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Patenting and Publishing: Substitutes or Complements For University Faculty?

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Section One: Introduction

Innovative activity in the university sector is generally studied at the institutional level. This paper refocuses the lens by examining characteristics that relate to the innovative behavior of individual faculty members. Using data from the 1995 Survey of Doctorate Recipients, we analyze the patent activity of a sample of 10,962 doctoral scientists and engineers working in institutions of higher education.

Technology transfer is the subject of numerous studies (Agrawal and Henderson 2002, Colyvas *et al*. 2002, Henderson, Jaffe and Trajtenberg 1998, Jensen and Thursby 1991, Murray 2002, Mowery *et al*. 2001, Owen-Smith and Powell 2001, 2002, Thursby and Kemp 2001, Thursby and Thursby 2002a, Thursby and Thursby 2002b).[1] These studies provide important insight into institutional factors that relate to patent activity and the importance (or unimportance) of the Bayh-Dole Act[2] to the dramatic increase in university patenting. The work of Thursby and Kemp, for example, shows that technology transfer offices play an important role in determining the number of disclosures that are made on a campus. The work of Owen-Smith and Powell (2002) suggests that academic medical centers can play a facilitating role in technology transfer. Mowery and his coauthor's work suggests that Bayh-Dole did not cause the dramatic increase in university patent activity but rather that the "principal effect of Bayh-Dole was to accelerate and magnify trends that already were occurring" in academe (Mowery *et al*., 2002, p. 2).

The institutional focus of technology transfer studies precludes insights concerning personal characteristics that affect patent activity and the interplay between these personal and institutional factors. We know remarkably little about who in the university is patenting and personal characteristics related to patenting. By contrast, we know considerably more concerning the publishing activity of university scientists and engineers. We know, for example, that the activity itself is highly skewed; that publishing and co-authorship patterns vary considerably by field; and that life-cycle effects are generally present in a fully specified model that controls for individual fixed effects such as motivation and ability (Levin and Stephan 1991, Stephan 1996, Stephan and Levin 1992). We also know that the human capital model comes up a bit short in modeling publishing activity (Stephan 1996). Stephan (p. 1219) attributes this failure to the "fact that the production of scientific knowledge is far more complex than the human capital model assumes and that these complexities have a great deal to say about patterns that evolve over the life cycle." She argues that a further reason human capital models

[1] The number of patents issued to academic institutions has grown dramatically in recent years. For example, in 1965, fewer than 100 U.S. patents were granted to 28 U.S. universities or related institutions. By 1992 almost 1500 patents were granted to over 150 universities or related institutions. This dramatic increase in patenting activity occurred during a time in which total U.S. patenting increased by less than 50% and patents granted to U.S. inventors remained almost constant (Henderson, Jaffe and Trajtenberg, 1998). This trend has continued throughout the 1990s, with more than 3000 patents being issued to academic institutions in 1998.

[2] The Bayh-Dole Act of 1980 gave universities the right to retain title to and license inventions resulting from research supported on federal grants.

come up short is that they place undue emphasis on the declining value of economic returns over the life cycle. It is not that scientists are not interested in economic rewards. They are. But, as Stephan and Levin argue (1991), scientists also value priority of discovery and the intrinsic returns that come from engaging in puzzle-solving behavior.

This paper examines the effects of individual and institutional characteristics on patent activity of scientists and engineers employed in institutions of higher education. Moreover, the level of analysis permits us to examine a question of widespread policy concern: whether the move towards commercialization at universities comes at the expense of placing knowledge in the public domain through publication. We address this "crowding out" issue by examining the relationship between patenting and publishing.

In section two we discuss factors leading university scientists and engineers to patent. We relate this to the crowding-out hypothesis that faculty patent instead of publish and offer an alternative hypothesis which suggests the presence of complementarity between patenting and publishing. In section three of the paper we discuss personal as well as institutional characteristics that we hypothesize to be related to patenting activity of academics. We also comment on why we expect these relationships to differ by field. Section four summarizes the data used for this study and the methodology employed. Section five presents our results and research findings. Of most importance for this study is the finding that publishing is a potent predictor of patent activity. We conclude that publishing and patenting at the individual level are complementary activities and that any crowding that is occurring is of an inward, not an outward, nature.

Section Two: Incentives to Patent in Academe: Crowding out?

Considerable concern has been expressed that the move towards commercialization in the university community comes at the expense of the production of basic knowledge (Stephan and Levin 1996). There are at least two variants of the crowding-out hypothesis. One variant argues that in the changing university culture scientists and engineers increasingly choose to allocate their time to research of a more applied as opposed to basic nature. Another variant of the crowding-out hypothesis is that the lure of economic rewards encourages scientists and engineers (and the universities where they work) to seek IP protection for their research results, eschewing (or postponing) publication and thus public disclosure.[3] Much of the work of Blumenthal and his collaborators (1996) focuses on the latter issue in the life sciences, examining the degree to which university researchers receive support from industry and how this relates to publication.

There is, of course, reason to believe that patenting is positively related to the activity of publishing. To see why, we first take a step back and ask why scientists in academe, for whom priority that comes from publication is widely held to be of primary importance, patent at all.

[3] Clearly, these two variants are not mutually exclusive.

Scientists and engineers in academe patent for several reasons. First, in many instances, it is the stated policy of the university that disclosure is required. But scientists and engineers patent for other reasons as well. Economic gain is clearly one. Considerable evidence exists concerning the large financial returns that have been realized by certain academic scientists engaged in technology transfer (Stephan and Everhardt 1998). In addition to economic protection, patents can also protect discoveries from being put in the private domain by others. Owen-Smith and Powell (2001) report that several university scientists gave this as a reason for seeking patents in the interviews that they conducted. Patenting can also be seen by university scientists as a means of building their reputation. Owen-Smith and Powell (2001) state that "many inventors reveal that they patent, in part, because they feel it increases their academic visibility and status by "reaffirming" the novelty and usefulness of their work."[4] Patents can also be used to leverage existing research by creating a chit to trade with industry. This may be particularly the case in the physical sciences where inventions tend to be incremental improvements on established processes of products. By exchanging patents on incremental innovations with industry, scientists can receive propriety technology, such as access to equipment or other opportunities (Owen-Smith and Powell 2001).

