The Impact of Academic Patenting on (Public) Research Output

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Abstract

We examine the influence of university-employed scientists' transitions to patenting on the rate of publication and of obtaining NIH grants in a panel dataset spanning the careers of 4,270 academic life scientists. Using inverse probability of treatment weights (IPTW) to account for the dynamics of self-selection into patenting, we find that patenting has a positive effect on the rate of publication of journal articles, and a much smaller — though still positive — effect on NIH grant awards. We also find that patenters may be shifting their research focus to questions of commercial interest, as evidenced by a positive effect of patenting in regressions of the rate of publication of papers that are coauthored with researchers in industry. We conclude that the often-voiced concern that patenting in academe has a nefarious effect of on public research output is, at least in its simplest form, misplaced.

Keywords: patents, economics of science, selection models.

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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; Di Gregorio and Shane, 2003). 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; Zucker and Darby 1998; 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 consequence of academic patenting on the rate and direction of scientific progress, as embodied in the *public* research output of *individual* academic scientists. We seek to determine, at the level of the individual scientist, whether the activities of patenting and of producing the conventional scholarly outputs-journal articles and (federal) research grants-are substitutes or complements.

This question is important and, we believe, unresolved. On one hand, surveys of academic scientists have found that patenting skews scientists' research agendas toward commercial priorities, causes delay in the public dissemination of research findings, and crowds out effort devoted to producing public research (Blumenthal, 1996; Campbell et al. 2002; Krimsky, 2003). In stark terms, this research has portrayed a tradeoff between patenting and the values and behaviors that traditionally have been thought to be conducive to the progress of academic science. On the other hand, a few studies have econometrically assessed the scientist-level relationship between patenting and publishing, and they have reached a different conclusion. Agrawal and Henderson (2002) estimated fixed effects regressions of the effect of patenting in a 15-year panel of 236 scientists in two MIT departments. They found that patenting did not affect publishing. Markiewicz and DiMinin (2004) constructed a sample of 166 academic patenters, the members of which were matched by university (employer) and field of research to an equivalent number of non-patenting scientists. In a fixed effects specification, they found a statistically positive effect of researchers' patent stocks on their publication counts. In a third study, Stephan et al. (2004) exploited the Survey of Doctorate recipients and used instrumental variables to estimate the cross-sectional relationship between patenting and publishing; they found that patenting and publishing relate positively.

Our findings concur with — and significantly extend — this latter set of results. Across many specifications, with and without scientist fixed effects and with careful adjustment for selection into patenting, we find that both the flow and the stock of scientists' patents are positively related to subsequent publication rates. The effect on the number of grants from the National Institutes of Health (NIH) is weaker, but not negative. Our results thus refute the loose pronouncements of the deleterious effects of academic patenting that pepper the literature on the commercialization of university science. However, we present tentative evidence that patenting may induce something of a shift in the content of scientists' research: we find that the rate of publication of papers that are coauthored with researchers in firms is higher for faculty holding patents. Furthermore, we present incidental analyses that unambiguously establish that the most accomplished scientists are more likely to patent. Thus, if patenting does in fact skew the research agendas of the best and brightest researchers away from questions of basic scientific importance, it is possible (but far from certain) that the commercial endeavors of university scientists could eventually detract from the pace of scientific progress.

Our paper makes two primary contributions, in addition to presenting findings pertinent to an ongoing policy debate and to an area of economic importance in which systematic evidence is scarce. First, we have assembled a comprehensive, longitudinal dataset: it is a prospective, 4,270-person random sample drawn from the population of life scientists in academia between 1967 and 1999. For the individuals in the sample, we have reconstituted entire career histories, including patent, publication and NIH grant information, as well as many employer-level variables. We believe that this is the most inclusive dataset available for assessing the relationship between patenting and public research productivity among academic scientists.

Second, we use a novel methodology to disentangle correlation from causality in the assessment of the effect of patenting. As we will show, patent holders differ from other researchers on many observable characteristics (see also Stephan et al. 2004). More accomplished researchers are much more likely to patent, and controlling for the stock of past publications, scientists with a recent good run are also more likely to patent. This evidence calls into question the ability of traditional fixed effect specifications to consistently estimate causal effects, since patenters and non-patenters do not appear to follow similar trends in publication rates *before* the initiation of patenting. Moreover, academic scientists almost surely differ in the intrinsic patentability of their research, and this too makes it difficult to obtain valid estimates of the effect of patenting on public research output. We use Inverse Probability of Treatment Weighted (IPTW) estimation (Robins, 1997; Hernán et al., 2001) to account for the self-selection of researchers into patenting, and to adjust for inter-individual differences in the patentability of scientific research. This methodology, which generalizes the propensity score to settings in which treatment is staggered over time, accounts for selection into patenting on the basis of observable characteristics, including (in our case) lagged productivity and the latent patentability of a scientists' research trajectory. While this approach naturally cannot rule out selection based on unobservable factors, we were able to generate an extensive list of covariates to model the probability of selection into patenting.

In addition to these two primary contributions, the paper indirectly relates to the literature on the tension between applied and basic research (Rosenberg, 1990; Cohen and Levinthal, 1989; Henderson and Cockburn, 1994; Cockburn, Henderson and Stern, 1999). This group of studies has sought to understand why for-profit firms fund basic research, and has generally concluded that basic and applied research are complements, although the mechanisms responsible for this relationship have yet to be crisply identified (see Stern 2004). This work bears an obvious similarity to our effort to assess the nature of the relationship between basic and commercial scientific projects conducted by individual scientists.

The rest of the paper proceeds as follows. In the next Section, we provide an overview of the controversies surrounding the academic patenting. Section 3 presents our econometric methodology. Section 4 describes the construction of the sample and data sources, presents descriptive statistics, and reports our econometric results. Section 5 concludes.

2 Basic and Commercializable Research: Substitutes or Complements?

Recent studies of university technology transfer have documented a precipitous increase in commercial outputs, which is borne out in statistics on three related activities: patenting (Henderson et al., 1998; Mowery et. al, 2001), license agreements with private sector firms (Jensen and Thursby, 2001), and the formation of university-originated startup companies (Di Gregorio and Shane, 2003). This shift toward commercializing university research has generated much controversy, particularly concerning the impact of intellectual property rights on the advancement of science. In the next section, we consider some of the legitimate arguments on both sides of the debate.

Substitutes. Critics of the rapid growth of commercial activity have voiced concern that patenting and licensing scientific discoveries may interfere with the traditional functions of research universities, most notably the production and dissemination of basic research. The shift toward commercialization has been claimed to have three primary, deleterious byproducts: increased secrecy, diversion of scientists' time, and distortion in the selection of areas of scientific inquiry.

Scientists contemplating patent-protecting research discoveries are thought to be more secretive, which may delay public dissemination of their research findings and deter open information exchange in the scientific community. In a survey of academic life scientists, Campbell et al. (2002) reported that more than 20 percent of those questioned admitted withholding information about their research from colleagues to protect potential commercial interests. In addition, three-fourths of those surveyed believed that data withholding was reducing open communication in science and slowing the rate of scientific advance in their fields. In an earlier survey, Blumenthal et al. (1996a; 1996b) also found that university faculty with funding from industry were considerably more likely to refrain from work-related communications with colleagues. Moreover, Thursby and Thursby (2002) report that private sector sponsors of university research often require scientists to accede to delay-of-publication clauses. If patent-holding scientists attract more industry funding for their research, they also will be frequently bound by delay-of-publication clauses. Thus, in commercially active areas or research, muted communication may decelerate awareness of new scientific opportunities, and individual researchers may delay or forego publications to safeguard the value of private intellectual property rights.

A second concern is that patenting and the other activities associated with commercializing science can consume significant amounts of time, thus diverting scientists' attention away from their research. The tasks of disclosing inventions and fleshing out patent applications require at least a modest investment of effort, but assisting companies in the process of assimilating the inventions they license can be quite time consuming. In addition, Stuart and Ding (2003) show that, after holding constant scientists' productivity, prestige, and the commercial relevance of their research, faculty members listed as inventors on patents were considerably more likely to found companies and to join scientific advisory boards. Thus, although patenting may not cause a shift in the allocation of scientists' time, it may signal a scientist's intention to divert effort from basic to applied research and technology transfer. Insofar as patenters hail from the group of very productive scientists, their decisions to dedicate time to commercial activities may deplete the ranks of talented researchers allocating full-time attention to the questions of basic science.[1]

The occupational incentive system in academic science may reinforce the decisions of the most experienced, accomplished researchers to allocate time to commercial pursuits. It is well document that, post-tenure, most scientists face relatively flat wage-experience profiles

[1] Significant inequality in scientists' productivity has been widely documented. In a classic paper, Lotka (1926) showed that the most productive 6% of publishing physicists produced 50% of the papers in the journals he examined. An extensive literature in the sociology of science presents further evidence of the skewed distribution of productivity (e.g., Merton, 1973; de Solla Price, 1986). Thus, it is conceivable that changes in the allocation of effort of a relatively small group of elite scientists could have a significant effect on the collective advancement of science. Moreover, the highly skewed distribution of scientific productivity underscores the importance of making the right comparisons in assessing the effect of patenting on publishing.

(Stephan, 1996). Moreover, life cycle human capital models also suggest changes in the allocation of effort over scientific careers: the present (pecuniary) value of a publication is likely to decline in scientist age (Levin and Stephan, 1991). The fact that academic patenters are known to be drawn predominantly from the ranks of tenured faculty is certainly consistent with this view. To the extent that patenting and commercialization activities can better be contracted upon than basic scientific pursuits, theories of optimal incentive contracting in the presence of career concerns also predict that commercial activities will substitute for academic output (Gibbons and Murphy, 1992).

The third concern is that the encroachment of commercial interests into universities will induce scientists to select research projects on the basis of their perceived marketability in the private-sector, rather than for their intrinsic scientific merit. Among critics of the increasing dependence of universities on private-sector funding, this is a frequently assumed and vigorously lamented consequence. To our knowledge, however, reliable evidence of a shift in research priorities is scant. The most systematic data come from Blumenthal et al. (1986). They surveyed academic life scientists, asking whether respondents had considered commercial potential when choosing research projects. 30 percent of life science faculty with industry funding replied affirmatively, compared to just 7 percent of faculty without private sector funding.

Complements. Although many researchers perceive a tradeoff between accomplishing universities' traditional missions and faculty patenting, others have hypothesized that patenting may assist scientists in producing public research outputs. Certainly, there is a natural analogy to the complementarities observed between applied and basic research in other settings. Rosenberg (1998), for example, documented that innovations born out of contact with commercial enterprises in the quintessentially applied field of chemical engineering ushered a new era of basic chemical discoveries. The possibility of such scope economies also exist at the individual level.

One possibility is that scientists who patent also are more likely to develop close relationships with researchers in companies, and that these contacts become sources of ideas for new research projects of scientific importance. The notion that connections with researchers in industry serve as fruitful sources for unearthing interesting research questions emerges in Agrawal and Henderson's (2002) interviews with MIT scientists. Likewise, Mansfield (1995) finds that many of the ideas that work on the contributions of academic research to industrial innovation also finds that applied work . It is also consistent with evolutionary theories of technological and scientific progress in which major advances are understood to represent insightful combinations of disparate pieces of knowledge (e.g., Hull, 1988; Cohen and Levinthal, 1990). Because scientists with industrial connections are privy to more diverse bits of information, they may be better positioned to identify important areas of scientific inquiry.

Another possible complementary between basic and commercial research is that many seminal scientific achievements have been made possible only by technological advances in instrumentation. For instance, much of our knowledge of how diseases operate has come from understandings gained from DNA and protein sequencers and synthesizers. In the biomedical fields and other areas or science, technological and scientific advances are therefore interdependent: new understandings are often beholden to progress in instrumentation. If patenting scientists are more likely to be in a position to negotiate access to state-of-the-art equipment in corporate laboratories (Owen-Smith and Powell, 2001), or if they are more likely to have developed the technical expertise to understand and modify research equipment, there is another potential, complementary relationship between basic and applied research.

Having reviewed the arguments and evidence on both sides of the debate about the consequences of patenting in academic science, we now discuss the econometric approach we use to estimate the relationship between patenting and public research output.

