Faculty Participation in Licensing: Implications for Research*

Jerry G. Thursby
Georgia Institute of Technology

Marie C. Thursby
Georgia Institute of Technology & NBER

ABSTRACT: We exploit a unique database on research and invention disclosure of faculty at 11 major US universities over a period of 17 years to explore whether university licensing has compromised basic research. We relate disclosures to industry and federally sponsored research, publications, citations, "expected citations" and basic publications. Recent disclosure activity is found to have a positive effect on industry and federal research funding. But, if faculty disclose multiple times, the positive effect on federal funding can disappear and become negative. Both recent disclosure and repeated disclosures increase the faculty member's publication count as well as the importance of these publications in terms of citation. There is weak evidence that disclosure activity is associated with increases in other measures of "basic" research. We also examine life cycle effects and find that the ability to attract funding and the rate of publication increase as the faculty member ages but at a decreasing rate. Research tends to be less basic as faculty age. We also find that post tenure, both types of funding decrease and work becomes less basic.

August, 2008

* Funding was provided by the National Science Foundation (SES 0094573), the Alan and Mildred Peterson Foundation and the Ewing Marion Kauffman Foundation. We thank participants of the conference "The Changing Role of Public Sector Research in Innovation," Center for Advanced Studies, Oslo, Norway, for comments.

I. Introduction

Licensing as a mechanism for university-industry technology transfer has increased dramatically under the auspices of Bayh-Dole legislation in the United States. This activity has been tracked by the Association of University Technology Managers (AUTM) since the early nineties. Licenses executed by 109 US non-profit institutions responding to AUTM in 1996 and 2004 increased 72 percent from an average of 19 per university to an average of 32. Inputs to licensing such as inventions disclosed increased from an average of 66.9 per institution to 115.4 (a growth of 72.5%).[1] New patent applications filed increased from an average of 22.8 per institution to an average of 73.4 per institution (a growth of 231%).

While many view this growth as evidence of the increasing role of universities in the innovation system, others view it with skepticism, arguing that this commercial activity may have come at the expense of the greater university mission of producing basic knowledge. In this paper, we examine one of the central issues in this debate — the extent to which faculty involvement in licensing compromises basic research. Proponents of licensing argue that without the financial incentives associated with licensing, neither faculty nor companies would undertake the development needed for effective technology transfer (for discussions, see Mowery *et al*. 2004, Rai 1999). However, critics claim publication would be sufficient for transfer (Colyvas *et al*., 2002), and more importantly, that potential financial returns from licensing may have diverted faculty away from basic research (Press and Washburn, 2000).

However, recent theoretical work shows that basic research might not suffer from licensing.[2] If faculty have a taste for doing basic research and/or the associated prestige, the financial returns may not be sufficient to outweigh any disutility from the development effort often involved in licensing (Thursby *et al*., 2001, Jensen and Thursby, 2004). Further, for those faculty members who engage in licensing, the activity need not reduce their basic research. Thursby *et al.* (2007) examine a series of life cycle models in which faculty can devote effort to basic research which is published and/or applied research which is licensed. Not surprisingly, the financial return to licensing increases applied relative to basic effort. Although basic research may decrease, in models where basic effort underlies the knowledge used for licensing and applied effort also leads to publication, basic research is actually higher over the life cycle.[3] Essentially the financial return to licensing causes faculty to substitute research for leisure, so that the amount of basic research rises.

---

[1] An invention disclosure is the formal document filed with the TTO by a faculty member when the faculty member believes she has an invention with commercial potential.

[2] The term basic research has various interpretations. Our use is in the sense that the work is fundamental research which can serve as the basis for future research (Trajtenberg *et al*. 1997). Thus we do not address an alternative notion that the research was purely curiosity-driven.

[3] This result holds whether or not applied applied work increases the marginal productivity of basic effort as in Mansfield (1995). But it does depend heavily on one of the types of research, which they call applied, being in Pasteur's Quadrant so that some research is published and licensed (Stokes, 1997).

These models suggest three possible regimes associated with increased licensing: 1) no effect on research, 2) a negative effect on basic research, or 3) an increase in basic research. In this paper, we exploit unique data on the research profile and disclosure activity of science and engineering faculty at 11 major US universities over a period of 17 years to explore which of these regimes is more empirically relevant. Since our data include faculty who never disclosed inventions as well as those who did, we are also able to examine the extent to which faculty who become involved in the license process differ from those not involved.

We take disclosure as our measure of faculty participation in licensing since it reflects the faculty member's willingness to engage in commercialization. It also reflects only her opinion on the commercial potential of her invention.[4] It does not reflect any judgment by the Technology Transfer Office (TTO) about an invention's commercial potential or patentability as would patent applications. Nor does it reflect the opinion of patent examiners or the market as would patents awarded or licenses executed. In the case of patents awarded, novelty and usefulness would influence the outcome, and in the case of licenses executed, both the TTO ability and the market's opinion would be reflected. Thus we argue that disclosures are the preferable measure of faculty participation.

We consider several econometric models of research inputs and outputs as functions of a set of regressors of individual characteristics including several measures of prior disclosure activity. The research inputs we model are a faculty member's federal and industry sponsored research funding and the output measure we model is the number of publications. Our measures of the nature of research output include citations to those publications, "expected citations" to the journals in which the articles are published, and the number of "basic" publications.

Our estimation shows recent disclosure activity generally has a positive effect on research funding both from the federal government and industry, with the impact being higher for industry funding. However, if faculty disclose multiple times, the positive effect can disappear and with substantial numbers of disclosures the effect can become negative. In the case of publication output, we find that recent disclosure and repeated disclosure both increase the faculty member's publication count. Recent disclosure also increases the importance of these publications as measured by the number of citations. We find weak evidence that disclosure activity is associated with increases in our other measures of basic research.

One of the complexities of examining the impact of commercial activity is that research profiles are also a function of other factors such as the stage of the life cycle, whether or not the faculty member is tenured, as well as gender. Thus we also include measures of faculty age, tenure, and gender. With regard to age, we find that the ability to attract funding and the rate of publication increase as the faculty member

[4] It is important to emphasize that a willingness to engage in commercialization entails active involvement of the faculty member. See Thursby and Thursby (2004) for a discussion of the role of faculty in commercialization.

ages but at a decreasing rate. As one might expect, we find that her research tends to be less basic as she ages. We also find that post tenure, both types of funding decrease and her work becomes less basic. The only significant gender effect is higher numbers of publications for males.

This analysis contributes to the growing empirical literature on commercial activity by faculty. Much of this literature has focused on the relationship between publishing and patenting, which we argue conflates effects of faculty interest and patent examiner behavior (Murray 2002, Agrawal and Henderson 2002, Breschi *et al.* (2005), Stephan *et al*. 2007, Fabrizio and DiMinin 2008). These studies tend to find a positive relationship between patenting and publication but they do not focus on the *nature* of research activity. Jensen *et al.* (2008) also study faculty involved with patenting (both with universities and firms) and show that the ability to license their university research will lead them to devote more time to their basic university research and less time to consulting on applied projects with firms.