Interest in patenting among university scientists and engineers may also be piqued through interaction with industry. Mansfield's work (1995) demonstrates that scientists and engineers often gain inspiration for their research through interaction with industry. Interviews by Agarwald and Henderson (2002) suggest that, in addition, interaction with industry may also steer scientists and engineers towards patenting.[5]

Complementarity between publishing and patenting can occur for several reasons. One argument for complementarity between patenting and publishing relates to the fact that scientists and engineers can selectively publish research findings while at the same time monopolizing other elements of their research. Rebecca Eisenberg (1987) argues that such behavior is more common among academics than might initially be presumed. Furthermore, she argues that this ability of faculty to have one's cake and eat it too is not only manifested in patenting and publishing from the same line of research. It is also manifested when professors refuse to share data or cell lines. This ability is facilitated by the fact that publication is not synonymous with providing the ability to replicate and that techniques can often be transferred only at considerable cost, in part because their tacit nature makes it difficult, if not impossible, to communicate in a written codified, form.

The ability to have one's cake and eat it too provides one reason why complementarity may exist between patenting and publishing. There are at least two other reasons why complementarity may exist. One relates to the low marginal cost of

[4] In this respect views have changed considerably during the past 90 years. In 1917 T. Brailsford Robertson patented a substance thought to promote growth, and donated the patent rights to the University of California, where he was head of the biochemistry department. Weiner recounts how this action was perceived as tarnishing Roberton's reputation (1986).

[5] An engineer told Awarwald and Henderson (58): . . ." it is useful to talk to industry people with real problems because they often reveal interesting research questions—but sometimes they try to steer you towards patenting. Sometimes that research results in something patentable, sometimes not."

disclosure when publication is used as the means of communicating the disclosure.[6] Owen-Smith and Powell (2002, p. 11) report that "invention disclosures made by academic inventors to university technology transfer offices often take the form of article manuscripts." Murray (2002, p. 6) states that, particularly in biomedical innovation "the same idea is often inscribed in both a patent and paper (scientific publication).

The other reason to expect publication and patenting to be complements, rather than substitutes, relates to what we call "the right stuff" argument. It is a well-established fact that science has extreme inequality with regard to scientific productivity and the awarding of priority. One indication of this is the highly skewed nature of publications, first observed by Alfred Lotka (1926) in a study of nineteenth century physics journals. The distribution that Lotka found showed that approximately six percent of publishing scientists produced half of all papers. Lotka's "law" has since been found to fit data from several different disciplines and varying periods of time (Price 1986).[7] Moreover, several recent case studies of patenting behavior of scientists and engineers show that patenting activity is highly skewed. Narin and Breitzman (1995) examine the number of patents per inventor for four companies in the semiconductors business. They find a Lotka-like distribution in all four cases, with a large number of inventors with their names on only one patent and a relatively small number of highly productive inventors with their names on ten or more patents. Ernst, Leptien and Vitt (2000) examine the patent activity of inventors working in 43 German companies in the chemical, electrical, and mechanical engineering industry. They, too, find that a small group of key inventors is responsible for the major part of the company's technological performance. Agrawal and Henderson (2002) find a highly skewed distribution of patents for the MIT engineers in their study: 44% were never an inventor on a patent during the 15-year period; less than 15% had been granted more than 5 patents; and less than 6% had been granted more than 10.

To the extent that inequality in scientific productivity results from differences among scientists in ability and motivation, one would expect patenting and publishing to be strongly correlated, since both are indicators that the scientist has the (unmeasurable) "right stuff" to be highly productive. But scientific productivity is not only characterized by extreme inequality at a point in time; it is also characterized by increasing inequality over the careers of a cohort of scientists, suggesting that at least some of the processes at work are state dependent. Weiss and Lillard (1982), for example, find that not only the mean but also the variance of publication counts increased during the first ten to 12 years of the career of a group of Israeli scientists.

Merton christened this inequality in science the Matthew Effect, defining it to be "the accruing of greater increments of recognition for particular scientific contributions to scientists of considerable repute and the withholding of such recognition from scientists

[6] Work by Thursby and Thursby (2002) suggests that the cost to the scientist of patenting comes, not at the time of disclosure, but afterwards, in working with the company that licenses the patent. See also Jensen and Thursby (2001).

[7] Lotka's law states that if k is the number of scientists who publish one paper, then the number publishing n papers is k/n^2. In many disciplines this works out to some five or six percent of the scientists who publish at all producing about half of all papers in their discipline.

who have not yet made their mark." (1968, p. 58). Merton argues that the effect results from the vast volume of scientific material published each year, which encourages scientists to screen their reading material on the basis of the author's reputation. Other sociologists (Allison and Stewart 1974; and Cole and Cole 1973, for example) have argued that additional processes are at work that result in scientists accumulating advantage, as they leverage past success into future success. While we have yet to understand these processes completely, a strong case can be made that a variety of factors are at work in helping able and motivated scientists leverage their early successes and that some form of feedback mechanism is at work. All of which gives reason to suspect that patents and publishing, both indicators of success, are correlated.

Although the two activities are correlated, it does not follow that there is a one-to-one relationship. A great deal of research that results in publications is unpatentable or is but one piece of a line of research, producing numerous articles but upon which only one patent is based. Moreover, as changing patterns in authorship demonstrate so well, increasingly scientists work in teams (Adams et al. 2002). But the article team is generally larger than the patent team. Recent research by Ducor (2000) matches 50 article-patent pairs and reports that the average number of authors was 10 while the average number of inventors was three. Murray (2002) reports similar results in her study of patent-paper pairs in tissue engineering.

The only paper to examine the relationship between patents and papers at the individual level for university faculty is by Agrawal and Henderson (2002).[8] In their study of engineers at MIT in the departments of Mechanical Engineering and Electrical Engineering and Computer Science, they relate patent activity, in a fixed-effects model, to publishing activity. They restrict their sample to faculty members who have either patented or published or done both during the period 1983-1997. They find absolutely no evidence that the two activities are substitutes; neither do they find evidence that they are complements. They do, however, demonstrate that "increased patent activity is correlated with increased rates of citation to the faculty member's publicatio -59). This may be related to the fact that industry seeks out well-known scientists to work on projects and in the process the scientists are steered towards patenting.