3 Econometric Considerations

Estimating the causal effect of academic patenting on research output must confront a basic selectivity problem: researchers choose whether, when, and how much to patent. As a result, traditional econometric techniques, which assume that exposure to "treatment" occurs randomly, cannot recover causal effects. Past researchers have used two types of methodological approaches to deal with this selection problem: instrumental variables techniques and fixed effects estimation. Using a random cross-section of academic scientists, Stephan et al. (2004) implement the first of these approaches, but the instruments they use — characteristics of the scientist's university and characteristics of a peer group of scientists — are unlikely to be legitimately excluded from their second stage. Markiewicz and DiMinin (2004) use a fixed effect specification in panel dataset of matched patenting and non-patenting researchers. In so doing, they purge their estimates from any influence of unobserved heterogeneity that is constant over time. However, it is well-known that for differences in differences estimation to be valid, it must be the case that the average outcome for the treated and control groups would have followed parallel paths over time in the absence of treatment. This assumption is implausible if pretreatment characteristics that are thought to be associated with the dynamics of the outcome variable are unbalanced between treatment and control units. Below, we provide strong evidence that selection into patenting is influenced by transitory shocks to recent publications. In this respect, estimating the causal effect of academic patenting on research output presents similar challenges to that of estimating the effect of a job-training program on wages. The two main differences are that (1) a recent flurry of publications *positively* influences subsequent patenting, a phenomenon we name "Ashenfelter's hump"; and (2) treatments are staggered over time, so that there is no clear "before" and "after" period for non-patenter controls.

To overcome these challenges, we make use of a novel approach that has recently gained acceptance in biostatistics: Inverse Probability of Treatment Weighted (IPTW) estimation (Hernán et al., 2001). These estimators are akin to propensity-score matching techniques (Rosenbaum and Rubin, 1983; Dehejia and Wahba, 2002) in that they make the (untestable) assumption that selection into treatment is based on variables that are observable to the econometrician, but extend it to the case of time-varying treatments. In particular, IPTW estimation allow one to recover average treatment effects even in the presence of *time-varying confounders*, i.e., time-varying variables that (1) are correlated with future values of the dependent variable; (2) predict selection into treatment; and (3) are themselves predicted by past treatment history. As we will show below, this applies to the case of academic patenting, since publication rates are strongly auto-correlated, the probability of patenting increases after a recent flurry of publications, and past patenting history influences future publication rates.

Implementing IPTW estimation is relatively straightforward. Let y_{it} denote the outcome of interest (e.g., publications), $TREAT_{it}$ denote treatment (e.g., $TREAT_{it} = 1$ if researcher i applies for at least one patent in year t, 0 otherwise), X_{it} denote a set of exogenous, possibly time-varying covariates, and ε_{it} denotes the model's residual. The canonical model to be estimated is:

$$y_{it} \quad = \quad \beta_0 + \beta_1 X_{it} + \beta_2 TREAT_{it} + \varepsilon_{it} \tag{1}$$

In the presence of time-varying confounders Z_{it}, the estimate $\widehat{\beta_2}$ is a biased estimate of the causal effect of treatment, even if the Z_{it}'s are a subset of the observed covariates X_{it} included as regressors. Under the assumption that the determinants of selection into treatment can be accurately captured by observable factors, then the bias can be removed by weighting the regression by:

$$w_{it} = \frac{1}{\prod_{k=0}^{t} Prob(TREAT_{ik} = T_{ik} | \widetilde{TREAT}_{i,k-1}, \widetilde{Z}_{i,k-1}, \widetilde{X}_{ik})}$$

where $\widetilde{X}_{ik}$ stands for the whole history of variable vector X up to time k. Each factor in the denominator is the probability that the researcher received her own observed treatment at time k, conditional on past treatment history and her past history of "prognosis factors" for treatment, whether time-varying or fixed over time. Therefore, w_{it} represents the conditional probability that an individual followed, possibly contrary to the fact, his or her own *history* of treatment up to time t. Thus, Robins et al. (2000) refer to these weighted estimators as IPTW estimators. Suppose that all relevant time-varying confounders are observed and included in Z_{it}. Then, weighting by w_{it} effectively creates a pseudo-population in which Z_{it}

no longer predicts selection into treatment and the causal association between treatment and outcome is the same as in the original population.[2]

The probabilities $Prob(TREAT_{ik} = T_{ik}|\widetilde{TREAT}_{i,k-1}, \widetilde{Z}_{i,k-1}, \widetilde{X}_{ik})$ may vary greatly between subjects when time-varying confounders are strongly associated with treatment. This variability can result in extremely large outlying values for w_i. These outliers will contribute heavily to the pseudo-population, and the resulting IPTW estimator will have a very large variance. This problem can be alleviated by replacing w_{it} by a "stabilized" weight sw_{it}:

$$sw_{it} = \prod_{k=0}^{t} \frac{Prob(TREAT_{ik} = T_{ik}|\widetilde{TREAT}_{i,k-1}, \widetilde{X}_{ik})}{Prob(TREAT_{ik} = T_{ik}|\widetilde{TREAT}_{i,k-1}, \widetilde{Z}_{i,k-1}, \widetilde{X}_{ik})}$$

Although this modification does not influence the consistency of IPTW estimators, it does increase their efficiency (Robins, 1997). Despite its simplicity and intuitiveness, IPTW estimation also presents some significant drawbacks. First and foremost, the assumption of no unobserved confounding is a strong one. Past research in the program evaluation literature has shown that techniques assume selection on observables perform well (in the sense of replicating an experimental benchmark) when (1) researchers use a rich list of covariates to model the probability of treatment; (2) units are drawn from similar labor markets, and (3) outcomes are measured in the same way for both treatment and control groups (Dehejia and Waba, 2002; Smith and Todd, 2001). All of these conditions would appear to be met in our setting and data, but this should not lead researchers to believe that IPTW estimation represents a universal solution for endogeneity problems. A second limitation is that IPTW estimates are just identified: the assumption of no unobserved determinants of selection into treatment cannot be tested; neither can misspecification of the selection equation used to estimate the weights. Third, the causal effect estimated by IPTW models is the population average treatment effect (ATE). In social science applications, however, the effect of treatment on the treated might be more policy-relevant.[3]

[2]Because time-varying confounders mediate the effect of treatment on outcome and are affected by past treatment, adjusting for these factors by simply adding them as variables on the right-hand side of (1) would not appropriately adjust for the confounding. For example, including a lagged dependent variable as a regressor would lead to an underestimate of the magnitude of the patenting effect, since this modeling approach effectively holds the lagged dependent variable constant.

[3]One might worry about performing statistical inference using "second stage" IPTW estimates, since the weights that are used as input in the outcome equation are themselves estimated. In contrast to two-step

Finally, IPTW estimation cannot easily be used in the context of fixed-effect specifications. To see why, rewrite the residual in (1) as $\varepsilon_{it} = \gamma_i + \delta_t + \eta_{it}$, where γ_i are fixed effects for each individuals, and δ_t are a set of calendar year effects. Thus, the model to be estimated is:

$$y_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 TREAT_{it} + \gamma_i + \delta_t + \eta_{it} \quad (2)$$

The specification above is the classic difference-in-differences framework whereby changes in outcomes for treated units are compared with changes in outcomes for control units. Depending on the set of observations used to estimate the model, these controls can be either individuals that never experience treatment, or individuals that have not yet experienced treatment but will in the future, or both. Because the weights used in IPTW estimation are time-varying, a difficulty arises when estimating versions of (2) with a limited dependent variable, such as a count or a binary outcome. In the linear case, while it is not possible to difference out the incidental parameter γ_i, one can estimate the least square dummy variable version of the model. Although this does not yield consistent estimates for the fixed effects, it allows one to recover consistent slope parameters for the coefficients on X and $TREAT$. In the non-linear case, time-varying weights preclude the conditioning out of the fixed effects in the cases of the logit, poisson, and negative binomial models often used by applied researchers (Chamberlain, 1984; Hausman et al., 1984). As a result, we present two sets of estimates. In the first set, fixed unit effects are ignored, and IPTW estimates implicitly compare the *levels* of the outcome variables for patenters and non-patenters, conditional on observables. The second set of results, which we favor, combines the difference-in-differences framework with IPTW estimation, but this exercise cannot be performed whenever the dependent variable of interest is a count (such as the number of coauthored articles with industry researchers) or exhibits a large mass point at 0 (such as the dollar amount of NIH grants).

Censoring and exit. Although we focused the first part of the discussion on the problem of non-random selection into patenting, a second problem arises because some subjects might

selection correction methods (Heckman, 1979), Robins (1999) has shown that the standard errors obtained in this case are conservative.

exit the sample for endogenous reasons. For instance, scientists might leave academia because of low scientific productivity, or because they receive attractive offers to join commercial firms. Even if treatment was randomly allocated across units, this type of informative censoring could jeopardize the validity of the statistical estimates. We deal with this problem by treating censoring as just another time-varying treatment. As Robins et al. (2000) note, from this point of view, adjusting for censoring is only to say that our interest lies in estimating the causal effect of $TREAT$ on y if, contrary to the fact, all subjects had remained in the sample rather than having followed their censoring history. We model the exit decision as a function of constant and time-varying observable factors, and compute weights corresponding to the probability of exit given these observables:

$$sw_{it}^{*} = \prod_{k=0}^{t} \frac{Prob(EXIT_{ik} = 0 | \widetilde{TREAT}_{i,k-1}, X_{ik})}{Prob(EXIT_{ik} = 0 | \widetilde{TREAT}_{i,k-1}, \widetilde{Z}_{i,k-1}, X_{ik})}$$

sw_{it}^{*} is the inverse of the ratio of a scientist's probability of remaining uncensored up to year t divided by that probability calculated as if there had been no time-dependent determinants of censoring except past treatment history and X. Robins (1999) shows that consistent estimates for β_2 can be obtained by combining the weight corresponding to the inverse probability of treatment sw_{it} and the weight corresponding to the inverse probability of exit sw_{it}^{*}. The denominator of the final weight, $sw_{it}^{*} \times sw_{it}$, is the probability that a subject would have followed his own treatment and censoring history up to year t, conditional on observables. As a result, we refer to Inverse Probability of Treatment and Censoring Weights (IPTCW) in the rest of the paper.

Estimation of the weights. The procedure followed to compute the weights depends on the way in which treatment is defined. According to a first definition, treatment is a *flow*: $TREAT_{it} = 1$ whenever researcher i gets at least one patent in year t, and 0 otherwise. This formulation implies that treatment does not necessarily have a lasting impact on the individual. In contrast, the *regime* formulation defines $TREAT_{it} = 1$ for all years subsequent to the first patent application. Defining treatment this way implies a one-time shift on the outcome of interest, with subsequent treatment episodes having no effect on the dependent variable.

In the flow formulation the weights are computed by estimating pooled cross-sectional logit specifications on the whole dataset. To compute the denominator of sw_{it}, one estimates:

$$logitprob(TREAT = 1) = \alpha_0 + \alpha_1 TREAT_{i,t-1} + \Phi(\widetilde{Z}_{i,t-1}, \alpha_2) + \alpha_3 X_{it} + \delta_t \tag{3}$$

where $\Phi(\widetilde{Z}_{i,t-1}, \alpha_2)$ corresponds to a parametric function of past values for time-varying confounders, X_{it} includes both time-varying and fixed over time characteristics of individuals in the sample (such as years of experience, gender, prestige of current employer, etc.), and δ_t represents calender year effects. In practice, we specify Φ as a linear function of publications in years $t-1$ and $t-2$, the stock of publications up to year $t-3$, and the number of past collaborations with industrial firms. Let T_1 denote the set of years in which scientist i gets at least a patent and T_2 the set of years during which i gets no patents. The estimate of the denominator of sw_{it} is $\prod_{t \in T_1} \widehat{p}_{it} \prod_{t \in T_2} (1 - \widehat{p}_{it})$. The numerator of sw_{it} stems from an almost identical specification, except that one omits the term $\Phi(\widetilde{Z}_{i,t-1}, \alpha_2)$ in the logit equation.

This approach needs to be slightly modified when treatment is modeled as a regime shift rather than as a flow, because the probability of getting treatment remains constant and equal to 1 once a scientist enters the treatment regime. As a result, it is only necessary to fit the model on a subset of the data, that of scientist-year observations before the first patent, along with the observations corresponding to the first patenting year for the scientists who get at least one patent over the sample period. In this risk set, $TREAT_{i,t-1}$ is uniformly 0, and we estimate

$$logitprob(TREAT = 1) = \alpha_0 + \Phi(\widetilde{Z}_{i,t-1}, \alpha_2) + \alpha_3 X_{it} + \delta_t \tag{4}$$

to compute the denominator of sw_{it}, and

$$logitprob(TREAT = 1) = \alpha_0 + \alpha_3 X_{it} + \delta_t \tag{5}$$

to compute the numerator of sw_{it}. Our estimate of the denominator of sw_{it} for scientist i in year t is $\prod_{k=0}^{t} 1 - \widehat{p}_{ik}$ if scientist i did not apply for at least one patent by year t, and $\prod_{k=0}^{t-1} (1 - \widehat{p}_{ik}) \times \widehat{p}_{it}$ if scientist i applied for his first patent in year t. Estimation of sw^*_{it} proceeds in the same fashion.

