

Scholarship and Inventive Activity in the University: Complements or Substitutes? *

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Abstract

Universities are engaging in more licensing and patenting activities than ever before, and the amount of research funded by industry is increasing. Academics' commercialization activities may inhibit traditional academic scholarship. If the output of such scholarship is an important input into technological innovation and economic growth, then such an inhibition would be cause for concern. We introduce new instruments and techniques and demonstrate them using a novel panel dataset of academic electrical engineers from Stanford University. We find no evidence that engaging in inventive activity reduces the quantity of scientific output and some evidence that it increases its quality. (JEL Codes: J22, J24, O31, O34).

Keywords: Science, Innovation, University, Commercialization

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1 Introduction

The growing involvement of industry in University-based scientific research has sparked a concern that academics' commercialization activities may inhibit traditional academic scholarship. The issue has been examined in the context of the Bayh-Dole Act (Mowery, Nelson, Sampat, and Ziedonis 2001), as well as more generally (see for example, Dasgupta and David 1994 or Brooks and Randazzese 1998).¹ Recently, this issue has become more salient as university licensing and patenting activities have sharply increased since 1980 (Henderson, Jaffe, and Trajtenberg 1998; Mowery et al. 2001). In addition, the amount of research funded by industry is increasing (Mowery 2002).

A significant body of evidence suggests that university research has contributed to economic growth in the United States. Cohen, Florida, Randazzese, and Walsh (1998) systematically review the literature that traces contributions of scientific research to industrial invention. For example, Mansfield (1991) estimates that the annual social rate of return to university research was 28% between 1975 and 1978. More recently, based on an analysis of citations from US patents to academic patents originating in major California universities, Branstetter and Ogura (2005) document an increased coupling of university and academic research, particularly in biotechnology and to a lesser extent in information technology related fields. A finding, therefore, that a diversion of effort from the production of such knowledge would be an important long-term concern for growth policy. In contrast, a finding that inventive activities enhance traditional output would suggest that current trends towards broad acceptance of commercialization activities among academics is likely to lead to enhanced growth rates in the future (see Owen-Smith and Powell 2001 for evidence of such trends).

In studies of research output, uncovering the relationship between the pursuit of commercialization activities and the pursuit of publication activities has been elusive since faculty effort is endogenously chosen.² Agrawal and Henderson (2002) find that patenting and

¹Of course, one should not lose sight of the fact that university-industry ties have always been an important aspect of university research in the U.S. (Rosenberg and Nelson 1994).

²We limit our discussion of the literature to papers that directly address the complementarity question.

publishing are positively correlated in a panel of MIT scientists, but they are unable to inform the causality debate. Using a matched longitudinal sample of 332 patenting and non-patenting scientists across several universities, Markiewicz and DiMinin (2005) find a positive relationship between patenting and publishing. To assess causality they instrument using both the number of total patents and the number of technology area patents at the inventor’s university. Stephan, Gormu, Sumell, and Black (2007) exploit the cross-sectional data derived from a survey of doctoral recipients and again find a similar result. Azoulay, Ding, and Stuart (2004) exploit a broad sample of life scientists and find a positive relationship between patent output and publication activities. They use the inverse probability of treatment weights to predict selection into patenting. In essence, theirs is a two stage method in which lagged output and demographic measures predict the first stage likelihood of entering a patenting regime (i.e., the existence of a treatment effect), and publication output is then regressed against these predicted values. Finally, though their methodology cannot address causality, Breschi, Lissoni, and Montobbio (2007) suggest that Italian academics who patent are more productive than those that do not.³

This paper advances the literature that looks for evidence of a tradeoff between the pursuit of commercialization activities and the pursuit of scholarly activities. We demonstrate improved methodology more appropriate for count panel data models, better instruments and more fine-grained measures of inventive activity. We estimate a fixed effects count data model with endogenous regressors that uses Wooldridge’s (1991; 1997) quasi-differencing transformation to remove fixed effects. To control for the potential endogeneity of the number of inventions, we supplement commonly used instruments associated with peer inventive

This omits a growing literature that explores the academic production function of patents at the individual or laboratory level more generally, but often does not seek to address the complementarity question (cf., Carayol 2007).

