Divergent Paths or Stepping Stones:
A Comparison of Scientists' Advising and Founding Activities

Waverly Ding & Emily Choi

Haas School of Business
545 Student Services #1900
University of California
Berkeley, CA 94720
wding@haas.berkeley.edu
echoi@haas.berkeley.edu

August 2008

Divergent Paths or Stepping Stones:

A Comparison of Scientists' Advising and Founding Activities

This paper investigates the difference in the profiles of university scientists who have founded or advised companies. We analyzed commercial activities of a sample of 6,138 university life scientists and found that the profiles of scientists who become academic entrepreneurs are different from those who become company scientific advisors. Founding activity occurs earlier during a scientist's career cycle than advising. Factors such as gender, research productivity, social networks and employer characteristics also shape the propensity of founding and advising in different patterns. In addition, regression analysis shows that being a company scientific advisor decreases the risk of becoming an academic founder. Overall, evidence from our analysis suggests that founding and advising are two divergent paths for commercially oriented university scientists.

I. Introduction

Scholars of university-industry relations have revealed multiple channels through which university scientists get involved with commercializing their research. At a minimum, scientists can disclose their research to the technology transfer (licensing) office at their universities, which negotiate with industrial firms that wish to license the research discovery (Jensen, Thursby and Thursby, 2003; Bercovitz and Feldman, 2008). Over the past decades, university scientists are increasingly involved in licensing their technology to the industry and sometimes actively involved in the process (Thursby and Thursby, 2002; 2004). University scientists are also reported as increasingly seeking patent protections for their research (Henderson, Jaffe, and Trajtenberg, 1998; Owen-Smith and Powell, 2001b; Agrawal and Henderson, 2002; Balconi, Breschi and Lissoni, 2004; Fabrizio & DiMinin, 2004; Stephan, et al., 2004; Azoulay, Ding and Stuart, 2007, 2008; Azoulay, Michigan and Sampat, 2007). Alternatively, some university scientists do collaborated research with industrial firms in the forms of contract research (Blumenthal et al., 1986; 1996), consulting (Jensen, Thursby, and Thursby, 2006) or joint R&D projects (Lam, 2007). In the life sciences, there are a significant number of scientists who are members of scientific advisory boards in biotech firms (Stuart and Ding, 2006). Finally, academic scientists can start their own company to commercialize their discoveries. Over the past few decades, there has been an increasing number of university scientists who found for-profit firms (Etzkowitz, 1983; Shane and Khurana, 2003; Stuart and Ding, 2006). One limitation of these studies on university-industry channels is that most focus on only one of the possible routes for scientist involvement in commercial activity (Louis et al., 1989 is an exception). As a result, though we have accumulated much knowledge about the antecedents and consequences of a single commercial activity, we lack comparative analysis of various routes of commercial involvement and the relationship among them.

We believe that a more integrative approach is important for us to better understand when and why university scientists embark on commercial activity. First, commercial activities such as disclosure, patenting, advising and founding companies call for different amount of input of time and effort, and can have different impact on scientist productivities and career trajectories. A comparative analysis of profiles of scientists who have engaged in different types of activities may help us understand who are inclined to engage in a specific activity and at which stage of their career. Second, each of these commercial activities requires different financial and social resources. For example, disclosure and patenting might require scientists to simply have research that is worth reporting and seeking patent protection. In comparison, to be advisors or founders of companies, scientists probably face a higher threshold in terms of human capital, academic status and risk tolerance. It is thus necessary to have a comparative analysis of how various factors (e.g., researcher human capital, status and social networks) affect the likelihood of pursuing different commercial activities. Third, an integrated approach is instrumental in revealing the relationship among the activities. For example, does relatively "light" commercial involvement such as patenting and consulting trigger more intensive commercial involvement such as founding a company, or is it the case that scientists sort into different camps—i.e., those who are more entrepreneurial-oriented versus those who are only willing to devote a fraction of their time to commercial activities?

With above interests in mind, in this paper we provide a comparative analysis of two types of commercial activities by life sciences researchers—joining a scientific advisory board (referred to as SAB in this paper) of a for-profit firm versus founding a company to develop a technology. We choose to focus on these two activities for three reasons. First, compared to patenting, subsidized research and ad-hoc consulting arrangements, advisory and entrepreneurial opportunities allow scientists more involvement with a firm's operations on a regular basis and hence more control over the process of commercial development of a technology. Given the degree of involvement, these activities may exert significant impact on the trajectories of the relevant industries. Second, we would like to resolve the debate on whether joining an SAB and founding a company happens early or later in a scientist's career. The profiles of scientists who found companies vary with the theoretical models used to generate predictions. While role identity theory predicts academic entrepreneurship transition happens early in a scientist's career, the academic life cycle model suggests that entrepreneurial transition should happen at a late stage of a scientist's career. Thus, we need to know more about the profiles of the participants of each of these activities and whether the paths leading to the activities converge. Lastly, the choice is partially determined by data availability. While it is possible to survey current scientists' activities and attitudes related to consulting and industry-subsidized research, there is no systematic longitudinal data that allow us to adequately analyze the relationship across activities. Founding and advising activities, however, are reported in firms' publicly disseminated corporate documents, hence it is feasible to construct historical data to trace them.

To empirically compare the profiles of advisors and founders and find linkages between the two activities, we assembled a data archive with career histories of approximately 6,100 life scientists. They have various degrees of involvement in commercial science, ranging from no significant commercial involvement, to patenting, advising and founding companies. Because the number of scientists participating in advising and founding activities is small, we employed a sampling procedure known as the "case cohort" design. We analyzed the propensity that a scientist embarks on either advising or founding activities using event history models, correcting for possible bias caused by the sampling design.

Among the key findings, we found that timing of advisory and entrepreneurial activities differ in a scientist's career cycle. The hazard of first-time involvement in entrepreneurial activity peaks much earlier than that of advisory activity in a scientist's life cycle. This pattern holds true for male and female, older and younger cohort of scientists, and for scientists employed at universities with different ranking. Second, we also identified differences in antecedents of the two activities including gender, research productivity, social network and employer influence. Lastly, in Cox regression analysis of whether prior advising activity increases the hazard of a scientist's transition to entrepreneurship, we find no evidence supporting a sequential engagement argument. In fact, being a company advisor decreases the likelihood a scientist transitions into an academic entrepreneur.

II. Scientific Advisors and Founders.

Relatively little research has been done on the form and function of firms' scientific advisory boards and their members. These boards have neither fiduciary responsibility nor a formal place in a firm's governance structure. Nevertheless, they have become a quite common organizational feature in many high tech industries. Typically these boards are formed by the founding scientist very early in the development of the firm and have between five and ten members. Board members are rewarded with stock grants and consulting fees.

What types of scientists join these scientific advisory boards? Ding, Murray and Stuart (2007) conducted in-depth interviews of about 50 scientists who have either joined SABs or are in fields that are often invited to such boards. The data they have collected offer some insights about the role of an SAB and who are likely to serve on them.

Broadly speaking, SABs perform three primary functions for companies. First, technology intensive firms rely on these scientific advisors for their expertise, ranging from very specific tacit knowledge to general advice on broad scientific strategy and experimental design. SAB members support the firm's internal research activities; during board meetings, scientists assess and critique experiments designed by the firm's internal researchers and debate the direction of the next series of experiments. In general, scientific advisors often have a combination of deep scientific expertise and a basic understanding of business issues. Second, SAB members are also chosen to signal scientific quality to external investors. In the interviews, those who have served on SABs often likened their advisory role to “window dressing”. In effect, prestigious academic scientists lend their reputations to the early stage firms they advise, which is thought to aid firms in the process of attracting resources (Stuart, Hoang, and Hybels 1999; Higgins and Gulati 2003). A third function that advisors are expected to fulfill, is to bridge their social networks to the firm.Advisors assist in identifying other academics that might provide a critical resource through collaborative research, and they locate suitable students to be hired by the firm (Murray 2004; Stuart, Ozdemir and Ding, 2007). Based on these descriptions, the image that emerges for the ideal type of scientific advisor would be a scientist who is at a later career stage, having deep expertise in a scientific field, is well-respected for his or her knowledge in a field, most likely affiliated with prestigious institutions, and possessing extensive collaborative networks in academia.