Relationship of IPTCW estimation with propensity-score matching methods. Rosenbaum and Rubin (1983) refer to $Prob(TREAT_i = 1|X, Z)$ as the propensity score, and show how to use this probability to estimate treatment effects when selection into treatment depends only on observables. Recently, Heckman et al. (1997) have combined the propensity score with difference-in-differences to estimate the causal effect of undergoing a job training program. Abrade (2003) proposes a semiparametric difference-in-differences estimate that weights observations by the inverse probability of (own) treatment. Although the goals of these earlier papers resembles ours, we follow a slightly different approach because the structure of our data differs significantly from the typical program evaluation setup. Labor econometricians generally study programs for which a "before" and "after" period can be unambiguously delineated for both treated and untreated units. In contrast, in our setting and many others, selection into treatment can occur at different times and/or in several disjoint episodes.[4] Matching on the propensity score is difficult in these cases. Intuitively, an untreated individual might be a good control for a treated subject in one period (in the sense that the difference in their propensity scores is close to 0) and a bad control for the same treated subject in another period. In contrast, IPTCW estimation readily generalizes to the case of treatments that are staggered over time.

4 Data and Sample Characteristics

We examine the association between patenting and publishing 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

[4]Similar challenges arise when estimating the effect of exporting activity on the productivity of manufacturing firms, or when using variation in the timing of state laws to identify the effect of various policies on firm or individual behaviors (Clerides et al., 1998; Bernard and Jensen, 1999; Bernard and Mulligatawny, 1999; Autos et al., 2004).

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.[5] This assures a random sample of Ph.D.s in areas in which academic research may have significant, short-term commercial value.

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,[6] we were left with 4,270 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.[7] The final panel contains 64,483 person-year observations between 1967 and 1999.

4.1 Variables

We examine three measures of scientists' research output. First, 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). Second, from the National Institutes of Health's CGAF database, we obtained the annual number of grants awarded to each scientist. Third, we used the affiliation data available from *Web of Science* to identify all instances in which a scientist

[5] 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.

[6] 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.

[7] 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.

wrote a paper that was coauthored with one or more individuals in a corporate research and development lab. We assume that 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.

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 flow and stock measures of patent applications, as well as corresponding dummy variables.

Following a number of studies of the determinants of scientists' productivity, we were also able to construct a rich set of 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), so we include 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 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' productivity and probability of patenting. These covariates are updated each year and when scientists change employers. First, we include a quality rank dummy variable analogous to the one constructed for Ph.D.-grating institutions. There are a variety of reasons why scientists at prominent universities are likely to be more productive, including the availability of more resources and easy access to high quality colleagues. 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. Similar quality rank and patent stock measures were constructed for scientists' doctoral training universities.

In the regressions for selection into patenting used to construct the inverse probability of treatment weights, it would obviously be desirable to 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 person-year. Specifically, the research patentability score for scientist i in year t is defined as:

$$PATENTABILITY_{it} = \sum_{j=1}^{J} w_{jt} \frac{n_{ijt}}{\sum_j n_{ijt}} \tag{6}$$

where $j = 1, , J$ indexes each of the scientific keywords appearing in the titles of the journal articles published by scientist i up to year t,[8] n_{ijt} is the number of times each of the keywords

[8]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.

j has appeared in scientist i's articles published by year t, and w_{jt} is a weight for each keyword that measures the relative 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 (the calculation of w_{jt} is detailed in the data appendix).

4.2 Descriptive Statistics

Among the 4,270 researchers in our sample, 814 (19%) hold one or more patents. In Figure 1, we plot the distribution of patents for the patenting researchers in our sample. Most of the patenters are listed on 1 or 2 patents throughout their career, and very few scientists in our data receive more than 10. Figure 2 displays the distribution of scientists' total publication count, broken out by their patenting status. The distribution for the patenter subsample is much less skewed than that of the non-patenter subsample.

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. Researchers who have sought and received patent rights for their discoveries appear more productive at each of these five stages: they publish almost twice as many research papers as those who have not yet entered the patenting regime. Except in the first period (the 5^{th} year subsequent to the year of Ph.D. degree), patenters appear to have more NIH grant support. The difference between the two groups in the grant measure is relatively small compared to that in the research publication count, though the gap widens as experience increases. At all career stages, scientists who have applied for patent rights appear 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.

4.3 Results

We begin by presenting results pertaining to the probability of obtaining a patent (flow formulation) or of becoming a patenter (regime formulation). We also perform a similar exercise for the probability of exit from academia. The results are displayed in Tables 4 and 5. It is important to note that the list of independent variables and the risk set differ significantly across the flow and regime models. In the former, all scientist-year observations are included, and the list of independent variables include a lag structure for patenting in order to address the possibility of structural state dependence. In the latter, the observations corresponding to years subsequent to the year of the first patent application are not part of the risk set; consequently, no lag structure for the dependent variable can be part of the set of right-hand side variables.

The econometric analysis confirms that time-varying confounders are important determinants of patenting activity for these scientists. First, controlling for the stock of publications up to year $t-2$, the probability of patenting in year t is significantly increasing in the flow of publications in year $t-1$: at the mean of the data, a standard deviation increase in the flow of lagged publications increases the probability of patenting by 14.4% for the flow specification (column 1) and by 17.8% for the regime specification (column 3). While no effect of past grants was detected, we also find that previous ties to industry in the form of coauthorships, and the stock of patents for the scientist's university increase the likelihood of patenting activities. Similarly, scientists working in areas of science that are inherently more amenable to patenting are, unsurprisingly, more likely to patent. At the mean of the data, a standard deviation increase in patentability increases the probability of patenting from 0.013 to 0.027 (column 1 – flow specification) and from 0.042 ro 0.142 (column 3 – regime specification). In light of these results, the shortcomings of some commonly used identification strategies become clearer. First, instrumental variables based on the characteristics of the employer are probably invalid, as the matching of scientists with employers appears to take into account patenting and traditional research activities. Second, selection into "treatment" is influenced by transitory shocks to outcome variables of interest, such as publications. While scientist fixed effects purge econometric estimates from selection bias stemming from immutable characteristics, they will fail to account for the dynamics of the selection process.

Table 5 displays the results corresponding to the models of the probability of exit from academia. A priori, one might imagine that academic scientists leave academia because they do not achieve success according to the most commonly used metrics of academic productivity: grants and publications.[9] One might also conjecture that very productive academics are more likely to be poached by the private sector, leading to a premature exit from the academic ranks. We find support only for the former story. Even controlling for the stock of past grants and publications, a dry spell in academic productivity significantly increases the likelihood of exit. The stock of patents or research patentability has no such effect.

Tables 6 through 9 present results pertaining to the effect of patenting on research output. We begin by reporting the results of pooled cross-sectional specifications in Table 6, which is divided in 5 panels corresponding to different dependent variables: the count of research publications (Table 6.1, negative binomial model), the log of count of research publications (Table 6.2, linear model), the count of NIH grants (Table 6.3, negative binomial model), the count of publications coauthored with industry scientists (Table 6.4, zero-inflated negative binomial model), and the proportion of publications coauthored with industry scientists (Table 6.5, two-sided tobit model). Each panel is further subdivided into three sets of results, corresponding to three definitions of the patenting variable: flow (Models 1 and 2), regime (Models 3 and 4), and stock (Models 5 and 6). Finally, in each of these sets, the first column corresponds to the estimates of a "naive" cross-section, while the second column reports IPTCW estimates. Table 6.1 produces two robust results: (a) patenting, however defined, is positively associated with publishing; and (b) the magnitude of this effect is much lower once we account for self-selection into patenting. However, the magnitudes of our estimates is implausibly high, even in the IPTCW specifications. This is most easily

[9]In the life sciences, grants play an especially large role, as academics do not draw a fixed salary from the university, but are expected to pay themselves from grants.

seen in Table 6.2, since the coefficients are directly interpretable in terms of elasticities: The elasticity of publication with respect to patenting is .219 for the flow specification and .234 for the regime specification. It is important to bear in mind that IPTCW estimates address selection on observables. Since the specifications of Table 6 perform a comparison in levels, these estimates are contaminated by unobserved heterogeneity; namely, "better" scientists (in a time-invariant sense of the word) are both more likely to patent and publish heavily. To the extent that such variation in quality is not captured by observable covariates, our estimates will remain biased and inconsistent.

The results in Table 6.3 indicate that the results above do not carry to the grant measure of output. In particular, the weighted estimates imply that patenting researchers are not significantly more successful at getting grants from the NIH than are non-patenting researchers. This is interesting, because the hurdle that needs to be cleared to get a grant from the NIH is much higher than that required to publish a scientific article. Indeed, in our sample, only about 20% of scientists secure one NIH grant during their career. Of course, patenting activities could be associated with easier access to research grants and contracts from industry, which we do not observe. Table 6.3 and 6.4 indicate that patenting researchers coauthor much more with corporate scientists than their non-patenting counterparts. The results hold even when one controls for selection into patenting.

Tables 7.1 through 7.4 report fixed effects estimates. These tables compare the change in research output that results from patenting activities. When the patenting effect is defined as a regime shift, this is similar to the classic "difference in differences" specification often used by labor and public economists. In each of these tables, we estimate the model on two distinct samples: the full sample, and the sample of scientists who eventually patent. This is important insofar as year effects and the patenting treatment effects are not separately identified in these models. The full sample estimates provide a comparison of the change in output for scientists who enter the patenting regime, relative to the change in output experienced by non-patenters and scientists who have not patented yet, but will in the future. Restricting the sample means that only these eventual patenters are "controls." The estimates produced by the fixed effects approach are of smaller magnitude than the cross-sectional estimates, though still large and statistically significant. The estimates using only "eventual patenters" as controls are about 1/3 smaller than those obtained with the full sample. This makes sense to the extent that researchers who patent are "more alike" than are patenting and non-patenting researchers.

One informal test of the validity of the "difference in differences" strategy is to examine the time-series evolution of the treatment effect. In Table 8 we interact the patenting regime dummy with a set of year effects. Columns (1) through (5) perform this exercise for the cross-section. Columns (6) through (10) perform it for the fixed-effects specifications. The cross-sectional estimates indicate that patenters and non-patenters have higher output even before the year of first patent application. This result also holds within scientist: the effect of patenting on productivity is already apparent a full two years before the year of first patent application (Models 7 and 10). This confirms our earlier suspicion that patenters and non-patenters do not follow similar output trends either before or after the patenting event.

Table 9 presents estimates that combines IPTCW weights with fixed effects. Intuitively, these specifications compare the changes in output of patenters with that of "comparable" non-patenters — subject to the assumption of selection on observables. To ease the comparison between the different econometric approaches, we display the "naive" fixed effect estimates side-by-side with the IPTCW estimates. As explained above, this exercise can only be performed when the dependent variable is the log of publications, since weighted fixed effect models cannot be consistently estimated in the case of limited dependent variables (such as a count, a proportion, or a dichotomous variable). The magnitudes of the patenting effect are halved by the use of the selection weights, but the estimates remain statistically and economically significant. For instance, Model (4) implies that entering the patenting regime is associated with a 8.7% increase in the numbers of papers published. While still sizable, this effect is of a more reasonable magnitude than those obtained in previous specifications.

5 Discussion and Conclusion

Our findings persuasively establish that the most prolific scientists in terms of the standard measures of professional achievement are the most likely to patent. We also find, contrary to the common perception in the literature, that academic scientists that patent are actually somewhat more productive than otherwise equivalent scientists that are not listed as inventors on patents. Thus, the evidence definitively rejects the first-order assertion that the increase in patenting in academe has come at the cost of diverting researchers' time, interest, and attention from their traditional focus on standard scientific research. However, there are a number of other avenues, all outside the scope of this analysis, through which patenting in academic science could yet have a significant—and possibly deleterious—effect on the advancement of scientific knowledge. These alternative paths of influence include "anti-commons" effects, the impact of senior researchers' patenting on the career trajectories of scientists in training, and the incentive that the option of patenting provides to change the focus of research. As a result, beyond the first-order effect of a scientist's decision to patent on his or her individual productivity, our conclusions must remain tempered.