³These empirical studies draw similar conclusions as a previous generation of literature based upon less direct measurement techniques. Generally, the evidence that industry involvement in academic research affects the nature of output is at best, weak (see Cohen et al. 1998 for a survey). There is limited anecdotal evidence that production of commercially-relevant output comes at the expense of the production of academic reputation. Florida and Cohen (1999) report a study by John Servos that documents a tension at MIT’s chemical engineering department. Some faculty members wished to pursue basic research, and others research of commercial relevance. The academic reputation of the department suffered when those in the “basic” camp chose to leave MIT. A similar tradeoff is reported in biotechnology where dissertations of students from a commercially-oriented university lab were, some claimed, of little academic importance (Kennedy 1986).

activity and use a novel instrument to capture demand for commercial innovation: the amount of venture capital investment in a scientist’s research area. The 10-fold increase in venture capital outlays in the 1990s is indicative of an exogenous shift in the demand for commercial innovation. Lerner (1999) suggests that the amount of venture capital financing is closely related to the emergence of commercialization opportunities in the university.

We demonstrate our improved methods on an 11-year sample of academic scientists in the Electrical Engineering department at Stanford University. This case-based approach allows us to follow inventive activity in much greater detail than in previous studies. At Stanford, about one third of disclosed inventions are never patented. Therefore, we pick up inventive activity that is missed by studies based on patenting data. Moreover, inventor effort is often necessary for successful commercialization (Thursby and Thursby 2004). By incorporating information about licensing, we measure the intensity of this post-disclosure commercialization activity. We find that commercialization enhances traditional scholarship. In particular, according to the most general specifications we run, we find that each additional invention disclosure may lead to a 16 percent increase in publications and a 18 percent increase in the importance of academic output in the electrical engineering department. We find the effect on number of publications is not robust across specifications, however.

Unfortunately, our data do not allow cross-university comparisons. Given this weakness, it is important to consider why Stanford is an interesting case to study. Stanford consistently ranks in the top 5 universities by several measures of inventive and commercialization activities (AUT 2002). At the same time, Stanford enjoys a leading reputation in engineering and science fields. Stanford has a history of encouraging interactions between its faculty and industry and has played an important role in the Silicon Valley phenomenon (Lenoir, Rosenberg, Rowen, Lecuyer, Colyvas, and Goldfarb 2006). Branstetter and Ogura (2005) find that Stanford University’s academic output in information technology is a uniquely important source of industrially relevant knowledge among research active schools in California. This suggests that Stanford is on the leading edge of the “commercialization” phenomenon, i.e., the canary in the mineshaft. If we were to find, say, that at Stanford commercialization

and academic outputs are complementary, we should be less concerned that increased commercialization of academia will lead to a substitution of outputs at other universities whose interface with industry is rudimentary but still developing. On the other hand, if we were to find that top academics are substituting inventive and commercialization activities for academic activities at Stanford, we should be concerned about similar phenomena at other institutions.

The paper proceeds as follows. In Section 2, we review the literature that describes potential reasons inventive and academic activities may be complements or substitutes. Our data are described in Section 3. Our methods and results are reported in Section 4. Discussion and Conclusion follow.