The characteristics of a scientist that becomes an entrepreneur[1], in comparison, are less straight-forward. While some theories suggest that academic entrepreneurs should have a different profile and motivated by different factors from advisors, other theories and empirical evidence find commonalities between founders and advisors.

Social psychological research on entrepreneurship suggests that entrepreneurs display some unique traits than the general population. For example, Scherer (1982) and Sexton and Bowman (1985) found that entrepreneurs have a higher tolerance for ambiguity. They also found entrepreneurs generally have higher need for autonomy, dominance and independence, and lower need for support and conformity. Shane’s (2004)

---

[1] Though the concept of academic entrepreneurs can be understood rather broadly as including those who engage in different types of commercial activities (e.g., patenting, consulting, sponsored research and founding companies) (Franzoni and Lissoni, 2007), we used the concept of academic entrepreneur to refer to those who have founded companies.

study of university-scientist-turned entrepreneurs confirm some of these findings among the academic entrepreneur population. He found that those scientists who have managed to transition to entrepreneurship have a stronger desire for wealth, a desire to bring the technological breakthroughs into practice, and a desire for independence and autonomy. The cognitive approach thus will suggest that academic founders have a different social psychological and behavior patterns from the advisors.

A scientist's transition to entrepreneurship can also be understood from the perspective of role identity change (Ibarra, 1999). University scientists have acquired strong professional identity given the duration and intensity of their academic training and the prevailing norms in most academic institutions. Hence, the transition from suspicion to acceptance of commercial activity is not likely a smooth process, during which many have experienced role contradictions (Owen-Smith and Powell, 2001a). George et al. (2005) analyzed the cognitive micro-process of academic entrepreneurs' transition to entrepreneurship using a combination of both qualitative and quantitative data. They found that scientists engage in a sense-making process of recognizing and internalizing their new commercial role identity. During the process, scientists are motivated by a desire for wealth and concerned with how they will be perceived in their new role as an entrepreneur and the level of collegial and institutional support in the environment. Assuming that a university scientist's identification with the role of an academician strengthens with the duration and intensity of the socialization process in academia, scientists who have stayed in academia for long duration will have a more difficult time making the transition to entreprenuership. These scientists have internalized the ethos of the public science more deeply than their junior colleagues, hence face greater impediments during the transitional process. This assumption suggests that scientists who have successfully made the transition to entrepreneurship are likely to be at an early stage of their career, and have internalized the academic value system to a lesser extent.

A third perspective on the academic-entrepreneur transition is Stephan and Levin's (1996) academic life cycle model. The authors proposed a model that accounts for university scientists' development of human capital and allocation of time and attention throughout their career cycle. They argue that academic scientists invest the early part of their career on accumulating human capital both for creating an area of expertise and for achieving important milestones (e.g., attaining tenure). This suggests that early on most university scientists devote the bulk of their attention to basic science research. Once these career goals have been reached, scientists then have more opportunities to embark on activities that may help gain financial returns on their human capital, among them is the creation of ventures to commercialize their research. Some empirical evidence lends support to this model (Audretch, 2000; Klofsten and Jones-Evans, 2000). From this perspective, we would expect that academic entrepreneurs are scientists who are at a later career stage and have more established reputation in their areas. Such a profile is more akin to that of a scientific advisor's than what role identity theory would predict.

A fourth perspective that offers insight into the academic-entrepreneur transition is the dynamics of social status. Sociological theory of status argues that individuals occupying the middle range of a status hierarchy are less likely to engage in activities unsanctioned by the environment. This is because high status provides actors with adequate resources to withstand the risks associated with deviant activities. At the same time, when actors are low on a status hierarchy, they have little to lose if they deviate from the prescribed norms, hence have more tolerance of the risks associated with novel practices yet to be sanctioned by the environment (Phillips and Zuckerman, 2001). During the past few decades, venture creation was a controversial behavior for most academicians (Bok, 2003). Under such circumstances, one might expect that scientists who engage in entrepreneurial activities occupy either the high or the low end of the status spectrum in academia, both in terms of their academic reputation and prestige of their employers. This perspective, again, suggests an image of academic entrepreneurs that is different from that of academic advisors along dimensions including experience, human capital, prestige and affiliation.

To summarize, several theories predict that academic advisors and founders should differ in their profiles even though they share some commonalities. While advisors are more likely to come out of senior, established scientists, there are reasons for expecting founders to emerge from both the senior, established scientists and the younger, less established ones. Academic entrepreneurs are expected to be more tolerant of risks and uncertainties than those who engage only in advising companies. While advisors' roles are to offer expertise, prestige and academic networks to the firms they serve, founders are eager to exploit opportunities to turn their technologies into practice. Indeed, to what extent do these two types of scientists differ from each other is an empirical question to be answered by the data.

III. Data, Estimator and Variables

Data and Sample Characteristics

We assembled a data archive with career histories of approximately 6,100 life scientists to empirically examine the determinants, timing and rate of SAB versus founding activities. Because these commercial activities are rare in the population of university scientists, we employed a sampling procedure known as the "case cohort" design. This method was developed by biostatisticians and is often used to analyze events that are rare in general populations (Prentice, 1986; Prentice & Self, 1988).

To construct our dataset, we first collected information about *all* Ph.D. scientific advisors and founders at *every* biotechnology firm that has filed an initial public offering (IPO) prospectus (form S1, SB2, or S-18) with the U.S. Securities and Exchange Commission.[2] 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. From these companies, we identified 821 unique members of scientific advisory boards with Ph.D.s (which constitute our advising event set) and 174 founders with Ph.D.s (which constitute our founding event set).[3]

---

[2] 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.

[3] A disadvantage of this design is that we missed the university researchers to have advised and founded firms that have never initiated an IPO procedure. Systematic data about university scientists involved in founding and advising private biotech companies over the past three decades are very difficult to collect. Hence, the advising and founding activities we analyzed in this paper are limited to relatively more successful biotech companies.

We then drew a stratified, random sample of 13,564 doctoral degree holders listed in the UMI Proquest Digital Dissertation database, matching the disciplinary composition and Ph.D. year distribution with our event set (e.g., 15 percent of biotechnology firm advisors are biochemistry Ph.D.s earned in 1975, so the random sample contains 15 percent biochemistry Ph.D.s earned in 1975). Thus, the randomly drawn sub-cohort of scientists resembles the event set scientists in the distribution of subject fields and degree years. The majority of scientists in our sample are in the life sciences and Table 1 reports the top 15 subjects in the sample. The members of this sample are then prospectively followed from the time they earned a Ph.D. degree. We created publication histories for all scientists in our database and used the affiliations listed on papers to identify each scientist's employer and, assuming frequent enough publications, to track job changes. The final matched sample contains 5,143 scientists in the randomly drawn sub-cohort, augmented by the 995 event cases (i.e., founders and SAB members).

--- INSERT TABLE 1 ABOUT HERE ---

The Estimator

We modeled the hazard rate of scientists' advising or founding biotech startups with an adjusted Cox model that employs a pseudo-likelihood estimator (Barlow 1994) to account for over-representation of the event observations. Each scientist is considered at risk of engaging in commercial science at the later of: (i) the time that he or she is issued a Ph.D. degree, or (ii) the year 1961, when the first ever biotechnology company was established. Letting $Z_i(t)$ be a vector of covariates for individual i at time t, the individual i's hazard can be written:

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

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 $Y_k(t)$ indicates whether person k is at risk at t and $Y_i(t)$ indicates whether person i has experienced an event at t. Equation (3), however, produces biased estimates if applied to case-cohort data. This occurs because including all events in a population and a randomly drawn sub-cohort of (mostly) censored cases causes the proportion of events in the dataset to over-represent the proportion of events in the actual population. This in turn results in an incorrect computation of the event cases' contribution to the Cox score function.