Azoulay *et al*. (2007) examine the life-cycle patenting behavior of 3,884 scientists in biomedical fields from 1967 to 1999 and find that, rather than diminishing or shifting in response to returns from patentable research, research creates opportunities for patenting. Azoulay *et al.* (2006) employ the same data to examine related questions in terms of the quality and content of publication, finding that scientists who patent are more prolific publishers than those who do not, controlling for other characteristics. This work complements other research on the dual use of research in the life sciences, where patenting and publishing may go hand in hand (Murray and Stern, 2006).

The only studies that consider the relationship between invention disclosures and research are Thursby and Thursby (2002, 2007a, and 2007b). Thursby and Thursby (2002) examine university level data and find that the primary factor behind the growth in licensing in the early 1990's was university administration decisions to patent and license, rather than a change in faculty disclosures. However, they say nothing about the character of research. Thursby and Thursby (2007a and 2007b) examine the publishing behavior of 3,241 faculty researchers at six major US universities from 1983 through 1999. Using the citation-based index developed by Narin *et al.* (1976) they find that the portion of research published in "basic" journals remained constant while the probability of an individual faculty member disclosing inventions increased tenfold.

None of these studies provides an econometric analysis of individual research profiles as a function of disclosure, nor do they examine the interaction of licensing behavior and research funding. To our knowledge, this paper along with Jensen et al. (2008), are the only empirical studies modeling the ability of faculty to obtain federal and industry sponsored research. .

II. Data

Our data are the research, demographic and disclosure profiles of all faculty scientists and engineers in PhD granting departments at 11 major universities: Georgia Institute of Technology, California Institute of Technology, University of Utah, Harvard University, Stanford University, Cornell University, Massachusetts Institute of Technology, University of Pennsylvania, Purdue University, Texas A&M University and University of Wisconsin - Madison. This choice of universities is not random. Each is a major research university and each has faculty actively engaged in licensing. As shown in Table 1, all of the universities in the sample compare favorably to the top 50 universities in terms of total research expenditures, licenses executed, patents awarded and invention disclosures as reported in the 2004 AUTM Survey.

Faculty included in this study are those on the list of science and engineering faculty in PhD granting departments provided in the 1995 National Research Council (NRC) report. Faculty not listed in PhD granting departments are excluded; importantly, this does not include medical school faculty unless they also hold appointments in PhD granting departments. Departments are excluded if one could not reasonably expect disclosure activity (for example, we exclude astronomy).

The TTO of each university supplied the names of disclosing faculty as well as dates of disclosure. Four universities provided disclosure information for 1983 to 1999, and the others provided information from 1983 to 1996 or from 1987 to 1999.[5] Matching these files with the NRC list provides a sample composed of multiple years of disclosure activity for faculty of the 11 universities in 1993. Not only are faculty in non-PhD granting departments excluded but we cannot include those who join a university after 1993 or who left a university before 1993. For years other than 1993 it was necessary to check to ensure that we include faculty only when they are at their university of record in 1993. In the sample are 4,988 faculty and 60,905 observations where an observation consists of a person in some year.

As noted above, an invention disclosure, rather than a license, is our measure of faculty interest in licensing. While disclosures and licenses are not independent, the former is more representative of faculty interest since the latter is influenced by expectations of the TTO and a firm as to commercial potential. A license disclosure indicates that an inventor has a research result she believes has commercial potential and that she is interested in commercializing. While all universities in the sample require their employees file such disclosures, this is hardly enforceable. Faculty may not disclose for a variety of reasons. In some cases they may not realize the commercial potential of their ideas, but often faculty do not disclose inven-

[5] We started with 1983 so as to be well past the date of passage of the Bayh-Dole Act of 1980. Universities supplied us with data as far back as disclosure information could easily be retrieved. The 1996 end was for Purdue University. Purdue was the basis for our pilot study in this project and that pilot was initiated in 1997, hence we only collected Purdue data through 1996.

tions because they are unwilling to risk delaying publication during the patent and license process.[6] Faculty who specialize in basic research may not disclose because they are unwilling to spend time on the applied research and development that is often needed for businesses to be interested in licensing university inventions (Thursby and Thursby 2002 and Jensen *et al.* 2003). While a disclosure signals a willingness to be involved with licensing, it need not indicate that the research was motivated by the desire to license. Curiosity driven research can often lead to commercially applicable results (Colyvas *et al*., 2002). In their interviews with MIT mechanical engineering faculty Agrawal and Henderson (2002) found that most conducted research with the primary goal of publishing.

There are five disclosure variables considered here. The first is whether a faculty member discloses in a given year. $DiscYr_{it}$ is equal to one if faculty member i made at least one disclosure in year t. This is a measure of interest in commercialization in year t as measured by disclosure activity in that year. Hereafter we use the term "disclosure year" to refer to an observation where $DiscYr_{it} = 1$. The second measure is the number of disclosures by year. $NumDisc_{it}$ is the number of disclosures made by faculty member i in year t. If $DiscYr_{it} = 1$, then $NumDisc_{it} > 0$. We create two variables that are measures of a faculty member's disclosure history, or history of interest in commercialization. Cumulative disclosure years is the count of the total number of prior years that had been disclosure years and is calculated as

$$CumDiscYr_{it-1} = \sum_{j=1}^{t-1} DiscYr_{ij} \ .$$

Cumulative disclosures is the number of disclosures made prior to the current year and is calculated as

$$CumDisc_{it-1} = \sum_{j=1}^{t-1} NumDisc_{ij} \ .$$

In each measure the year 1 is the first year a faculty member appears in the data. Clearly, *CumDiscYr* and *CumDisc* are undercounts since we do not have disclosure activity prior to 1983.[7] Finally, we create $EverDisc_i$ which is equal to one if the faculty member had at least one disclosure over the sample preriod. This variable is designed to measure whether those who never disclose are fundamentally different from those who do disclose at some point.

We supplement the disclosure data with data from Thomson ISI on the total number of publications by year for each of the faculty as well as the total number of citations those publications receive through 2003. $PubCount_{it}$ is the number of publications of faculty member i in year t. $Cites_{it}$ is the number of citations to those publications that were received through 2003. For example, if faculty member i had three publications in 1995, then $Cites_{it}$ would be the total number of citations those three publications had received through 2003. The citation data is truncated but we have at least four years of citation informa-

---

[6] Half of the firms in an industry survey noted that they include delay of publication clauses in at least 90% of their university contracts (Thursby and Thursby 2004). The average delay is nearly 4 months, with some firms requiring as much as a year's delay.