2 Complements and Substitutes

The fundamental explanation of why inventive and academic activities may be substitutes is the presumption that effort directed towards the production of inventive output decreases the effort directed towards the production of academic output. Academic scientists face strong incentives to publish, as publication is the primary mechanism through which to assess research output (Dasgupta and David 1994). Cole (1978) relates academic salaries directly to publication output. Stephan and Levin (1992) find life-cycle career motivations are strong predictors of publication patterns over academics' careers. Tenure decisions are commonly based on publication outputs (Stephan and Levin 2001). Sociologists have long argued that the pursuit of publications may be motivated by its associated prestige (Merton 1957). Finally, curiosity alone may be sufficient to motivate some scientists (Stephan and Levin finds that physicists are particularly likely to be intrinsically motivated, and Stern (2004) finds that industrial researchers will accept lower pay if allowed to conduct scientific research). The recent increase in the technology commercialization orientation of some universities and the changing nature of commercial opportunities associated with academic output in some academic research fields (c.f., biotechnology), has not only increased the

benefits of commercialization activities, but has decreased its costs as well through the growth and routinization of technology licensing office activities (c.f., Mowery and Sampat 2001). Subsequently, academics' negative attitudes towards commercialization activity have attenuated (Owen-Smith and Powell 2001).

While it is clear that effort allocated towards one activity is necessarily not directed towards another, there are several theoretical reasons why this might not lead to observable substitution effects in scientific output composition. Commercializable results and publishable results are, at times, one and the same (Stokes 1997). As Stokes argues, the extent of this sameness is almost certainly field-specific. If the post-discovery marginal costs of both disclosing and publishing are low, then we should expect to measure little substitution between the two activities. Stephan et al. (2007) note that this duality might be facilitated “by the fact that scientists and engineers can selectively publish research findings while at the same time monopolizing other elements of research.” Murray and Stern (2005) find that about 50% of articles in *Nature Biotechnology* have accompanying patents, and that the issuance of such patents increases the cost of doing research in a particular area. Finally, interaction with industry may inspire research by focusing inventors on interesting problems (Mansfield 1995; Siegel, Waldman, and Link 2003). We refer the reader to Azoulay et al. (2004); Breschi et al. (2007); Stephan et al. (2007), and Markiewicz and DiMinin (2005) for similar discussions.

3 Method

Our unit of analysis is the academic scientist. The object of our study is his or her scholarly and inventive productivity. We assume academic scientists exert two kinds of effort, effort whose primary purpose is publication and effort that yields laboratory inventions.⁴ We do not have direct measures of these efforts. However, we observe their results. Let P_{it} and I_{it}

⁴Of course, academic scientists also devote time to teaching, administration, consulting activities, and leisure. While data on teaching activities for the faculty studied here are available, we omit a measure of teaching effort because such effort is likely to be jointly determined with research effort. We do not have data on administration consulting activities, or leisure, however, so we exclude them from our analysis.

be respectively the number of publications and number of inventions produced by scientist i in a given period. P_{it} and I_{it} are assumed a function of ability and effort. We examine whether efforts devoted to publication and research are complements or substitutes. On the one hand, effort is subject to a budget constraint—loosely, that efforts must add up to an available effort endowment—so that efforts expended on P_{it} and I_{it} may be negative “inputs” in each other’s production. This is the substitution concern expressed above. The two efforts across activities may also be complementary, however. Effort in the laboratory directed at producing an innovation may complement the production of publications because it may suggest new avenues of inquiry.

Based on the above discussion, we assume over a given period P_{it} is determined according to:

$$P_{it} = X_{it}\beta + I_{it}\delta + \alpha_i + \varepsilon_{it} \tag{1}$$

where X_{it} is a vector that includes the number of years since receiving a Ph.D., its square, a variable indicating whether i is tenured, lagged output and a dummy indicating whether $t \leq 1995$ (i.e., the observation occurs during the “dot com” era). Tenure status and number of years since receiving a Ph.D. reflect i ’s experience and skills. They may also reflect i ’s incentives. Number of years since Ph.D. may pick up life-cycle effects on productivity; some researchers have found that age is negatively correlated with a scientist’s output (see Stephan and Levin 1992 and the references cited therein).⁵ Tenure status and years since Ph.D. are measured as of the year of output. α_i is a fixed effect that captures i ’s ability. ε_{it} is an error term, assumed independently and identically distributed across individuals and time.

