The Determinants of Faculty Patenting Behavior: Demographics or Opportunities?

Pierre Azoulay
Columbia University and NBER
Graduate School of Business
3022 Broadway, 704 Uris Hall
New York, NY 10027

Waverly Ding
University of California
Haas School of Business
545 Student Services #1900
Berkeley, CA 94720

Toby Stuart
Columbia University
Graduate School of Business
3022 Broadway, 710 Uris Hall
New York, NY 10027

March 11, 2005

Abstract

We examine the individual, contextual, and institutional determinants of faculty patenting behavior in a panel dataset spanning the careers of 3,884 academic life scientists. Using a combination of discrete time hazard rate models and fixed effects logistic models, we find that that patenting events are preceded by a flurry of publications, even holding constant time-invariant scientific talent and the latent patentability of a scientist's research. Moreover, the magnitude of the effect of this flurry is influenced by context — such as the presence of coauthors who patent and the patent stock of the scientist's university. Whereas previous research emphasized that academic patenters are more accomplished on average than their non-patenting counterparts, our findings suggest that patenting behavior is also a function of scientific opportunities. This finding has important implications for the public policy debate surrounding academic patenting.

Keywords: university patenting, academic science.
JEL Codes: O31, O32, O33.

*Preliminary and incomplete. Send all correspondence to pa2009@columbia.edu. We thank Scott Stern for useful discussions. The usual disclaimer applies.

1 Introduction

In the past few decades, universities and other public-sector research organizations have become more proactive in their efforts to commercialize scientific discoveries (e.g., Jaffe and Lerner, 2001; Jensen and Thursby, 2001; Thursby and Thursby, 2002). This change has spawned a growing academic literature on university technology transfer, one stream of which has assessed trends in university patenting and the spillover of university science into the private sector (Jaffe, 1989; Mansfield, 1995; Henderson et al., 1998). Underlying the well documented upswing in university patenting has been a sharp increase in the number of individual academic scientists who are listed as inventors on patents. In this paper, we examine the individual, contextual, and institutional determinants of academic patenting for a panel dataset of 3,884 academic life scientists.

Past research on this topic has emphasized three inter-related aspects of faculty patenting behavior. First, academic patenters are disproportionately recruited from the ranks of elite scientists and institutions (Zucker and Darby, 1998; Azoulay and Sampat, 2005). Second, there are important differences in the propensity to patent across fields, and in the motivations underlying patenting activity, most notably between the life and physical sciences/engineering (Owen-Smith and Powell, 2001). Finally, institutional context exerts a strong influence on the propensity to patent, either in the form of well-funded technology licensing offices, or through the presence of prominent peers who themselves are engaged in this activity (Di Gregorio and Shane, 2003). Most of this evidence, however, stems from analyses of survey data or from qualitative accounts. While consistent with these previous findings, the results in this paper qualify them in some important respects. Our study also generates a novel set of results, underscoring the benefits of fine-grained longitudinal data at the researcher level of analysis.

The paper's findings include the following. First, we estimate pronounced life-cycle effects on the propensity to patent, with mid-career academics being much more likely to patent than younger and older faculty members. Second, we uncover a very strong gender effect, with female faculty members being 67% less likely to patent than their male counterparts. This result is interesting in light of the accreting evidence that, although women have made significant inroads in gaining faculty positions in the life sciences, female academic scientists are severely under-represented in commercial activity (Ding et al., 2005). Third, we establish a relationship between the latent patentability of a faculty's research and his/her propensity to patent. While latent patentability is often thought to be unobservable, we compute a patentability score for each scientist in our sample by using keywords in the publications of scientists that have already applied for patent rights as a benchmark for patentable research, and then comparing the research of each scientist in our dataset to this benchmark. Although there is noise in this proxy, it nevertheless predicts quite strongly the likelihood of a patenting event.

Fourth, we document that patenting is often accompanied by a flurry of publication activity in the year preceding the patent application, even after accounting for the lagged stock of publications (in hazard rate models) or controlling for scientist fixed effects. This result highlights the fact that academic patenting, rather than merely reflecting the influence of time-invariant demographic factors, also responds to variation in scientific opportunities. Holding life-time scientific achievement constant, we find that surges of scientific productivity, not steady performance, is most likely to be associated with a patent. Moreover, the magnitude of the effect of this flurry decreases with the presence of a patenting coauthor, or with the intensity of patenting activity in the scientist's university. These findings suggest that institutional and contextual factors may partially substitute for scientific opportunities in determining individual rates of patenting.

Lastly, independent of any specific finding, the general analysis herein is relevant to the broader question of the impact of patenting on the development of academic science. Surveys of university faculty have found rampant concern that patenting is skewing research agendas toward commercial priorities, causing delay in the public dissemination of research findings, and crowding out effort devoted to the pursuit of fundamental knowledge (Blumenthal et al., 1996; Campbell et al. 2002; Krimsky, 2003). Insofar as our results relate to this issue, the finding that patenting follows a flurry of publications suggests to us that the crowd-out hypothesis is unlikely to hold true.[1] Although we cannot adjudicate between opposing

[1]However, if scientific trajectories associated with patents exhaust themselves more quickly than those remaining free of associations with the world of commerce, then intertemporal substitution of "basic,"

claims regarding the *effect* of patenting on individual-level or university-level outcomes in the present study, one can construe our results as providing the "first stage" of an econometric analysis of the effect of academic patenting on the rate and direction of scientific progress, an evaluation we are pursuing in other research (Azoulay et al., 2005).

The rest of the paper proceeds as follows. In the next section, we situate our contribution in the large and growing literature on academic patenting, and highlight what we regard as outstanding issues that can only be resolved with researcher-level longitudinal data of the kind we analyze. Section 3 describes data sources and the construction of the sample, presents descriptive statistics, and discusses our econometric approach. Section 4 reports our results. Section 5 concludes.

2 Who Patents?

In recent times, the region of overlap between the spheres of academic science and commercial markets has experienced significant growth. The expanding interface between these two domains raises myriad questions, ranging from the amount of near-term economic value created by the spillovers of university research, to the emergence of select universities as engines of entrepreneurial activity, to the influence of opportunities to commercialize scientific research on the traditional incentive systems that have governed academic science. Researchers have engaged a variety of these questions, and advancement in our understanding is occurring along many fronts.

Spurred in part by accessible data, many studies have assessed the role of universities as direct sources of commercial innovations, primarily considering the quality and quantity of their innovative outputs. For instance, Henderson et al. (1998) examine the relative importance of university patents, finding that there has been a secular decline in the positive quality gap separating university patents from those assigned to for-profit firms. Mowery et al. (2001) have investigated the consequence of the policy changes brought about by the Bayh-Dole Act. They challenge the conventional wisdom that Bayh Dole has accelerated

fundamental knowledge by "applied," patentable output could still be consistent with the patterns we observe in the data.

universities' production of patents, showing that the legislation was not a primary factor in explaining the uptick in patenting at three prominent universities. At the level of the university, Thursby and Thursby (2002) find that university administrators have become more proactive in pursuing patents and licensing opportunities. Di Gregorio and Shane (2003) explore cross-university differences in the formation of start up companies, discovering that intellectual eminence is a central factor distinguishing the universities that spawn start up companies.

The majority of the archival work that has looked at the commercial outputs of not-for-profit organizations has treated the university as the level of analysis. Because the preponderance of the empirical studies have been performed at the university level (notable exceptions include Murray, 2002; Argawal and Henderson, 2002; and Stephan et al. 2004), less is known about the factors that underlie individual scientists' participation in patenting. In this article, we analyze the probability of patenting in a large, longitudinal sample of university faculty in the biomedical area. Our analysis is guided by an interest in four issues. First, how does the proclivity to patent vary with scientists' experience in the profession? Second, what is the relationship between scientific productivity (measured as papers produced) and patenting? Third, are there significant differences across research areas within scientific disciplines in terms of the apparent "patentability" of the work, and is there any evidence to suggest that scientists may be altering their research to move toward patentable research? Fourth, to what extent is the propensity to patent sensitive to the work context of the individual scientist, particularly the level of commercial orientation of a scientist's university and his or her coauthors?

Treating each of these in turn, we first ask, how does the propensity to patent change over the scientific career? Economists and sociologists alike have a long-standing interest in career dynamics in academic science, in part because incentives in science vary over the professional lifecycle. Two elements of the institutionalized incentive system in science are generally thought to be tenure invariant: the tying of peer recognition to priority in research discovery, and the intrinsic satisfaction garnered from solving vexing problems. However, monetary incentives in science do depend on the career stage, and it is well known that the wage-tenure profile in academic science is not steep (Stephan, 1996). Given the shallow slope of salary increases, Levin and Stephan (1991) suggest that levels of investment in research should vary over the career lifecycle. In particular, senior scientists with tenured appointments may reallocate some of their effort to consulting and other extra-university income generating opportunities. Therefore, if widely held assumptions about changing incentives over the career hold, we should observe that the rate of patenting accelerates in the post-tenure interval.

A countervailing possibility is implied by a growing body of ethnographic research that portrays the increasing acceptance of patenting as a legitimate activity in academic science (Etzkowitz, 1998). If the pendulum has swung to the point that patenting is perceived to contribute to scientists' reputation and influence, we would expect to observe that, viewing successive cohorts of scientists, patenting occurs with increasing frequency in the early career stage. Consistent with this perspective, Owen-Smith and Powell (2001) describe interviews with scientists that have come to view patents as reaffirmations of the originality of their work and as contributing to their scientific visibility. Recent interview-based accounts thus raise the possibility of a significant shift in the norms and reward system in science, with implications for lifecycle effects in patenting.