Regarding the third of these possibilities, although the evidence we have presented that patenting may induce scientists to shift their research focus to more applied projects is admittedly assailable, the very strong effect of the research patentability covariate on the likelihood that scientists patent demonstrates considerable variation across scientific areas in amenability to patenting. Thus, it appears that scientists can choose research projects on the basis of ease of patenting. Insofar as scientists perceive the chance for significant remuneration from patenting, either from their entitlement to a share of royalties on patent licenses or from increased options for consulting or advisory board memberships, one would expect that the presence of the option to patent will in fact lead scientists to choose research topics that differ from what they would have chosen if the option were unavailable.

Although we have found that patenting does not detract from the patenter's research productivity, the question of the consequences of the patenter's action on the output of colleagues is outside of the scope of this paper's analysis. It would be reasonable to speculate that social learning about the process of patenting would lead to local contagion (e.g., within university department) in the decision to patent. Moreover, relative to non-patenters, patenting scientists self-report a greater tendency to withhold information about their research projects. As patenting within a department or research area continues to grow, is there a point at which a negative effect on the collective output sets in, either because researchers are deterred or blocked by intellectual property rights held by others, or because concerns about intellectual property rights diminish open communications among scientists?

Finally, it is possible that the most significant effect of faculty patenting manifests in the career choices of the graduate students and post-doctoral fellows that work in the laboratories of patenters. For instance, patenters may have much thicker and more diverse relationships with researchers in firms than non-patenting scientists, which may in turn facilitate apprentice scientists' job searches in the private sector. Therefore, patenters may (perhaps unintentionally) encourage their students to select private-sector careers above academic posts. Conversely, if patenters enlist the help of scientists-in-training in the research streams that lead to patents, and if these projects are different in character from the research topics that intrigue non-patenters, it is is possible that apprentices training under patenters may be less appealing to academic departments searching for new faculty. In short, the most significant impact of patenting on public research output may well lie in the consequence of the behavior for non-patenting and soon-to-be scientists.

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Tables and Figures

Figure 1: Distribution of Patent Count for Patenting Scientists

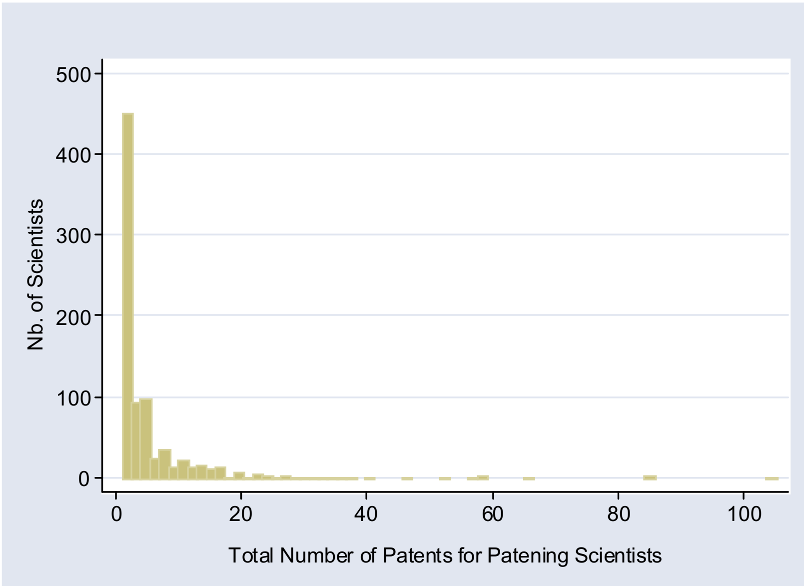

Figure 2: Distribution of Publication Count for Patenting and Non-patenting Scientists

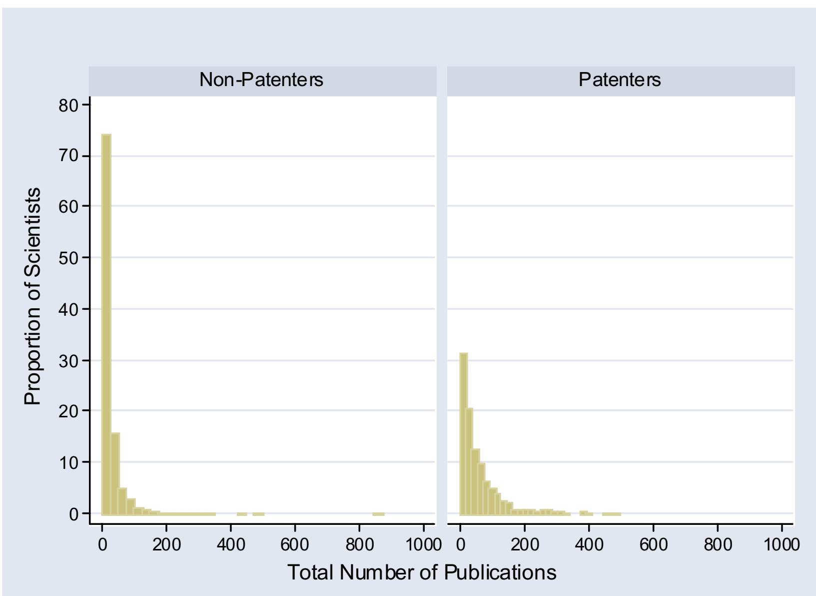

Table 1

Top 15 Scientific Disciplines in the Sample

UMI Subject Code	UMI Subject Description	Frequency	
487; 303	Biochemistry	972	(22.8%)
306	Biology, General	611	(14.3%)
410	Biology, Microbiology	513	(12.0%)
419	Health Sciences, Pharmacology	248	(5.8%)
490	Chemistry, Organic	233	(5.5%)
786	Biophysics, General	231	(5.4%)
369	Biology, Genetics	221	(5.2%)
982	Health Sciences, Immunology	186	(4.4%)
433	Biology, Animal Physiology	185	(4.1%)
307	Biology, Molecular	114	(2.7%)
301	Bacteriology	67	(1.6%)
287	Biology, Anatomy	60	(1.4%)
571	Health Sciences, Pathology	53	(1.2%)
542	Engineering, Chemical	34	(0.8%)
572	Health Sciences, Pharmacy	34	(0.8%)

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 (64,483 person-year observations)				
Patent flow dummy	0.039	0.193	0	1
Patent regime dummy	0.123	0.329	0	1
Patent stock	0.512	2.835	0	105
Count of research publications	1.687	2.764	0	103
Log of count of research publications	0.701	0.703	0	4.64
Count of NIH Grants	0.269	0.635	0	16
Count of res. pub. with company scientists	0.136	0.578	0	26
Research patentability score	10.411	9.385	0	57.785
Experience	10.227	7.158	1	32
Employer graduate school in top 20	0.234	0.423	0	1
Employer has TTO	0.487	0.500	0	1
Employer patent stock (in hundred)	0.733	1.492	0	21.89
Calendar year	1986	7.770	1968	1999
Time-invariant (4,270 observations)				
Female	0.214	0.410	0	1
Ph.D. univ. grad. school in top 20	0.310	0.462	0	1
Ph.D. univ. 5-yr patent stock (in hundred)	0.205	0.442	0	6.11

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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	
Ever applied for patents	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*
Count of research publications	2.403	1.180	3.028	1.728	3.709	1.973	4.011	2.141	3.873	2.069
Count of NIH Grants	0.157	0.164	0.367	0.345	0.449	0.413	0.511	0.441	0.454	0.341
Count of res. pub. with firm scientists	0.305	0.059	0.339	0.112	0.480	0.153	0.464	0.216	0.415	0.172
Research Patentability	11.759	6.046	15.398	11.369	20.123	15.919	25.015	20.953	28.313	24.035
Employer grad. school rank in top20	0.254	0.266	0.251	0.220	0.241	0.198	0.190	0.191	0.171	0.191
Employer has TTO	0.449	0.386	0.565	0.476	0.690	0.581	0.728	0.674	0.820	0.716
Employer Patent stock (in 100)	0.708	0.566	1.051	0.645	1.215	0.740	1.254	1.097	1.523	1.266
Observations	236	3,937	354	2,479	381	1,641	364	1,065	205	507

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 4
Probability of Patenting

	Model 1	Model 2	Model 3	Model 4
Dependent Variable	Patent flow dummy		Patent regime dummy	
	Denominator	*Numerator*	*Denominator*	*Numerator*
Experience = [5, 8]	0.006	0.374	-0.448	0.008
	(0.087)	(0.080)***	(0.115)***	(0.105)
Experience = [9, 15]	-0.252	0.484	-1.004	0.011
	(0.113)**	(0.095)***	(0.143)***	(0.109)
Experience = [16, 22]	-0.680	0.419	-1.550	0.009
	(0.150)***	(0.119)***	(0.195)***	(0.128)
Experience = [23, 35]	-1.252	0.019	-2.326	-0.567
	(0.191)***	(0.152)	(0.283)***	(0.201)***
Female	-1.203	-1.266	-1.068	-1.162
	(0.147)***	(0.152)***	(0.135)***	(0.132)***
Patent flow (t-1)	1.103	1.254		
	(0.067)***	(0.072)***		
Patent stock (t-2)	0.162	0.182		
	(0.025)***	(0.025)***		
Research patentability (t-1)	0.079		0.142	
	(0.008)***		(0.010)***	
Research publications flow (*t*-1)	0.051		0.071	
	(0.010)***		(0.013)***	
Research publications stock (*t*-2)	-0.000		-0.007	
	(0.001)		(0.003)**	
Has collaborated with firm researchers (*t*-1)	0.489		0.256	
	(0.079)***		(0.096)***	
Employer patent stock (*t*-1) (in hundred)	0.033		0.078	
	(0.020)		(0.027)***	
PhD univ. patent 5-yr stock > 17 (75th percentile)	0.085	0.088	0.150	0.140
	(0.077)	(0.079)	(0.087)*	(0.083)*
Constant	-8.314	-8.234	-8.567	-8.244
	(1.003)***	(0.997)***	(1.138)***	(0.998)***
Observations	64483	64483	57335	57335
Num. of researchers	4270	4270	4270	4270
Log-likelihood	-7845.52	-8185.10	-3856.43	-4099.48
Wald Chi2	2138.54	1477.98	636.00	256.44
Model degrees of freedom	46	41	44	39
Peudo R-square	0.26	0.22	0.10	0.04

Notes:
(1) Models 3 and 4 exclude observations after a researcher's year of first patent application.
(2) All models control for PhD subject and year effects.
(3) Experience = [1, 4] is the base category.
(4) Robust standard errors in parentheses, clustered around individual researchers. .
(5) * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5
Probability of Exiting Academia

	Model 1-Denominator	Model 2-Numerator
Experience = [9, 15]	-0.324	-0.551
	(0.059)***	(0.055)***
Experience = [16, 22]	-0.387	-0.747
	(0.084)***	(0.073)***
Experience = [23, 30]	-0.176	-0.565
	(0.113)	(0.096)***
Female	0.145	0.261
	(0.056)***	(0.055)***
Patent stock (t-1)	-0.037	-0.058
	(0.013)***	(0.014)***
Research patentability	-0.007	
	(0.005)	
Research publications flow (*t*-1)	-0.172	
	(0.020)***	
Research publications flow (*t*-2)	-0.122	
	(0.019)***	
Research publications stock (*t*-3)	-0.007	
	(0.003)***	
NIH grants flow dummy (*t*-1)	-1.198	
	(0.129)***	
NIH grants flow dummy (*t*-2)	-0.321	
	(0.127)**	
NIH grants stock dummy (*t*-3)	0.105	
	(0.063)*	
Has collaborated with firm researchers (*t*-1)	0.012	
	(0.008)	
Employer grad. school in top 20 (*t*)	0.066	
	(0.061)	
Employer has TTO (*t*)	0.123	
	(0.052)**	
Employer patent stock (*t*-1) (in hundred)	0.037	
	(0.016)**	
PhD univ. grad. school rank in top 20	-0.146	-0.210
	(0.053)***	(0.052)***
PhD univ. patent 5-yr stock $>$ 17 (75th percentile)	0.024	0.023
	(0.059)	(0.058)
Constant	-3.069	-3.414
	(0.274)***	(0.272)***
Observations	47321	47321
Num. of researchers	4179	4179
Log-likelihood	-8482.97	-8921.67
Wald Chi2	803.51	382.90
Model degrees of freedom	51	40
Pseudo R-square	0.07	0.02