[7] This is likely not a major problem given the small amount of disclosure activity in the late 70's and early 80's.

tion for every publication. $Cites_{it}$ not only provides information about the importance of the research conducted in year *t*, but it also indicates how fundamental the work is in the sense that fundamental research is likely to be cited more often than is applied research. The ISI data also includes the average number of citations received by articles published in any given journal and year. This average is a measure of expected citations for an article in the journal.. $ExpCites_{it}$ is the aggregate of these average numbers of citations received by articles published by faculty member *i* in year *t* for the articles included in $PubCount_{it}$.[8] It is a measure of the nature of the faculty member's research in the sense that journals with higher expected citations are considered to publish the results of fundamental research

An additional measure of the nature of research is a mapping of each journal publication into Narin et al.'s (1976) classification of the 'basicness' of journals. This classification characterizes journals by their influence on other research and it has been updated regularly. They argue that basic journals are cited more by applied journals than *vice versa*, so that journals are considered to be basic if they tend to be heavily cited by other journals. For example, if journal A is heavily cited by journal B, but B does not tend to be cited by A, then A is said to be a more basic journal than is B. Advantages of the Narin classification are not only its measure of influence, but also ease of extending the measure to a large number of journals and articles. The ratings are on a 5-point scale, and we classify as basic only publications in the top basic category, which covers about 62% of all ranked journal publications in our sample. About a third of all publications could be rated, but we found no systematic change over time in the number of publications that could be rated.[9] Unfortunately, not all journals in our data are rated and some faculty do not publish in some years. If none of a professor's publications are rated in some year (to include years in which they do not publish) then those observations are dropped. This leaves 14,401 person/year observations for which we can measure how basic is the research according to this measure. $Basic_{it}$ is the calculated number of basic publications made by faculty member *i* in year *t*. This measure is determined by finding the fraction of rated publications that are in the most basic category of the Narin classification. It is then assumed that this same fraction of basic work extends to all of the researcher's publications in that year. That is, $Basic_{it} = f_{it}*PubCount_{it}$ where f_{it} is the fraction of faculty member *i*'s rated publications in year *t* that are basic.

Another indicator of the type of research conducted by a faculty member is the type of research funding received , where it is natural to expect federal funding to support more basic research than indus-

[8] For example, if in 1995 a faculty member published two articles, one in journal A and another in journal B, and if the article in journal A (B) received 20 (10) citations, then the value for $Cites_{i1995}$ is 30. If the articles in journal A in 1995 received on average 30 citations and those in B received on average 15 citations, then the value for $ExpCites_{i1995}$ is 45.

[9] In a regression of the fraction of rated publications (where we drop observations with no publications, rated or otherwise) on a set of indicator variables for the year of the observation, we found an R^2 of only .0016 and very few significance differences in the coefficients of early *versus* later years.

try sponsored funding. For eight of the universities (Purdue, MIT, Stanford, Wisconsin, Georgia Tech, Cornell, Pennsylvania and Texas A&M) the office of sponsored research provided information on sponsored research funds from federal and industry sources. The number of faculty at these 8 universities is 4,240. Only one of the universities (MIT) was able to provide annual expenditure data. For the remaining we have the names of the principal and co-principal investigators as well as the start and end dates of each award. We assume that all funds are expensed equally across time and investigator. That is, if an award started on September 1 of some year and ended on August 31 of the following year and if there are two investigators, then we allocate a sixth of the funding to each of the investigators in the first year and two sixths to each investigator in the second year. $FedFnd_{it}$ and $IndFnd_{it}$ are the amounts of federal and industry sponsored research funds received by faculty member i in year t.

There are three life cycle variables included in our analysis: age (Age_{it}) in year t, the year that the Ph.D. was awarded ($PhDYear_i$) and whether the faculty member has tenure ($Tenure_{it}$=1 if tenure is held in year t).[10] In many cases the date of birth is unavailable; in such cases we assume date of birth to be 21 years prior to year of undergraduate degree, or if date of undergraduate degree is not available we assume birth year was 29 years prior to date of Ph.D. $PhDYear_i$ is included to account for any PhD "cohort" effects. Clearly, age and year of PhD are highly correlated (the simple correlation is –0.87), but there may be independent information in the year of Ph.D. that is not captured by age. Whether the researcher has tenure is expected to be important. Unfortunately, we do not know for certain if or when a faculty member obtains tenure, but we do know the start date at their university. In the event that the "tenure clock" started when they were first employed at this university we can measure tenure as starting in the 7th year of their employment. $Tenure_{it}$ = 1 indicates that faculty member i has tenure in year t according to our algorithm. Our measure of tenure provides an undercount.

Other demographic variables are gender ($Male_i$=1 if faculty i is male) and the major program in which faculty work. We divide major programs into engineering, physical sciences and biological sciences. Approximately 35% of those in our sample are in the biological sciences, about 37% are in engineering and the remaining 28% are in the physical sciences. In our econometric analysis we use indicator variables for engineering (Eng_i = 1 if the faculty is in an engineering department) and physical sciences ($PhySci_i$ =1 if the faculty is in a physical science department). University indicator variables are included. Universities differ in their license policy with respect to such things as inventor share of income or outreach programs to encourage disclosures. To account for that heterogeneity (much of which we cannot observe) we include university indicator variables. Finally, we include year indicator variables to capture

[10] Thursby *et al.* (2007c) provide a theoretical life cycle model that predicts dramatic effects on research output pre and post tenure.

any annual effects not accounted for by our time varying regressors. The year effects will also mitigate to some extent the fact that *Cites* and *ExpCites* are truncated.

The academic quality of *i*'s department, $DeptQual_i$, is taken from the National Research Council's (1995) survey. Departments are rated on a 6-point scale from 0 to 5 where 5 is an indication of a distinguished department. The measure is included to possibly capture faculty quality that is not reflected in individual specific research output measures such as numbers of publications; faculty in high quality departments are expected to have undergone a more rigorous vetting in the hiring process and face more rigorous tenure standards. However, research in high quality departments might have different characteristics than that in other departments – for example, it might be more theoretical and fundamental.

$FirstAuthor_{it}$ is the count of the number of times faculty member *i* is first author on an article in year *t*; this is a subset of $PubCount_{it}$. *FirstAuthor* is considered since it is generally the case that the first author has contributed at least as much as others to the publication. The average number of publications per year for our sample is 3.62 whereas the average number of articles where they are the first author is 1.02. This variable should be affected by the size of the inventor's lab. Inventors in larger labs will, in general, generate more publications per year, but they will be first author less often. Our use of *FirstAuthor* is as a proxy for lab size.

III. Summary Statistics

In Table 2 are summary statistics. Before turning to our econometric analysis we present some simple tabulations of the research output and input variables.