Next, we seek to identify the relationship between scientists' productivity and the likelihood that they patent. Gradually accreting evidence suggests that the scientists with the most stellar academic credentials are also the most likely to be involved in commercial endeavors. In particular, Zucker et al. (1998) describe the importance of the geographic location of star scientists in the emergence of the biotechnology industry. They argue that the direct participation of leading academic scientists in early stage biotechnology companies was so important that the locations of the stars served as geographical constraints on the development of the industry. Stuart and Ding (2005) directly analyze the probability that academic scientists either found or join scientific advisory boards of biotechnology firms. They find that standard measures of human capital strongly associate with the participation of scientists in entrepreneurial initiatives.

The existing literature provides reason to expect that patenting is concentrated among the group of eminent scientists. Yet, beyond the general association between research output and the likelihood of engaging in market-related activities, identifying more precisely the relationship between the production of papers and patents holds the promise to adjudicate among the competing mechanisms that might generate the relationship. In particular, if the magnitude of the stock of scientists' research output predicts the onset of patenting, it may be that faculty members' scientific reputations are important considerations in the decision to patent. The reason for this could be that the prominence of the inventor on a patented technology may influence the university's ability to capitalize on the intellectual property by affecting the probability that potential licensees become aware of and interested in the technology.

Consider instead the implication of a positive relationship between the flow, but not the stock, of scientists' research output and the probability that a patent is issued. If the flow of output is the determining factor, we would suggest that technological "opportunity" looms large in the transition to patenting. A flurry of scientific output—a high flow of publications—occurs when a scientist unearths a productive domain of research. If patenting is a byproduct of a surge in productivity, we think it reasonable to conclude that a patent is often an opportunistic response to the uncovering of a promising research area.

The third issue we consider is how the specific areas of expertise of academic scientists affect the likelihood of patenting. Obviously, there exists heterogeneity across scientists in the potential commercial value of the research they produce. If one needs to account for such differences, it is tempting to argue that the analyst can accommodate them by incorporating scientist fixed effects in the analysis. We believe, however, that this represents just a partial solution given the volume and the diversity of research projects that scientists participate in throughout their careers. We therefore attempt to develop a direct measure of the "patentability" of scientific research. The intuition behind the measure is that knowledge of the research foci of academic scientists who have already patented can be used to identify the domains of science in which research is patentable. With such a measure in hand, we ask two questions. First, does the latent patentability of scientists' research in fact affect the probability of patenting? Second, is it the patentability of the stock or the flow of research outputs that most consequentially influences the propensity to patent?

Fourth, we explore two elements of scientists' work contexts. While it is well established that propensities to patent vary substantially across universities, we do not have a clear sense for the influence of organizational characteristics on the patenting rates of otherwise similar scientists within different universities. Numerous studies suggest that the decision to engage in commercial activity of all sorts is strongly influenced by factors ranging from the norms and culture of an institution vis-à-vis commercial activity, to the quality of the university's technology transfer office (Thursby and Thursby 2002; Owen-Smith and Powell, 2001). Two prevalent considerations are thus the (potentially endogenous) role of a smooth functioning technology transfer office in encouraging faculty to disclose possibly patentable research findings, and more generally, a pro-commercialization "entrepreneurial culture" at a university. In our analysis, we ask whether university-level variables influence the patent rate net of controls for a variety of observable individual-level characteristics.

A related question concerns the influence of especially proximate colleagues on the patent proclivities of individual scientists. There are a set of reasons to expect that scientists who work closely with commercially-inclined peers will be more likely themselves to pursue commercial applications of their scientific research. Stuart and Ding (2005) argue that there are two mechanisms through which colleagues affect the probability that a particular scientist engages in commercial activities. First, peers exert attitudinal influences, in particular shaping the degree to which a given scientist is likely to embrace patenting as both a legitimate undertaking for an academic scientist and as a potential contributor to his or her professional standing. Second, peers convey information that may lower the cost of patenting, such as contacts in the technology transfer office and advice about how to minimize the amount of time consumed in patenting. We thus look for what might be labeled as "peer effects" on the transition to patenting. Specifically, we examine whether scientists who have coauthorship links with patent holders, and those who coauthor with researchers employed in the private sector, are more likely themselves to patent.

A necessary caveat pertains to the thorny issue of causality. Many of our independent variables, such as publications or latent patentability, could be considered outcomes of interest. Moreover, it would be incorrect to interpret our findings as providing evidence, *inter alia*, that publications and patents are complements, or that latent patentability "causes" patent applications. Rather, we have identified correlates of patenting. The conditional correlations we estimate can still be useful insofar as they help narrow the range of plausible theories regarding the *effect* of academic patenting on scientific productivity. In addition, since our most interesting results pertain to what are in fact lagged dependent variables, the study highlights the need to use correct econometric methodologies to recover causal effects. This is pursued in a companion paper (Azoulay et al., 2005).

3 Data, Sample Characteristics, and Econometric Approach

We examine the determinants of faculty patenting behavior in a panel dataset of academic life scientists employed at universities and non-profit research institutes. This area was chosen because the biomedical fields have accounted for the preponderance of university patenting and licensing activity (Mowery et al., 2001). While we have not selected scientists because they have patented, we have sampled from scientific disciplines that we know to have significantly contributed to a vibrant area of technological development. We began by drawing 12,000 doctoral degree recipients from UMI Proquest Digital Dissertations, which lists Ph.D. recipients from more than one thousand universities. In forming the sample, we randomly selected individuals, but only those with Ph.D.s in scientific disciplines that have informed commercial biotechnology.[2] This assures a random sample of Ph.D.s in areas in which academic research may have significant, short-term commercial value.

[2]To identify the scientific disciplines that have been most important to biotechnology, we coded the educational backgrounds of the Ph.D.-holding, university-employed scientific advisory board members of all publicly traded biotechnology firms. The source of information on scientific advisors' degrees was the IPO prospectuses of the 533 U.S.-based biotechnology firms have filed with the U.S. Securities and Exchange Committee. We then stratified the random draw from UMI to correspond to the disciplines and Ph.D. years of firms' scientific advisors. For example, 22 percent of biotechnology company scientific advisors hold biochemistry Ph.D.s; we drew a corresponding proportion of biochemists into our sample. Table 1 lists the top 15 disciplines from which scientists in our sample are selected.

Next, we obtained scientists' publication records from the ISI's *Web of Science* database. Because the Web of Science includes authors' affiliations, we were able to identify Ph.D. graduates who pursued careers outside of academe. After removing individuals that (i) had no publications in any post-graduate year, (ii) published exclusively under corporate affiliations, or (iii) exited academe early in their careers,[3] we were left with 3,884 scientists, all of whom we know to have been employed at research institutions. Each scientist is observed from the year after he or she earned a Ph.D. until 1999, unless the individual exited academia.[4] The final panel contains 59,069 person-year observations between 1967 and 1999.

3.1 Variables

The patents of the academic scientists in our data were assembled from the NBER patent database (Hall, Jaffe, and Trajtenberg, 2001). To identify academic patenters, we matched the scientists in our dataset to the list of inventors in the NBER patent database. Matches were done on the basis of last names and initials, and we used information on assignee (university) and geographic region to eliminate false matches. For each scientist in our data, we generated two dependent variables: time of transition to first patent and a dummy variable indicating whether the researcher applied for at least one patent in a given year.

Research Output and Latent Patentability. We create three measures of scientists' research output. From the *Web of Science* we computed annual paper publication counts for each scientist. We count all papers on which a scientist is listed as an author (in other words, we treat sole authored and coauthored papers as equivalents). While this seems a good proxy for the rate of a given scientist's output, we would also like to measure the content of this output. We do this in two different ways. First, we use the affiliation data available from *Web of Science* to identify all instances in which a scientist wrote a paper that was coauthored with one or more individuals in a corporate research and development lab. We assume that

[3] Ph.D.s with academic affiliations lasting less than five years dropped from the dataset to exclude post-doctoral fellows that later moved to jobs in industry.

[4] We assume a researcher has exited academia when he or she fails to publish for five consecutive years, or in fewer instances, when the scientist begins to publish almost exclusively under a corporate affiliation. In either case, we censor observation in the year in which a scientist last publishes under a university affiliation.

papers coauthored with researchers in industry are more likely to be of an applied nature, and thus we consider the rate of publication of papers with coauthors in industry as an indicator of the degree to which scientists are engaging in commercially-oriented research.

Second, it would be desirable to directly account for differences among scientists in the inherent "patentability" of their research. To construct such a measure, we have used the title words in scientists' publications to identify the areas in which they have conducted research, and then applied weights to theses areas based on an (endogenous to the sample) measure of the extent to which other scientists working in these 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 compared 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 score for scientist i in year t is defined as:

$$PATENTABILITY_{it} = \sum_{j=1}^{J} w_{ij,t-1} \frac{n_{ijt}}{\sum_w n_{iwt}}$$

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,[5] 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_{ijt} 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_{ijt} is detailed in the data appendix). Intuitively, the inherent 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 $\frac{n_{ijt}}{\sum_w n_{iwt}}$, the latter by the weights $w_{ij,t-1}$. 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.

[5]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.