Our parameter of interest is δ , which reflects the effect of inventive effort on publication output. As suggested, I_{it} is endogenous and determined by effort allocations among academic and inventive and/or commercialization activities. The key to the identification strategy is

⁵Because publications often occur with a lag, we report results from estimations that lag inventions by one year. See below.

to find demand shifters that affect relative preferences for inventive and commercialization activity as opposed to publication activity. Because we use fixed-effects regressions, it is critical that these shifters vary throughout the period 1990-2000, and further that scientists' research incentives are influenced by these changes. We propose two types of measures: the amount of venture capital (VC) disbursed in a scientist's broad area of interest and the number of inventions and revenue of inventions by colleagues in the scientist's department. We include the latter type because of evidence that individuals weight strongly the experiences of those in their near vicinity when formulating expectations of returns to particular events (Rabin 1998). During this period, the size of total national VC disbursements in new firms increased *8-fold* from a rate of \$12B annually in 1990 to close to \$94B at the height of the technology bubble in 2000.⁶ This general trend is echoed in information technology and more weakly in the biological sciences (Goldfarb, Kirsch, and Pfarrer 2005). While individual scientists are unlikely to be aware of precise venture capital disbursements, these disbursements are likely to be correlated with information flows that would influence beliefs as to the potential returns to inventive activity. When new and fertile areas appear, venture capital flows towards it (Gompers and Lerner 1998). These dramatic year-to-year changes in venture capital should reflect changes in the perceived relative returns to invention within a discipline.

We describe the two dependent variables that we use in our analysis (publications and weighted publications) in detail below. Presently we note that publications is a count variable whereas weighted publications, which is publications multiplied by the impact factor of the journal in which the publication was published, is not. In this latter case, we can

⁶VC figures are taken from Thompson Financial Venture Economics database. Reported as the annual sum of all "PWC" deals. This classification is provided by Venture Economics.

PWC Money Tree deals include "cash-for-equity" investments by the professional venture capital community in private emerging companies in the U.S. The survey excludes debt, buyouts, recapitalizations, secondary purchases, IPOs, investments in public companies such as PIPES (private investments in public entities), investments for which the proceeds are primarily intended for acquisition such as roll-ups, change of ownership, and other forms of private equity that do not involve cash such as services-in-kind and venture leasing. Investee companies must be domiciled in one of the 50 US states or DC even if substantial portions of their activities are outside the United States (see <http://www.pwcmoneytree.com/moneytree/nav.jsp?page=definitions>)." PWC deals specifically exclude buyouts.

estimate specification (1) as a linear model with scientist fixed effects on the right hand side, and weighted publications on the left hand side (whose values theoretically can take on any non-negative real number, not just the non-negative integers). We control for the potential endogeneity of number of inventors using two-staged least squares, with our measures of venture capital and colleagues' inventions or invention revenues as instruments. As a robustness check, we also estimate (1) using a generalized method of moments (GMM) technique for panel data with endogenous regressors (see e.g. Arellano and Bond 1991).

In specifications in which the count variable, publications, is our dependent variable, we control for the potential endogeneity of number of inventions only in the GMM specifications, as follows. We assume that the random variable P_{it} is related to the explanatory variables according to

$$P_{it} = \exp(\alpha_i + X_{it}\beta + I_{it}\beta^I) + u_{it} = \mu_{it}q_i + u_{it} \quad (2)$$

where $\mu_{it} = \exp(X_{it}\beta + I_{it}\beta^I)$, α_i is the scientist-specific fixed effect, $q_i = \exp(\alpha_i)$, and u_{it} is the error term. I_{it} is assumed endogenous, that is, $E(I_{it}u_{it}) \neq 0$. We use Wooldridge's quasi-differencing transformation to remove the fixed effects (see Wooldridge 1991; Wooldridge 1997; and Windmeijer 2000), which leads to the following moment conditions:

$$E\left(Z_{it-s}\left(\frac{P_{it}}{\mu_{it}} - \frac{P_{it-1}}{\mu_{it-1}}\right)\right) = 0 \quad (3)$$

where $s \geq 2$ for $Z_{it} = I_{it}$, and $s \geq 0$ for X_{it} and additional instruments. In our empirical work, the instruments and lags we use produce more moment conditions than the number of parameters we wish to estimate. Our estimates of the parameters minimize a quadratic function formed by the weighted sample moment conditions corresponding to Equation (3) and the data.