Notes:
(1) We treat a researcher as having exited academia when he or she stops publishing research for five consecutive years or is observed to have published predominantly under corporate affiliations. In either case, the year when the researcher is last observed as publishing under an academic institution is recorded as his or her last year in academia. A researcher is at risk of exiting academia for the 30 years subsequent to the grant of his or her Ph.D. degree.
(2) All models control for PhD subject and year effects.
(3) Experience = [5, 8] is the base category; observations for experience = [1, 4] were excluded as exit status is completely determined for the period due to our data collection method.
(4) Robust standard errors in parentheses, clustered around individual researchers.
(5) * significant at 10%; ** significant at 5%; *** significant at 1%

Table 6.1
Negative Binomial Regression of Count of Research Publications

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Type of patent effect	Patent Flow		Patent Regime		Patent Stock	
	Pooled Cross-section	*IPTCW*	*Pooled Cross-section*	*IPTCW*	*Pooled Cross-section*	*IPTCW*
Experience = [5, 8]	0.395	0.346	0.371	0.337	0.390	0.344
	(0.019)***	(0.019)***	(0.019)***	(0.019)***	(0.019)***	(0.019)***
Experience = [9, 15]	0.711	0.629	0.665	0.592	0.697	0.623
	(0.029)***	(0.029)***	(0.030)***	(0.030)***	(0.030)***	(0.030)***
Experience = [16, 22]	0.886	0.765	0.805	0.692	0.851	0.752
	(0.049)***	(0.048)***	(0.050)***	(0.048)***	(0.050)***	(0.048)***
Experience = [23, 35]	0.841	0.658	0.752	0.560	0.782	0.631
	(0.069)***	(0.070)***	(0.069)***	(0.070)***	(0.070)***	(0.070)***
Female	-0.207	-0.243	-0.163	-0.222	-0.204	-0.241
	(0.055)***	(0.050)***	(0.055)***	(0.049)***	(0.055)***	(0.050)***
Employer grad school in top20 (t)	0.049	0.049	0.063	0.067	0.055	0.047
	(0.044)	(0.041)	(0.044)	(0.044)	(0.044)	(0.041)
Employer has TTO (t)	0.163	0.159	0.152	0.155	0.154	0.157
	(0.036)***	(0.035)***	(0.036)***	(0.034)***	(0.036)***	(0.035)***
Employer patent stock (t) (in hundred)	0.031	0.015	0.028	0.020	0.029	0.015
	(0.012)***	(0.011)	(0.013)**	(0.012)	(0.012)**	(0.011)
PhD univ. grad school in top 20	0.053	0.089	0.059	0.079	0.052	0.089
	(0.041)	(0.039)**	(0.041)	(0.039)**	(0.041)	(0.039)**
PhD univ. 5-yr patent stock (in hundred)	0.033	0.032	0.028	0.008	0.042	0.036
	(0.051)	(0.053)	(0.051)	(0.053)	(0.051)	(0.053)
Patent flow dummy (t)	0.733	0.433				
	(0.049)***	(0.053)***				
Patent regime dummy (t)			0.608	0.438		
			(0.047)***	(0.054)***		
Patent stock (t)					0.059	0.041
					(0.009)***	(0.011)***
Constant	-0.927	-0.944	-0.938	-0.942	-0.928	-0.943
	(0.108)***	(0.107)***	(0.108)***	(0.107)***	(0.108)***	(0.107)***
Observations	64483	63193	64483	63198	64483	63193
Num. of researchers	4270	4268	4270	4269	4270	4268
Log likelihood	-109930.46	-99963.58	-109584.56	-100184.04	-109969.71	-99956.98
Wald Chi2	2472.08	1725.06	2381.23	1620.46	2086.37	1565.30
Change in d.f.	47	47	47	47	47	47
p>Chi2	0.00	0.00	0.00	0.00	0.00	0.00

Notes:
(1) Models 2 , 4 and 6 use Inverse Probability of Treatment and Censoring Weights (IPTCW), which is the product of (a) Inverse Probability of Treatment Weights (IPTW) derived from the logit regression of treatment (i.e., the researcher applying for one or more patents in a given year for Models 2 and 6, and the researcher entering patenting regime for Model 4) on variables that may confound the patenting effect, and (b) Inverse Probability of Censoring Weights (IPCW) derived from the logit regression of censoring (i.e., the researcher exiting academia in a given year).
(2) Models 2, 4 and 6 exclude observations with extremely large (top 1%) and small (bottom 1%) weights.
(3) All models control for PhD subject and year effects
(4) Experience = [1, 4] is the base category for the experience dummies.
(5) Robust standard errors in parentheses; clustered around researchers.
(6) * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6.2
Regression of Log of Count of Research Publications

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Type of patent effect	Patent Flow		Patent Regime		Patent Stock	
	Pooled Cross-section	*IPTCW*	*Pooled Cross-section*	*IPTCW*	*Pooled Cross-section*	*IPTCW*
Experience = [5, 8]	0.184	0.164	0.174	0.159	0.185	0.164
	(0.008)***	(0.008)***	(0.008)***	(0.008)***	(0.008)***	(0.008)***
Experience = [9, 15]	0.335	0.288	0.311	0.269	0.333	0.286
	(0.013)***	(0.013)***	(0.013)***	(0.013)***	(0.013)***	(0.013)***
Experience = [16, 22]	0.407	0.332	0.367	0.295	0.397	0.326
	(0.022)***	(0.022)***	(0.022)***	(0.021)***	(0.022)***	(0.022)***
Experience = [23, 35]	0.383	0.276	0.333	0.225	0.352	0.262
	(0.035)***	(0.034)***	(0.035)***	(0.034)***	(0.035)***	(0.034)***
Female	-0.111	-0.122	-0.094	-0.110	-0.112	-0.121
	(0.019)***	(0.017)***	(0.019)***	(0.017)***	(0.019)***	(0.017)***
Employer grad school in top20 (t)	0.020	0.017	0.024	0.019	0.019	0.016
	(0.019)	(0.018)	(0.019)	(0.018)	(0.019)	(0.018)
Employer has TTO (t)	0.086	0.080	0.081	0.080	0.085	0.079
	(0.015)***	(0.014)***	(0.015)***	(0.014)***	(0.015)***	(0.014)***
Employer patent stock (t) (in hundred)	0.018	0.010	0.016	0.010	0.017	0.009
	(0.006)***	(0.005)*	(0.007)**	(0.005)*	(0.006)***	(0.005)*
PhD univ. grad school in top 20	0.038	0.052	0.040	0.052	0.039	0.053
	(0.018)**	(0.017)***	(0.018)**	(0.017)***	(0.018)**	(0.017)***
PhD univ. 5-yr patent stock (in hundred)	-0.002	-0.008	-0.002	-0.015	-0.000	-0.007
	(0.023)	(0.022)	(0.022)	(0.022)	(0.023)	(0.023)
Patent flow dummy (t)	0.445	0.219				
	(0.036)***	(0.031)***				
Patent regime dummy (t)			0.353	0.234		
			(0.028)***	(0.030)***		
Patent stock (t)					0.031	0.021
					(0.006)***	(0.005)***
Constant	0.217	0.209	0.214	0.209	0.217	0.209
	(0.019)***	(0.019)***	(0.019)***	(0.019)***	(0.019)***	(0.019)***
Observations	64483	63193	64483	63198	64483	63193
Num. of researchers	4270	4268	4270	4269	4270	4268
F-statistics	58.04	44.87	58.48	43.70	57.15	43.70
Model degrees of freedom	47	47	47	47	47	47
Adjusted R^2	0.11	0.08	0.12	0.08	0.11	0.08

Notes:
(1) Models 2 , 4 and 6 use Inverse Probability of Treatment and Censoring Weights (IPTCW), which is the product of (a) Inverse Probability of Treatment Weights (IPTW) derived from the logit regression of treatment (i.e., the researcher applying for one or more patents in a given year for Models 2 and 6, and the researcher entering patenting regime for Model 4) on variables that may confound the patenting effect, and (b) Inverse Probability of Censoring Weights (IPCW) derived from the logit regression of censoring (i.e., the researcher exiting academia in a given year).
(2) Models 2, 4 and 6 exclude observations with extremely large (top 1%) and small (bottom 1%) weights.
(3) All models control for PhD subject and year effects
(4) Experience = [1, 4] is the base category for the experience dummies.
(5) Robust standard errors in parentheses; clustered around researchers.
(6) * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6.3
Negative Binomial Regression of Count of NIH Grants

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Type of patent effect	Patent Flow		Patent Regime		Patent Stock	
	Pooled Cross-section	*IPTCW*	*Pooled Cross-section*	*IPTCW*	*Pooled Cross-section*	*IPTCW*
Experience = [5, 8]	1.606	1.553	1.603	1.548	1.608	1.554
	(0.050)***	(0.050)***	(0.050)***	(0.050)***	(0.049)***	(0.050)***
Experience = [9, 15]	2.138	2.036	2.131	2.023	2.143	2.037
	(0.065)***	(0.066)***	(0.066)***	(0.067)***	(0.065)***	(0.066)***
Experience = [16, 22]	2.376	2.190	2.363	2.147	2.384	2.193
	(0.086)***	(0.090)***	(0.086)***	(0.090)***	(0.086)***	(0.090)***
Experience = [23, 35]	2.226	1.912	2.211	1.831	2.237	1.913
	(0.128)***	(0.135)***	(0.128)***	(0.137)***	(0.128)***	(0.135)***
Female	-0.291	-0.397	-0.281	-0.398	-0.302	-0.399
	(0.090)***	(0.088)***	(0.091)***	(0.088)***	(0.090)***	(0.088)***
Employer grad school in top20 (t)	0.052	0.029	0.055	0.038	0.053	0.029
	(0.069)	(0.072)	(0.069)	(0.073)	(0.069)	(0.072)
Employer has TTO (t)	0.325	0.367	0.323	0.373	0.326	0.368
	(0.055)***	(0.057)***	(0.055)***	(0.056)***	(0.055)***	(0.057)***
Employer patent stock (t) (in hundred)	0.048	0.029	0.047	0.025	0.049	0.028
	(0.017)***	(0.018)	(0.017)***	(0.018)	(0.017)***	(0.018)
PhD univ. grad school in top 20	0.246	0.271	0.246	0.282	0.246	0.271
	(0.064)***	(0.068)***	(0.065)***	(0.068)***	(0.065)***	(0.068)***
PhD univ. 5-yr patent stock (in hundred)	0.131	0.180	0.131	0.149	0.131	0.180
	(0.089)	(0.099)*	(0.089)	(0.099)	(0.089)	(0.099)*
Patent flow dummy (t)	0.147	0.106				
	(0.075)*	(0.099)				
Patent regime dummy (t)			0.129	0.156		
			(0.074)*	(0.110)		
Patent stock (t)					-0.006	0.001
					(0.008)	(0.011)
Constant	-4.226	-4.222	-4.228	-4.237	-4.226	-4.223
	(0.275)***	(0.275)***	(0.275)***	(0.276)***	(0.275)***	(0.275)***
Observations	64483	63193	64483	63198	64483	63193
Num. of researchers	4270	4268	4270	4269	4270	4268
Log likelihood	-38283.95	-32850.64	-38276.98	-33120.91	-38288.53	-32852.29
Wald Chi2	2032.50	1732.81	2031.99	1734.00	2028.54	1733.83
Model degrees of freedom	47	47	47	47	47	47
p>Chi2	0.00	0.00	0.00	0.00	0.00	0.00

Notes:
(1) Models 2 , 4 and 6 use Inverse Probability of Treatment and Censoring Weights (IPTCW), which is the product of (a) Inverse Probability of Treatment Weights (IPTW) derived from the logit regression of treatment (i.e., the researcher applying for one or more patents in a given year for Models 2 and 6, and the researcher entering patenting regime for Model 4) on variables that may confound the patenting effect, and (b) Inverse Probability of Censoring Weights (IPCW) derived from the logit regression of censoring (i.e., the researcher exiting academia in a given year).
(2) Models 2, 4 and 6 exclude observations with extremely large (top 1%) and small (bottom 1%) weights.
(3) All models control for PhD subject and year effects
(4) Experience = [1, 4] is the base category for the experience dummies.
(5) Robust standard errors in parentheses; clustered around researchers.
(6) * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6.4
Zero Inflated Negative Binomial Regression of Count of Research Publications in Collaboration with Company Researchers