Finally, to capture the idea that the inherent patentability of past research might influence 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 research should influence current behavior more strongly than scientific trajectories that unfolded in the more distant past:

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

Following a number of studies of the determinants of scientists' productivity, we were also able to construct many control variables to account for individual and institutional attributes that may influence rates of publication and patenting. To account for life cycle effects (Stephan, 1996), we include the number of years since a scientist earned his or her Ph.D. An extensive literature in the sociology of science has documented gender differences in productivity (e.g., Long and Fox, 1995), but little is known about the relationship between gender and patenting. To assess this, we examined scientists first names to construct a "scientist is female" dummy variable. Because the time involved in publishing scientific research varies across fields, the regressions include a full set of dummies for researchers' dissertation subject areas. Some of the regressions control for time invariant quality differences among researchers through the inclusion of scientist fixed effects. In specifications without fixed effects, we enter a dichotomous measure of the quality of a scientists' Ph.D.-degree granting institution—a dummy variable indicating whether or not a scientists' doctoral program was ranked in the top 20. Specifically, we collected Gourman Report rankings for all institutions in our dataset. Gourman ranking are available at the field level and were issued for the first time in 1980. Because biochemistry is the modal discipline in our dataset, we used universities' rankings in that field. We assigned universities their original rating for all years prior to 1980 (and updated them every other year for the subsequent period).

We also include a number of employer-level variables that may influence scientists' patenting. These covariates are updated each year and when scientists change employers. First, given the existing evidence that prominent universities are more likely to be involved in commercial activities, we include a quality rank dummy variable analogous to the one constructed for Ph.D.-grating institutions. Second, we used the AUTM surveys to create a technology transfer office (TTO) dummy variable, which is set to one in all years in which a scientist's employing university has an active TTO. Third, a university's stock of patents is entered in the model, among other things to further control for institutional differences in support for patenting. We include an analogous patent stock measure for scientists' doctoral training universities.

Finally, we include variables that capture the patenting proclivities of our scientists' coauthors. We measure both the number of collaborators and whether coauthors have applied for patents, but we are able to do so only for coauthors that are also members of our sample. Since the set of scientists analyzed here are drawn randomly from the population, this limitation should not introduce any bias, although it the resulting count is clearly a noisy proxy for the underlying concept.

3.2 Descriptive Statistics

Among the 3,884 researchers in our sample, 758 (20%) hold one or more patents. In Figure 1, we plot the distribution of patents for the patenting researchers in our sample. The histogram illustrates a rapid drop off after one—most patenters are listed on 1 or 2 patents throughout their career, and very few scientists in our data receive more than 10 patents. Figure 2 displays the distribution of scientists' total publication count, broken out by their patenting status. Consistent with the notion that patenting is concentrated among the group of academically productive scientists, the distribution for the patenter subsample is much less skewed than that of the non-patenter subsample (Figure 2).

Table 2 presents the summary descriptive statistics for variables used in our analysis. Table 3 reports, by scientists' patenting status, the mean research and employer characteristics measured at five career stages. This table shows that researchers who have sought and received patent rights for their discoveries are more productive at each career stage: they publish almost twice as many research papers as those who have not yet entered the patenting regime. Likewise, the intrinsic patentability of their research appears higher at each career stage. At all career stages, scientists who have applied for patent rights are closer to commercial research than their non-patenting counterparts, as indicated by the fact that they have collaborated more often with researchers in the private sector. Finally, patenters are more likely to work in settings where a technology transfer office exists and patenting activity is intensive, and they are more likely to have coauthors in our sample that have themselves patented.

Figure 3 displays the distribution of patenting events over time. Although we observe an uptick in the years following Bayh-Dole, it is also clear that patenting activity was taking place even before the adoption of the Act. This is consistent with the findings of Mowery et al. (2001). Finally, Figure 4 displays, for the first decade of scientists careers, the unconditional hazard of first patent application against experience (as measured by years since graduation) for three distinct cohorts of scientists: those who received their PhD between 1967 and 1975, those who earned their degree between 1976 and 1985, and those who matriculated between 1986 and 1990. For each of these cohorts, the hazard of patenting is increasing over the life cycle. However, of particular interest is the *slope* increase that appears during the first years in the profession of the most recent cohort.[6] The increase in slope is consistent with the view that patenting is increasingly perceived to be a legitimate scientific output in the academic life sciences.

3.3 Econometric Considerations

Estimating the determinants of faculty patenting behavior requires a procedure that accommodates the discrete nature of the event. Since our interest lies in analyzing the dynamics associated with the onset of patenting in scientific careers, we employ discrete-time hazard rate models (Cox 1972, Myers, Hankey and Mantel 1973, Allison 1982). The use of discrete-time models (as opposed to continuous-time models such as the Cox) is motivated by the fact that our failure time variable displays multiple events within each time period. For a researcher i during experience interval t, let the discrete time hazard rate be

[6] The decline in the unconditional hazard for the third cohort after the fifth year of experience is caused by the gradual censoring of the patent data. Specifically, the NBER patent database contains data on patents issued until 1999. Because our measure of patenting is dated to the time of application of a patent eventually issued, the final years of our data contain fewer patenting events because we do not observe patents that were applied for prior to 1999, but did not issue until after this year.

$p_{it} = Pr[T_i = t | T_i \geq t, X_{it}]$, where T_i is the time at which research i experiences an event and X_{it} a vector of covariates. We use a logistic regression function to link the hazard rate with time and the explanatory covariates:

$$Ln[\frac{p_{it}}{1 - p_{it}}] = \alpha_t + \beta' X_{it}$$

where α_t is a set of experience interval dummies. In practice, we estimate a simple logit of the decision to apply for a patent, where the observations corresponding to years subsequent to the first event have been dropped from the estimation sample.

These models essentially rely on between-scientist covariate variation to identify the determinants of the first transition to patenting. A complementary approach is to consider how within-scientist changes in covariates influence the propensity to patent. We do so by estimating so-called "fixed-effects" logit models by conditional maximum likelihood (Chamberlain, 1984). In contrast to our implementation of the standard logits, this approach analyzes the careers of patenting scientists in their entirety, rather than just until the year of first patent application. In other words, we treat patenting as a repeatable event in the fixed-effects logit regressions. There is, however, a countervailing cost in the fixed-effects approach, in that it drops all observations corresponding to scientists who never patent.[7] We believe that, together, the discrete-time hazard models and the fixed effects logit models provide a comprehensive picture of the academic patenting phenomenon.

4 Results

We begin by presenting results from the discrete-time hazard rate (unconditional logit) regressions. The results can be found in Tables 4a, b and c. Model (1) includes the variables often thought to be associated with academic patenting, but without the paper count and the patentability variables. All models control for (unreported) Ph.D subject areas and calendar year dummies. The results are consistent with the findings of previous researchers, and confirm the patterns that were already apparent in the descriptive statistics. We find strong

[7] Conditional maximum likelihood estimation requires some variation in the dependent variable to condition out the individual scientist effects. Because scientists that have never patented have no variation on the outcome variable, they must be dropped from the analysis.

evidence of a gender effect, with female faculty being 67% less likely to patent than their male counterparts, ceteris paribus. We find evidence that controling for the number of coauthors, scientists with at least one patenting coauthor are more likely to patent. We caution readers against interpreting this correlation as evidence of patenting peer effects, as it could merely reflect assortative matching among scientists along some other dimension correlated with patenting. We also find a strong influence of coauthorship with corporate researchers on the likelihood of first patent application. At the mean of the other covariates, having coauthored with researchers in industry increases the predicted probability of patenting by 74%.

In contrast to the individual-level covariates, the impact of employer-related variables is mixed. We fail to find an effect of the presence of a technology licensing office (although this could be due to the fact that this organizational innovation diffused quite rapidly among Tier-1 universities following Bayh-Dole). However, we do find an effect for the patent stock of the university, as well as for the intensity of patenting at the university where the scientist earned his/her doctorate in the five years preceding the award of the degree.[8]

Model (2) adds two variables to the specification: a scientist's count of publications in year $t-1$, and a cumulative stock of publications up to year $t-2$. Only the flow variable is significant, suggesting that patenting is accompanied by a flurry of scientific activity. At the mean of the data, each additional research publication increases the researcher's odds of entering the patenting regime during the next year by 6%; a one standard deviation increase (2.7) in the flow of research publications leads to a 14% increase in the likelihood of patenting relative to baseline. In Models (3) and (4), we explore further the timing of this flurry by using more flexible specifications for the distributed lag of publications. In Model (3), we include the flow of publications in year $t-2$ and the stock up to year $t-3$. In Model (4), we include the flow of publications in year $t-3$ and the stock up to year $t-4$. In both cases, only the coefficient for the one-year lagged variable is significant; in other words, Model (2) appears to capture accurately the timing of the publication flurry associated with patenting.

[8]In contrast to the trends displayed on Figure 4, the hazard of patenting appears to be monotonically decreasing in experience. However, this trend is an artifact of our decision to limit the analysis to the first transition to patenting. Because we drop scientists from the data once they have patented, we would expect to observe negative duration dependence as only those scientists that have not yet patented prior to an experience interval remain in the risk set. In other words, the scientists that remain in the risk set to inform the coefficient estimates for the later experience intervals are for the most part non-patenters.