4 Data

We collected comprehensive output histories of tenure track faculty employed in Stanford’s Electrical Engineering department from 1990 through 2000. Faculty members were identified from annual Stanford course catalogues, available in Stanford libraries.

For each academic in the sample, we extracted publication histories from the Institute of Scientific Information (ISI)’s Science Citations Index (SCI). Matching articles to scientists is a non-trivial exercise. The SCI catalogues authors by their first and middle initial and their last name. Affiliations are also reported, although a one to one matching between author and affiliation is not provided when authors have multiple affiliations. Hence, accurate matching of articles retrieved from an SCI search to sample researchers required painstaking evaluation of each search result to identify sample-researcher authored articles. Because citations take some time to occur, citations of articles are not strictly comparable for articles of different vintages. Moreover, this problem is most severe for articles of recent vintage (see Hall, Jaffe, and Trajtenberg 2001 for a discussion of this problem in the patent context). To address this problem, as in Arora, David, and Gambardella (1998), we use ISI’s journal citation reports to assess the scientific value of particular articles. ISI’s journal impact factor is the total number of citations to a journal divided by the total number of articles in a journal in a two year moving window. Although the SCI is not a comprehensive database of all publications, it does cover the most important and influential publications in any field. The ISI builds its database with an explicit bias towards work of scientific importance. Garfield (1996) observes that only 150 journals account for half of what is cited and that a core of 2000 journals account for 85% of published articles and 95% of cited articles. The small number of citations to journals not covered by the database suggests that most academically important results are contained within the journals that the SCI covers. The variable *publications*, which is the number of publications measured by year and *weighted publications* which is the sum of the impact factors of journals in which a scientist published by year, are our two dependent variables measuring “traditional” academic output.

Comprehensive data of inventive output come from Stanford’s Office of Technology Licensing (OTL). Stanford has kept comprehensive, computerized records of all inventive and licensing activity since 1996, partial computerized records from 1980-1995 and complete archival hard-copy (paper-based) records from the 1970s through the present. The earlier the year, the less likely information will be included in the OTL’s computerized database. Because of this, where necessary, we exhaustively examined paper files of all inventions between 1990 and 1996.

The data include a comprehensive list of all Stanford inventions that were disclosed to the OTL and deemed of some commercial value. OTL licensing associates estimate that roughly one third of disclosures do not reach a minimal bar of estimated commercial value and a docket, which is a record of an invention disclosure, is not opened for these innovations. Stanford had 1,844 invention disclosures from 1990 through 2000, corresponding to 2,268 unique inventors. These inventors include faculty members and other affiliated individuals such as students, post-doctoral fellows and other research associates. From 1990-2000, Stanford was issued 670 US patents; that is, roughly one third of disclosures lead to a patent, although at times an individual disclosure may lead to multiple patents. A patent is a significant hurdle, as Stanford generally does not pursue a patent unless it has identified a licensee.⁷ We also observe how each disclosure was licensed (that is, exclusively, non-exclusively, with or without equity), the term of license, whether or not a product was sold, the amount of royalties earned, and any complementary relationships between faculty members and licensing firms. Hence we have comprehensive measures of inventive output of Stanford faculty from 1990 through 2000. In the 11-year sample we analyze, in electrical engineering, we observed a total of 197 inventions and 1362 publications distributed among 57 faculty members.