Section Three: Characteristics Related to Patent Activity

We expect the patent activity of faculty to be related to institutional as well as individual characteristics. The institutional characteristics most likely to affect patent activity are the culture of the university and the field of specialization. The work by Thursby and Kemp (2001) concerning the role that technology transfer offices play in determining the number of disclosures at a university is consistent with the observation that although academic scientists don't need to be taught how to publish they do need to be educated concerning the patent process. A strong technology transfer office can

[8] Colyvas *et al.* report case studies of inventions created at Columbia University and Stanford University. Five of the eleven cases involved publication. IP protection, usually in the form of a patent, was involved in all of the eleven.

facilitate that process and create an entrepreneurial culture on campus.[9] We expect this culture to be proxied by the number of patents that the institution has received in the past.

We also expect patent activity to be related to field of specialization. For example, in certain fields patenting is not the preferred means of intellectual property protection. In computer sciences, by way of example, it is much more common to copyright than to patent research in the area of software. In other fields with a strong emphasis on applied research, such as engineering, it is fairly common to apply for patents for intellectual property protection. Murray makes the case (2002) that in the field of biomedical research the marginal cost of patenting can be quite low and may flow directly out of a line of research This is one reason why the majority of both issued patents and revenues resulting from innovation at most universities come from innovations in the biomedical field (Powell and Owen-Smith 1998, Henderson, Jaffe and Trajtenberg 1998.)[10] There are also fields where the innovation that is patented is an input into the scientist's research, as in the case with the invention of equipment designed to advance a line of research or discovered serendipitously during the course of a larger research project. This can, for example, be the case in the physical sciences.[11]

Personal characteristics expected to relate to patent activity include age (or some variant of age such as the number of years since receipt of the Ph.D.) in a non-linear form, citizenship status, gender and receipt of federal funding. If patenting and publishing are, indeed, substitutes, we might hypothesize that older scientists are more likely to patent than younger scientists, choosing later in their careers to cash in their reputation for commercial gain.[12] But, to the extent that the two activities are complements we would expect the rate of patenting to decline (or eventually decline) with age, following a pattern similar to that observed in age-publishing profiles. Citizenship status may be a factor because certain research opportunities (especially those related to defense) require citizenship. We include it here for this reason and because of the widespread interest in issues related to citizenship in science and engineering (Levin and Stephan 1999). The large number of studies examining publishing differentials between men and women (see Levin and Stephan 1998 for a summary) leads us to include gender as well. Federal support is included to see if, holding other variables

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[9] Owen-Smith and Powell (2001) report that Jim Helfenstein, a faculty member who has never disclosed an invention, though his research has many potential commercial applications, stated to them that "For people like me it [awareness of patenting] is essentially zero. I probably know less about that than I do about Medieval European social history. Really, that happens to be something I'm interested in. It just no information provided here, no advice urged upon us. If we wanted to do anything about this we'd have to be very highly motivated to go out and seek the information, get the advice. We'd have to, I think, be more sophisticated than most of us are – than I certainly am –to know when to do that or what sort of thing should trigger it."

[10] This is not to downplay the tremendous importance of demand factors in leading scientists to seek patent protection in areas of biomedical research.

[11] Colyvas *et al* (2002). report a case study of a patent granted for a "proof of concept" for a process generating light of a particular wavelength. The discovery occurred in the course of a funded basic research project in the field of astrophysics.

[12] Audretsch and Stephan (1999) make such an argument, contrasting scientists in industry with scientists in academe. Dasgupta and David (1987) discuss the difference between being in the "science club" and in the "technology club" and how this affects incentives.

constant, individuals who receive federal support for research are more likely to patent than those who do not.

Section Four: Data Description and Methods

Data for this study come from the biennial Survey of Doctorate Recipients[13], which in 1995 included a question on patent activity and publishing activity during the past five years.[14] For the purposes of this paper, we use the number of patent applications made in the past five years as an indicator of patent activity and the number of articles published in the past five years as a measure of publishing activity. We restrict the sample to those working fulltime in academic institutions which grant a four year degree or higher and exclude individuals working in areas other than science and engineering, such as the humanities, the social sciences (including psychology) and business. We further subdivide the sample into four fields: computer sciences, life sciences, physical sciences and engineering.

Both the patent and paper measures are highly skewed, as is shown in Table 1. The distribution of patents is considerably more skewed, however, than that of publications. For example, while only about 9% of the sample made a patent application (and only .5% made more than five applications) almost 85 percent published at least one article and almost 45% published more than five in the past five years. Among the sample, engineers are most likely to patent, computer scientists the least likely to patent. Computer scientists are also the least likely to publish one or more articles and have the lowest percent reporting 10 or more articles during the previous five years.[15]

Table 2 explores the degree to which patents and publications are related, by examining the joint distribution of those who produce one or more patent applications during the period and publish one or more articles. Approximately 14% neither publish nor patent; almost 9% do both. The table demonstrates that the two measures of productivity are strongly related to each other. In all instances, Chi Square tests indicate that the hypothesis of independence in the distributions can be rejected at the .001 level.

In order to investigate the relationship more thoroughly, we initially estimate a zero-inflated negative binomial (ZINB) model. We choose this model given the discrete nature of the data and the high occurrence of zeros. The ZINB model adds an additional mass at the zero value of patent applications resulting in higher proportion of zeros than is consistent with the underlying negative binomial regression. The main justification for using zero-inflated counts is to allow for the potential of misrecording of zero patents.

[13] National Science Foundation, Science Resources Statistics. Morgan, Kruytbosch and Kannankutty (2002) use the Survey of Doctorate Recipients to explore characteristics of academics who patent

[14] The specific patent question was "Since April 1990, have you been named as an inventor on any application for a U.S. patent?" If the answer to this question was "Yes," survey participants were asked "How many applications for U.S. patents have named you as an inventor?"

[15] Agrawal and Henderson (2002) find patents to be more highly skewed than publications for the MIT engineers that they study.