This conditional correlation strikes us as being an important finding, for it can help distinguish between competing interpretations of the association between scientific productivity and involvement with the world of commerce. In the first interpretation, commercialization activities correspond to attempts by academics to monetize established reputations and professional status. In the second interpretation, publications and patents are co-occuring outputs that encode the same set of scientific insights; patents, just like publications, reflect genuine shocks to scientific opportunities. We see the correlation between the onset of patenting and the lagged flow, but not the stock — of publications as much more consistent with the latter interpretation.[9]

Using the specification in Model (2) as a benchmark, Table 4b examines the influence of the latent patentability of the scientist's research on his/her propensity to enter the patenting regime. We proceed with the analysis parallel to the approach taken in Table 4a. Model (5) adds the flow of our research patentability score in year $t-1$ (*i.e.,* based on our endogenous-to-the-sample measure, the extent to which the papers a scientist has published in the previous year are substantively similar to the work previously published by patenting scientists) and the corresponding cumulative stock up to year $t-2$. Here again, we find that only the flow influences the likelihood of patenting. At the mean of the data, increasing the patentability score by one standard deviation increases the likelihood of first patent application by 14%. Moreover, as can be seen in Models (6) through (8), the conclusion is not altered when using a more flexible way to model the distributed lag of the latent patentability score. Just as in the case of publications, the onset of patenting appears simultaneous with a change in the content of a scientist's research in a direction that makes it more similar to that of scientists who have already applied for patent rights. But because it is the flow, and not the stock of this measure that seems to matter, the evidence is more consistent with the idea that a patent application reflects the seizing of opportunities along a novel research trajectory, rather than a deliberate, well-planned change of research agenda in response to changes in the formal and informal incentives faced by academic scientists.

[9] This interpretation is also consistent with Murray and Stern's (2005) analysis of paper-patent pairs, but it suggests that this phenomenon is not confined to the single journal whose articles they analyze.

Using Model (5) as a benchmark, Table 4c examines a variety of interactions between known determinants of patenting behavior and the flurry of publications observed in Table 4a. Model (9) interacts the flurry with five dummies corresponding to different levels of experience. Although the patterns are not very pronounced, it appears that the magnitude of the publication flurry required to shift a scientist into the patenting regime varies over the life cycle and follows an inverted U-shape. In particular, it is during the first five to eight years of the experience clock that the effect of the flurry is most pronounced. For life scientists, this typically corresponds to their first job as established, independent investigators. The decrease observed in subsequent years is consistent with human capital vintage effects that have been frequently mentioned (though not often estimated) in the economics of science literature. Models (10) through (13) interact the flurry with different institutional and contextual measures. We find that the magnitude of the flurry is smaller for scientists working in "patent-intensive" universities (Model 10), for scientists working in universities where other scientists have founded companies or sit on corporate advisory boards, and for scientists who have coauthors who themselves patent. In other words, the evidence suggests that the magnitude of the opportunity necessary to shift an individual into the patenting regime is larger in academic environments in which the costs of patenting are higher, either because of bureaucratic hurdles, or a lack of cultural support for involvement in commercial activity.

Taken together, these results do not invalidate the view that social influences operating in graduate school, in the scientist's current university, or through his "invisible college" of collaborators influence commercial activities among academics. To the contrary, the direct effects of proxies for these attributes were found to positively influence the likelihood of patenting in our random sample of researchers. But we also find that individual rates of patenting respond to scientific opportunities, and that patenting coincides with a genuine change in the content of the research published by scientists.

The results presented above suffer from two limitations. First, they only pertain to the decision to apply for the *first* patent. For a sizable proportion of scientists, patenting is a repeated event, and the determinants of patenting could differ in that group. Moreover, one might object that our result regarding the flurry of publications contemporaneous with patenting assumes that the lagged stock of publications adequately captures differences in talent among scientists. It would be desirable to subject this set of results to a more stringent test. For these reasons, Tables 5a, 5b and 5c replicate the analyses presented in tables 4a, 4b and 4c using fixed-effects logit models. In these models, patenting is treated as a repeated event, and there are as many observations in the estimation sample as there are person-years for patenting scientists. We also drop the stock variables from the specifications, since they move too slowly to be separately identified from the individual effects. Table 5a shows that the impact of the one-year lagged count of publications remains even after accounting for time-invariant talent differences among scientists through fixed individual effects, and that the inclusion of additional lags do not modify the result. We interpret this finding as sugesting that within-scientist changes in scientific opportunities influence their likelihood of patenting.

Similarly, Table 5b highlights the role of changes in the latent patentability of a scientist's research that appear to correlate with patenting events, although the statistical significance of these results is weaker than in the corresponding "cross-sectional" hazard rate models. In Model (8), we partition the one-year lag of the patentability measure in three separate dummy variables corresponding to 0, above 0 but below the 75^{th} percentile, and above the 75^{th} percentile. Using this more flexible specification, Model (8) implies a statistically significant influence of changes in latent research patentability on individual rates of patenting. Finally, Table 5c replicates the specifications in Table 4c. While we cannot replicate the results pertaining to the life cycle, the other results are qualitatively similar, in that they indicate that an environment conducive to patenting and scientific opportunities are substitute inputs in the decision to patent among "serial patenters."

5 Discussion and Conclusion

The policy debate regarding interactions between industry and academia in general, and academic patenting in particular, has often taken for granted the idea that patenting represents a fundamental departure from the norms of the "Republic of Science." According to this view, academic researchers toil in relative obscurity by producing fundamental knowledge up until the time they receive tenure; subsequently, they may monetize their reputation by involving themselves in commercial pursuits. Patents, though not necessarily remunerative in and of themselves, provide academic researchers with visibility and status in the world of commerce, for example by enabling them to sit on corporate advisory boards (Stuart and Ding, 2005).

The findings in this paper challenge the standard account. First and foremost, our results suggest that patents and publications correspond to two types of output that have more in common than previously believed. Certainly, the positive relationship between patent applications and the flow, but not the stock, of publications suggest that patents and papers encode similar pieces of knowledge, a fact exploited by Murray and Stern (2005) in their investigation of the anti-commons hypothesis. Second, our results suggest that the academic incentive system is evolving in ways that accommodate deviations from traditional scientific norms of openness. Many patenting events in our data take place in the early years of scientists' careers, and the slope of the patent-experience curve has become steeper with more recent cohorts of scientists. This finding dovetails with qualitative accounts that emphasize that patents are becoming *de rigueur* on academic vitas in many institutions, and are even considered legitimate forms of research output in promotion decisions.

If the present paper investigates the antecedents of academic patenting, much work remains to be done on the effects of this now-prevalent practice on the rate of scientific progress. Does applied research (as embodied in patents) crowd out the fundamental pursuit of knowledge (as measured by publications)? Answering this question is difficult, because patenting is a choice variable for scientists, and the outcome of a decision that could easily reflect expectations of future scientific productivity. Our paper provides an important input into this analysis by presenting the results of a selection equation whose estimation is necessary to recover causal effects of patenting on scientific output (Azoulay, Ding, and Stuart 2005). But our results also alert us to the possibility that substantive content of post-patent publications might be different from these scientists' pre-patent output, leading naturally to the study of the effect of patenting on the *direction* of scientific progress. Our measure of latent patentability, whose construction is an important contribution of this paper, can be used on the left-hand side of a regression equation to investigate this important question.

We find the magnitude of the gender effect intriguing. What explains the differential attainment of male and female scientists in the realm of patenting, and why is the pattern so much more pronounced than that known to exist for publications? It is well documented that the biological sciences are among the few scientific fields in which women have gained equal representation in graduate school, and they have made significant advances in obtaining faculty positions. Yet, there is anything but equality in rates of participation in patenting. One potential, although perhaps second-order, explanation is suggested by apparent gender differences in the *content* of scientific research: in supplemental explorations, we have found that, holding year and experience constant, the latent patentability of female scientists' research is considerably lower than the corresponding values for male researchers.

Finally, our findings suggest that social contagion might be an important mechanism through which the practice of academic patenting diffuses among the population of life scientists. The result that scientists whose coauthors patent are more likely to patent themselves is consistent with genuine "peer effects," but it is also consistent with assortative matching of coauthors along some other dimension correlated with patenting — such as scientific productivity. Distinguishing between these competing hypotheses remains a valuable goal for future research.

References

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

Allison, Paul D. 1982. "Discrete-Time Methods for the Analysis of Event Histories," in Sociological Methodology. S. Leinhardt ed. San Francisco: Jossey-Bass, pp. 61-98.

Azoulay, Pierre, Waverly W. Ding, and Toby E. Stuart. 2005. "The Impact of Academic Patenting on (Public) Research Output." Working Paper, Columbia University.

Azoulay, Pierre, Ryan Michigan, and Bhaven N. Sampat. 2005. "The Anatomy of Medical School Patenting, 1981-2000." Working Paper, Columbia University.

Blumenthal, David, Eric G. Campbell, Nancyanne Causino, and Karen Seashore Louis. 1996. "Participation of Life-Science Faculty in Research Relationships with Industry." *New England Journal of Medicine*, 335:23, pp. 1734-39.

Campbell, Eric G. , B. R. Clarridge, N. N. Gokhale, L. Birenbaum, S. Hilgartner, N.A. Holtzman, and D Blumenthal. 2002. "Data Withholding in Academic Genetics — Evidence from a National Survey." *JAMA*, 287:4, pp. 473-80.