III.1 Disclosures

For each person in our sample, it is known whether she disclosed in each year that she was on the faculty, and if so how many times she disclosed in that year. The sample has 5,133 person/year observations (this is 8.4% of the sample) in which there is at least one invention disclosure (that is, $DiscYr_{it} = 1$). Taking into account multiple disclosures in a year the total number of disclosures is 9,240; this is the sum of $NumDisc_{it}$ across all *i* and *t*. In light of the attention that has been given to university licensing and the fact that about one in ten of these faculty are disclosing late in the sample period (see below), the number of faculty who ever disclose is low. For the 4,988 faculty in the sample 63.5% of them never disclosed an invention and another 14.6% disclosed in only a single year. Only 109 (2.2%) disclosed in 8 or more of the years they were in the sample. When a faculty member discloses in some year it is typically a single event. For 3,304 of the 5,133 disclosure years (64.4%) there is only a single disclosure. In 1,040 of the disclosure years (20.3%) the faculty member has disclosed twice; that is, $NumDisc_{it} = 2$. Forty-five of the disclosure years are cases of 10 or more disclosures by a faculty member in a single year. The distribution of $DiscYr_{it}$ also varies substantially by university from a low of 4.41% over all years to a high of 17.7%.

In Table 3 are observations by year as well as the percent of those observations that are disclosure year observations (that is, observations on a faculty member who has disclosed at least once in a given year) and the average number of disclosures per faculty member. The percent of disclosure observations rises from 2.7% of the faculty in 1983 to around 10% to 11% by the mid-nineties where it appears to have leveled off. The average number of disclosures per faculty member per year rises from about 0.04 to about 0.25. This trend in disclosure activity is consistent with our earlier observations about the growth in university license activity. In Figure 1 are the disclosure year observations and the average number of disclosures mapped as a fraction of their value in 1983. The upward trend in the average number of disclosures is more marked than the rise in the percent of faculty who disclose in each year further emphasizing that disclosure activity is concentrated in a minority of the faculty.

III.2 Federal and Industry Funding

Federal and industry funding by researcher by year is available for only eight of the eleven universities in our sample. This subsample includes 4,240 researchers and 51,951 person/year observations. Thirty-two percent did not have federal money in any year in which they are in the sample and almost 63% never received industry funding. For all person/years 54.8% are observations for which there is nether source of funding. In 9.4% of the sample both types of funding are observed.

Graphed in Figure 2 are annual average funding levels (in real terms) as a fraction of their average levels in 1983. Disclosure activity increased substantially over the period of our sample. If disclosure activity has come at the expense of faculty research funding, then it does not show up in the raw data on funding. Relative to 1983, average federal funding has increased almost six fold. A part of the reason for this increase is clearly the fact that we have only faculty in residence in 1993 in our sample, and with each successive year faculty are further along in their careers. The increase in industry funding (which could be a function of increasing interest in commercialization) has been even greater though most of the increase had taken place by 1989.

III.3 Publications and Citations

The average number of publications per year is 3.84. Almost 31% of the person/year observations are ones in which there are no publications and for another 15.2% there is only a single publication. In only 11.2% of the sample are there 10 or more publications. The average number of citations to a year‘s publications (*Cites*) is 120.5. This is substantially larger that the 101.4 average for expected citations (*ExpCites*). Thus the faculty in this sample receive, on average, more citations to their work than do others who publish in the same journals and in the same year. The average number of citations per publication is 27.3 and 6.8% of those who publish in some year have no citations.

Annual averages for publications, citations and expected citations in comparison to their values in 1983 are in Figure 3. As was the case with funding the raw data appear not to show an effect from increased commercialization. For each measure there is an increase from the 1983 averages. The largest increase occurs for publications. Both *Cites* and *ExpCites* are truncated so that the latter year observations in particular should be examined with caution.

III.4 Basic Publications

Basic publications are determined according to Narin et al.'s (1976) classification. As noted above person/year observations are dropped if there are no rated publications. This leaves 14,401 observations. The average number of basic publications is 1.94 in 1983 and it rises slightly to 2.19 by 1999 after dipping in the mid 1980s. For the observations for which we have a basic measure the average number of publications rises from 6.3 in 1983 to 11.1 in 1999. In Figure 4 are graphed the annual averages of *Basic* as well as the comparable set of publications and their citations as fractions of their 1983 figures. The amount of basic research according to this measure has remained fairly steady as has the number of citations while the average count of publications has risen substantially.

IV. Econometric Analyses

With the possible exception of the ratio of basic to total publications the raw data do not suggest an increase in disclosure activity has been accompanied by a change in research. But those comparisons do not control for other factors that might affect research inputs and outputs. In this section we consider econometric models of funding, publications, citations, expected citations and basic publications. The level of funding appears in each of the regressions so that we can only consider the eight universities for which we have that information. There are six dependent variables of interest: $FedFnd_{it}$, $IndFnd_{it}$, $PubCount_{it}$, $Cites_{it}$, $ExpCites_{it}$ and $Basic_{it}$ all of which are measured in logarithms.

IV.1 Models

IV.1.A Funding Models

The funding regressions explain both the amount of federal funding ($FedFnd_{it}$) and industry funding ($IndFnd_{it}$) received by faculty member *i* in year *t*. $FedFnd_{it}$ and $IndFnd_{it}$ are modeled as simultaneously determined (see Jensen *et al.* (2008)) so in the federal funding equation we include the current level of industrial funding, and in the industry funding equation the current level of federal funding is included. Lagged federal spending is included in the federal funding equation and lagged industry funding is included in the industry sponsored research funding equation to pick up possible funding inertia. Inclusion of lagged funding might pick up unobservable individual specific factors not captured by the publication data, major program area, etc. To be clear, we model federal funding with regressors $IndFnd_{it}$ and $FedFnd_{it-1}$. The industry funding equation is similar: regressors include $IndFnd_{it-1}$ and $FedFnd_{it}$.

$EverDisc_i$ is included in both funding equations. Recall that *$EverDisc_i$* is equal to one if the faculty member discloses in any year they are in the sample. It is included to pick up unobserved heterogeneity associated with the faculty who ever disclose *versus* those who never disclose; we do not have priors on the effect. The other disclosure variables are entered in one of two ways. In the first we measure whether or not the faculty member disclosed in the prior year and how many prior years had been disclosure years – that is, we include $DiscYr_{it-1}$ and $CumDiscYr_{it-1}$. These variables measure only the existence of disclosures in some year rather than the number of disclosures. Regressions which include $DiscYr_{it-1}$ and $CumDiscYr_{it-1}$ are referred to as "disclosure-year" regressions. In the second we use the counts of annual disclosures by including $NumDisc_{it-1}$ and $CumDisc_{it-1}$. Regressions which include these measures are referred to as "disclosure-number" regressions. If disclosure activity signals a change in research direction or interests, then subsequent changes in funding are expected. If research has been diverted from basic to applied then the coefficients of $DiscYr_{it-1}$ and $CumDiscYr_{it-1}$ or $NumDisc_{it-1}$ and $CumDisc_{it-1}$ should be positive in the industry funding equation and negative in the federal funding equation. If, however, the research leading to disclosure is also publishable, as in Thursby *et al*. (2007c), then the effects on both types of funding should be positive.