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Type of patent effect	Patent Flow		Patent Regime		Patent Stock	
	Pooled Cross-section	*IPTCW*	*Pooled Cross-section*	*IPTCW*	*Pooled Cross-section*	*IPTCW*
Count model						
Experience = [5, 8]	0.301	0.191	0.241	0.188	0.143	0.111
	(0.213)	(0.214)	(0.207)	(0.185)	(0.138)	(0.280)
Experience = [9, 15]	0.863	0.768	0.754	0.717	0.518	0.648
	(0.255)***	(0.221)***	(0.242)***	(0.189)***	(0.180)***	(0.316)**
Experience = [16, 22]	1.103	1.056	0.963	0.969	0.633	0.886
	(0.333)***	(0.272)***	(0.305)***	(0.223)***	(0.226)***	(0.401)**
Experience = [23, 35]	1.134	1.041	0.951	0.894	0.598	0.794
	(0.368)***	(0.304)***	(0.340)***	(0.266)***	(0.252)**	(0.446)*
Female	-0.085	-0.062	0.004	-0.070	-0.083	-0.077
	(0.187)	(0.189)	(0.194)	(0.174)	(0.195)	(0.182)
Employer grad school in top20 (t)	0.103	0.115	0.152	0.218	0.062	0.097
	(0.118)	(0.113)	(0.115)	(0.121)*	(0.121)	(0.117)
Employer has TTO (t)	-0.115	-0.160	-0.135	-0.213	0.016	-0.101
	(0.126)	(0.130)	(0.129)	(0.134)	(0.122)	(0.185)
Employer patent stock (t) (in hundred)	-0.048	-0.054	-0.056	-0.058	-0.047	-0.058
	(0.030)	(0.034)	(0.028)*	(0.034)*	(0.023)**	(0.031)*
PhD univ. grad school in top 20	-0.082	-0.036	-0.104	-0.115	-0.109	-0.037
	(0.124)	(0.114)	(0.125)	(0.111)	(0.113)	(0.156)
PhD univ. 5-yr patent stock (in hundred)	0.013	-0.000	0.037	0.006	0.248	0.126
	(0.299)	(0.260)	(0.319)	(0.262)	(0.183)	(0.571)
Patent flow dummy (t)	0.616	0.278				
	(0.208)***	(0.189)				
Patent regime dummy (t)			0.602	0.515		
			(0.158)***	(0.136)***		
Patent stock (t)					0.034	0.005
					(0.012)***	(0.010)
Constant	-1.972	-1.964	-1.936	-1.973	-1.742	-1.893
	(0.462)***	(0.548)***	(0.414)***	(0.474)***	(0.253)***	(0.420)***

Continued in next page

Table 6.4
Zero Inflated Negative Binomial Regression of Count of Research Publications in Collaboration with Company Researchers (Continued)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Type of patent effect	Patent Flow		Patent Regime		Patent Stock	
	Pooled Cross-section	*IPTCW*	*Pooled Cross-section*	*IPTCW*	*Pooled Cross-section*	*IPTCW*
Logit model (Y=0)						
Experience = [5, 8]	-0.392	-0.455	-0.385	-0.411	-0.488	-0.536
	(0.256)	(0.238)*	(0.247)	(0.229)*	(0.194)**	(0.353)
Experience = [9, 15]	-0.056	-0.025	-0.056	0.018	-0.415	-0.157
	(0.414)	(0.356)	(0.365)	(0.316)	(0.240)*	(0.415)
Experience = [16, 22]	0.028	0.154	0.067	0.265	-0.529	-0.074
	(0.612)	(0.525)	(0.521)	(0.451)	(0.333)	(0.592)
Experience = [23, 35]	0.394	0.620	0.413	0.689	-0.241	0.240
	(0.798)	(0.719)	(0.691)	(0.632)	(0.372)	(0.698)
Female	0.339	0.398	0.309	0.287	0.142	0.306
	(0.234)	(0.243)	(0.242)	(0.246)	(0.215)	(0.235)
Employer grad school in top20 (t)	0.313	0.363	0.350	0.498	0.133	0.310
	(0.245)	(0.249)	(0.230)	(0.275)*	(0.177)	(0.208)
Employer has TTO (t)	-0.519	-0.578	-0.498	-0.625	-0.244	-0.452
	(0.254)**	(0.253)**	(0.231)**	(0.254)**	(0.159)	(0.240)*
Employer patent stock (t) (in	-0.242	-0.260	-0.245	-0.293	-0.167	-0.260
hundred)	(0.099)**	(0.080)***	(0.0998)**	(0.094)***	(0.083)**	(0.094)***
PhD univ. grad school in top 20	0.170	0.197	0.103	0.097	0.094	0.172
	(0.273)	(0.260)	(0.248)	(0.212)	(0.156)	(0.306)
PhD univ. 5-yr patent stock (in	-0.369	-0.468	-0.268	-0.304	0.195	-0.054
hundred)	(1.476)	(1.526)	(1.312)	(1.233)	(0.232)	(1.598)
Patent flow dummy (t)	-1.631	-0.867				
	(0.352)***	(0.285)***				
Patent regime dummy (t)			-1.050	-0.692		
			(0.229)***	(0.212)***		
Patent stock (t)					-1.282	-0.542
					(0.658)*	(0.849)
Constant	2.204	2.263	2.224	2.133	2.442	2.339
	(0.484)***	(0.595)***	(0.439)***	(0.547)***	(0.264)***	(0.388)***
Observations	64483	63193	64483	63198	64483	63193
Num. of observations = 0	58964	58067	58964	57921	58964	58067
Num. of researchers	4270	4268	4270	4269	4270	4268
Log likelihood	-23000.33	-19578.99	-22843.70	-19636.95	-22836.89	-19567.19
Wald Chi2	120.50	129.57	128.59	157.59	78.98	97.46
Model degrees of freedom	23	23	23	23	23	23
p>Chi2	0.00	0.00	0.00	0.00	0.00	0.00

Notes:
(1) Models 2 , 4 and 6 use Inverse Probability of Treatment and Censoring Weights (IPTCW), which is the product of (a) Inverse Probability of Treatment Weights (IPTW) derived from the logit regression of treatment (i.e., the researcher applying for one or more patents in a given year for Models 2 and 6, and the researcher entering patenting regime for Model 4) on variables that may confound the patenting effect, and (b) Inverse Probability of Censoring Weights (IPCW) derived from the logit regression of censoring (i.e., the researcher exiting academia in a given year).
(2) Models 2, 4 and 6 exclude observations with extremely large (top 1%) and small (bottom 1%) weights.
(3) All models control for PhD subject period effects (periods are coded as 1968-1975, 1976-1980, 1981-1985, 1986-1990, 1991-1995, 1996-2000; the first period is the base category).
(4) Experience = [1, 4] is the base category for the experience dummies.
(5) Robust standard errors in parentheses; clustered around researchers.
(6) * significant at 10%; ** significant at 5%; *** significant at 1%.
(7) Vuong test was conducted for models 1, 3 and 5, and are positive and significant at 0.01. Vuong statistics can not be computed in models 2, 4 and 6 due to the inclusion of weights. However, we believe that given the proportion of zero observations in the dataset, the applicability of the inflated model is not likely to be influenced by the inclusion of weights.

Table 6.5
Two-sided Tobit Regression of Proportion of Research Publications with Company Researchers

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Type of patent effect	Patent Flow		Patent Regime		Patent Stock	
	Pooled Cross-section	*IPTCW*	*Pooled Cross-section*	*IPTCW*	*Pooled Cross-section*	*IPTCW*
Experience = [5, 8]	0.300	0.309	0.275	0.291	0.305	0.311
	(0.040)***	(0.048)***	(0.041)***	(0.048)***	(0.040)***	(0.048)***
Experience = [9, 15]	0.467	0.492	0.415	0.444	0.467	0.492
	(0.051)***	(0.061)***	(0.052)***	(0.061)***	(0.051)***	(0.061)***
Experience = [16, 22]	0.546	0.597	0.465	0.508	0.533	0.595
	(0.064)***	(0.078)***	(0.066)***	(0.077)***	(0.064)***	(0.078)***
Experience = [23, 35]	0.459	0.434	0.358	0.314	0.412	0.418
	(0.084)***	(0.106)***	(0.086)***	(0.102)***	(0.086)***	(0.107)***
Female	-0.158	-0.187	-0.114	-0.142	-0.167	-0.192
	(0.055)***	(0.062)***	(0.055)**	(0.062)**	(0.055)***	(0.062)***
Employer grad school in top20 (t)	-0.016	-0.026	-0.002	-0.001	-0.019	-0.028
	(0.050)	(0.058)	(0.050)	(0.058)	(0.050)	(0.058)
Employer has TTO (t)	0.096	0.126	0.083	0.113	0.095	0.127
	(0.045)**	(0.053)**	(0.046)*	(0.052)**	(0.045)**	(0.053)**
Employer patent stock (t) (in hundred)	0.014	0.021	0.010	0.018	0.012	0.020
	(0.010)	(0.013)	(0.010)	(0.013)	(0.010)	(0.013)
PhD univ. grad school in top 20	-0.103	-0.111	-0.099	-0.117	-0.103	-0.111
	(0.049)**	(0.056)**	(0.048)**	(0.055)**	(0.048)**	(0.056)**
PhD univ. 5-yr patent stock (in hundred)	0.058	0.065	0.057	0.044	0.064	0.069
	(0.059)	(0.079)	(0.059)	(0.074)	(0.060)	(0.078)
Patent flow dummy (t)	0.679	0.471				
	(0.060)***	(0.070)***				
Patent regime dummy (t)			0.569	0.520		
			(0.049)***	(0.063)***		
Patent stock (t)					0.035	0.022
					(0.007)***	(0.007)***
Constant	-3.069	-3.606	-3.059	-3.569	-3.056	-3.602
	(0.126)***	(0.146)***	(0.126)***	(0.145)***	(0.126)***	(0.146)***
Num. of observations	64483	63193	64483	63198	64483	63193
Num. of uncensored observations	4049	3700	4049	3851	4049	3700
Num. of left censored obs	58964	58067	58964	57921	58964	58067
Num. of right censored obs	1470	1426	1470	1426	1470	1426
Num. of researchers	4270	4268	4270	4269	4270	4268
Log likelihood	-20194.97	-17886.91	-20094.69	-17900.34	-20234.23	-17901.36
Wald Chi2	688.37	545.48	722.49	581.85	565.16	526.75
Model degrees of freedom	23	23	23	23	23	23
p>Chi2	0.00	0.00	0.00	0.00	0.00	0.00

Notes:
(1) Models 2 , 4 and 6 use Inverse Probability of Treatment and Censoring Weights (IPTCW), which is the product of (a) Inverse Probability of Treatment Weights (IPTW) derived from the logit regression of treatment (i.e., the researcher applying for one or more patents in a given year for Models 2 and 6, and the researcher entering patenting regime for Model 4) on variables that may confound the patenting effect, and (b) Inverse Probability of Censoring Weights (IPCW) derived from the logit regression of censoring (i.e., the researcher exiting academia in a given year).
(2) Models 2, 4 and 6 exclude observations with extremely large (top 1%) and small (bottom 1%) weights.
(3) All models control for PhD subject period effects (periods are coded as 1968-1975, 1976-1980, 1981-1985, 1986-1990, 1991-1995, 1996-2000; the first period is the base category).
(4) Experience = [1, 4] is the base category for the experience dummies.
(5) Robust standard errors in parentheses; clustered around researchers.
(6) * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7.1
Fixed Effects Negative Binomial Regression of Count of Research Publications