Chamberlain, G. 1984. "Panel Data," in *Handbook of Econometrics.* Zvi Griliches and Michael D. Intriligator, eds. Volume 2, pp. 1248-1318. Amsterdam: North-Holland.

Cox, D. R. 1972. "Regression Models and Life Tables." Journal *of the Royal Statistical Society Series B,* 34:2, pp. 187-220.

Di Gregorio, Dante and Scott Shane. 2003. "Why Do Some Universities Generate More Start-ups Than Others?" *Research Policy*, 32:2, pp. 209-27.

Ding, Waverly W., Fiona Murray, and Toby E. Stuart. 2005. "Technology: A New Arena for Gender Stratification in Scientific Careers?" Working Paper, Columbia University.

Etzkowitz, Henry. 1998. "The Norms of Entrepreneurial Science: Cognitive Effects of the New University-Industry Linkages." *Research Policy,* 27:8, pp. 823-33.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg. 2001. "The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools." NBER Working Paper #8498.

Henderson, Rebecca M., Adam B. Jaffe, and M. Trajtenberg. 1998. "Universities as a Source of Commercial Technology: A Detailed Analysis of University Patenting, 1965-1988." *Review of Economics and Statistics*, 80:1, pp. 119-27.

Jaffe, Adam B. 1989. "Real Effects of Academic Research." *American Economic Review*, 79, pp. 957-70.

Jaffe, Adam B. and Josh Lerner. 2001. "Reinventing Public R&D: Patent Policy and the Commercialization of National Laboratory Technologies." *Rand Journal of Economics,* 32:1, pp. 167-98.

Jensen, Richard and Marie C. Thursby. 2001. "Proofs and Prototypes for Sale: The Licensing of University Inventions." *American Economic Review*, 91:1, pp. 240-59.

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

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

Long, J. Scott and Mary Frank Fox. 1995. "Scientific Careers: Universalism and Particularism." *Annual Review of Sociology,* 21, pp. 45-71.

Mansfield, Edwin. 1995. *Innovation, Technology, and the Economy: The Selected Essays of Edwin Mansfield.* Aldershot, UK: Brookfield.

Mowery, David C., Richard R. Nelson, Bhaven N. Sampat, and Arvids A. Ziedonis. 2001. "The Growth of Patenting and Licensing by US Universities: an Assessment of the Effects of the Bayh-Dole Act of 1980." *Research Policy*, 30:1, pp. 99-119.

Murray, Fiona. 2002. "Innovation as Co-evolution of Scientific and Technological Networks: Exploring Tissue Engineering." *Research Policy,* 31:8-9, pp. 1389-1403.

Murray, Fiona and Scott Stern. 2005. "Do Formal Intellectual Property Rights Hinder the Free Flow of Scientific Knowledge? Evidence from Patent-Paper Pairs." Working Paper, Northwestern University.

Myers, M.H., B.F. Hankey, and N. Mantel. 1973. "A Logistic Exponential Model for Use with Response-Time Data Involving Regressor Variables." *Biometrics,* 29, pp. 257-69.

Owen-Smith, Jason and Walter W. Powell. 2001. "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.

Stephan, Paula E. 1996. "The Economics of Science." *Journal of Economic Literature*, 34:3, pp. 1199-235.

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

Stuart, Toby E. and Waverly W. Ding. 2005. "The Social Structural Determinants of Academic Entrepreneurship: An Analysis of University Scientists' Participation in Commercial Ventures." Working Paper, Columbia University.

Thursby, Jerry G. and Marie C. Thursby. 2002. "Who is selling the Ivory Tower? Sources of Growth in University Licensing." *Management Science*, 48:1, pp. 90-104.

Zucker, Lynne G., Michael R. Darby, and Marilynn B. Brewer. 1998. "Intellectual Human Capital and the Birth of U.S. Biotechnology Enterprises." *American Economic Review*, 88:1, pp. 290-306.

Table 1
Top 15 Scientific Disciplines in the Sample

UMI Subject Code	UMI Subject Description	Frequency	
487; 303	Biochemistry	861	(22.2%)
306	Biology, General	568	(14.6%)
410	Biology, Microbiology	469	(12.1%)
419	Health Sciences, Pharmacology	240	(6.2%)
490	Chemistry, Organic	213	(5.5%)
786	Biophysics, General	211	(5.4%)
369	Biology, Genetics	191	(4.9%)
433	Biology, Animal Physiology	171	(4.4%)
982	Health Sciences, Immunology	167	(4.3%)
307	Biology, Molecular	102	(2.6%)
301	Bacteriology	63	(1.6%)
287	Biology, Anatomy	54	(1.4%)
571	Health Sciences, Pathology	52	(1.3%)
349	Psychology, psychobiology	37	(1.0%)
572	Health Sciences, Pharmacy	34	(0.9%)

Legend: Table 1 reports the top 15 disciplines from which our sample was drawn. These disciplines have spawned the most of biotechnology firm founders, scientific advisors and executives. The table also reports the number and the proportion of scientists of our sample in each scientific discipline

Table 2
Descriptive Statistics

	Mean	Std. Dev.	Min.	Max.
Time-varying (59,069 person-year observations)				
Experience	10.22	7.127	1	32
Patent flow dummy	0.039	0.194	0	1
Patent regime dummy	0.125	0.330	0	1
Publications flow	1.677	2.667	0	100
Publications stock	16.48	27.68	0	645
Research patentability flow	0.084	0.108	0	5.185
Research patentability stock	0.460	0.417	0	5.659
Collaboration tie with company scientists	0.263	0.441	0	1
Average number of identified coauthors per paper	0.131	0.248	0	10
Identified coauthors have patents	0.200	0.400	0	1
Employer graduate school in top 20	0.232	0.422	0	1
Employer has TTO	0.489	0.500	0	1
Employer patent stock (in hundred)	0.717	1.450	0	22
Employer entrepreneurial faculty count	8.634	22.89	0	199
Calendar year	1986	7.741	1968	1999
Time-invariant (3,884 observations)				
Female	0.211	0.408	0	1
Ph.D. univ. grad. school in top 20	0.308	0.462	0	1
Ph.D. univ. 5-yr patent stock (in hundred)	19.02	40.89	0	566
Ph.D. univ. entrepreneurial faculty count	2.294	8.304	0	182

.

Table 3
Mean Research and Employer Characteristics at Five Career Stages, by Patent Application Status

	Experience = 5		Experience = 10		Experience = 15		Experience = 20		Experience = 25	
Has at least one patent application	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*
Research publications stock	9.610	4.456	23.082	12.485	39.579	22.003	55.917	32.843	77.679	41.747
Research patentability stock	0.342	0.244	0.613	0.491	0.856	0.662	1.021	0.788	1.103	0.833
Count of collaboration ties with company scientists	0.968	0.206	2.282	0.697	3.562	1.280	4.838	2.168	7.540	2.562
Identified coauthors have patents	0.197	0.081	0.367	0.176	0.525	0.265	0.611	0.337	0.636	0.396
Employer grad. school rank in top20	0.261	0.266	0.261	0.220	0.249	0.196	0.195	0.182	0.187	0.170
Employer has TTO	0.463	0.383	0.576	0.482	0.698	0.586	0.735	0.682	0.829	0.727
Employer Patent stock (in 100)	0.738	0.537	1.072	0.650	1.223	0.741	1.279	1.089	1.571	1.212
Employer entrepreneurial faculty count	7.110	6.260	11.815	8.683	14.983	10.736	14.723	12.905	16.652	12.251
Observations	218	3612	330	2286	354	1503	339	978	187	454

Legend: Table 3 reports the mean research and employer characteristics measured at five different stages in scientists' career: the 5th, 10th, 15th, 20th and 25th year after the scientist was granted a Ph.D. Within each career stage, the table is further broken out by whether a scientist has ever applied for a patent right.

Table 4a
Discrete-Time Hazard Models of Probability of Patenting

	(1)	(2)	(3)	(4)
Experience [1, 4]	0.852 (0.225) **	0.959 (0.245) **	0.989 (0.247) **	0.983 (0.252) **
Experience [5, 8]	0.759 (0.212) **	0.771 (0.232) **	0.717 (0.234) **	0.656 (0.234) **
Experience [9, 15]	0.699 (0.198) **	0.693 (0.216) **	0.643 (0.217) **	0.590 (0.217) **
Experience [16, 22]	0.591 (0.195) **	0.587 (0.202) **	0.558 (0.202) **	0.530 (0.202) **
Female	-1.138 (0.137) **	-1.117 (0.138) **	-1.107 (0.138) **	-1.104 (0.138) **
Collaboration tie with company scientists$_{t-1}$	0.566 (0.093) **	0.431 (0.095) **	0.407 (0.094) **	0.400 (0.094) **
Average number of identified coauthors per paper $_{t-1}$	0.346 (0.122) **	0.341 (0.124) **	0.357 (0.126) **	0.368 (0.125) **
Identified Coauthors have patent $_{t-1}$	0.513 (0.096) **	0.381 (0.102) **	0.361 (0.101) **	0.352 (0.101) **
Ph.D. University Grad School in Top 20	-0.037 (0.086)	-0.048 (0.086)	-0.052 (0.086)	-0.053 (0.086)
Ph.D. University 5-year Patent Stock	0.002 (0.001) †	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)
Ph.D. University Entrepreneurial Faculty Count	0.003 (0.006)	0.004 (0.005)	0.004 (0.006)	0.004 (0.006)
Employer Grad School in Top 20	-0.023 (0.103)	-0.040 (0.104)	-0.039 (0.104)	-0.039 (0.104)
Employer has a TTO$_{t-1}$	0.116 (0.092)	0.101 (0.093)	0.099 (0.093)	0.096 (0.094)
Employer Patent Stock$_{t-1}$	0.055 (0.031) †	0.054 (0.033) †	0.054 (0.033) †	0.054 (0.033)
Employer Entrepreneurial Faculty Count$_{t-1}$	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)
Research Publication Stock$_{t-2}$		-0.0005 (0.003)		
Research Publication Stock$_{t-3}$			-0.002 (0.003)	
Research Publication Stock$_{t-4}$				-0.004 (0.003)
Research Publication Flow$_{t-1}$		0.060 (0.019) **	0.056 (0.018) **	0.052 (0.018) **
Research Publication Flow$_{t-2}$			0.009 (0.022)	-0.001 (0.024)
Research Publication Flow$_{t-3}$				0.029 (0.021)
Constant	-9.038 (1.022) **	-8.926 (1.028) **	-8.781 (1.029) **	-8.721 (1.030) **
Number of observations	52,466	52,466	52,466	52,466
Number of researchers	3,884	3,884	3,884	3,884
Number of first patenting events	758	758	758	758
Log-likelihood	-3743.28	-3714.59	-3710.51	-3709.07
Wald Chi^2	385.86	411.35	428.23	433.61
Model d.f.	48	51	53	55
Pseudo-R^2	0.06	0.06	0.06	0.06