To address this problem, biostatisticians have proposed a pseudo-likelihood estimator. Letting S denote membership in the sub-cohort, the pseudo-likelihood can be written:

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

where the $w_i(t)$ and $w_k(t)$ in the denominator are weights assigned to each observation in the risk set, and all other terms are as defined above. The numerator of the pseudo-likelihood (eq. 4) is equivalent to that of the partial likelihood (eq. 3). The first term in the denominator of equation (4) represents the contribution of the event cases to the likelihood and the second term represents the contribution of the randomly drawn sub-cohort members in the risk set. We use a modification of the weighting scheme proposed by Barlow (1994). In it, the event case weight $w_i(t)$ is always "1," and the weights on the members of the sub-cohort, $w_k(t)$, are $1 / p_k$, where p_k is the probability that member k of the matched sample is drawn from the relevant population *and* remains in our data set. Our goal is that with the application of different weights, the contribution of the event and matched sample observations will be more in line with the (true) underlying population.[4]

Variables

We analyzed two commercial activities by university scientists: (i) founding one or more for-profit companies, and (ii) joining companies' scientific advisory boards. We identified advising and founding information from biotech firms' IPO prospectus documents. Most firms report their founders in their IPO prospectuses. Even though this

[4] The Pseudo-likelihood estimator for Cox model is similar to the weighted exogenous maximum likelihood sampling (WESML) estimator proposed by Manski and Lerman (1977). In the empirical example, Manski and Lehman used a logistic model that incorporate weights to adjust for the over-sampling of events.

is not legally required, research-intensive firms such as biotechs often opt to report them to increase their legitimacy, particularly when university-affiliated scientists are involved in the founding process. For companies that do not report founder information in the prospectuses, we conducted a thorough web search to fill in the missing information. We used the date of firm incorporation as the year in which a scientist founded the firm. Hence, for an entrepreneurial scientist, the incorporation year of the first firm he or she founded is the year of his or her first-time transition to entrepreneurship.

In comparison, there is more information about company SAB members, if the company has an SAB. However, for SAB members, the difficulty is that most prospectuses do not provide information on when a scientist joined the SAB. We assume that an SAB member joins at the time of firm founding, thus when a scientist joins his or her first SAB, we coded him or her as experiencing the first SAB event when the firm he or she joined was founded.

We constructed several measures of individual level variables that may affect commercial activities. We coded gender based on scientists' first names. From the *Web of Science* we retrieved annual research publication count (publication flow) for each scientist. We counted all papers on which a scientist is listed as an author. We also computed each scientist's cumulative research publication count (publication stock) and updated the measure annually. To measure a scientist's standing in academia, we computed the total citation count a scientist has received. The Web of Science database supplies the total citation count for each published article at the time we downloaded these data (i.e., 2002). Thus, we know the total number of citations garnered by all articles in our database between the date of publication and calendar year 2002. However, to compute annually updated citation counts we need to know the total number of citations each article has received up to any given year. We therefore must distribute each paper's total citations backward through time. We did so by assuming that the arrival of citations follows an exponential distribution with hazard rate (i.e., inverse mean) equal to 0.1. The bibliometric literature suggests that citations accumulate according to an exponential distribution (Redner 1998). We assume that this distribution is true of the typical paper in our database.

We included several measures for the commercial orientation of scientists' research. First, using the informative keywords reflected in the titles of scientists' research papers, we computed a patentability score to proxy the extent of commercial appeal of a scientist's research. The details of this measure are described in Appendix 1. Second, since collaboration with company scientists often indicate projects to solve industrial problems, we counted the total number of company scientists with whom a scientist has coauthored by a given year, and again updated this variable every year. Third, we gathered scientists' patents from NBER patent database and computed yearly updated patent application flow and stock. High research patentability score, high number of industrial collaborators, and more patent applications are associated with stronger commercial orientation of a scientist's research.

We also included two measure of a scientist's network structure. First, as a general measure of a scientist's academic network, we computed the total number of coauthors he has accumulated in his research publications. Having more coauthors indicates an extensive social network in academia. Second, we counted and annually updated the number of scientist-turned-entrepreneurs (i.e., university scientists in our sample who have already become founders) with whom a scientist has co-authored publications.

At the institutional level, we included three measures of a scientist's employing university. First, we enter a dichotomous measure of the ranking of a scientists' employer, which is a dummy variable indicating whether or not a scientists' employer was ranked in the Top 20. Specifically, we collected the Gourman Report rankings for all institutions in our dataset. Gourman rankings are available at the field level and were issued for the first time in 1980. We assigned universities the 1980 ranking for all years prior to 1980 (and updated them every other year for the subsequent period). Second, we used the AUTM surveys (AUTM, 2003) to create a technology transfer office (TTO) dummy variable, which is set to one in all years when a scientist's employing university has an active TTO. Finally, we counted the number of patent applications filed by a scientist's employer university and used the employer patent count as a more nuanced measure of how effective the university's TTO is in facilitating the transfer of academic science to the commercial sector.

To control for period-specific effects, we created a series of dummies of 3-calender-year windows. These dummies and the Ph.D. subject field dummies are included in all models.

IV. Results

We conduct the following comparison of scientists' advising and founding activities. First, we draw unconditional hazard graphs that reveal the timing of scientists' first-time engagement in advising or founding activity. Second, we run Cox proportional hazard models that estimate the effects of individual, peer and institutional factors on the likelihood that a scientist engages in one of the activities. Table 2 reports descriptive statistics.

--- INSERT TABLE 2 & FIGURE 1 ABOUT HERE ---

Unconditional Hazard Profiles

When do scientists start engaging in advising and founding activities? Figure 1 summarizes unconditional hazard of the first time commercial engagement, broken out by activity type. In the founding graph of the top row, we present the risk that a scientist founds a company at different stages of his professional life cycle. The graph for advising activity in the first row presents the risk that a scientist becomes a SAB member at different stages of his professional life cycle. Kernel smoothing method is used in drawing the unconditional hazard graphs.

The graphs suggest that the two activities take place at different points in a scientist's career cycle. As we have expected, advising tends to happen at a later professional age, as the role of a scientific advisor requires that the scientist has established his human capital and reputation in the academic community and has accumulated significant academic networks. In comparison, those who found companies to commercialize their discoveries are relatively younger—the hazard of founding a company peaks at around 12 years after the Ph.D. is granted while the hazard of joining a SAB peaks at a much later point, about 31 years after the Ph.D grant. In addition, the propensity to advise companies climbs up gradually as a scientist gets more experienced. For founding activity, however, the propensity increases relatively more precipitately during a scientist's career, but decreases gradually once it has peaked.

The next few sub-graphs in Figure 1 break down the comparison by cohort, gender and employer prestige. First, we ask whether the career cycle effect on SAB and founding activities is stable over time. Past research has suggested vintage effects on scientists' research productivity (Levin and Stephan, 1991; Levin and Stephan, 1992) and commercial orientations (Ding, Murray and Stuart, 2006). We examined the hazard curves separately for two different Ph.D. cohorts—those who obtained their Ph.D. in or before 1973 and those with a Ph.D. between 1974 and 1984.[5] The hazard of both founding and advising companies for the younger cohort increases faster than the older cohort of scientists, and they peak at an earlier professional age. The hazard of founding activity of the younger cohort peaks around 10 years after the Ph.D. is granted, much earlier than the 16th year point of peak hazard for the older cohorts. A similar trend is found for the hazard of advising companies. It seems that the younger cohorts are more open to commercial opportunities overall. However, founding events tend to take place at an earlier career stage than advising, which is consistent with the earlier finding.

[5] The year 1973 is chosen as a cutoff because it is the median value of the Ph.D. year variable. In drawing these graphs, we excluded scientists with a Ph.D. degree after 1984 because the window of observation might not be long enough to draw the hazard graph properly.