The zeros reported by individuals who did not make patent applications may arise from two sources. Zero patents may be recorded for those who either never made patent applications or for those who do but did not do so during the past five years. Ignoring this potential error in recording would lead to misspecification.

To specify the zero-inflated model, let $h(y_i, \theta | X_i)$ denote the negative binomial density with mean $exp(X_i\beta)$, dispersion parameter α, and $\theta = (\beta' \alpha)'$. Here $i = 1, 2, \ldots, n$ denotes individuals, X is a vector of explanatory variables having direct impact on the number of patent applications, defined here as y = Usapp95, and β is the parameter vector associated with X. The zero-inflated negative binomial density for patent applications can be presented as

$$Pr(y_i) = \begin{cases} = \lambda_i + (1 - \lambda_i)\, h(y_i = 0, \theta | X_i), & \text{for } y_i = 0 \\ = (1 - \lambda_i)\, h(y_i, \theta | X_i), & \text{for } y_i = 1, 2 \ldots, \end{cases} \tag{1}$$

where the parameter λ $(0 < \lambda < 1)$ is used to increase (inflate) the proportion of zeros; that is, the proportion of individuals with zero number of patent applications during the last five years. For generality, we allow the zero-inflation parameter, λ, to depend on observed vector of covariates, Z, shown in Column 4 of Table 3. The parameter is specified as a logit function of Z:

$$\lambda_i = exp(Z_i\gamma) / (1 + exp(Z_i\gamma)). \tag{2}$$

This ensures that the inflation parameter is restricted to be between 0 and 1, as it should be[16]. Gurmu and Trivedi (1994) and Cameron and Trivedi (1998), and references therein discuss zero-inflated and related models.

In the zero-inflated negative model, the mean number of patent applications, given explanatory variables in X_i and Z_i, is

$$(1 - \lambda_i)\ exp(X_i\beta). \tag{3}$$

Using equations 3 and 2, the marginal effect (ME) of a specific explanatory variable, say u, on the mean number of patent applications takes the form

$$ME_u = (1 - \lambda_i)\, exp(X_i\beta)\, \beta_u - \lambda_i (1 - \lambda_i)\, exp(X_i\beta)\, \gamma_u, \tag{4}$$

where β_u is the coefficient of u in the main equation; u is in X. Similarly, γ_u is the coefficient of u in the inflation part; u is in Z[17]. If u is a dummy variable, the marginal

[16] The density in (1) may be thought of as a mixture of two distributions, a distribution whose mass is concentrated at zero number of patents and a negative binomial distribution. That is, the density for the number of patent applications can be represented as $y_i = 0$ with probability λ_i and y_i is distributed as negative binomial with probability $(1 - \lambda_i)$.

[17] So, the first component in (4) gives the direct effect. The first component will be zero if u is not included in the y = Uspapp95 equation – as in the case of the variable Instpat in Table 3. The second component in

effects will be computed for discrete change in (3) from $u = 0$ to $u = 1$. The elasticity of the number of patent applications with respect to factor u is

$$\text{Elasticity}_u = \text{ME}_u \times u/(\text{predicted \# of patent applications}), \qquad (5)$$

where predictions are obtained from equation 3. Equations 4 and 5 show that elasticities are also composed of two components.

As argued in section three above, the two measures of productivity of scientists – patenting and publishing – are likely to be strongly correlated. Since the latent variable on scientific productivity is unobserved, the variable ‘Article95’ used as a regressor in patent equation is likely to be endogenous. As such, Article95 is likely to be correlated with unobservable determinants of the patent equation. For now, we assume that the number of articles published during the past five years follows a negative binomial distribution. The mean number articles published, given observed characteristics, is specified as

$$exp(W_i\boldsymbol{d}), \qquad (6)$$

where W_i is a vector covariates affecting Article95, listed in Column 5 of Table 3, and $\boldsymbol{d}$ is the associated vector of unknown parameters. Predictions from 6 are used as instrument for Article95 in the zero-inflated negative binomial model[18].

Variables are defined in Table 3. The table also indicates the component of the model in which the variable is to be used: the main equation for Uspapp95, inflation (logit) part for Uspapp95 or, in light of “the right stuff” discussion above, instrumental variables for the number of articles published, Article95. Means and standard deviations by field are given in Table 4.

Section Five: Estimation Results and Research Findings

The ZINB results, ignoring endogeneity in Article 95, are presented in Table 5. A positive coefficient in the inflation part of the model implies a negative impact on the number of patent applications; a negative coefficient implies a positive impact. Results are given for “all” scientists and engineers working in academe regardless of field as well as those in the broad fields of the life sciences, computer sciences, physical sciences and engineering.

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(4) gives the indirect impact of u on Uspapp95. Note that if $\gamma_u > 0$ ($\gamma_u < 0$) the second component is negative (positive). The second component of equation 4 will be zero if u is not included in the zero-inflation part of the model (as is the case of article95 in Table 3). If w is included in both parts of the model, the marginal effect will be composed of both components in (4)

[18] In future versions of this paper, we will formally test and correct for endogneity in publications using a generalization of Mullahy’s (1997) non-linear instrumental variable approach. Identification issues will also be discussed.

Table 5 demonstrates the need to estimate the model in two components as well as by field. Variables included in both the inflation part and the negative binomial often have opposite effects or lack significance in one equation but have significance in the other. For example, while there is no indication that the number of patents relates to gender, in three of the equations ("all," life sciences, and physical sciences) women are significantly less likely to patent than are men. Likewise, there is no indication that in all but the physical sciences citizenship status affects the number of patent applications. However, in both the "all" field and in engineering, citizens are more likely to patent than non-citizens. In the physical sciences, we find just the opposite, notably that citizens are less likely to patent than their non-citizen peers but once they do patent, patent more than non-citizens. Another case in point is tenure. With the exception of computer science, the influence of tenure, to the extent it matters, is on the probability of patenting, not on the number of patents. Moreover, the influence is negative—that is tenured faculty are less likely to patent than non-tenured faculty. Likewise, individuals who say their primary or secondary work activity is in applied or basic research, development or design are (with the exception of computer scientists) more likely to patent than those who do not but there is no indication that work activity affects the number of patents. We also find evidence that computer scientists and engineers trained at research and doctoral institutions are more likely to patent than those who do not receive their degrees from such institutions. The number of patents awarded is positively related to working in a medical institution for computer scientists, physical scientists and engineers. Receipt of federal support increases the likelihood of patenting across all fields, but when the analysis is done at the field level, it is only in the physical sciences that the effect is observed. Particularly of interest is the fact that we find no indication that receipt of federal funds in the life sciences—the most heavily federally funded area—relates to either component of the model.