We also include several controls to accommodate life-cycle theories of academic productivity. While we do not observe academics’ ages, we do observe their date of Ph.D. This allows us to calculate their “academic age”, which is calculated as the observation year minus

⁷Personal communication with Kathy Ku, Head of Stanford’s Office of Technology Licensing, June 2003.

the year of Ph.D.

As described above, we collected venture capital outlays by broad industrial category from Thompson Financial’s Venture Economics database. We used Thompson Financial’s broad industrial category. The number of inventions and licenses of other scholars in an inventor’s department was calculated in a straightforward manner from the Stanford OTL data.

5 Results

Table 1 shows the means of the variables we use in our analysis for all scientist-years. (An academic appears in these data as many times as her years at Stanford between 1990 and 2000). Note that over the 1990-2000 period, the average annual number of inventions per researcher in Electrical Engineering was .4. Our measures of inventive output are highly skewed. The median Electrical Engineering faculty member generated 0 inventions and no license income over the period.

All models include fixed effects which capture (fixed) ability. Results are reported in Tables 2 and 3. In each specification, we include years since Ph.D. (academic age) and its square, tenure status (an indicator variable, equal to one if the faculty member is tenured), and whether the year precedes the Dot Com Era (pre-1995). All variables (including inventions) are measured with a one year lag to allow for the lag between the time the research is conducted and the time the results appear in print. In model 1, we measure the effect of inventive activity on total publications using a Poisson regression. In the Poisson and in the GMM estimations described below the coefficients can be interpreted as semi-elasticities. In the Poisson regression, we find a positive and significant relationship between inventive activity and the number of publications. To be clear, this is not a statement of causality, but rather association. In model 2, we report the results of a GMM estimation where we use the first and second lags of venture capital as well as the average inventions and license revenue produced by the scientist’s colleagues (each lagged one year) as instruments.⁸ The

⁸We thank Frank Windmeijer for providing his Gauss program, EXPEND, used to estimate these models

coefficient estimate on inventions remains positive and significant and implies that each invention leads to a 16% increase in publications the following year. In models 3 and 4, we substitute total licenses (lagged one year) emanating from the individual's inventions—a proxy for invention value—for total inventions. Model 3 is a Poisson specification and 4 is a GMM specification that controls for the endogeneity of the licensing variable. In neither regression is the estimate of the coefficient on the license variable statistically different from zero by conventional standards of significance.

The column headed by model 5 in Table 3 presents results from a fixed-effects, least squares estimation of the determinants of weighted publications, where each publication is weighted by the ISI impact factor of the journal in which the publication appears. The estimated coefficient for the inventions variable is negative but imprecisely measured. Models 6 and 7 use two alternative instrumental variables specifications to address the endogeneity problem. In model 6, the two-stage least square specification, we again find a negative but statistically insignificant relationship between inventions and weighted publications. In model 7, the GMM specification generates a coefficient estimate on total inventions that is positive and statistically significant by conventional standards of significance (the associated p value is about .03).⁹ The implied semi-elasticity from model 7 suggests that an extra invention increases weighted publications by 18%. Alternatively, recalling that weighted publications are weighted by ISI journal impact measures, we can interpret the

(see Windmeijer 2002). An issue of small sample bias arises in our use of the GMM with our relatively narrow dataset. In a Monte Carlo analysis of a quasi-differenced model similar to ours, Windmeijer (2008) shows that with good instruments the point estimates of the coefficients are not biased in small samples. He shows that with poor instruments, however, one-step estimates of the coefficients can be severely biased while two-step estimates, though biased, are less so. The fact that our one- and two-step estimates of the key parameters (the latter are available from the authors) are similar suggests that the point estimates we report do not suffer from such bias. Monte Carlo studies have also shown that for small samples the estimated asymptotic standard errors of the efficient two-step standard errors in GMM are severely downward biased (see Arellano and Bond 1991, Windmeijer 2005, 2008). The downward bias in the two-step procedure arises due to the extra variation introduced by the presence of estimated parameters in the weight matrix that is used to form the quadratic function that GMM minimizes. Though inefficient the one-step standard errors appear to be minimally biased (Arellano and Bond, Windmeijer 2005, 2008). Thus Tables 2 and 3 report only the one-step standard error estimates. The tables report Sargan tests based on two-step standard errors which are not biased in small samples.