The two graphs in the third row of Figure 1 break down the hazard rate of the two events by gender. Consistent with prior research (Ding, Murray and Stuart, 2007; Murray and Graham, 2007), women are much less likely to either found or advise companies. For both activities, the hazard rate of women scientists never passes those of men. The general pattern in the overall sample—that founding tends to happen earlier than advising, remains valid for both men and women scientists. However, it is worth noting that the hazard of women's advising activity peaks much earlier than men's (for women, the hazard of advising peaks around 20th year after the Ph.D. is granted, which predates the 33-year-or-so wait time for male scientists to reach peak hazard). This could have to do with the demographics of women advisors. Ding et al. (2006) found that female scientists who venture into the commercial arena (e.g., patenting research discoveries) are more likely to come from the younger cohort, who seems to be less hesitant at commercial engagement at an earlier career stage.

The last row in Figure 1 compares the hazard of founding and advising across scientists employed by universities with different prestige. For a scientist working at a university ranked below top 20, the hazard of founding companies arrives at its peak around the 13th year after the Ph.D. is granted, much earlier than that of advising companies, which peaks close to the end of a scientist's career. However, for a scientist who works at a top-20 university, though the actual shape of the hazard curves differ by activity type, the peaks of both hazards arrive at a similar career stage—between the 25th and 30th year after the Ph.D. grant. It is also interesting to note that though overall hazards of founding and advising are lower for lower ranked university scientists, the shape of the hazard curves for these scientists are quite different from the curves of their counterparts employed in higher ranked universities. For founding events, scientists working at lower ranked universities are at their highest risk much earlier than those working in top ranked schools. In contrast, for advising events, scientists working at lower ranked universities are at their highest risk somewhat later than their counterparts in top schools. Two reasons might explain this observation. One, lower ranking university scientists have less vested interests. They stand to lose less in transitioning towards entrepreneurship, hence might have more incentives to make the transition early on in their career. Two, advisors are invited based on their deep expertise, academic reputation and extensive social networks. Higher ranking university scientists have more opportunities to obtain these credentials and meet the requirements for an advisor faster than scientists working for less well-known employers.

To summarize, in comparing unconditional hazard curves, we find that founding activities tend to take place at an earlier stage of a scientist's professional life cycle than advising. Moreover, the sub-graphs in the last row also hint to us that founders and advisors are likely to command different levels of human or social capital.

Antecedents of Founding and Advising Companies

In this section, we assess the impact of factors that can potentially influence scientists' propensity to advise or found a biotech company. Table 3 reports Cox proportional hazard models of founding and advising companies, with weights included to adjust for case cohort sampling design. Models 1a and 2a use the full sample as the risk pool. Models 1b and 2b replicate the results in 1a and 2a with a restricted sample—all advising scientists (i.e., those who advised one or more companies in their life time, regardless of the timing of their first advising activity) have been excluded in the estimation of model 1b and all founding scientists (i.e., those who founded one or more companies in their life time, regardless of the timing of their first founding activity) have been excluded from the risk pool of model 2b. These models are estimated to ensure that different specifications of the risk set do not lead to significant difference in the results. Because the set of results of models 1a and 2a do not differ substantially from those of models 1b and 2b, we focus on comparing the results of 1a and 2a in the following section.

--- INSERT TABLE 3 & FIGURE 2 ABOUT HERE ---

Our first observation is that the directions of the effects of most of the included variables do not differ between founding and advising activities. Figure 2 presents the standardized coefficients of models 1a and 2a in Table 3. Except for the effects of publication stock and number of coauthors, most factors either increase the probability of both founding and advising activities or decrease these probabilities.

However, when examining the strength of effects of these factors, we find that several of them show notable differences. Among the factors that significantly shape the propensity of founding or advising activity, the impact of gender is one of the strongest. The chance of a female scientist to become a founder is only 22% than that of a male scientist while the propensity of a female scientist to become a company advisor is only 37% than that of her male colleagues. Though in both areas female lag behind male scientists, the gender gap for advising, a less deviant and risky activity for university scientists, is about one third narrower than the gender gap in founding.

Next, research productivity affects advising and founding differently. Contemporaneous research productivity (publication flow) has a weakly significant and positive effect on founding but no significant effect on advising. The magnitude of the effect of publication flow is also much higher in the founding model than in the advising model. This suggests that contemporaneous productivity is more important for founders than for advisors. In contrast, long-term research productivity reflected in publication stock has significant effect on advising and no effect on founding. This might be due to the fact that scientists found companies to capture the scientific opportunities in their recent surge of scientific discoveries. Hence, when a scientist has a good run of research and made some potentially commercially valuable discoveries, he is more likely to capitalize on the scientific breakthrough and make the transition into entrepreneurship. In comparison, advisors are sought after for their deep expertise and academic reputation. Hence, when a scientist enjoys high level of research publication stock, it makes him a more attractive candidate for the role of a scientific advisor. Total citation count seems to affect equally founding and advising.

How does scientists' research orientation affect founding and advising? Among the variables, research patentability score increase both founding and advising propensities. One standard deviation increase in research patentability score raises the probability of founding by 26 percent and the probability of advising by 29 percent. The other factor that significantly affects both founding and advising is scientists' patent flow. This factor increases the propensity of founding by 8.2 percent and the propensity of advising by 6.5 percent. The number of industry coauthors and patent stock do not affect the two commercial activities significantly. Hence, overall scientists' research orientation has similar effect on founding and advising.

A scientist's social network is important in explaining academic scientists' commercial engagement (Shane and Cable, 2002; Stuart and Ding, 2006). In our models, two variables have been included. Among them, the effect of the number of academic coauthors (measuring the overall extensiveness of a scientist's academic network) differs substantially between founding and advising. While the variable has no effect on founding, a good academic network helps increase the propensity to become an advisor significantly (one standard deviation increase in the number of academic coauthors raises the hazard of advising by 9 percent). However, the effect of the more instrumental type of network—ties to coauthors who have already transitioned to entrepreneurship—shows a different pattern for the two activities. One standard deviation increase in the variable "number of academic entrepreneurs (AE) coauthors" raises the hazard of founding by 19 percent while one standard deviation increase in this variable raises the hazard of advising by only 14 percent, slightly lower than that for founding. This confirms our expectation that scientific advisors and academic entrepreneurs need to bring different types of human and social capital into their new roles. One key value of advisors is to help a firm with their extensive academic networks in evaluating scientific projects and hiring key employees. Hence, maintaining an extensive academic network is crucial for advisors. Founders, on the other hand, benefit more from task-specific social network ties. Knowing other university-scientist-turned entrepreneurs provides access to information on how to navigate through patent process, negotiate with the TTO office, negotiate contracts with potential business partners, or how to manage a new venture. Thus, having entrepreneurial coauthors may reduce the hurdles in the process of the entrepreneurial transition and significantly increases the propensity of founding a firm.

Finally, the institutional environment may affect how scientists perceive commercial activities (Krimsky, 2003; Kenny and Goe, 2004). In our models, all institutional variables appear to affect the propensity of founding and advising. The effect of employer patent count is the same on founding and advising. However, employer ranking and institutional support for commercial activity show different impact on founding and advising. Being employed by the top 20 universities helps increase the propensity of founding by 57 percent and advising by 105 percent. The effect of a prestigious employer on advising is about twice that on founding. Consistent with previous research (Colyvas, 2007), being employed by universities with a technology office raises the probability of founding by 68 percent and the probability of advising by 36 percent. Thus founding activity seems to benefit from university institutional support while the advising activity seems to benefit more from university prestige.

To summarize, we find that antecedents of scientists' commercial activities differ by the activity type. First, women scientists are less likely than men to become either founders or advisors, but the negative effect of gender is stronger for founding than advising. Second, research productivity affects the two activities differently. While the surge in contemporaneous research productivity is associated higher risk of founding firms, high level of long-term research productivity is associated with higher risk of advising firms. Third, founding and advising are also affected by a scientist's social network. Having network ties with other scientists who have already become entrepreneurs increases the propensity of founding more than advising, but it is the general academic network that helps scientific advisors most. Lastly, institutional support at a scientist's employing university (e.g., having a technology transfer office) raises his propensity of founding a firm about twice as much as that of advising a firm while the university employer's prestige increases a scientist's advising risk twice as much as it does to the founding risk.

Are Advisors More Likely to Found Companies?