The expected number of citations, $ExpCites_{it-1}$, is included in both funding equations. To the extent that federal funding is directed more toward fundamental than applied research, the coefficient is expected to be positive in the federal funding equation since. To the extent that industry funding is more applied, the coefficient in the industry funding equation is expected to be negative.

Since current funding is based upon funding applications made in the past and successful applications are based in part on a researcher's productivity we include the prior year's number of publications ($PubCount_{it-1}$) and the citations those publications receive through 2003 ($Cites_{it-1}$). Lagged publications are expected to have a positive effect on both types of funding. We also include the square of lagged publications ($PubSq_{it-1}$) which is expected to have a negative coefficient thereby moderating the effect of $PubCount_{it-1}$. Note that the inclusion of expected cites in the funding equations implies that the effect of citations holds constant, to some extent, how fundamental the journal is so that the coefficient of citations can be interpreted as a measure of the importance of the work and not as a measure of how fundamental the work of the faculty member. Lagged citations are expected to have positive effects on federal and industry funding.

The lagged value of the number of times the faculty member is first author on a paper, $FirstAuthor_{it-1}$, is included in both funding equations along with the life cycle variables Age_{it}, ,$PhDYear_t$, and $Tenure_{it}$. Thursby *et al.* (2007c) derive life-cycle implications of both age and tenure. In their model research output increases at a decreasing rate and declines in the later years; by implication we would expect the same for research funding. To capture that effect we also include the square of age ($AgeSq_{it}$). Tenure has the effect of reducing basic and increasing applied research. Gender ($Male_i$ = 1 if the faculty member is male) is included as are the indicator variables Eng_i and $PhySci_i$. We also include the department quality score $DeptQual_i$.

IV.1.B Other Models

The dependent variables for the other models are our measures of research output and the nature of the research: $PubCount_{it}$, $Cites_{it}$, $ExpCites_{it}$ and $Basic_{it}$. The set of regressors is the same for each of these four models with three exceptions. First, $PubCount_{it}$ is included in the $Cites_{it}$, $ExpCites_{it}$ and $Basic_{it}$ regressions since more publications generally imply more citations and, for those who conduct basic research, more basic publications. Second, $FirstAuthor_{it}$ is included in the $PubCount_{it}$ regression since those in larger labs – which we proxy with $FirstAuthor_{it}$ – generally will have more publications. Finally, $ExpCites_{it}$ is included in the citation regression, thus we are looking at the deviation of citations from the average received by all articles so that we are directly measuring the importance of the faculty member's research net of how basic the research is.

$EverDisc_i$ is included in each regression along with either $DiscYr_{it-1}$ and $CumDiscYr_{it-1}$ or $NumDisc_{it-1}$ and $CumDisc_{it-1}$. The effects of these variables are, in general, unclear. If the research leading to disclosure is also publishable, as in Thursby *et al*. (2007c) then the effects on $PubCount_{it}$ should be positive. The theoretical models give less guidance on the effects on $Cites_{it}$, $ExpCites_{it}$ and $Basic_{it}$ because neither citations nor the nature of publication outlets is explicitly characterized. Intuitively, however, one could expect an increase in the ratio of applied to basic research effort could lead to fewer expected citations and relatively fewer publications in basic journals, that is, negative coefficients for $Disc_{it-1}$ and $CumDisc_{it-1}$ (or $NumDisc_{it-1}$ and $CumDisc_{it-1}$) in the equations for $ExpCites_{it}$ and $Basic_{it}$.

Current research output and type are also modeled as functions of research funding in the prior year. $FedFnd_{it-1}$ and $IndFnd_{it-1}$ are expected to be positively related to publications. $FedFnd_{it-1}$ is expected to have a positive effect on citations, expected citations and basic publications. Negative effects are expected for $IndFnd_{it-1}$. Finally, we include the demographic regressors as well as department quality and university and year fixed effects.

IV.2 Estimation and Results

Because of the many zero observations for each of the dependent variables, we use the Tobit estimator. We do not use counts models for publications, citations or expected citations since the numbers are often large. For example, the average number of publications for observations with non-zero publications is 5.34 and the maximum is 130. Most of the faculty are in the sample multiple years so we use cluster standard errors. With the exception of industry funding, all equations include university and year fixed effects to account for unobserved heterogeneity. The year effects also should mitigate the truncation in $Cites_{it}$ and $ExpCites_{it}$. The industry funding regression would only converge when the year fixed effects are omitted. We include university fixed effects in the funding regression.

As noted above, $FedFnd_{it}$ and $IndFnd_{it}$ are simultaneously determined. Instrumental variables estimation is used with the prior year value as the instrument. That is, the instrument for $FedFnd_{it}$ is the prior year's federal funding $FedFnd_{it-1}$, and the instrument for $IndFnd_{it}$ is $IndFnd_{it-1}$. Both instruments are highly correlated with the endogenous regressor (0.89 for federal and lagged federal funding and 0.82 for industry and lagged industry funding).

After dropping missing observations there are 43,506 observations. There are many individuals in the sample who did not receive funding in any year they are in the sample. Because there may be some unobserved effects associated with this lack of funding we do not include those faculty when estimating the funding equations. Our initial estimate of the industry funding equation had a coefficient of lagged industry funding in excess of one (1.28 and statistically significantly larger than one) which implies a non-stationary process. If we restrict estimation to those who received industry funding in at least one of the years they are in the sample, then the estimated model is stationary. Our estimate of the federal funding equation using only those who received some funding is based on 33,596 observations. Our estimate of the industry funding equation using only those who received industry funding is based on 17,457 observations.

Similarly, in the *PubCount*, *Cites* and *ExpCites* regressions there are concerns that there might be unobserved effects associated with faculty who never published during the sample years. These are dropped from the sample when estimating those regressions, and each regression is based upon 40,674 observations. Since *Basic* is unobserved if there are no publications, this restriction is automatically imposed. The equation for *Basic* is based upon 11,552 observations.

Dropping those who do not publish or receive funding does not introduce any unwanted sampling bias. To the extent that there are concerns about a reorientation of research it is a concern about faculty who are conducting research. Table 4 gives the results. For ease of presentation we have changed some of our variable names in an obvious way. For example, $DiscYr_{it-1}$ is presented as *LagDiscYr* in the table and $NumDisc_{it-1}$ is presented as *LagNumDisc.*

IV.2.A Disclosures

In the federal and industry funding equations there are statistically significantly higher levels of funding in the year following a disclosure – the coefficients of *LagDisc* and *LagNumDisc* are positive and significant. *CumDiscYr* and *CumDisc* have negative coefficients for both types of funding although they are significant only for federal funding. Not surprisingly, the effect of disclosing in the prior year has a substantially larger effect on industry funding than on federal funding.