Table 4b
Discrete-Time Hazard Models of Probability of Patenting

	(5)	(6)	(7)	(8)
Experience [1, 4]	0.939	0.982	1.014	0.906
	(0.247)**	(0.248)**	(0.254)**	(0.247)**
Experience [5, 8]	0.737	0.709	0.696	0.727
	(0.232)**	(0.235)**	(0.238)**	(0.233)**
Experience [9, 15]	0.656	0.629	0.617	0.644
	(0.215)**	(0.216)**	(0.217)**	(0.216)**
Experience [16, 22]	0.571	0.556	0.549	0.556
	(0.202)**	(0.202)**	(0.202)**	(0.202)**
Female	-1.102	-1.094	-1.092	-1.104
	(0.138)**	(0.138)**	(0.138)**	(0.138)**
Collaboration tie with company scientists$_{t-1}$	0.419	0.402	0.397	0.429
	(0.095)**	(0.094)**	(0.094)**	(0.096)**
Average number of identified coauthors per paper $_{t-1}$	0.325	0.334	0.343	0.321
	(0.126)**	(0.126)**	(0.126)**	(0.124)**
Identified Coauthors have patent $_{t-1}$	0.359	0.350	0.345	0.350
	(0.102)**	(0.102)**	(0.102)**	(0.102)**
Ph.D. University Grad School in Top 20	-0.046	-0.049	-0.050	-0.052
	(0.087)	(0.087)	(0.087)	(0.087)
Ph.D. University 5-year Patent Stock	0.002	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Ph.D. University Entrepreneurial Faculty Count	0.004	0.004	0.004	0.005
	(0.006)	(0.006)	(0.006)	(0.005)
Employer Grad School in Top 20	-0.043	-0.041	-0.040	-0.047
	(0.104)	(0.104)	(0.104)	(0.104)
Employer has a TTO$_{t-1}$	0.102	0.100	0.100	0.097
	(0.094)	(0.094)	(0.094)	(0.094)
Employer Patent Stock$_{t-1}$	0.058	0.058	0.057	0.056
	(0.033)†	(0.033)†	(0.033)†	(0.033)†
Employer Entrepreneurial Faculty Count$_{t-1}$	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Research Publication Stock$_{t-2}$	-0.001	-0.001	-0.002	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Research Publication Flow$_{t-1}$	0.057	0.057	0.058	0.069
	(0.017)**	(0.017)**	(0.017)**	(0.018)**
Research Patentability Stock$_{t-2}$	-0.034			0.054
	(0.137)			(0.130)
Research Patentability Stock$_{t-3}$		-0.037		
		(0.148)		
Research Patentability Stock$_{t-4}$			-0.044	
			(0.157)	
Research Patentability Flow$_{t-1}$	1.692	1.623	1.608	
	(0.463)**	(0.469)**	(0.472)**	
Research Patentability Flow$_{t-2}$		-0.567	-0.540	
		(0.487)	(0.483)	
Research Patentability Flow$_{t-3}$			-0.217	
			(0.498)	
Intermediate Research Patentability Flow$_{t-1}$				0.439
				(0.098)**
High Research Patentability Flow$_{t-1}$				0.523
				(0.111)**
Constant	-8.930	-8.768	-8.710	-9.228
	(1.028)**	(1.030)**	(1.032)**	(1.029)**
Number of observations	52064	52064	52064	52466
Number of researchers	3884	3884	3884	3884
Number of first patenting events	758	758	758	758
Log-likelihood	-3676.44	-3672.88	-3672.33	-3705.48
Wald Chi^2	429.96	440.88	442.14	439.91
Model d.f.	53	55	57	53
Pseudo-R^2	0.06	0.07	0.07	0.07

Table 4c
Discrete-Time Hazard Models of Probability of Patenting

	(9)	(10)	(11)	(12)	(13)
Experience [1, 4]	0.845	0.928	0.942	0.956	1.023
	(0.261)**	(0.246)**	(0.245)**	(0.248)**	(0.250)**
Experience [5, 8]	0.607	0.744	0.757	0.772	0.825
	(0.234)**	(0.233)**	(0.232)**	(0.235)**	(0.236)**
Experience [9, 15]	0.581	0.652	0.663	0.680	0.721
	(0.222)**	(0.215)**	(0.215)**	(0.217)**	(0.218)**
Experience [16, 22]	0.586	0.548	0.567	0.577	0.592
	(0.211)**	(0.200)**	(0.200)**	(0.202)**	(0.201)**
Female	-1.113	-1.128	-1.123	-1.104	-1.116
	(0.140)**	(0.140)**	(0.140)**	(0.138)**	(0.139)**
Collaboration tie with company scientists$_{t-1}$	0.385	0.402	0.414	0.423	0.393
	(0.096)**	(0.095)**	(0.095)**	(0.095)**	(0.095)**
Average number of identified coauthors per paper $_{t-1}$	0.354	0.339	0.329	0.326	0.311
	(0.124)**	(0.123)**	(0.124)**	(0.124)**	(0.127)*
Identified Coauthors Have Patents $_{t-1}$	0.316	0.324	0.341	0.343	0.566
	(0.102)**	(0.102)**	(0.101)**	(0.101)**	(0.125)**
Ph.D. University Grad School in Top 20	-0.061	-0.062	-0.057	-0.056	-0.064
	(0.086)	(0.087)	(0.087)	(0.087)	(0.087)
Ph.D. University 5-year Patent Stock	0.002	0.002	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ph.D. University Entrepreneurial Faculty Count	0.005	0.004	0.004	0.005	0.005
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Employer Grad School in Top 20	-0.038	-0.024	-0.041	-0.040	-0.034
	(0.103)	(0.103)	(0.104)	(0.103)	(0.103)
Employer has a TTO$_{t-1}$	0.086	0.093	0.087	0.182	0.091
	(0.094)	(0.093)	(0.094)	(0.113)	(0.094)
Employer Patent Stock$_{t-1}$	0.060	0.083	0.058	0.057	0.058
	(0.033)†	(0.031)**	(0.032)†	(0.032)†	(0.033)†
Employer Entrepreneurial Faculty Count$_{t-1}$	-0.001	-0.001	0.002	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Research Publication Stock$_{t-2}$	0.002	-0.001	-0.001	-0.001	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Research Publication Flow$_{t-1}$		0.099	0.089	0.095	0.118
		(0.023)**	(0.021)**	(0.031)**	(0.029)**
Research Patentability Stock$_{t-2}$	0.003	0.008	0.029	0.039	-0.035
	(0.130)	(0.130)	(0.128)	(0.128)	(0.135)
Intermediate Research Patentability Flow$_{t-1}$	0.402	0.410	0.422	0.426	0.386
	(0.102)**	(0.099)**	(0.099)**	(0.099)**	(0.102)**
High Research Patentability Flow$_{t-1}$	0.495	0.503	0.513	0.514	0.484
	(0.114)**	(0.112)**	(0.111)**	(0.112)**	(0.113)**
Publication Flow$_{t-1}$ × Experience [1,4]	0.109				
	(0.078)				
Publication Flow$_{t-1}$ × Experience [5,8]	0.123				
	(0.024)**				
Publication Flow$_{t-1}$ × Experience [9,15]	0.077				
	(0.023)**				
Publication Flow$_{t-1}$ × Experience [16,22]	0.024				
	(0.027)				
Publication Flow$_{t-1}$ × Experience [23,29]	0.017				
	(0.023)				

	(9)	(10)	(11)	(12)	(13)
Publication Flow$_{t-1}$ × Employer Patent Stock$_{t-1}$		-0.017 (0.006) **			
Publication Flow$_{t-1}$ × Employer Entrepreneurial Faculty$_{t-1}$			-0.001 (0.001)†		
Publication Flow$_{t-1}$ × Employer has a TTO$_{t-1}$				-0.042 (0.032)	
Publication Flow$_{t-1}$ × Identified Coauthors have patent $_{t-1}$					-0.091 (0.031)**
Constant	-9.186 (1.030) **	-9.266 (1.028) **	-9.271 (1.028) **	-9.297 (1.029)**	-9.358 (1.029)**
Number of observations	52,466	52,466	52,466	52,466	52,466
Number of researchers	3,884	3,884	3,884	3,884	3,884
Number of first patenting events	758	758	758	758	758
Log-likelihood	-3,698.68	-3,699.65	-3,702.58	-3,703.64	-3,697.71
Wald Chi^2	471.48	467.55	449.16	449.56	454.25
Model d.f.	57	54	54	54	54
Pseudo-R^2	0.07	0.07	0.07	0.07	0.07

Notes:

(1) For all researchers in the sample, only observations on or before the year of the first patenting event or censoring have been used, i.e., for all researchers that have patented, the observations after the year of their first patent application were not used in the analysis.