In this section, we explore whether advisors are more likely to become founders, or whether scientists focus on one activity and ignore the other. Among all scientists in the sample who have founded or advised companies, 71 (7%) of them have engaged in both founded and advised companies. It is likely that becoming an advisor triggers scientist's interests in becoming an entrepreneur. Or it is likely that scientists tend to use an advisory opportunity as a way to learn how to start up his or her own company.

--- INSERT TABLE 4 ABOUT HERE ---

Table 4 reports results from the adjusted Cox model of hazard of founding a firm. The first model in this table uses the full sample and the same set of variables as in Table 3. The new variable included in this model is a "SAB dummy", which indicates whether a scientist has been a scientific advisor at any point during his career. The result of model 1 in this table suggests that those scientists who have or will become advisors are less likely to become company founders. Being an advisor lowers the risk of founding a company by half.

Model 2 uses a different indicator of a scientist's advising activity. We included a "SAB regime dummy" which is coded 1 in years after a scientist has advised a company. This is to test whether the actual advising experience increases the likelihood of founding a firm. Because the randomly selected university scientists can dilute the risk pool, we used a restricted sample of all scientists who have experienced either a founding or advising activity in this model. The result of model 2 suggests that once a scientist has advised a company and entered the advisory regime, his probability to become a founder is reduced by half when compared to other commercially oriented scientists.

In both models, being a SAB or the experience of SAB appear to have a negative effect on a scientist's propensity to found a company. Together, the results suggest that the founding and advising are two separate paths and those scientists who are likely to advise companies are no more likely to found companies than the group of scientists who have never been an advisor.

IV. Conclusion

We investigated the question whether university scientists who have become company scientific advisors differ in profile from those who have become company founders. We constructed a case cohort sample that consists of (i) all Ph.D.-trained university scientists who have been reported in biotech firms' IPO documents as either founders or scientific advisory board members, and (ii) a stratified random sample of scientists who are university faculty members, from corresponding Ph.D. years and fields. We follow the career development, research productivity and commercial activity of the combined sample of approximately 6100 scientists. We analyze the timing and determinants of advising and founding activities of these scientists.

Our results find differences in the effects of scientists' career cycle and various determinants of founding and advising activities. First, examining the timing of founding and advising activities during scientists' career cycle reflected in unconditional hazard graphs, we found that the probability of founding rises relatively faster than that of advising and peaks much earlier in one's career cycle. Next, Cox regression analysis suggests that human capital, social capital and institutional characteristics affect founding and advising differently. The gender gap is more significant for founding than for advising. Contemporaneous research productivity boosts founding while long-term research productivity boosts advising. Different types of social networks and institutional support also contribute differently to advising and founding activities. Lastly, regressions that assess the effect of scientists' advising experience show that being an advisor negatively influences the propensity to become a founder. Together, these results lend more support to the view that founding and advising represents divergent paths for commercially-oriented scientist, rather than the view that one is a stepping stone for another.

References

Agrawal, A. K. and R. M. Henderson. 2002. "Putting Patents in Context: Exploring Knowledge Transfer from MIT." *Management Science*, 48:1, pp. 44-60.

Audretsch, D. B. 2000. "New perspectives on economic growth and technological innovation." *Journal of Economic Literature*, 38:4, pp. 981-82.

AUTM ed. 2003. *A Survey Summary of Technology Licensing (and Related) Performance for US and Canadian Academic and Nonprofit Institutions, and Technology Investment Firms*.

Azoulay, P., W. Ding, and T. Stuart. 2007. "The determinants of faculty patenting behavior: Demographics or opportunities?" Journal of Economic Behavior & Organization, 63:4, pp. 599-623.

Azoulay, P., W. Ding, and T. Stuart. 2008. "The Impact of Academic Patenting on the Rate, Quality and Direction of (Public) Research Output." forthcoming*, Journal of Industrial Economics*.

Azoulay, P., R. Michigan, and B. N. Sampat. 2007. "The anatomy of medical school patenting." *New England Journal of Medicine*, 357:20, pp. 2049-56.

Balconi, M., S. Breschi, and F. Lissoni. 2004. "Networks of inventors and the role of academia: an exploration of Italian patent data." *Research Policy*, 33:1, pp. 127-45.

Barlow, W. E. 1994. Robust Variance Estimation for the Case Cohort Design. *Biometrics*, 50: 1064-1072.

Bercovitz, J. and M. Feldman. 2008. "Academic entrepreneurs: Organizational change at the individual level." *Organization Science*, 19:1, pp. 69-89.

Blumenthal, D., N. Causino, E.G. Campbell, and K. S. Louis. 1996. "Relationships between Academic Institutions and Industry in the Life Sciences - An Industry Survey." *New England Journal of Medicine*, 334:6, pp. 368-73.

Blumenthal, D., M. Gluck, K. S. Louis, and D. Wise. 1986. "Industrial Support of University Research in Biotechnology." *Science*, 231:4735, pp. 242-46.

Bok, D. 2003. *Universities in the Marketplace: The Commercialization of Higher Education*. Princeton, NJ: Princeton University Press.

Colyvas, Jeannette A. 2007. "From divergent meanings to common practices: The early institutionalization of technology transfer in the life sciences at Stanford University." Research Policy 36(4): 456-476.

Ding, W. W., F. Murray, and T. E. Stuart. 2006. "Gender differences in patenting in the academic life sciences." *Science*, 313:5787, pp. 665-67.

Ding, W. W., F. Murray, and T. E. Stuart. 2007. "Commercial Science: A New Arena for Gender Differences in Scientific Careers." Working paper.

Etzkowitz, H. 1983. "Entrepreneurial Scientists and Entrepreneurial Universities in American Academic Science." *Minerva*, 21:2-3, pp. 198-233.

Fabrizio, K. R. and A. DiMinin. 2004. "Commercializing the Laboratory: The Relationship Between Faculty Patenting and Publishing." *Working Paper*.

Franzoni C., Lissoni F. 2007. "Academic entrepreneurs: critical issues and lessons for Europe", in: Varga A. (ed.), /Universities and regional economic development/, Edward Elgar, Cheltenham (forthcoming)

George, Gerard, Sanjay Jain, and Mark A. Maltarich. 2005. "Academics or Entrepreneurs? Entrepreneurial Identity and Invention Disclosure Behavior of University Scientists " Working Paper.

Henderson, R. M., A. B. Jaffe, and M. Trajtenberg. 1998. "Universities as a source of commercial technology: A detailed analysis of university patenting, 1965-1988." *Rev. Econ. Stat.*, 80:1, pp. 119-27.

Higgins, M. C. and R. Gulati. 2003. "Getting off to a good start: The effects of upper echelon affiliations on underwriter prestige." *Organization Science*, 14:3, pp. 244-63.

Ibarra, H. 1999. "Provisional selves: Experimenting with image and identity in professional adaptation." *Administrative Science Quarterly*, 44:4, pp. 764-91.

Jensen, R., J. G. Thursby, and M. C. Thursby. 2006. "In or Out: Faculty research and Consulting." *paper presented at the 2006 Annual REER conference*: Atlanta.

Jensen, R. A., J. G. Thursby, and M. C. Thursby. 2003. "Disclosure and licensing of University inventions: 'The best we can do with the s**t we get to work with'." *International Journal of Industrial Organization*, 21:9, pp. 1271-300.

Kenney, M. and W. R. Goe. 2004. "The role of social embeddedness in professorial entrepreneurship: a comparison of electrical engineering and computer science at UC Berkeley and Stanford." *Research Policy*, 33:5, pp. 691-707.

Klofsten, M. and D. Jones-Evans. 2000. "Comparing academic entrepreneurship in Europe - The case of Sweden and Ireland." *Small Bus. Econ. Group*, 14:4, pp. 299-309.

Krimsky, S. 2003. *Science in the Private Interest: Has the Lure of Profits Corrupted Biomedical Research*. Lanham, MD: Rowman & Littlefield.

Lam, Alice. 2007. "Knowledge Networks and Careers: Academic Scientists in Industry-University Links." Journal of Management Studies 44:993-1016.