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	All researchers			*Patenters Only*		
Experience = [5, 8]	0.300	0.296	0.296	0.343	0.330	0.331
	(0.016)***	(0.016)***	(0.016)***	(0.030)***	(0.030)***	(0.030)***
Experience = [9, 15]	0.351	0.344	0.344	0.409	0.391	0.392
	(0.023)***	(0.023)***	(0.023)***	(0.040)***	(0.041)***	(0.041)***
Experience = [16, 22]	0.217	0.207	0.206	0.280	0.257	0.258
	(0.035)***	(0.035)***	(0.035)***	(0.060)***	(0.060)***	(0.060)***
Experience = [23, 35]	-0.047	-0.056	-0.057	-0.035	-0.055	-0.054
	(0.049)	(0.049)	(0.049)	(0.081)	(0.082)	(0.082)
Employer grad. school in	-0.009	-0.007	-0.007	-0.014	-0.011	-0.011
top20 (t)	(0.019)	(0.019)	(0.019)	(0.031)	(0.031)	(0.031)
Employer has TTO (t)	0.007	0.006	0.007	-0.015	-0.016	-0.017
	(0.014)	(0.014)	(0.014)	(0.023)	(0.023)	(0.023)
Employer patent stock (t)	0.030	0.029	0.029	-0.012	-0.011	-0.011
$\geq$ 90 (75th percentile)	(0.014)**	(0.014)**	(0.014)**	(0.023)	(0.023)	(0.023)
Patent flow dummy (t)	0.125			0.100		
	(0.018)***			(0.018)***		
Patent regime dummy (t)		0.157			0.108	
		(0.018)***			(0.022)***	
Patent stock = 1 (t)			0.150			0.110
			(0.021)***			(0.024)***
Patent stock = 2 (t)			0.152			0.101
			(0.028)***			(0.031)***
Patent stock > 2 (t)			0.173			0.104
			(0.024)***			(0.032)***
Constant	-0.184	-0.188	-0.188	-0.315	-0.309	-0.309
	(0.076)**	(0.076)**	(0.076)**	(0.165)*	(0.165)*	(0.165)*
Observations	63225	63225	63225	15456	15456	15456
Number of researchers	4106	4106	4106	803	803	803
Log likelihood	-81847.27	-81829.47	-81828.95	-24588.04	-24590.72	-24590.67
Wald Chi2	4294.84	4325.67	4326.98	1917.23	1907.24	1907.37
Model degrees of freedom	37	37	39	37	37	39
p>Chi2	0.00	0.00	0.00	0.00	0.00	0.00

Notes:
(1) Models 4-6 contains only researchers who have applied for one or more patents at some point in his or her career.
(2) All models control for year effects.
(3) * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7.2
Fixed Effects Regression of Log of Count of Research Publications

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	All researchers			*Patenters Only*		
Experience = [5, 8]	0.098	0.097	0.098	0.155	0.151	0.151
	(0.009)***	(0.009)***	(0.009)***	(0.020)***	(0.020)***	(0.020)***
Experience = [9, 15]	0.091	0.089	0.090	0.156	0.150	0.150
	(0.015)***	(0.015)***	(0.015)***	(0.033)***	(0.033)***	(0.033)***
Experience = [16, 22]	-0.029	-0.031	-0.031	0.014	0.007	0.007
	(0.022)	(0.022)	(0.022)	(0.046)	(0.046)	(0.046)
Experience = [23, 35]	-0.218	-0.218	-0.218	-0.250	-0.256	-0.256
	(0.030)***	(0.030)***	(0.030)***	(0.059)***	(0.059)***	(0.059)***
Employer grad. school in	-0.008	-0.007	-0.008	-0.004	-0.003	-0.004
top20 (t)	(0.018)	(0.018)	(0.018)	(0.036)	(0.037)	(0.036)
Employer has TTO (t)	0.013	0.012	0.012	-0.005	-0.005	-0.005
	(0.011)	(0.011)	(0.011)	(0.024)	(0.024)	(0.024)
Employer patent stock (t)	0.035	0.034	0.034	0.006	0.006	0.007
$\geq$ 90 (75th percentile)	(0.013)***	(0.013)***	(0.013)***	(0.024)	(0.025)	(0.025)
Patent flow dummy (t)	0.106			0.076		
	(0.016)***			(0.015)***		
Patent regime dummy (t)		0.136			0.052	
		(0.019)***			(0.021)**	
Patent stock = 1 (t)			0.113			0.049
			(0.020)***			(0.021)**
Patent stock = 2 (t)			0.132			0.052
			(0.029)***			(0.031)*
Patent stock > 2 (t)			0.183			0.079
			(0.031)***			(0.036)**
Constant	0.103	0.108	0.109	0.139	0.144	0.147
	(0.027)***	(0.027)***	(0.026)***	(0.062)**	(0.062)**	(0.062)**
Observations	64483	64483	64483	15586	15586	15586
Number of researchers	4270	4270	4270	814	814	814
F statistics	48.07	48.24	45.90	20.39	16.70	19.12
Model degrees of freedom	36	36	38	36	36	38
Adjusted R2	0.45	0.45	0.45	0.52	0.52	0.52

Notes:
(1) Models 4-6 contains only researchers who have applied for one or more patents at some point in his or her career.
(2) All models control for year effects.
(3) Robust standard errors in parentheses, clustered around researchers.
(4) * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7.3
Fixed Effects Negative Binomial Regression of Count of NIH Grants

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	All researchers			*Patenters*		
Experience = [5, 8]	1.390	1.386	1.390	1.398	1.393	1.401
	(0.045)***	(0.045)***	(0.045)***	(0.082)***	(0.082)***	(0.082)***
Experience = [9, 15]	1.542	1.537	1.544	1.587	1.578	1.591
	(0.057)***	(0.057)***	(0.057)***	(0.101)***	(0.102)***	(0.102)***
Experience = [16, 22]	1.404	1.397	1.403	1.486	1.474	1.483
	(0.079)***	(0.079)***	(0.079)***	(0.138)***	(0.139)***	(0.139)***
Experience = [23, 35]	1.021	1.013	1.020	1.231	1.216	1.227
	(0.106)***	(0.106)***	(0.106)***	(0.184)***	(0.184)***	(0.184)***
Employer grad. school in	-0.023	-0.019	-0.017	0.028	0.028	0.027
top20 (t)	(0.038)	(0.038)	(0.038)	(0.068)	(0.068)	(0.068)
Employer has TTO (t)	0.002	0.004	0.007	-0.047	-0.045	-0.034
	(0.028)	(0.028)	(0.028)	(0.050)	(0.050)	(0.050)
Employer patent stock (t)	-0.001	-0.002	-0.002	-0.028	-0.029	-0.028
≥ 90 (75th percentile)	(0.027)	(0.027)	(0.027)	(0.046)	(0.046)	(0.046)
Patent flow dummy (t)	0.094			0.059		
	(0.039)**			(0.040)		
Patent regime dummy (t)		0.142			0.048	
		(0.036)***			(0.046)	
Patent stock = 1 (t)			0.054			0.008
			(0.043)			(0.049)
Patent stock = 2 (t)			0.188			0.131
			(0.057)***			(0.065)**
Patent stock > 2 (t)			0.304			0.220
			(0.052)***			(0.069)***
Constant	13.159	12.906	12.920	12.967	12.981	13.489
	(61.767)	(51.585)	(53.208)	(97.579)	(96.936)	(112.434)
Observations	26956	26956	26956	8034	8034	8034
Number of researchers	1364	1364	1364	380	380	380
Log likelihood	-19514.13	-19509.30	-19499.09	-6059.83	-6060.37	-6053.90
Wald Chi2	2222.77	2231.33	2250.09	713.49	712.60	724.99
Model degrees of freedom	37	37	39	37	37	39
p>Chi2	0.00	0.00	0.00	0.00	0.00	0.00

Notes:
(1) Models 4-6 contains only researchers who have applied for one or more patents at some point in his or her career.
(2) All models control for year effects.
(3) * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7.4
Fixed Effects Negative Binomial Regression of Count of Research Publications in Collaboration with Company Researchers

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	All Researchers			*Patenters Only*		
Experience = [5, 8]	0.210	0.203	0.206	0.177	0.148	0.164
	(0.052)***	(0.052)***	(0.052)***	(0.090)**	(0.091)	(0.092)*
Experience = [9, 15]	0.272	0.262	0.268	0.264	0.225	0.249
	(0.064)***	(0.064)***	(0.064)***	(0.105)**	(0.106)**	(0.107)**
Experience = [16, 22]	0.279	0.264	0.273	0.208	0.156	0.189
	(0.090)***	(0.090)***	(0.090)***	(0.140)	(0.141)	(0.143)
Experience = [23, 35]	0.266	0.247	0.257	0.238	0.181	0.215
	(0.117)**	(0.117)**	(0.118)**	(0.179)	(0.181)	(0.182)
Log of count of research publications (t)	1.573	1.572	1.572	1.367	1.364	1.363
	(0.026)***	(0.026)***	(0.026)***	(0.041)***	(0.041)***	(0.041)***
Employer grad. school in top20 (t)	-0.136	-0.135	-0.141	-0.126	-0.128	-0.142
	(0.066)**	(0.066)**	(0.066)**	(0.101)	(0.101)	(0.102)
Employer has TTO (t)	0.004	-0.001	-0.002	0.045	0.041	0.034
	(0.044)	(0.044)	(0.044)	(0.066)	(0.066)	(0.066)
Employer patent stock (t) $\geq$ 90 (75th percentile)	0.013	0.010	0.012	-0.055	-0.061	-0.058
	(0.044)	(0.044)	(0.044)	(0.063)	(0.063)	(0.063)
Patent flow dummy (t)	0.051			0.050		
	(0.041)			(0.043)		
Patent regime dummy (t)		0.113			0.144	
		(0.050)**			(0.061)**	
Patent stock = 1 (t)			0.144			0.168
			(0.056)**			(0.064)***
Patent stock = 2 (t)			0.104			0.101
			(0.077)			(0.087)
Patent stock > 2 (t)			0.043			0.044
			(0.067)			(0.086)
Constant	10.051	10.178	9.585	-2.017	-1.975	-2.035
	(112.921)	(110.323)	(86.634)	(0.330)***	(0.333)***	(0.325)***
Observations	32426	32426	32426	11173	11173	11173
Number of researchers	1706	1706	1706	538	538	538
Log likelihood	-11868.93	-11867.18	-11865.96	-5188.42	-5186.27	-5184.81
Wald Chi2	4860.14	4860.94	4860.67	1736.91	1738.99	1736.71
Model degrees of freedom	14	14	16	14	14	16
p>Chi2	0.00	0.00	0.00	0.00	0.00	0.00

Notes:
(1) Models 4-6 contains only researchers who have applied for one or more patents at some point in his or her career.
(2) All models control for 5 period dummies:1968-1975, 1976-1980, 1981-1985, 1986-1990, 1991-1995, 1996-1999, among them period 1968-1975 is the base group).
(3) * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8.1
Dynamic Effect of Patenting on Research Publications

Count of Research Papers										
Time around 1st patent Application	*Pooled Cross-section Negative Binomial Model*					*Fixed Effects Negative Binomial Model*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
2 years before		0.437			0.437		0.102			0.096
		(0.049)***			(0.049)***		(0.035)***			(0.035)***
1 years before	0.507	0.516			0.516	0.156	0.171			0.165
	(0.046)***	(0.047)***			(0.047)***	(0.032)***	(0.033)***			(0.033)***
Year of 1st patent	0.602	0.611	0.590	0.590	0.611	0.206	0.222	0.182	0.177	0.215
	(0.047)***	(0.048)***	(0.047)***	(0.047)***	(0.048)***	(0.031)***	(0.032)***	(0.031)***	(0.031)***	(0.032)***
1 year or more after	0.621	0.629				0.181	0.198			
	(0.049)***	(0.050)***				(0.019)***	(0.020)***			
1 year after			0.584	0.584	0.603			0.182	0.177	0.215
			(0.046)***	(0.046)***	(0.047)***			(0.031)***	(0.031)***	(0.032)***
2 years or more after			0.614					0.147		
			(0.050)***					(0.019)***		
2 years after				0.576	0.595				0.186	0.225
				(0.046)***	(0.048)***				(0.032)***	(0.032)***
3 years after				0.627	0.644				0.212	0.252
				(0.049)***	(0.050)***				(0.032)***	(0.033)***
4 years after				0.603	0.621				0.171	0.211
				(0.055)***	(0.056)***				(0.034)***	(0.035)***
5 years or more after				0.620	0.638				0.107	0.153
				(0.058)***	(0.058)***				(0.022)***	(0.024)***
Log-likelihood	-109512.55	-109464.89	-109584.24	-109583.77	-109464.23	-81810.24	-81806.15	-81820.61	-81813.00	-81799.13
Wald Chi-square	2410.53	2430.35	2391.97	2408.62	2445.70	4369.45	4378.30	4347.66	4367.26	4395.63
Model d.f.	49	50	49	52	54	39	40	39	42	44

Continued in next page

Table 8.1
Dynamic Effect of Patenting on Research Publications (Continued)