⁹The GMM method we use for models 7 and 9, like the one used to estimate (2) and (4), allows for scientist-specific fixed effects. We use Arellano and Bond's DPD98 program to estimate this model (Arellano and Bond 1998).

semi-elasticity more precisely: in our sample the mean number of annual publications for electrical engineering faculty is three and each of these publications is cited in two years an average of 1.83 times. An engineer who increases her invention count by one in a given year will also likely publish in journals whose articles receive, on average, 0.97 more citations over a two year timeframe. We take the two findings together to be evidence that Electrical Engineers from Stanford enjoy a small to moderate positive effect of invention on weighted publications.

In models 8 and 9 we substitute total licenses for total inventions and find that the effect of licensing on weighted publications is imprecisely estimated in the two-stage least squares estimation. In the GMM estimation, the coefficient estimate is marginally significant (p value is .09) and implies that each license granted increases the researcher's weighted publication count the following year by 27%.¹⁰

In the specifications that produced the most precise estimates (models 1, 3, 4, 7, and 9) the point estimates suggested that tenure reduced publication effort. Across the specifications, the sign of the coefficient estimate on academic age and its square consistently support Levin and Stephan's (1991) life cycle hypothesis and the estimates are often statistically significant (in models 2, 5, 6, and 8 the coefficient estimate for age is insignificant). We find only mild evidence that the boom years had an important effect on publication activity, where publication activity is measured by simple publication counts; the estimated coefficient on the pre-1995 dummy is positive and at least marginally significant in the GMM specifications (models 2 and 4).

¹⁰In Engineering, time to publication is very short. We therefore re-ran all of the specifications reported in Tables 2 and 3 using contemporaneously measured inventions and licenses. Temporally aligning publications and inventions weakened the correlations found between the variables, in some of the specifications. The estimated effects of inventions on number of publications remained positive, but became insignificant (model 2). The estimated coefficient on licenses in model 9 became insignificant. The coefficient estimate in model 7 changed little and remained statistically significant, however.

6 Discussion & Conclusions

We introduce novel methods to control for the endogeneity of effort allocation between two activities among academics: inventive activities and traditional publication activities. Our results improve on previous scholarship by employing better instruments and a richer set of specifications that make fewer functional form assumptions.

Given the limited sample of our study, we believe that our contribution to this literature is largely methodological. However, with an important caveat (below) about generalizability, it is a useful exercise to consider broader implications of our results. In our study of the Stanford's electrical engineering department, we find no relationship between inventive activity and the number of published articles. However, we do find some evidence that innovation effort increases publication importance. To the extent we can generalize, this finding is puzzling. It suggests that increased incentives towards commercialization activities either led researchers to engage in research topics that were more productive academically, or there were unknown complementarities between commercialization activities and traditional academic activities. This interpretation would lead us to ask why all researchers are not engaging in commercialization activities, as doing so would shift their production closer to the frontier. While our regressions control for fixed effects and even changes in output opportunity, as measured by lagged output, it is still possible that our results are driven by discoveries that can be contemporaneously exploited in both academic and commercial realms and that any substitution effects are thus overwhelmed. If this is true, however, it suggests that the case against engaging in both activities is very weak: It must be better to substitute a small amount of publication effort and be in a more productive research space.

An important disclaimer is in order. Our data pertain to a single department at Stanford University, which is arguably at the frontier of the commercialization of science. However, the ability of researchers at this institution to successfully integrate the two activities, without deleterious effects, suggests that as other institutions approach Stanford's level of integration, they too will have such results. Indeed, if we found deleterious effects at such a

leading institution, then it would have been cause for serious concern.