Life-cycle effects are found for "all scientists" and for life scientists, with significant coefficients of the predicted sign on the measures yearsofphd and (in the case of life scientists) phdsq. There is no indication that life-cycle issues affect whether or not an application is made or affect the number of applications in other fields. Caution must be taken interpreting these results, of course, since it is well known that cross-sectional data produce biased estimates on variables related to time, such as years since receipt of Ph.D. (Levin and Stephan 1991).

The measure for the number of patents that the institution has received during the past five years (Instpat) is included in the inflation equation but not in the main patent equation to control for the patenting culture of the institution. The variable consistently has the expected sign but only in the case of "all" fields and computer sciences does it approach being significant at the 5% level.

The variable of most interest to this study, the number of articles published in the past five years (articl95), is included in the negative binomial; not in the inflation part. With but one exception, we find it to have a strong and highly significant effect on the number of patents issued, demonstrating that patents and articles are complement, not substitute, outputs of productive scientists. The exception, once again, is computer sciences where article counts is insignificant.

Given that independent variables often affect both parts of the zero-inflated negative binomial models in opposite ways, and given the large differences that exist across fields, marginal effects and elasticities, for ease of interpretation, are presented in Table 6**.** Using expressions in equations 4 and 5, all marginal effects and elasticities are evaluated at the sample average values of explanatory variables. Unlike the coefficient estimates reported in Table 5, marginal effects and elasticities in Table 6 give the total impact of a given explanatory variable on the number of patent applications. As such, when the coefficients from the two parts of the ZINB are marginally insignificant, it is possible for the marginal effects to be significant. (See also notes to Table 6.)

For all fields combined, the evidence suggests that certain environments are more conducive to patenting than others. For example, those working in a medical institution have about .10 more patent applications than those who do not work in medical schools. Likewise, those working in a university research institute make about .07 more patents than those not working in such an institute. Individuals whose primary or secondary activity is R&D make almost .12 more patent applications than those whose primary or secondary activity is not. Likewise, and again looking at the effects for all fields combined, those with federal support submit about .06 more patent applications over a five-year period than those who do not have federal support. In terms of personal characteristics, we find that women submit approximately .08 fewer patent applications than men; citizens about .05 more than non-citizens. Tenured faculty make .07 fewer patent applications than non-tenured faculty and those who were trained at Research I institutions about .04 more than those who were not trained at Carnegie-rated institutions.

Patent elasticity with regard to publishing is .347. This indicates that, starting from sample values of characteristics, a 1% increase in articles published raises the number of patent applications by more than 1/3 percent. Because this is the first elasticity of patenting with respect to publishing that we know to have been computed, we cannot compare it with others. But the estimated magnitude suggests that technology transfer offices would benefit not only from encouraging disclosure of existing research but also by augmenting the research (and publication activity) of faculty.

Table 6 emphasizes the strong variation in patent behavior across fields that was already noted above. First and foremost, in terms of broad differences and in comparison to the life sciences, we see that engineers make about .28 more patent applications; physical scientists about .05 more and computer scientists about .07 fewer. But, the differences are also manifest in the elasticities and marginal effects. Unlike the other fields, the elasticity of patenting with respect to publications is not significantly different from zero in computer science while the other three elasticities are reasonably close to the "all" elasticity, especially those of engineering and life sciences. Differences in marginal effects are particularly noticeable in the field of computer science. First, and as noted, we find absolutely no indication that publications and patent applications are complements in the field of computer science. Neither do we find that working in a research institute or medical school, or heavy involvement in R&D activity, are predictive of patenting among university computer scientists. On the other hand, computer scientists receiving federal support applied for almost .09 more patents than their non-supported colleagues and computer scientists who were citizens made a slightly larger number of applications. Another difference between computer scientists and scientists and engineers in other fields comes in the impact that doctoral institutional ranking has on patent activity. We find that computer scientists who received their Ph.D. at Research I institutions are more likely to patent than are those who did not attend a Carnegie-rated institution.

In section three we argue that one reason to expect patents and article counts to be complements stems from the fact that both are directly affected by unmeasurable characteristics, which we have labeled "the right stuff." Specifically, the article counts in the patent model may be endogenous. Consequently, the parameter estimates given in Table 5 are tenuous[19]. We have estimated ZINB regressions using instruments for Article95; see the discussion around equation 6. As expected, the results from our preliminary estimates are noisy and not reported here. However, Table 7 reports preliminary elasticities derived from the ZINB, which uses instruments for Article95. Overall we find minimal change in the "all" elasticity while the size of the life sciences elasticity has increased considerably. The computer science elasticity remains insignificant. Somewhat troubling is the fact that in these preliminary estimates the elasticity for the physical sciences and engineering are now insignificant. In future revisions of this paper, we will consider a general approach of modeling patent counts making allowance for excess-zeros and endogeneity.

Section Six: Summary and Conclusion

This research uses the Survey of Doctorate Recipients to examine the relationship between publishing and patenting at the level of the individual scientist. We find the marginal effect of another article on patents to be significant for faculty working in the life sciences, the physical sciences and engineering. Patent elasticities with respect to publishing are largest for engineers and smallest for physical scientists. Not surprisingly, given the relative unimportance of patent protection among computer scientists, especially those working in software, we find the relationship between publishing and patenting to be insignificant in this field. We also find that considerable variation occurs across fields in terms of variables affecting patenting such as receipt of federal support for research, gender and citizenship status.

We find little evidence of life-cycle effects but the cross-sectional nature of our data detracts from the robustness of this result. We do find that tenured faculty in several fields are less likely to patent than non-tenured faculty. This may be a cohort effect that will disappear as new faculty (trained in the technology transfer environment) join the

[19] If unobserved characteristics are correlated with the number of published articles in the patent equation, then standard estimation methods will be inconsistent.

professoriate, or it may be related to the inclusion of "non-faculty" in the sample.[20] Our data will permit us to examine the latter possibility; not the former.

