/patents.)

Gourman reports provide rankings of all graduate schools since 1980. We created a "top 20" department dummy designating that a scientist's employer is a top 20 biochemistry department. (Biochemistry is the modal discipline in our data set.)

The Association of University Technology Managers surveys (2001) report detailed information on the technology transfer activities of universities. We use these to identify when each university started its TTO.

We use scientists' personal Web sites to obtain résumés or bios when available to verify affiliations.

We use three primary sources to identify biotechnology firms. First, we use the Compustat database, which categorizes companies by primary

SIC. Second, we use the Bioscan Directories, which lists public and private biotechnology firms and provides historical information about the industry. Third, we use the Recombinant Capital database, which also contains detailed information about biotechnology companies and is used to augment the list of biotechnology firms (http://www.recap.com).

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