Levin, S. G. and P. E. Stephan. 1991. "Research Productivity over the Life-Cycle - Evidence for Academic Scientists." *American Economic Review*, 81:1, pp. 114-32.

Levin, S. G. and P. E. Stephan. 1992. *Striking the Mother Lode in Science: The Importance of Age, Place and Time*. New York: Oxford University Press.

Louis, K.S., D. Blumenthal, M.E. Gluck, M.A. Stoto. 1989. "Entrepreneurs in Academe-An Exploration of Behaviors among Life Scientists." *Administrative Science Quarterly* 34(1): 110-131.

Manski, C.F. and S.R. Lerman. 1977. "Estimation of Choice Probabilities from Choice-based Samples." *Econometrica* 45(8): 1977-1988.

Murray, F. 2004. "The role of academic inventors in entrepreneurial firms: sharing the laboratory life." *Research Policy*, 33:4, pp. 643-59.

Murray, F. and L. Graham. 2007. "Buying science and selling science: gender differences in the market for commercial science." *Industrial and Corporate Change*, 16:4, pp. 657-89.

Owen-Smith, J. and W. W. Powell. 2001a. "Careers and Contradictions: Faculty Responses to the Transformation of Knowledge and its Uses in the Life sciences." *Research in the Sociology of Work*, 10, pp. 109-40.

Owen-Smith, J. and W. W. Powell. 2001b. "To Patent or Not: Faculty Decisions and Institutional Success at Technology Transfer." *Journal of Technology Transfer*, 26:1-2, pp. 99-114.

Phillips, D. J. and E.W. Zuckerman. 2001. "Middle-status conformity: Theoretical restatement and empirical demonstration in two markets." *American Journal of Sociology*, 107:2, pp. 379-429.

Prentice, R. L. 1986. "A case-cohort design for epidemiologic cohort studies and disease prevention trials." *Biometrika*, 73:1, pp. 1-11.

Prentice, R. L. and S. G. Self. 1988. "Asymptotic Distribution Theory and Efficiency Results for case cohort studies." *The Annals of Statistics*, 16:1, pp. 64-81.

Redner, S. 1998. "How Popular is Your Paper? An Empirical Study of the Citation Distribution." *The European Physical Journal B*, 4, pp. 131-34.

Schere, J. 1982. "Tolerance of Ambiguity s a Discriminating Variable between Entrepreneurs and Managers." *Academy of Management Proceedings*: 404-08.

Sexton, D. L. and N. Bowman. 1985. "The Entrepreneur: A Capable Executive and More." *Journal of Business Venturing*, 1:1, pp. 129-40.

Shane, S. 2004. *Academic Entrepreneurship: University Spin-offs and Wealth Creation*: Edward Elgar Publishing, Northampton.

Shane, S. and D. Cable. 2002. "Network ties, reputation, and the financing of new ventures." *Management Science*, 48:3, pp. 364-81.

Shane, S. and R. Khurana. 2003. "Bringing individuals back in: the effects of career experience on new firm founding." *Industrial and Corporate Change*, 12:3, pp. 519-43.

Stephan, P. E., S. Gurmu, A.J. Sumell, and G. Black. 2004. "Who's Patenting in the University? Evidence from the Survey of Doctorate Recipients." *Working Paper*.

Stephan, P. E. and S. G. Levin. 1996. "Property rights and entrepreneurship in science." *Small Bus. Econ. Group*, 8:3, pp. 177-88.

Stuart, T. E. and W. W. Ding. 2006. "When do scientists become entrepreneurs? The social structural antecedents of commercial activity in the academic life sciences." *American Journal of Sociology*, 112:1, pp. 97-144.

Stuart, T. E., H. Hoang, and R. C. Hybels. 1999. "Interorganizational endorsements and the performance of entrepreneurial ventures." *Adm. Sci. Q.* (Adm. Sci. Q.), 44:2, pp. 315-49.

Stuart, T. E., S. Z. Ozdemir, and W. W. Ding. 2007. "Vertical alliance networks: The case of university-biotechnology-pharmaceutical alliance chains." *Research Policy*, 36:4, pp. 477-98.

Thursby, J. G. and M. C. Thursby. 2002. "Who is selling the Ivory Tower? Sources of growth in university licensing." *Management Science*, 48:1, pp. 90-104.

Thursby, J. G. and M. C. Thursby. 2004. "Are faculty critical? Their role in university-industry licensing." *Contemporary Economic Policy*, 22:2, pp. 162-78.

Table 1
Top 15 Scientific Disciplines Spawning Biotechnology Company Scientific Advisors

UMI Subject Code	UMI Subject Description	Match Sample Frequency	
487; 303	Biochemistry	1,161	(22.5%)
306	Biology, General	608	(11.8%)
410	Biology, Microbiology	503	(9.7%)
369	Biology, Genetics	301	(5.8%)
419	Health Sciences, Pharmacology	298	(5.8%)
490	Chemistry, Organic	288	(5.6%)
433	Biology, Animal Physiology	253	(4.9%)
786	Biophysics, General	234	(4.5%)
301	Bacteriology	192	(3.7%)
982	Health Sciences, Immunology	181	(3.5%)
307	Biology, Molecular	114	(2.2%)
485	Chemistry, General	98	(1.9%)
472	Biology, Zoology	74	(1.4%)
494	Chemistry, Physical	71	(1.4%)
571	Health Sciences, Pathology	71	(1.4%)

Legend:This table reports the 15 disciplines that produced the most biotechnology company SAB members. This table also reports the number of scientists (and proportions of the overall total) in our random sample. The proportions are set to match the disciplinary composition of the SAB members

Table 2
Descriptive Statistics

	Mean	Std. Dev.	Min.	Max.	N
Publication flow	2.214	3.595	0	157	121094
Publication stock	28.91	55.45	0	2262	121094
Total citation count	16.01	21.42	0	647.4	121094
Research patentability score	0.048	0.085	0	4.112	121094
Number of industry coauthors	2.025	9.548	0	453	121094
Patent Flow	0.069	0.462	0	36	121094
Patent Stock	0.594	3.404	0	142	121094
Number of coauthors	21.16	36.54	0	1134	121094
Number of AE coauthors	0.222	0.873	0	32	121094
Employer in top 20	0.274	0.446	0	1	121094
Employer has TTO	0.469	0.499	0	1	121094
Employer patent count	81.73	187.2	0	2189	121094
Experience (Career Age)	13.58	9.920	0	45	121094
Female	0.177	0.382	0	1	6138

Table 3 Cox Proportional Hazard Model of Advising and Founding Firms

	(1a) Founding	**(1b)** Founding	**(2a)** Advising	**(2b)** Advising
Female	-1.553	-1.342	-0.981	-0.937
	(0.437)**	(0.382)**	(0.185)**	(0.185)**
Publication flow $_{t-1}$	0.061	0.062	0.009	0.006
	(0.036)†	(0.043)	(0.016)	(0.016)
Publication stock $_{t-2}$	-0.002	0.001	0.006	0.006
	(0.004)	(0.003)	(0.001)**	(0.001)**
Total citation count $_{t-1}$	0.012	0.013	0.013	0.013
	(0.001)**	(0.002)**	(0.002)**	(0.002)**
Research patentability score $_{t-1}$	2.820	3.573	3.927	3.939
	(0.247)**	(0.643)**	(0.264)**	(0.270)**
Number of industry coauthors$_{t-1}$	0.004	-0.021	-0.024	-0.021
	(0.017)	(0.036)	(0.017)	(0.016)
Patent flow $_{t-1}$	0.192	0.188	0.177	0.185
	(0.041)**	(0.041)**	(0.028)**	(0.028)**
Patent stock $_{t-2}$	0.014	0.016	0.009	0.006
	(0.012)	(0.012)	(0.008)	(0.008)
Number of coauthors $_{t-1}$	-0.0004	-0.001	0.003	0.003
	(0.003)	(0.003)	(0.001)*	(0.001)*
Number of AE coauthors $_{t-1}$	0.205	0.401	0.254	0.260
	(0.064)**	(0.085)**	(0.066)**	(0.067)**
Employer in top 20	0.448	0.346	0.716	0.691
	(0.208)*	(0.211)	(0.116)**	(0.118)**
Employer has TTO	0.520	0.508	0.311	0.284
	(0.212)*	(0.218)*	(0.110)**	(0.111)*
Employer patent count	0.001	0.002	0.001	0.001
	(0.0004)**	(0.0004)**	(0.0003)**	(0.0003)**
Risk pool excluding		Advising scientists		Founding scientists
Number of subjects	6138	5381	6138	5995
Number of events	174	174	821	786
Time at risk	119885	97772	111953	109444