Our results lead us to conclude that patents and publications are complements, not substitutes. From a policy perspective this is of considerable importance, given the widespread concern that has been expressed that patents are crowding out publications in the university sector. It also suggests that technology transfer offices at universities should work closely with offices of institutional research in stimulating overall research activity.

Our results must be considered preliminary. In future work we will expand the work that we have done using instruments for publication counts, explore the patenting activity of the non-faculty and further divide the field of computer science to see if distinctions are found between software researchers and hardware researchers. There are, however, areas of research that our data preclude. For example, we have no information on citations, either to articles or patents, and thus have no prospect of relating the quality of publications to the quality of patents. Moreover, we are limited to using cross sectional data while longitudinal data would be preferred. It is our hope that this research whets the appetite of others doing research in the area of technology transfer—and of data gathering agencies—to continue this line of research.

[20] We define non-faculty to include individuals working in post doctorate positions and in non-tenure track positions such as research scientists.

Table 1
Distribution of ***Patents*** and **Articles**
Percent

Sector	0	1-5	6-10	>10
Academe (n=10,962)	***90.9*** **14.4**	***8.7*** **40.8**	***0.4*** **20.9**	***0.1*** **23.9**
Computer (n=1,159)	***97.8*** **23.5**	***2.2*** **47.3**	*** **16.7**	*** **12.5**
Life (n=5,936)	***91.6*** **12.7**	***7.9*** **0.3**	***0.3*** **12.5**	***0.1*** **25.2**
Physical (n=2,156)	***90.7*** **15.5**	***8.7*** **37.3**	***.5*** **20.4**	***0.1*** **27.1**
Engineer (n=1,711)	***83.5*** **12.6**	***15.5*** **41.8**	***1.0*** **22.7**	*** **23.0**

Table 2
Patent by Publish Distribution
Frequency
Percent
Row PCT
Col PCT

PATENT	PUBLISH		
	0	1	Total
0	1541 14.1 15.5 97.7	8418 76.8 84.5 89.7	9959 90.9
1	36 .33 3.6 2.3	967 8.82 96.4 10.3	1003 9.2
Total	1557 14.4	9385 85.6	10962 100.00

Chi Square = 104.49; prob <.0001

Table 3
Definitions of Explanatory Variables Affecting Various Model Components

Variable	Description	*Uspapp95* Equation	Zero-Inflation Part	*Article95* Equation)
Uspapp95	Number of patent applications during the past 5 years.			
Patent	Zero-one dummy if one or more patents applied for during past 5 years			
Article95	Number of articles published during past 5 years	×		
Yrsofphd	Years since individual has earned highest degree	×	×	×
Yrsofphdsq	Yrsofphd-squared	×	×	×
Femdum	Zero-one dummy if female	×	×	×
Ctzusdum	Zero-one dummy if U.S. citizen	×	×	×
Fedsup	Zero-one dummy if receive federal research support.	×	×	×
*Lifefield**	Zero-one dummy if in field of life sciences			
Compfield	Zero-one dummy if in field of computer sciences	×	×	×
Phyfield	Zero-one dummy if in field of physical sciences	×	×	×
Engfield	Zero-one dummy if in field of engineering	×	×	×
*Univemp**	Zero-one dummy for individuals employed in four-year college or university, excluding Medidum and Reserdum			
Reseremp	Zero-one dummy if employed in a university research institute	×	×	×
Medemp	Zero-one dummy if employed in a medical school or center	×	×	×
Tenure	Zero-one dummy if individual works in academe and has tenure	×	×	×
Instpat	Number of patents awarded to academic institution individual worked for between 1990-1994		×	
Ru1empc	Zero-one dummy if working for school with Carnegie classification of Research University I.			×

Ru2empc	Zero-one dummy if working for school with Carnegie classification of Research University II			×
Doc1empc	Zero-one dummy if working for school with Carnegie classification of Doctoral Granting I.			×
Doc2empc	Zero-one dummy if working for school with Carnegie classification of Doctoral Granting II.			×
Mediempc	Zero-one dummy if working for school with Carnegie classification of a Medical school.			
*Otherempc**	Zero-one dummy if Carnegie classification of school employed at is anything besides Ru1, Ru2, Doc1, Doc2, Medi dummies			
Ru1deg	Zero-one dummy if Carnegie classification of school awarding degree is Research University I.	×	×	
Ru2deg	Zero-one dummy if Carnegie classification of school awarding degree is Research University II	×	×	
Doc1dg	Zero-one dummy if Carnegie classification of school awarding degree is Doctoral Granting I.	×	×	
Doc2dg	Zero-one dummy if Carnegie classification of school awarding degree is Doctoral Granting II.	×	×	
Medideg	Zero-one dummy if Carnegie classification of school awarding degree is Medical school.	×	×	
Rdactivity	Zero-one dummy if primary or secondary work activity is in applied or basic research or development or design	×	×	

* Indicates the benchmark or control group.