(2) Models (5)-(7) use a restricted sample, in which 402 person-year observations in the unrestricted sample were excluded from the analysis. These 402 observations account for the top 1% of the research patentability flow measure.

(3) All models control for Ph.D. subject areas and calendar year dummies.

(4) Experience [23, 29] is the base category.

(5) A dummy variable indicating whether the researcher has zero publication in year t-1 is included in models (2)-(7), though not reported in the table; a dummy variable indicating whether the researcher has zero publication in year t-2 is included in models (3), (4), (6) and (7), though not reported in the table; a dummy variable indicating whether the researcher has zero publication in year t-3 is included in models (4) and (7), though not reported in the table.

(6) Robust standard errors in parentheses, clustered by scientist.

(7) † significant at 10%; * significant at 5%; ** significant at 1%.

Table 5a
Fixed-Effects Logit Models of Probability of Patenting

	(1)	(2)	(3)	(4)
Experience [1, 4]	0.293	0.291	0.319	0.338
	(0.318)	(0.318)	(0.318)	(0.322)
Experience [5, 8]	0.652	0.594	0.574	0.575
	(0.268)*	(0.268)*	(0.268)*	(0.268)*
Experience [9, 15]	0.692	0.635	0.617	0.617
	(0.202)**	(0.202)**	(0.203)**	(0.203)**
Experience [16, 22]	0.534	0.496	0.487	0.487
	(0.132)**	(0.133)**	(0.133)**	(0.133)**
Collaboration tie with company scientists$_{t-1}$	0.388	0.328	0.313	0.309
	(0.096)**	(0.097)**	(0.098)**	(0.098)**
Average number of identified coauthors per paper $_{t-1}$	0.367	0.339	0.345	0.350
	(0.148)**	(0.151)**	(0.151)**	(0.152)**
Identified Coauthors Have Patents$_{t-1}$	-0.025	-0.059	-0.066	-0.069
	(0.100)	(0.101)	(0.101)	(0.101)
Employer Grad School in Top 20	0.066	0.083	0.083	0.084
	(0.144)	(0.144)	(0.145)	(0.145)
Employer has a TTO$_{t-1}$	0.098	0.097	0.097	0.096
	(0.094)	(0.094)	(0.094)	(0.094)
Employer Patent Stock$_{t-1}$	-0.010	-0.011	-0.012	-0.012
	(0.031)	(0.031)	(0.031)	(0.031)
Employer Entrepreneurial Faculty Count$_{t-1}$	0.005	0.005	0.006	0.006
	(0.002)**	(0.002)**	(0.002)**	(0.002)**
Research Publication Flow$_{t-1}$		0.027	0.026	0.025
		(0.011)**	(0.012)**	(0.012)**
Research Publication Flow$_{t-2}$			-0.002	-0.003
			(0.012)	(0.013)
Research Publication Flow$_{t-3}$				0.003
				(0.013)
Number of observations	14,507	14,507	14,507	14,507
Number of researchers	758	758	758	758
Log-likelihood	-3,932.78	-3,924.24	-3,922.65	-3,922.56
Wald Chi^2	805.64	822.72	825.89	826.08
Model d.f.	20	22	24	26
Pseudo-R^2	0.09	0.09	0.10	0.10

Table 5b
Fixed-Effects Logit Models of Probability of Patenting

	(5)	(6)	(7)	(8)
Experience [1, 4]	0.249	0.246	0.247	0.283
	(0.319)	(0.319)	(0.320)	(0.318)
Experience [5, 8]	0.540	0.536	0.536	0.596
	(0.269) *	(0.269) *	(0.269) *	(0.268) *
Experience [9, 15]	0.593	0.592	0.592	0.633
	(0.203) **	(0.203) **	(0.203) **	(0.202) **
Experience [16, 22]	0.482	0.482	0.482	0.494
	(0.133) **	(0.133) **	(0.133) **	(0.133) **
Collaboration tie with company scientists$_{t-1}$	0.319	0.322	0.322	0.336
	(0.098) **	(0.098) **	(0.098) **	(0.097) **
Average number of identified coauthors per paper $_{t-1}$	0.332	0.325	0.325	0.336
	(0.151) *	(0.151) *	(0.151) *	(0.150) *
Identified Coauthors Have Patents$_{t-1}$	-0.063	-0.061	-0.061	-0.072
	(0.101)	(0.101)	(0.102)	(0.101)
Employer Grad School in Top 20	0.082	0.083	0.083	0.092
	(0.146)	(0.146)	(0.146)	(0.144)
Employer has a TTO$_{t-1}$	0.089	0.087	0.087	0.097
	(0.095)	(0.095)	(0.095)	(0.094)
Employer Patent Stock$_{t-1}$	-0.011	-0.011	-0.011	-0.011
	(0.031)	(0.031)	(0.031)	(0.031)
Employer Entrepreneurial Faculty Count$_{t-1}$	0.005	0.005	0.005	0.005
	(0.002) **	(0.002) **	(0.002) **	(0.002) **
Research Publication Flow$_{t-1}$	0.026	0.026	0.026	0.033
	(0.011) *	(0.011) *	(0.011) *	(0.011) **
Research Patentability Flow$_{t-1}$	0.735	0.737	0.737	
	(0.383)†	(0.383)†	(0.383)†	
Research Patentability Flow$_{t-2}$		-0.389	-0.389	
		(0.371)	(0.371)	
Research Patentability Flow$_{t-3}$			0.011	
			(0.304)	
Intermediate Research Patentability Flow$_{t-1}$				0.173
				(0.080) *
High Research Patentability Flow$_{t-1}$				0.252
				(0.083) **
Number of observations	14,332	14,332	14,332	14,507
Number of researchers	755	755	755	758
Log-likelihood	-3,881.96	-3,881.39	-3,881.39	-3,922.42
Wald Chi^2	816.11	817.24	817.24	826.36
Model df	23	24	25	23
Pseudo-R^2	0.10	0.10	0.10	0.10

Table 5c
Fixed-Effects Logit Models of Probability of Patenting

	(9)	(10)	(11)	(12)	(13)
Experience [1, 4]	0.208 (0.336)	0.279 (0.318)	0.289 (0.318)	0.281 (0.318)	0.283 (0.318)
Experience [5, 8]	0.645 (0.289)*	0.592 (0.268)*	0.594 (0.268)*	0.592 (0.268)*	0.574 (0.268)*
Experience [9, 15]	0.664 (0.225)**	0.628 (0.202)**	0.627 (0.203)**	0.628 (0.202)**	0.612 (0.202)**
Experience [16, 22]	0.671 (0.161)**	0.495 (0.133)**	0.501 (0.133)**	0.491 (0.133)**	0.486 (0.133)**
Collaboration tie with company scientists$_{t-1}$	0.332 (0.098)**	0.333 (0.097)**	0.328 (0.097)**	0.334 (0.097)**	0.311 (0.097)**
Average number of identified coauthors per paper $_{t-1}$	0.302 (0.154)*	0.331 (0.150)*	0.337 (0.150)*	0.334 (0.150)*	0.303 (0.152)*
Identified Coauthors Have Patents$_{t-1}$	-0.042 (0.102)	-0.067 (0.101)	-0.065 (0.101)	-0.067 (0.101)	0.148 (0.123)
Employer Grad School in Top 20	0.090 (0.145)	0.082 (0.145)	0.081 (0.145)	0.089 (0.145)	0.078 (0.145)
Employer has a TTO$_{t-1}$	0.099 (0.094)	0.090 (0.094)	0.092 (0.094)	0.150 (0.110)	0.093 (0.094)
Employer Patent Stock$_{t-1}$	-0.007 (0.031)	0.030 (0.035)	-0.007 (0.031)	-0.010 (0.031)	-0.010 (0.031)
Employer Entrepreneurial Faculty Count$_{t-1}$	0.006 (0.002)**	0.006 (0.002)**	0.008 (0.002)**	0.005 (0.002)**	0.005 (0.002)**
Research Publication Flow$_{t-1}$		0.046 (0.012)**	0.047 (0.012)**	0.046 (0.017)**	0.071 (0.016)**
Intermediate Research Patentability Flow$_{t-1}$	0.157 (0.080)†	0.172 (0.080)*	0.172 (0.080)*	0.171 (0.080)*	0.160 (0.080)*
High Research Patentability Flow$_{t-1}$	0.240 (0.083)**	0.252 (0.083)**	0.254 (0.083)**	0.252 (0.083)**	0.241 (0.083)**
Publication Flow$_{t-1}$ × Experience [1,4]	0.111 (0.030)**				
Publication Flow$_{t-1}$ × Experience [5,8]	0.034 (0.023)				
Publication Flow$_{t-1}$ × Experience [9,15]	0.042 (0.016)**				
Publication Flow$_{t-1}$ × Experience [16,22]	0.005 (0.014)				
Publication Flow$_{t-1}$ × Experience [23,29]	0.050 (0.018)**				
Publication Flow$_{t-1}$ × Employer Patent Stock$_{t-1}$		-0.011 (0.005)*			
Publication Flow$_{t-1}$ × Employer Entrepreneurial Faculty$_{t-1}$			-0.001 (0.000)*		
Publication Flow$_{t-1}$ × Employer has a TTO$_{t-1}$				-0.016 (0.018)	
Publication Flow$_{t-1}$ × Identified Coauthors have patent $_{t-1}$					-0.055 (0.018)**
Number of observations	14,507	14,507	14,507	14,507	14,507
Number of researchers	758	758	758	758	758
Log-likelihood	-3,915.25	-3,919.65	-3,919.74	-3,922.01	-3,917.53
Wald Chi^2	840.71	831.90	831.71	827.19	836.14
Model d.f.	27	24	24	24	24
Pseudo-R^2	0.10	0.10	0.10	0.10	0.10