Log of Count of Research Papers										
Time around 1st	*Pooled Cross-section Regression*					*Fixed Effects Regression*				
patent Application	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
2 years before		0.213			0.213		0.078			0.077
		(0.026)***			(0.026)***		(0.024)***			(0.024)***
1 years before	0.257	0.261			0.261	0.103	0.116			0.114
	(0.026)***	(0.026)***			(0.026)***	(0.024)***	(0.026)***			(0.025)***
Year of 1st patent	0.297	0.301	0.292	0.292	0.301	0.142	0.154	0.125	0.124	0.153
	(0.027)***	(0.027)***	(0.027)***	(0.027)***	(0.027)***	(0.025)***	(0.026)***	(0.023)***	(0.023)***	(0.026)***
1 year or more after	0.365	0.368				0.155	0.169			
	(0.030)***	(0.030)***				(0.022)***	(0.023)***			
1 year after			0.319	0.319	0.327			0.143	0.141	0.170
			(0.028)***	(0.028)***	(0.028)***			(0.023)***	(0.023)***	(0.025)***
2 years or more after			0.366					0.136		
			(0.032)***					(0.021)***		
2 years after				0.324	0.331				0.146	0.175
				(0.029)***	(0.029)***				(0.025)***	(0.027)***
3 years after				0.355	0.362				0.170	0.199
				(0.032)***	(0.032)***				(0.026)***	(0.028)***
4 years after				0.332	0.339				0.143	0.173
				(0.033)***	(0.034)***				(0.028)***	(0.030)***
5 years or more after				0.380	0.387				0.122	0.156
				(0.037)***	(0.037)***				(0.026)***	(0.028)***
F-statistics	56.45	55.51	56.42	53.28	51.53	46.23	45.28	46.19	42.84	41.11
Model d.f.	49	50	49	52	54	38	39	38	41	43
Adjusted R^2	0.12	0.12	0.12	0.12	0.12	0.45	0.45	0.45	0.45	0.45

Notes:
(1) Number of observations in models 1-5 and 11-20 = 64,483; number of observations in models 6-10 = 63,225.
(2) Number of researchers in models 1-5 and 11-20 = 4,270; number of researchers in models 6-10 = 4106.
(3) All models control for calendar years, experience category dummies, employer prestige, employer TTO dummy and employer patent stock.
(4) Models 1-5 and 11-20 report robust standard errors, clustered around researchers.
(5) * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8.2
Dynamic Effect of Patenting on Count of NIH Grants

Time around 1st patent Application	*Pooled Cross-section Negative Binomial Model* (1)	(2)	(3)	(4)	(5)	*Fixed Effects Negative Binomial Model* (6)	(7)	(8)	(9)	(10)
2 years before		0.252			0.252		0.105			0.112
		(0.077)***			(0.077)***		(0.069)			(0.069)
1 years before	0.233	0.237			0.237	0.091	0.106			0.114
	(0.074)***	(0.076)***			(0.076)***	(0.067)	(0.068)			(0.068)*
Year of 1st patent	0.241	0.246	0.237	0.236	0.246	0.128	0.143	0.116	0.121	0.152
	(0.077)***	(0.078)***	(0.075)***	(0.075)***	(0.078)***	(0.065)*	(0.066)**	(0.065)*	(0.065)*	(0.066)**
1 year or more after	0.122	0.126				0.160	0.178			
	(0.078)	(0.079)				(0.040)***	(0.042)***			
1 year after			0.201	0.200	0.209			0.095	0.100	0.132
			(0.079)**	(0.079)**	(0.081)***			(0.066)	(0.066)	(0.068)**
2 years or more after			0.109					0.157		
			(0.081)					(0.040)***		
2 years after				0.230	0.238				0.149	0.181
				(0.075)***	(0.077)***				(0.065)**	(0.066)***
3 years after				0.170	0.178				0.107	0.140
				(0.078)**	(0.079)**				(0.067)	(0.069)**
4 years after				0.139	0.147				0.130	0.164
				(0.080)*	(0.081)*				(0.071)*	(0.073)**
5 years or more after				0.076	0.085				0.192	0.231
				(0.097)	(0.098)				(0.048)***	(0.051)***
Log-likelihood	-38271.26	-38266.29	-38275.10	-38272.62	-38271.26	-19500.87	-19499.74	-19501.31	-19500.25	-19497.95
Wald Chi-square	2048.66	2050.14	2051.70	2078.30	2048.66	2246.17	2247.87	2245.41	2246.80	2250.46
Model d.f.	49	50	49	52	49	39	40	39	42	44

Notes:
(1) Number of observations in models 1-5 = 64,483; number of observations in models 6-10 =26,956.
(2) Number of researchers in models 1-5 = 4,270; number of researchers in models 6-10 = 1,364.
(3) All models control for calendar years, experience category dummies, employer prestige, employer TTO dummy and employer patent stock.
(4) Models 1-5 report robust standard errors, clustered around researchers.
(5) * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8.3
Dynamic Effect of Patenting on Count of Research Publications Written in Collaboration with Company Scientists

Time around 1st patent Application	*Pooled Cross-section Negative Binomial Model* (1)	(2)	(3)	(4)	(5)	*Fixed Effects Negative Binomial Model* (6)	(7)	(8)	(9)	(10)
2 years before		0.270			0.270		0.111			0.105
		(0.117)**			(0.117)**		(0.095)			(0.095)
1 years before	0.323	0.330			0.330	0.170	0.194			0.188
	(0.103)***	(0.104)***			(0.104)***	(0.083)**	(0.086)**			(0.086)**
Year of 1st patent	0.443	0.450	0.434	0.434	0.450	0.215	0.239	0.172	0.171	0.232
	(0.098)***	(0.099)***	(0.097)***	(0.097)***	(0.099)***	(0.081)***	(0.084)***	(0.079)**	(0.079)**	(0.084)***
1 year or more after	0.280	0.287				0.140	0.166			
	(0.079)***	(0.080)***				(0.057)**	(0.061)***			
1 year after			0.407	0.407	0.423			0.189	0.187	0.249
			(0.102)***	(0.102)***	(0.104)***			(0.078)**	(0.079)**	(0.084)***
2 years or more after			0.255					0.073		
			(0.081)***					(0.055)		
2 years after				0.268	0.283				0.110	0.173
				(0.102)***	(0.103)***				(0.080)	(0.085)**
3 years after				0.339	0.355				0.091	0.154
				(0.100)***	(0.102)***				(0.078)	(0.084)*
4 years after				0.257	0.273				0.011	0.078
				(0.110)**	(0.112)**				(0.086)	(0.091)
5 years or more after				0.240	0.257				0.065	0.139
				(0.092)***	(0.094)***				(0.064)	(0.073)*
Log-likelihood	-19389.92	-19387.29	-19393.41	-19392.96	-19389.92	-11863.50	-11862.84	-11864.35	-11863.80	-11861.29
Wald Chi-square	4436.65	4447.44	4433.65	4448.06	4436.65	4865.51	4864.92	4863.44	4864.33	4866.02
Model d.f.	26	27	26	29	26	16	17	16	19	21

Notes:
(1) Number of observations in models 1-5 = 64,483; number of observations in models 6-10 =32,426.
(2) Number of researchers in models 1-5 = 4,270; number of researchers in models 6-10 = 1,706.
(3) All models control for calendar years, experience category dummies, employer prestige, employer TTO dummy and employer patent stock.
(4) Models 1-5 report robust standard errors, clustered around researchers.
(5) * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9
Regression of Log of Count of Research Publications

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Type of patent effect	Patent Flow		Patent Regime		Patent Stock	
	Fixed Effects	*Fixed Effects with IPTCW*	*Fixed Effects*	*Fixed Effects with IPTCW*	*Fixed Effects*	*Fixed Effects with IPTCW*
Experience = [5, 8]	0.098	0.091	0.097	0.095	0.099	0.092
	(0.009)***	(0.009)***	(0.009)***	(0.009)***	(0.009)***	(0.009)***
Experience = [9, 15]	0.090	0.079	0.089	0.084	0.091	0.079
	(0.015)***	(0.015)***	(0.015)***	(0.015)***	(0.015)***	(0.015)***
Experience = [16, 22]	-0.029	-0.052	-0.031	-0.042	-0.030	-0.052
	(0.022)	(0.023)**	(0.022)	(0.022)*	(0.022)	(0.023)**
Experience = [23, 35]	-0.218	-0.242	-0.217	-0.229	-0.221	-0.243
	(0.030)***	(0.032)***	(0.030)***	(0.032)***	(0.030)***	(0.032)***
Employer grad school in top20 (t)	-0.020	-0.021	-0.019	-0.022	-0.019	-0.021
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Employer has TTO (t)	0.015	0.020	0.014	0.018	0.015	0.020
	(0.011)	(0.012)*	(0.011)	(0.011)	(0.011)	(0.012)*
Employer patent stock (t) (in hundred)	0.018	0.017	0.018	0.018	0.018	0.017
	(0.005)***	(0.005)***	(0.005)***	(0.005)***	(0.005)***	(0.005)***
Patent flow dummy (t)	0.106	0.051				
	(0.016)***	(0.019)***				
Patent regime dummy (t)			0.135	0.087		
			(0.019)***	(0.020)***		
Patent Stock (t)					0.004	0.006
					(0.003)*	(0.003)*
Constant	0.105	0.046	0.110	0.056	0.104	0.047
	(0.027)***	(0.027)*	(0.026)***	(0.027)**	(0.027)***	(0.027)*
Observations	64483	63193	64483	63198	64483	63193
Num. of researchers	4270	4268	4270	4269	4270	4268
F-statistics	48.57	46.80	48.66	46.56	47.95	46.83
Model degrees of freedom	36	36	36	36	36	36
Adjusted R^2	0.45	0.41	0.45	0.41	0.45	0.41

Notes:
(1) Models 2, 4 and 6 use Inverse Probability of Treatment and Censoring Weights (IPTCW), which is the product of (a) Inverse Probability of Treatment Weights (IPTW) derived from the logit regression of treatment (i.e., the researcher applying for one or more patents in a given year for Models 2 and 4 and the researcher entering patenting regime for Model 4) on variables that may confound the patenting effect, and (b) Inverse Probability of Censoring Weights (IPCW) derived from the logit regression of censoring (i.e., the researcher exiting academia in a given year).
(2) Models 2 and 4 exclude observations with extremely large (top 1%) and small (bottom 1%) weights.
(3) All models control for year effects.
(4) Experience = [1, 4] is the base category for the experience dummies.
(5) Robust standard errors in parentheses, clustered around researchers
(6) * significant at 10%; ** significant at 5%; *** significant at 1%.

Data Appendix

Research patentability score. w_{jt}, the patentability weight for each keyword j in year t is defined as:

$$w_{jt} = \frac{\sum_{i \in I'} \frac{m_{ijt}}{\sum_j m_{ijt}}}{\sum_{i \in I''} \sum_j m_{ijt}}$$

where m_{ijt} denotes the number of times each of the keywords j has appeared in scientist i's articles published between $t-5$ and t, $i = 1, \ldots, I^{'}$ in the numerator indexes the subset of scientists in our sample that have already applied for one or more patents, and $i = 1, \ldots, I^{''}$ in the denominator indexes the subset of scientists in our sample that have not yet applied for any patent. Note that $w_{jt} = 0$ for all keywords that have never appeared in the titles of papers written by scientists that have patented before t.

To compute the research patentability score, we first created a row normalized matrix for year t, with each scientist in the patenting regime listed in a row and each of the keywords used to describe their papers listed in a column. The ij^{th} cell in the matrix, $[m_{ijt}/\sum_j m_{ijt}]$, is defined to be the proportion of commercial scientist i's total research output that is devoted to keyword j. We then take the column sums from this matrix, which form a vector of weights corresponding to keywords that are large to the extent that a keyword j frequently has been used to describe articles written by scientists who had entered the patenting regime before t.

Next, we collected all papers published by the scientists in our dataset who had not applied for patents by year t and computed the frequency that each keyword j appeared in the titles of their papers, a process captured in the denominator. The raw weight for keyword j — captured by the numerator — was deflated by the frequency of use for j by non-patenters. These deflated weights w_{jt} are large for keywords that have appeared with disproportionate frequency as descriptors of papers written by scientists already in the patenting regime.

Finally, for each individual i in the dataset, we produced a list of the keywords in the individual's papers published in all time periods before t, calculated the proportion of the total represented by each keyword j, applied the appropriate keyword weight w_{jt}, and summed over keywords to produce a composite score. The resulting variable increases in the degree to which keywords in the titles of a focal scientist's papers have appeared frequently in the titles of academic scientists who have applied for patents. This score is entered in the regressions to control for the research patentability of scientists' areas of specialization.