× Means the variable is an explanatory variable included in the equation

Table 4
Means (Standard Deviations) of Variables By Field

Variable	Academe Total	Life Sciences	Computer Sciences	Physical Sciences	Engineering
Uspapp95	0.196 (0.96)	0.167 (0.80)	0.033 (0.25)	0.218 (1.09)	0.376 (1.45)
Patent	0.091 (0.29)	0.084 (0.28)	0.022 (0.15)	0.092 (0.29)	0.165 (0.37)
Article95	8.090 (10.43)	8.358 (10.36)	4.969 (7.44)	9.093 (11.91)	8.013 (10.06)
Yrsofphd	13.898 (10.13)	13.946 (9.98)	14.890 (9.98)	15.422 (10.83)	11.136 (9.20)
Yrsofphdsq	295.659 (364.46)	294.139 (356.72)	321.144 (344.59)	355.165 (405.72)	208.69 (330.86)
Femdum	0.241 (0.43)	0.324 (0.47)	0.201 (0.40)	0.151 (0.36)	0.099 (0.30)
Ctzusdum	0.896 (0.31)	0.933 (0.25)	0.852 (0.35)	0.891 (0.31)	0.802 (0.40)
Fedsup	0.524 (0.50)	0.541 (0.50)	0.279 (0.45)	0.575 (0.69)	0.565 (0.50)
Lifefield	0.541 (0.50)	**	**	**	**
Compfield	0.106 (0.31)	**	**	**	**
Phyfield	0.197 (0.40)	**	**	**	**
Engfield	0.156 (0.36)	**	**	**	**
Univemp	0.628 (0.48)	0.499 (0.50)	0.895 (0.31)	0.728 (0.44)	0.767 (0.42)
Reseremp	0.121 (0.33)	0.077 (0.27)	0.081 (0.27)	0.215 (0.41)	0.178 (0.38)
Medemp	0.252 (0.43)	0.423 (0.49)	0.024 (0.15)	0.057 (0.23)	0.055 (0.23)
Tenure	0.467 (0.50)	0.434 (0.50)	0.646 (0.48)	0.467 (0.50)	0.458 (0.50)
Instpat	56.142 (109.15)	59.717 (111.00)	39.006 (94.45)	56.923 (116.42)	54.365 (101.23)
Ru1empc	0.454 (0.50)	0.488 (0.50)	0.325 (0.47)	0.415 (0.49)	0.475 (0.50)
Ru2empc	0.080 (0.27)	0.077 (0.27)	0.084 (0.28)	0.070 (0.25)	0.098 (0.30)
Doc1empc	0.042	0.033	0.070	0.045	0.052

	(0.20)	(0.18)	(0.26)	(0.21)	(0.22)
Doc2empc	0.057 (0.23)	0.043 (0.20)	0.063 (0.24)	0.059 (0.24)	0.098 (0.30)
Mediempc	0.081 (0.27)	0.138 (0.34)	0.008 (0.09)	0.017 (0.13)	0.016 (0.12)
Otherempc	0.286 (0.52)	0.221 (0.41)	0.450 (0.61)	0.394 (0.57)	0.260 (0.55)
Ru1deg	0.673 (0.47)	0.665 (0.47)	0.632 (0.48)	0.692 (0.46)	0.705 (0.46)
Ru2deg	0.087 (0.28)	0.081 (0.27)	0.114 (0.32)	0.093 (0.29)	0.081 (0.27)
Doc1dg	0.037 (0.19)	0.030 (0.17)	0.076 (0.27)	0.036 (0.19)	0.034 (0.18)
Doc2dg	0.023 (0.15)	0.023 (0.15)	0.026 (0.16)	0.025 (0.15)	0.020 (0.14)
Medideg	0.025 (0.16)	0.045 (0.21)	0.001 (0.03)	0.000 (0.00)	0.001 (0.02)
Rdactivity	0.482 (0.50)	0.246 (0.55)	0.246 (0.43)	0.481 (0.50)	0.418 (0.49)
Sample Size	*10962*	*5936*	*1159*	*2156*	*1711*

Table 5
Results from Zero-Inflated Negative Binomial Regression
Dependent Variable: Uspapp95[a]

Model	Variable	Academe Total	Life Sciences	Computer Sciences	Physical Sciences	Engineering
Uspapp 95						
	Article95	0.0430 (12.22)	0.0456 (10.07)	0.0354 (0.62)	0.0269 (3.50)	0.0454 (1.81)
	Yrsofphd	0.0498 (2.81)	0.0844 (2.61)	-0.0142 (-0.08)	0.0617 (1.79)	-0.0143 (0.32)
	Phdsq	-0.0004 (-0.94)	-0.0014 (-1.92)	0.0023 (0.58)	-0.0003 (-0.45)	0.0010 (2.09)
	Femdum	-0.0055 (-0.03)	0.2041 (0.46)	0.7469 (1.02)	-0.1974 (-0.68)	-0.3509 (-0.16)
	Ctzusdum	-1.2552 (-2.03)	-0.0650 (-0.24)	0.1034 (0.06)	0.6937 (2.08)	-0.3683 (-2.64)
	Fedsup	-0.0018 (-0.01)	0.0311 (0.14)	2.2817 (1.85)	-0.4994 (-1.75)	-0.0674 (-0.98)
	Compfield	0.5116 (1.24)	***	***	***	***
	Phyfield	0.5098 (2.89)	***	***	***	***
	Engfield	0.9309 (6.27)	***	***	***	***
	Reseremp	0.4183 (2.75)	0.2535 (0.82)	3.6062 (4.67)	0.9944 (3.08)	0.1047 (0.44)
	Medemp	0.2355 (1.64)	-0.0911 (-0.40)	2.4409 (3.16)	1.3878 (4.12)	0.7911 (2.92)
	Tenure	0.0095 (0.07)	-0.0689 (-0.38)	3.5400 (4.13)	-0.2438 (-0.66)	0.0225 (0.10)
	Ru1deg	0.0841 (0.56)	-0.0252 (-0.11)	-4.1979 (-2.04)	-0.5029 (-1.07)	0.5606 (1.54)