In the disclosure-year equation for federal funding the coefficient of *LagDisc* is positive and significant and the coefficient of *CumDiscYr* is negative and significant. The sum of the two is positive and significantly different from zero (p-value = 0.057) so that disclosing once, conditional on ever disclosing, results in higher federal funding. Disclosing a second time has no statistically significant effect. It is only after disclosing 6 times is the effect negative and significantly different from zero (p-value = 0.068). Note that, individuals who ever disclose have a statistically significantly higher level of federal funding until they have disclosed 11 times (p-value = .082). Similar effects operate in the disclosure-number equation for federal funding except that it takes many more disclosures before the effect becomes either zero or negative.

In both the disclosure-year and disclosure-number regressions for publications and citations, prior year disclosures have a positive and significant effect. In the citations equation expected citations are held constant, thus this positive effect implies that research in the year following a disclosure is generally more important. Furthermore more disclosure activity over the life cycle – as measured either by cumulative disclosures or cumulative disclosure years – implies more publications. There is weak evidence that both expected citations and basic publications increase with cumulative disclosures. Finally, the significance of *EverDisc* in a number of the regressions suggests that there are important differences between those who never disclose and those who disclose at some point in the life cycle that are not accounted for by the other regressors.

IV.2.B Funding regressors

Both industry and federal funding have positive, significant effects in the regression for the other type of funding. The positive coefficients suggest that federal and industrial funding are complements rather than substitutes. Thus neither type of funding appears to crowd out the other. The coefficient of industrial funding in the federal equation is smaller that the coefficient of federal funding in the industrial equation; that is, federal funding has a greater impact on industry funding than industry funding has on federal funding. In both cases, however, the coefficients (which are elasticities) are small.

The coefficients of lagged federal and industry funding have the expected signs in the *PubCount*, *ExpCites* and *Basic* regressions. More of each type of funding increases publications. Increased federal funding has a statistically significant, positive effect on expected citations and basic publications. Increased industrial funding, on the other hand, reduces these measures. The results for *ExpCites* and *Basic* are in accord with our priors that industry funding is more applied while federal funding is for more fundamental research. In the citation equation, the coefficient of lagged industry is positive and statistically significant while the coefficient of lagged federal funding is insignificant. This seemingly counterintuitive result may be due to the fact that expected citations is included in the regression; thus the funding coefficients are partial effects holding constant how fundamental is the journal being cited.

IV.2.C Other Effects

For the life-cycle variables, our age results accord with Thursby *et al.* (2007c) and Azoulay *et al.* (2006). Publications and both types of funding increase with age but at a decreasing rate. In the case of federal funding and publications, the marginal effect of age becomes negative early in a career, but the marginal effect of age on industry funding becomes negative late in a career. Expected citations and basic publications decrease over the life cycle. The other life-cycle effect we consider is tenure. Tenure is negative and significant in the funding, expected citation, and the basic publication regressions.

Thursby and Thursby (2005) find significant gender effects in disclosures with men more likely to disclose and Ding et al. (2006) find men more likely to patent and men who patent have higher numbers of publications and NIH funding. Here we find gender is significant only in the publication equation where the coefficient of *Male* is positive and significant. Since only 8.4% of the sample are females and they represent only 6.6% of disclosures it is difficult to statistically distinguish gender effects.

IV.3 Robustness checks

In our econometric analysis of federal funding we excluded observations on faculty who never received federal or industry funding in a year. In the industry funding equation we excluded observations on faculty who had never received industry funding in some year. Likewise, in the publication, citation and expected citation regressions we dropped those who never published in any year. This was over concerns for unobserved heterogeneity associated with those who did not receive funding or publish articles. We re-estimated each of these regressions using the full sample. The coefficients and levels of significance in these new regressions are almost identical to the above results.

There is truncation with *DiscCumYr* and *DiscCum* since we do not have disclosure activity prior to 1983. In addition, we have been told that in the case of Stanford populating electronic files from the early year paper files generally included only the more “important inventions.”[11] This might also be the case for some of the other universities. All regressions are re-estimated after dropping the years 1983 – 1986 which should reduce the truncation problems. Results do not change in any material way. There are also truncation problems with citations and expected citations since our citation data end in 2003. To lessen the error we dropped the years 1998 and 1999. The coefficients and levels of significance are not changed in a material way.

Concluding Remarks

In this paper, we examine the extent to which faculty involvement in licensing has compromised basic research. Although much of the policy discussion has focused on the potential negative impact of

[11] David Mowery provided this insight into Stanford practices.

licensing, recent theoretical work shows that licensing may have no effect (because faculty care more about curiosity driven research) or because the financial incentive causes them to conduct more research, *per se* (Thursby *et al.*, 2007c). In this paper, we exploit unique data on the research profile and disclosure activity of science and engineering faculty at 11 major US universities over a period of 17 years to explore which of these regimes is more empirically relevant. Importantly, our data allow us to examine not only the relationship between research outputs and license disclosure, but also research funding.

We find that recent disclosure activity generally has a positive effect on research funding both from the federal government and industry, with the impact being higher for industry funding. However, if faculty disclose multiple times, the positive effect on federal funding can disappear and with substantial numbers of disclosures the effect can become negative. In the case of publication output, we find that both recent disclosure and repeated disclosure increase the faculty member's publication count. Recent disclosure also increases the apparent importance of these publications as the number of citations increases. We find weak evidence that disclosure activity is associated with increases in our other measures of "basic" research.

Thus the evidence is more in accord with the Thursby *et al.*'s (2007) theoretical finding of a positive effect of licensing rather than the diversion from basic research suggested by others. It is essential to emphasize that this finding is based on faculty in residence at our sample of universities in 1993. Importantly, it does not include new faculty who have entered the profession post 1993. There may be a cohort effect with new faculty more attuned to applied research in order to capture gains from licensing.

In addition to addressing the issue of a reorientation of faculty research, this paper and Jensen et *al.* (2008) are the only ones to our knowledge to empirically link research funding with causal factors. Of particular note is our finding that federal and industry funding are complements. In our empirical analysis we also include measures of faculty age and tenure. With regard to age, we find that the ability to attract funding and the rate of publication increase as the faculty member ages but at a decreasing rate. Research tends to be less basic as faculty age. We also find that post tenure, both types of funding decrease and work becomes less basic. The only significant gender effect is higher numbers of publications for males.

References

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

Association of University Technology Managers (various years). *Annual Survey*.