Notes:

(1) Models (5)-(7) use a restricted sample, in which 175 person-year observations in the unrestricted sample were excluded from the analysis. These 175 observations account for the top 1% of the research patentability flow measure.

(2) All models control for period dummies 1975-76, 1977-79, 1980-82, 1983-85, 1986-88, 1989-91, 1992-94, 1995-97, 1998-99; base category is 1967-74.

(3) Experience [23, 29] is the base category.

(4) A dummy variable indicating whether the researcher has zero publication in year t-1 is included in models (2)-(7), though not reported in the table; a dummy variable indicating whether the researcher has zero publication in year t-2 is included in models (3), (4), (6) and (7), though not reported in the table; a dummy variable indicating whether the researcher has zero publication in year t-3 is included in models (4) and (7), though not reported in the table.

(5) † significant at 10%; * significant at 5%; ** significant at 1%.

Figure 1: Distribution of Patent Count for Patenting Scientists

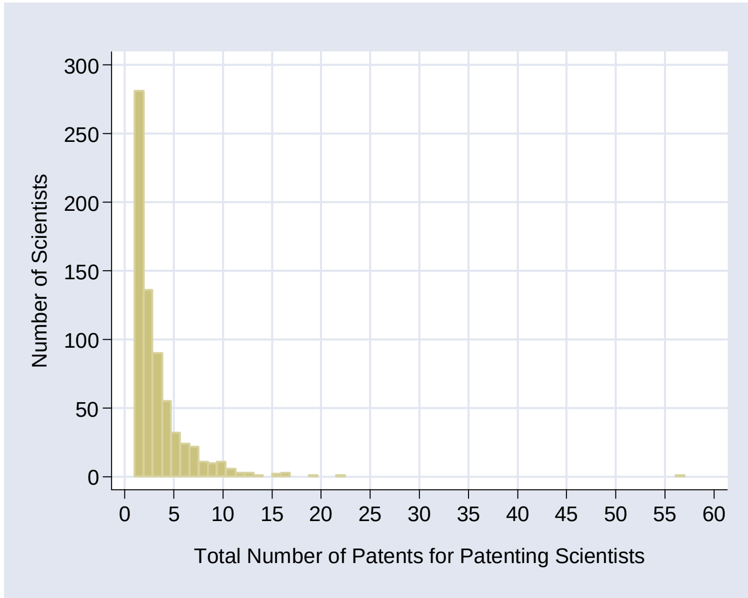


Figure 2: Distribution of Publication Count for Patenting and Non-Patenting Scientists

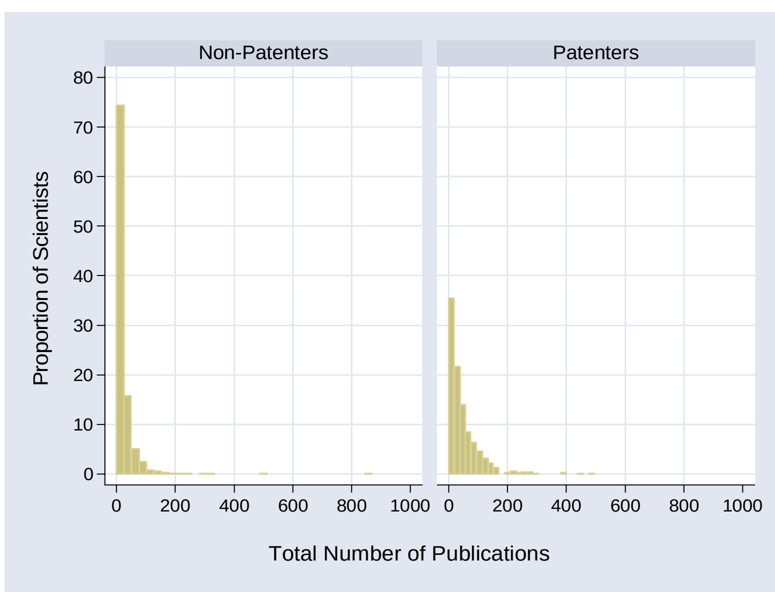


Figure 3: Distribution of Patenting Events over Time

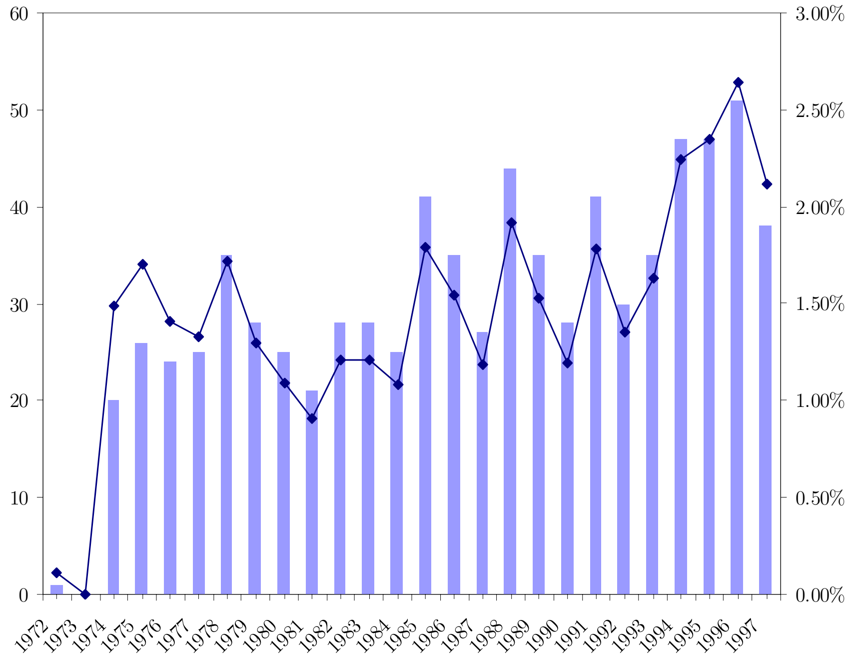
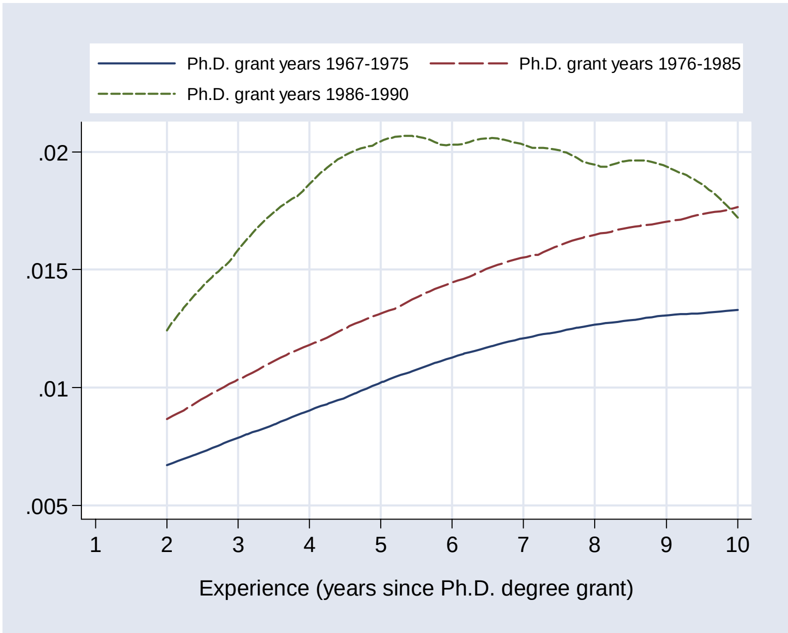


Figure 4: Unconditional Hazard of First Patent Application, by Ph.D. Cohort



Data Appendix: Keyword Patentability Weights

w_{ijt}, the patentability weight for each keyword j and scientist i in year t is defined as:

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

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.

To create the numerator of w_{ijt}, 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 sj^{th} cell in the matrix, $[m_{sjt}/\sum_k m_{skt}]$, 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_{ijt} 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, $w_{ijt} = 0$ 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_{ijt}. 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, applied the appropriate keyword weight $w_{ij,t-1}$, 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 entered in the regressions to control for the research patentability of scientists' areas of specialization.