	Ru2deg	*0.0295* (0.12)	0.1450 (0.33)	-3.0607 (-1.67)	-0.3380 (-0.52)	-0.2449 (-0.52)
	Doc1deg	*-0.1472* (-0.46)	0.4082 (0.30)	-2.2716 (-1.01)	0.2228 (0.35)	0.1086 (0.17)
	Doc2deg	*-0.6543* (-1.35)	-0.3162 (-0.34)	-5.8932 (-2.92)	-0.5336 (-0.54)	-1.0275 (-1.88)
	Medideg	*0.4383* (1.46)	0.4541 (1.18)	***	***	***
	Rdactivity	*0.6043* (2.07)	0.6472 (1.29)	-0.4328 (-0.54)	-0.8829 (-1.56)	-0.0376 (-0.11)
	Constant	*-3.3095* (-6.85)	-3.2749 (-4.18)	-1.7778 (-0.79)	-1.6233 (-2.20)	-1.1501 (-2.00)
Inflation (Logit)						
	Yrsofphd	0.0281 (0.56)	0.0472 (0.38)	0.0561 (0.19)	-0.0124 (-0.12)	-0.0140 (-0.15)
	Phdsq	-0.0001 (-0.13)	-0.0009 (-0.38)	0.0021 (0.27)	0.0006 (0.27)	0.0010 (0.51)
	Femdum	1.5725 (3.33)	1.6912 (2.86)	1.6676 (1.23)	1.9431 (2.33)	0.2591 (0.32)
	Ctzusdum	-1.2552 (-2.03)	-0.7729 (-0.69)	-2.5893 (-1.41)	3.7760 (2.39)	-1.3906 (-2.52)
	Fedsup	-1.2128 (-4.01)	-0.8651 (-1.44)	0.4975 (0.26)	-3.0967 (-3.31)	-0.6270 (-1.19)
	Compfield	2.1468 (3.43)	***	***	***	***
	Phyfield	0.5083 (1.32)	***	***	***	***
	Engfield	-1.2797 (-2.48)	***	***	***	***
	Reseremp	0.0089 (0.02)	-0.2659 (-0.44)	8.3126 (1.99)	2.0104 (1.81)	-1.2515 (-1.45)
	Medemp	-1.4479 (-2.39)	-1.6588 (-1.76)	8.1722 (1.98)	0.3115 (0.32)	0.3341 (0.53)
	Tenure	1.4824 (2.06)	0.7341 (1.01)	10.5842 (2.30)	2.0117 (2.09)	0.2178 (0.41)
	instpat	-0.0047 (-1.85)	-0.0054 (-0.86)	-0.0061 (-1.93)	-0.0004 (-0.16)	-0.0035 (-1.28)
	Ru1deg	-0.6926 (-1.29)	-0.1931 (-0.22)	-10.8257 (-2.85)	-3.4951 (-2.64)	0.4834 (0.60)
	Ru2deg	-0.4301 -(0.80)	0.6196 (0.68)	-9.9962 (-2.69)	-1.5235 (-0.98)	-12.9557 (-4.70)
	Doc1deg	-1.6572 (-1.16)	1.5847 (0.69)	-10.7038 (-2.92)	-2.3801 (-1.42)	0.3389 (0.28)
	Doc2deg	-1.6413	1.1587	-14.2575	-2.7157	-11.8365

		(-0.70)	(0.78)	(-3.12)	(-1.14)	(-4.69)
	Medideg	0.2700 (0.36)	0.6849 (0.84)	***	***	***
	Rdactivity	-1.1856 (-2.64)	-1.5833 (-2.21)	-0.0744 (-0.07)	-3.8841 (-4.16)	-1.3413 (-1.99)
	Constant	1.6779 (2.02)	1.7675 (1.45)	4.2301 (1.68)	1.5025 (0.76)	2.0063 (2.03)
	Ln-alpha	1.5824 (10.78)	1.4676 (3.74)	-162.34 (0.00)	1.704 (13.38)	0.9898 (3.27)
	Log-likelihood	-4345.2	-2149.84	-108.927	-883.94	-1130.56
	N	10962	5936	1159	2156	1711

(a) Figures with brackets are t-ratios based on robust standard errors.
* (**) Statistically significantly different from zero at the 5% (1%) level of significance.

Table 6
Marginal Effects and Elasticities:
Estimates from Zero-inflated Negative Binomial Model
Dependent Variable: Uspapp95[a]

Variable	Academe Total	Life Sciences	Computer Sciences	Physical Sciences	Engineering
Article95	0.0060** (0.347)[b,**]	0.0053** (0.381)**	0.0010 (.176)	0.0062** (0.245)**	0.0192** (0.364)**
Yrsofphd	0.0043* (0.425)*	-0.0227* (-3.220)*	-0.0015 (-0.814)	0.0115 (0.766)	0.0033 (0.086)
Femdum	-0.0786[c,**]	-0.0588**	-0.0183[c]	-0.1660	-0.1430
Ctzusdum	0.0546*	0.0312	0.0372*	0.0495	-0.0249
Fedsup	0.0566**	0.0432*	0.0884*	0.1035*	0.0136
Lifefield					
Compfield	-0.0681**				
Phyfield	0.0491*				
Engfield	0.2830**				
Univemp					
Reseremp	0.0685**	0.0476	-0.0376	0.0392	0.1110
Medemp	0.1005**	0.0603**	-0.0317	0.5705*	0.4391*
Tenure	-0.0679**	-0.0415*	-0.0279	-0.1789**	-0.0045
Instpat	0.0002** (0.089)*	0.0003 (0.130)	0.0002 (0.215)	0.00002 (0.006)	0.0002 (0.029)
Ru1deg	0.0444*	0.0062	0.0544*	0.3148*	0.1895*
Ru2deg	0.0238	-0.0156	0.0064*	0.0074	0.0614
Doc1dg	0.0287	-0.0466	0.0214*	0.0317	0.0214
Doc2dg	-0.0389	-0.0716**	-0.0225*	0.0052	-0.2321*
Medideg	0.0559	0.0155			
Rdactivity	0.1167**	0.1172**	-0.0111	0.1416**	0.0999
Sample Size	10962	5936	1159	2156	1711

* (**) Statistically significantly different from zero at the 5% (1%) level of significance.

a) The underlying coefficient estimates and t-ratios are shown in Table 6. In non-linear models, such as ours, the t-ratios associated with coefficient estimates, marginal effects and elasticities may be somewhat different. The t-ratios corresponding to coefficient estimates are generally more reliable because the underlying standard errors are less noisy.
b) Figures within brackets indicate elasticities of the number of patent applications with respect to the variable.
c) For a dummy variable, the marginal effect is for discrete change from 0 to 1.

Table 7.
Elasticities:
Estimates from Zero-inflated Negative Binomial Model Using Instruments for Article95
Dependent Variable: Uspapp95[a]

Variable	Academe Total	Life Sciences	Computer Sciences	Physical Sciences	Engineering
Article95	0.0059* **(0.303)**[a,*]	0.0093* **(0.538)***	0.0014 **(0.024)**	0.0063 **(0.220)**	0.0146 **(0.262)**
Sample Size	10962	5936	1159	2156	1711

* (**) Statistically significantly different from zero at the 5% (1%) level of significance.

(a) Figures within bracket indicate elasticities of the number of patent applications with respect to Article95.

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