Azouley, P., W.W. Ding, and T. E. Stuart. 2006. The Impcat of Academic Patenting on (Public) Research Output, NBER Working Paper 11917.

___________________. 2007. The Determinants of Faculty Patenting Behavior: Demographics or Opportunities? *Journal of Economic Behavior and Organization* 63, 599-623.

Breschi, Stefano, Francesco Lissoni and Fabio Montobbio. 2005. The Scientific Productivity of Academic Inventors: New Evidence from Italian Data. CESPRI Working Paper 168, Center for Research on Innovation and Internationalization, University of Bocconi, Milan, Italy.

Colyvas, Jeannette, Michael Crow, Annetine Gelijns, Roberto Mazzoleni, Richard Nelson, Nathan Rosenberg, and Bhaven Sampat. 2002. How do University Inventions Get into Practice? *Management Science*, 48:1, 61-72.

Ding, W.W., F. Murray, T.E. Stuart. 2006. Gender Differences in Patenting in the Academic Life Sciences. *Science* 303 (5787), 665-667.

Fabrizio, Kira and Alberto DiMinin. 2008. Commercializing the Laboratory: The Relationship Between Faculty Patenting and the Open Science Environment. *Research Policy* 37, 914-931.

Henderson, Rebecca, Adam Jaffe and Manuel Trajtenberg. 1998. Universities as a Source of Commercial Technology: A Detailed Analysis of University Patenting, 1965-1988. *Review of Economics and Statistics* 80:1, 119-127.

Jensen, Richard and Marie Thursby. 2001. Proofs and Prototypes for Sale: The Licensing of University Inventions. *American Economic Review* 91:1, 240-259.

Jensen, Richard, Jerry Thursby and Marie Thursby. 2003. Disclosure and Licensing of University Inventions: 'The Best We Can Do With the S**t We Get to Work With.' *International Journal of Industrial Organization* 21, 1271-1300.

Jensen, Richard, Jerry Thursby and Marie Thursby. 2008. In or Out? Faculty Research and Consulting. Mimeo.

Mansfield, E., 1995. Academic research underlying industrial innovations: sources, characteristics, and financing. *The Review of Economics and Statistics*, 77, 55-65.

Mowery, David, Richard R. Nelson, Bhaven Sampat and Arvids Ziedonis. 2004. *Ivory Tower and Industrial Innovation: U.S. University-Industry Technology Transfer Before and After the Bayh-Dole Act*. Stanford: Stanford University Press.

Murray, Fiona. 2002. Innovation as Overlapping Scientific and Technological Trajectories: Exploring Tissue Engineering. *Research Policy* 31, 1389-1403.

Murray, Fiona and Scott Stern. 2006. When Ideas are Not Free: The Impact of Patents on Scientific Research. *Innovation Policy and the Economy*. Cambridge MA: MIT Press.

Narin, F., G. Pinski, and H. Gee. 1976. Structure of the biomedical literature. *Journal of the American Society for Information Science*, 25-45.

National Research Council. 1995. *Research Doctorate Programs in the United States*, M. Goldberger, B. Maher and P. Flattau (eds.), Washington, D.C.: National Academy Press.

National Science Board. 2008a. *Science and Engineering Indicators*. Washington D.C.: National Academy Press.

_______________. 2008b. *Research and Development: Essential Foundation for U.S. Competitiveness in a Global Economy*. Washington D.C.: National Academy Press.

Press, E. and J. Washburn. 2000. The Kept University. *Atlantic Monthly* 285, 239.

Rai, Arti. 1999. Regulating Scientific Research: Intellectual Property Rights and the Norms of Science. *Northwestern University Law Review* 94:1, 77-152.

Stephan, Paula, Shiferaw Gurmu, A.J. Sumell, and Grant Black. 2007. Who's Patenting in Universities? *The Economics of Innovation and New Technology* 16, 71-99.

Stokes, Donald. 1997. *Pasteur's Quadrant: Basic Science and Technological Innovation*. Brookings Institution Press, Washington, D.C.

Thursby, Jerry and Marie Thursby. 2002. Who Is Selling the Ivory Tower? Sources of Growth in University Licensing. *Management Science* 48:1, 90-104.

Thursby, Jerry and Marie Thursby. 2004. Are Faculty Critical? Their Role in University-Industry Licensing, *Contemporary Economic Policy*, Vol. 22:2, 162-178.

Thursby, Jerry and Marie Thursby. 2005. Gender Patterns of Research and Licensing Activity of Sciences and Engineering Faculty. *Journal of Technology Transfer*, Vol. 30:4, 343-353.

Thursby, Jerry and Marie Thursby. 2007a. University Licensing." *Oxford Review of Economic Policy*, Vol. 23:4, 620-639.

Thursby, Jerry and Marie Thursby. 2007b. Patterns of Research and Licensing Activity of Science and Engineering Faculty." *Science and the University*, edited by Ronald Ehrenberg and Paula Stephan, University of Wisconsin Press.

Thursby, Marie, Jerry Thursby and Swasti Gupta-Mukherjee. 2007c. Are There Real Effects of Licensing on Academic Research? A Life-Cycle View. *Journal of Economic Behavior & Organization*, Vol. 63:4, 577-598.

Thursby, Jerry, Richard Jensen and Marie Thursby. 2001. Objectives, Characteristics and Outcomes of University Licensing: A Survey of Major U.S. Universities. *Journal of Technology Transfer* 26:1-2, 59-72.

Trajtenberg, M., R. Henderson, and A. Jaffe, 1997, "University Versus Corporate Patents: A Window on the Basicness of Invention," *Economic Innovation and New Technology* 5, 19-50.

Table 1. Research and Licensing at the Sample Universities

Institution Name	Total Research Expenditures	Licenses/ Options Executed	Invention Disclosures Received	U.S. Pat-ents Issued
MIT	$1,027,000,000	134	515	159
Wisconsin	$ 763,875,000	203	405	93
Stanford	$ 693,529,925	89	350	87
Pennsylvania	$ 654,457,805	87	392	45
Harvard	$ 590,592,500	50	160	35
Cornell	$ 537,700,000	80	225	53
Texas A&M	$ 456,235,000	81	117	27
Georgia Tech	$ 446,712,572	35	277	41
Purdue	$ 394,500,000	87	208	29
Cal Tech	$ 388,897,000	45	549	142
Utah	$ 289,727,719	33	161	23
Average of Top 50	$ 475,547,857	59	195	44

Table 2. Summary Statistics

	Observations	**Mean**	**Standard deviation**	**Min**	**Max**
Federal funding*	51732	0.2978	4.53	0	383.57
Industry*	51732	0.0208	0.16	0	8.7
Age	59325	48.87	10.79	23	90
Male	57416	0.91	0.28	0	1
Departmant Quality	60905	3.85	0.92	0	5
Year of Ph.D.	59384	1970.82	26.45	0	1996
Tenure	60905	0.76	0.42	0	1
Total first author	51732	0.69	1.84	0	82
Total publications	60905	3.83	5.95	0	148
Basic publications	14401	1.85	2.81	0	69
Total citations	60905	120.48	362.51	0	16162
Total expected citations	60905	101.34	232.76	0	6616.85
Disclosure years	60905	0.0843	0.28	0	1
Number of disclosures	60905	0.1517	0.73	0	32
Cumulative disclosure years	60891	0.5155	1.29	0	14
Cumulative disclosures	60891	0.8824	3.46	0	143

* Hundreds of thousands of dollars.