On a more fundamental level, it is reasonable to question why we should expect questions of interest to academic scholars, and hence publishable to be different than the question of interest to industry. We do know that industry-funded research tends to produce output of more short-term value, (Blumenthal, Causino, Campbell, and Louis 1996), but we do not know if it is also of less long-term value. We also know that industry and utilitarian-oriented government agencies tend not to take academic reputation into consideration when choosing which academics to fund (Cohen et al. 1998; Goldfarb 2008; Mansfield 1995). If academic citations are correlated with the ultimate depth and breadth of applicability, and investment in the production of such academically relevant knowledge is a wise long-term investment, then reducing the relative rewards to the pursuit of such goals would be, theoretically, detrimental to growth.

The above discussion presumes that the pursuit of short term applicability implies a substitution of effort away from the pursuit of academically relevant research. Our results suggest that this is not necessarily true. We find no deleterious effects of increased commercial orientation of academic researchers.

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Table 1: Descriptive Statistics for Selected Variables - Electrical Engineering Department

Variable	Mean	Std. Dev.	Min	Max
Total Publications	2.961	3.567	0	24
Weighted Publications	5.452	8.301	0	58.667
Total Inventions	.428	.953	0	7
Total Licenses	.141	.507	0	5
Academic Age (yrs)	20.591	11.243	0	44
Tenure	.867	.340	0	1

Note: 460 observations (scientist years) for 57 scientists

Table 2: Regression Results—Total Publications

Dependent Variable	(1) <i>Poisson MLE</i> total publications	(2) <i>GMM</i> total publications	(3) <i>Poisson MLE</i> total publications	(4) <i>GMM</i> total publications
Academic Age	.150 (.039)	.180 (.108)	.155 (.039)	.279 (.111)
Academic Age Squared	-.004 (.001)	-.004 (.002)	-.004 (.001)	-.006 (.002)
Temure	-.429 (.203)	-1.174 (1.146)	-.435 (.202)	-2.065 (1.170)
Pre1995 (=1 if year < 1995)	.021 (.117)	.273 (.109)	.018 (.117)	.241 (.144)
Total Inventions	.067 (.029)	.159 (.044)		
Total Licenses			-.063 (.060)	.118 (.159)
Observations	N = 366, n = 49	N = 289, n = 54	N = 366, n = 49	N = 289, n = 54
Log Likelihood	-547.410		-549.373	
Sargan P-value		.290		.287
<i>Note:</i> Standard errors in parentheses. Models include fixed effects.				

Table 3: Regression Results—Weighted Publications

Dependent Variable	(5) <i>Least Squares</i> weighted publications	(6) <i>2SLS</i> weighted publications	(7) <i>GMM</i> weighted publications	(8) <i>2SLS</i> weighted publications	(9) <i>GMM</i> weighted publications
Intercept	7.016 (5.434)	-3.862 (6.788)	1.842 (1.694)	3.512 (6.880)	-3.610 (3.166)
Academic Age	.315 (.381)	.392 (.489)	.719 (.228)	.438 (.525)	1.869 (.667)
Academic Age Squared	-.014 (.007)	-.012 (.009)	-.016 (.005)	-.013 (.009)	-.040 (.014)
Tenure	.537 (2.035)	1.312 (2.474)	-3.144 (2.039)	.586 (2.820)	-9.229 (4.019)
Pre1995 (=1 if year < 1995)	-1.082 (1.231)	-.583 (1.410)	-.175 (.983)	-.399 (1.387)	.191 (.937)
Total Inventions	-.005 (.414)	-1.037 (2.266)	.977 (.455)		
Total Licenses				-1.905 (3.982)	1.467 (.868)
Observations	N = 403, n = 57	N = 346, n = 57	N = 346, n = 57	N = 346, n = 57	N = 346, n = 57
R ²	.002	.002		.004	
Sargan P-value			.883		.866

Note: Standard errors in parentheses. Models include fixed effects.