Notes:
(1) All models control for 3-year period dummies and Ph.D. field dummies.
(2) Founding-event-specific Barlow weights are applied to Model 1a and 1b to adjust for over-sampling of founders; advising-event-specific Barlow weights are applied to Model 2a and 2b to adjust for over-sampling of advisors.
(3) Robust standard errors in parentheses;
(4) † significant at 10%; * significant at 5%; ** significant at 1%

Table 4
Cox Proportional Hazard Model of Founding Firms

	(1)	(2)
female	-1.430	-1.342
	$(0.391)^{**}$	$(0.644)^{**}$
Publication flow $_{t-1}$	0.047	0.034
	(0.032)	(0.039)
Publication Stock $_{t-2}$	-0.001	-0.007
	(0.003)	$(0.004)^{\dagger}$
Total citation count $_{t-1}$	0.011	0.001
	$(0.002)^{**}$	(0.002)
Research patentability score $_{t-1}$	2.148	0.417
	$(0.239)^{**}$	(0.499)
Number of industry coauthors $_{t-1}$	0.007	0.006
	(0.006)	(0.004)
Patent flow $_{t-1}$	0.195	0.187
	$(0.045)^{**}$	$(0.065)^{**}$
Patent stock $_{t-2}$	0.003	0.011
	(0.016)	(0.028)
Number of coauthors $_{t-1}$	0.0005	-0.001
	(0.002)	(0.003)
Number of AE coauthors $_{t-1}$	0.088	0.003
	(0.058)	(0.085)
Employer in top 20	0.402	-0.286
	$(0.198)^{*}$	(0.271)
Employer has TTO	0.571	0.153
	$(0.203)^{**}$	(0.244)
Employer patent count	0.001	0.001
	$(0.0004)^{**}$	$(0.0004)^{\dagger}$
SAB dummy	-0.687	
	$(0.309)^{*}$	
SAB regime dummy		-0.729
		$(0.298)^{*}$
Risk pool	All	Founders and Advisors
Number of subjects	6138	936
Number of events	174	174
Time at risk	119889	24728

Notes:
(1) All models control for 3-year period dummies and Ph.D. field dummies.
(2) Founding-event-specific Barlow weights are applied to all models.
(3) Robust standard errors in parentheses.
(4) † significant at 10%; * significant at 5%; ** significant at 1%.

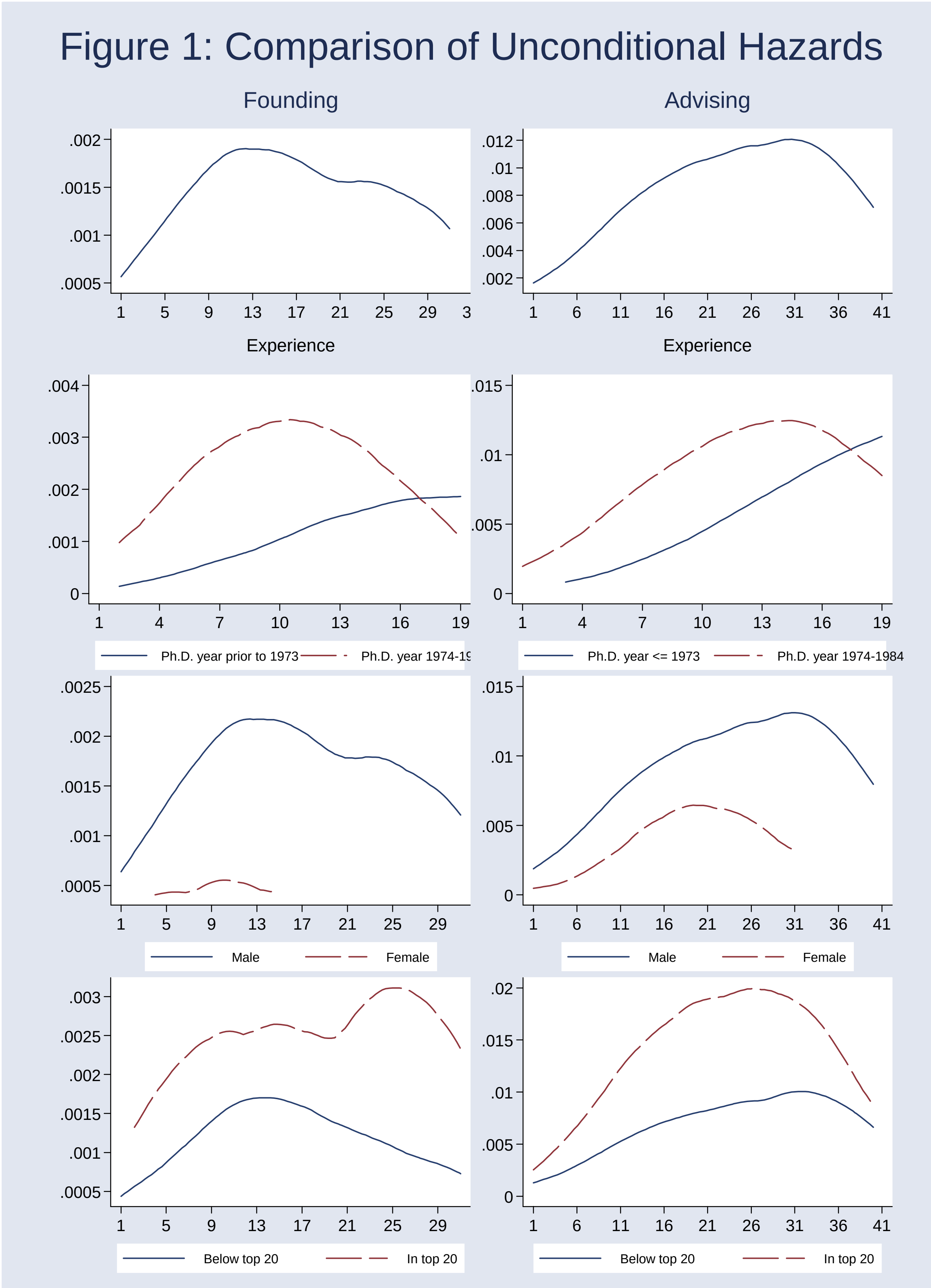
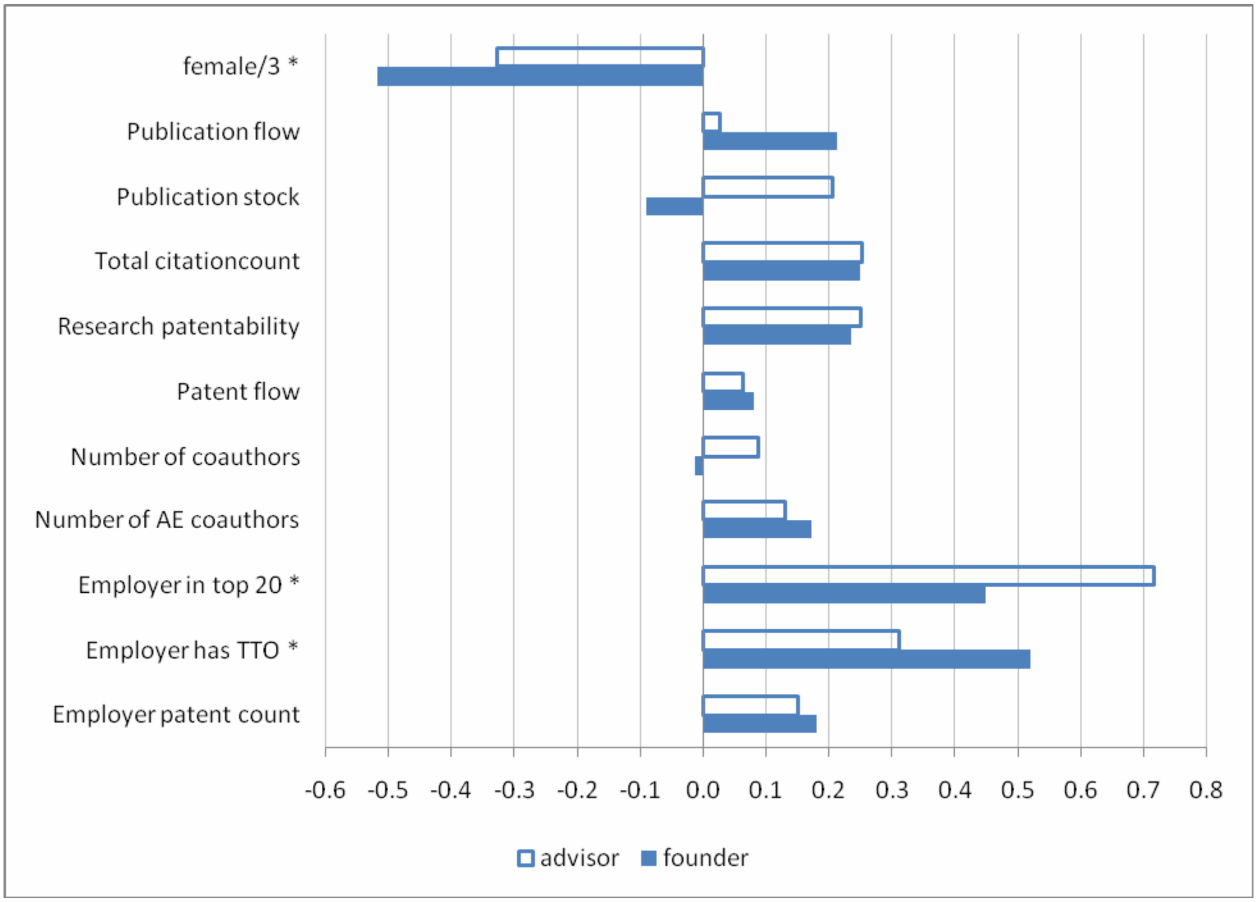


Figure 1: Comparison of Unconditional Hazards
Founding
Advising
Experience
Experience
Ph.D. year prior to 1973
Ph.D. year 1974-19
Ph.D. year <= 1973
Ph.D. year 1974-1984
Male
Female
Male
Female
Below top 20
In top 20
Below top 20
In top 20

Figure 2
Antecedents of Advising and Founding Activities: Comparison of Standardized Coefficients



Legend: Figure 2 compares the standardized coefficients reported in Table 3. The value for each variable is obtained by multiplying the raw coefficient for the variable with its standard deviation. The exceptions are made for the three dummy variables: "female", "employer in top 20", and "employer has TTO". The values for these variables presented in the graph are obtained by multiplying raw coefficients with value 1. The values for the variable "female" are also rescaled (divided by 3) for this presentation purpose.

Appendix 1

We attempt to measure patentability directly by using the title words in scientists' publications. We first identify the areas in which the scientists have conducted research, and then apply weights to thesis (or subject) areas based on an endogenous-to-the-sample measure. This measure is endogenous to the extent that other scientists working in these subject areas have patented their discoveries. Intuitively, we use the publications of scientists that have already applied for patent rights as the benchmark for patentable research, and then compare the research of each scientist in our dataset to this benchmark to generate a research patentability score for each scientist-year. Specifically, the research patentability (RP) score for scientist i in year t is defined as:

$$Patentability_{it} = \sum_{j=1}^{j} w_{j,t-1}^{i} \frac{n_{ijt}}{\sum_k n_{ikt}}$$

where $j = 1, \ldots, J$ indexes each of the scientific keywords appearing in the titles of the journal articles published by scientist i in year t, n_{ijt} is the number of times each of the keywords j has appeared in scientist i's articles published in year t, and w_{jt}^{i} is a weight for each keyword that measures the frequency with which word j is used in the titles of articles published by scientists who have entered the patenting regime in year t or earlier, relative to those who have not entered the patenting regime as of year t (the calculation of w_{jt}^{i} is detailed below). Intuitively, the patentability of a scientist's research can change because of a change in the direction of the research of that scientist, or because other patenters' research increasingly comes to resemble that of the scientist. The former effect is captured by the ratio $\frac{n_{ijt}}{\sum_k n_{ikt}}$; the latter by the weights $w_{j,t-1}^{i}$. Because the benchmark in year $t-1$ is used to weight title words in year t, year-to-year changes in the research patentability score will only reflect actions of the scientist (through their choices of title keywords), rather than contemporaneous changes in the benchmark.

Finally, to capture the idea that the inherent patentability of past research might still influence the current propensity to patent, we compute a depreciated stock of the research patentability score using a perpetual inventory model. Through the impact of the depreciation rate δ, this formulation captures the fact that the recent substantive research orientation of a scientist's work should influence current behavior more strongly than scientific trajectories that unfolded in the more distant past:

$$Stock\_RP_{it} = (1-\delta)Stock\_RP_{i,t-1} + Flow\_RP_{it} = \sum_{\tau=0}^{t}(1-\delta)^{t-\tau} \cdot Flow\_RP_{i\tau}$$

Keyword Weights

w_{jt}^{i} , the patentability weight for each keyword *j* in year *t* is defined as:

$$w_{jt}^{i} = \frac{\sum_{s \in I_t^p - \{i\}} \frac{m_{sjt}}{\sum_k skt}}{\sum_{s \in I_t^{np} - \{i\}} m_{sjt}}$$

where m_{sjt} denotes the number of times keyword *j* has appeared in articles published up to year *t* by scientist *s*, I_t^p is the subset of scientists in our sample that have already applied for one or more patents as of year *t*, and I_t^{np} is the subset of scientists in our sample that have not yet applied for any patent as of year *t*. The weight is also indexed by scientist *i*, because *i*'s publications are taken out of the set of articles used to compute the formula above.

To create the numerator of w_{jt}^{i}, we first create a row-normalized matrix with each scientist in the patenting regime listed in a row and each of the keywords used to describe their papers up to year *t* listed in a column. The $s_j{}^{th}$ cell in the matrix, $\frac{m_{sjt}}{\sum_k skt}$, corresponds to the proportion of title keywords for scientist s that corresponds to keyword *j*. We then take the column sums from this matrix, i.e., we sum the contributions of individual patenting scientists for keyword *j*. Turning next to the denominator, we proceed in a similar manner, except that the articles considered only belong to the set of scientists who have not applied for patents as of year *t*. The numerator is then deflated by the frequency of use for *j* by non-patenters (in the rare case of keywords exclusively used by patenters, we substitute the number 1 for the frequency).

The weights w_{jt}^{i} are large for keywords that have appeared with disproportionate frequency as descriptors of papers written by scientists already in the patenting regime, relative to scientists not yet in the patenting regime.

Two things should be noted about the construction of these weights. First, $w_{jt}^{i} = 0$ for all keywords that have never appeared in the titles of papers written by scientists that have patented before *t*. Second, the articles written by scientist *i* him/herself do not contribute at all to the weights w_{jt}^{i}. Therefore, no scientist can directly influence year-to-year changes in these weights. The final step for each scientist *i* in the dataset is to produce a list of the keywords in the individual's papers published in year *t*, calculate the proportion of the total represented by each keyword *j*, apply the appropriate keyword weight $w_{j,t-1}^{i}$ and sum over keywords to produce a composite score. The resulting variable increases in the degree to which keywords in the titles of a focal scientist's papers have appeared relatively more frequently in the titles of other academics who have applied for patents. This score is to measure the research patentability of scientists' areas of specialization.