Table 3. Disclosures by Year

Year	Observations	Percent *DiscYr*	*Average Disclosures per Faculty*
1983	1,768	2.66	0.035
1984	1,824	3.34	0.045
1985	1,883	3.19	0.037
1986	2,123	3.77	0.048
1987	3,496	5.61	0.088
1988	3,686	6.59	0.112
1989	3,836	6.67	0.115
1990	4,007	6.24	0.109
1991	4,183	8.34	0.136
1992	4,535	8.71	0.152
1993	4,621	9.74	0.161
1994	4,588	10.42	0.172
1995	4,473	10.17	0.185
1996	4,410	11.00	0.195
1997	3,862	11.96	0.244
1998	3,828	11.81	0.256
1999	3,782	10.95	0.246
Total	60,905		

Figure 1. Disclosure Activity as a Fraction of Activity in 1983

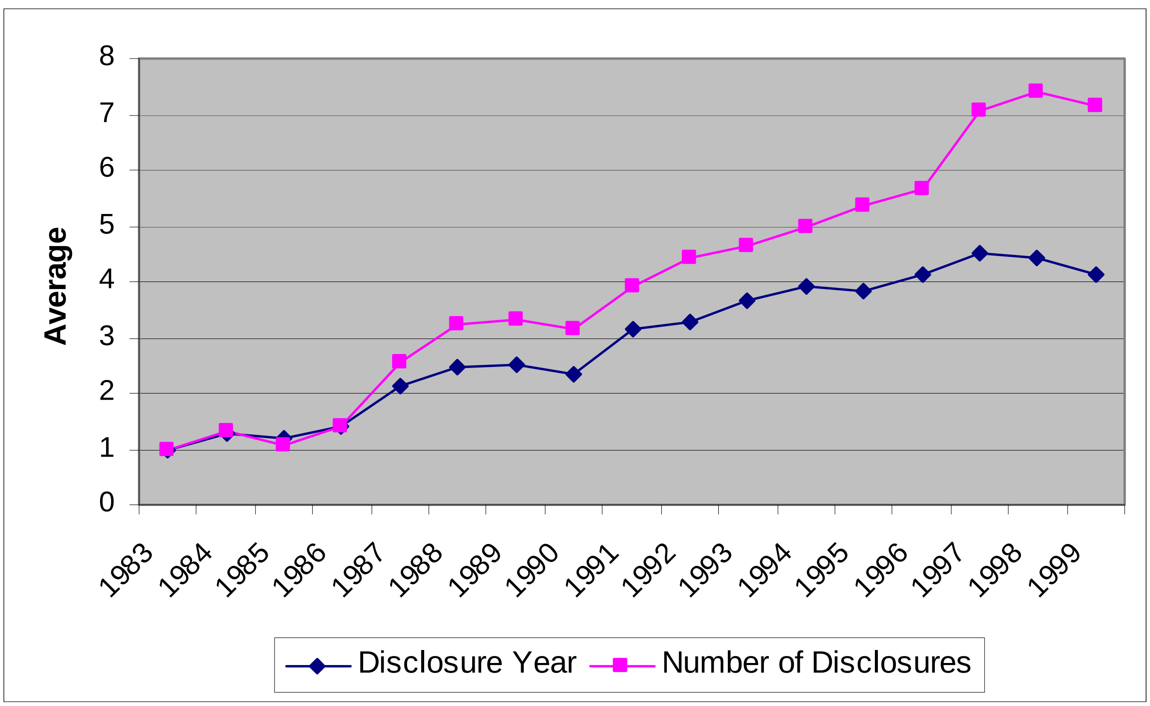


Figure 2. Average Annual Funding Levels as a Fraction of 1983

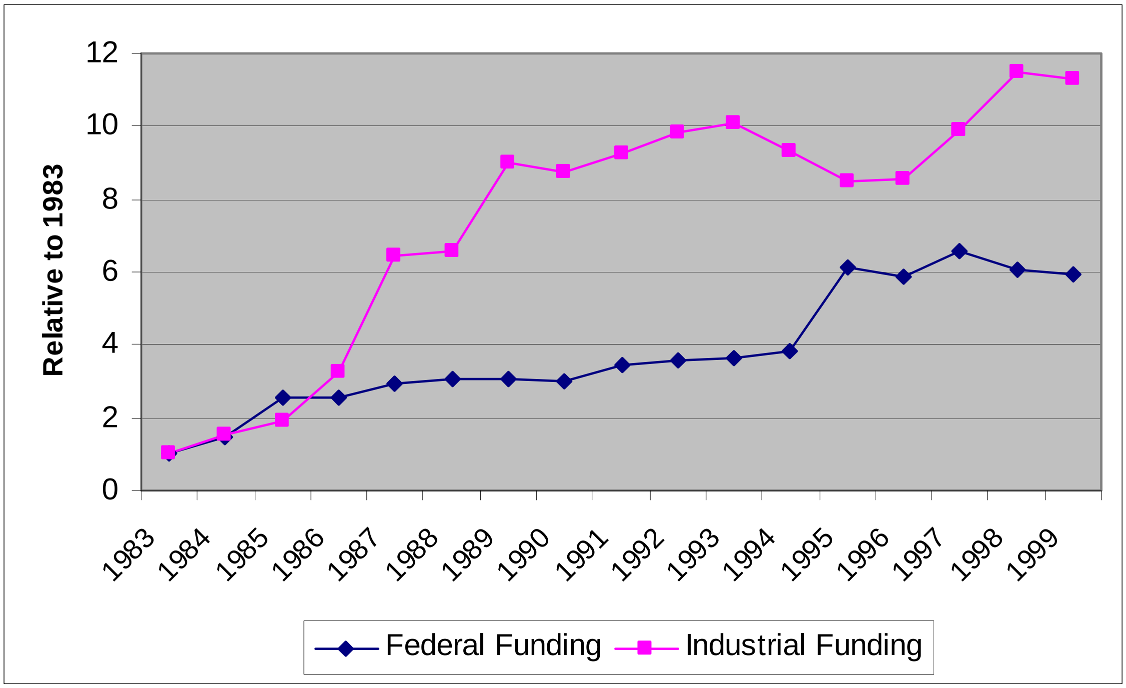
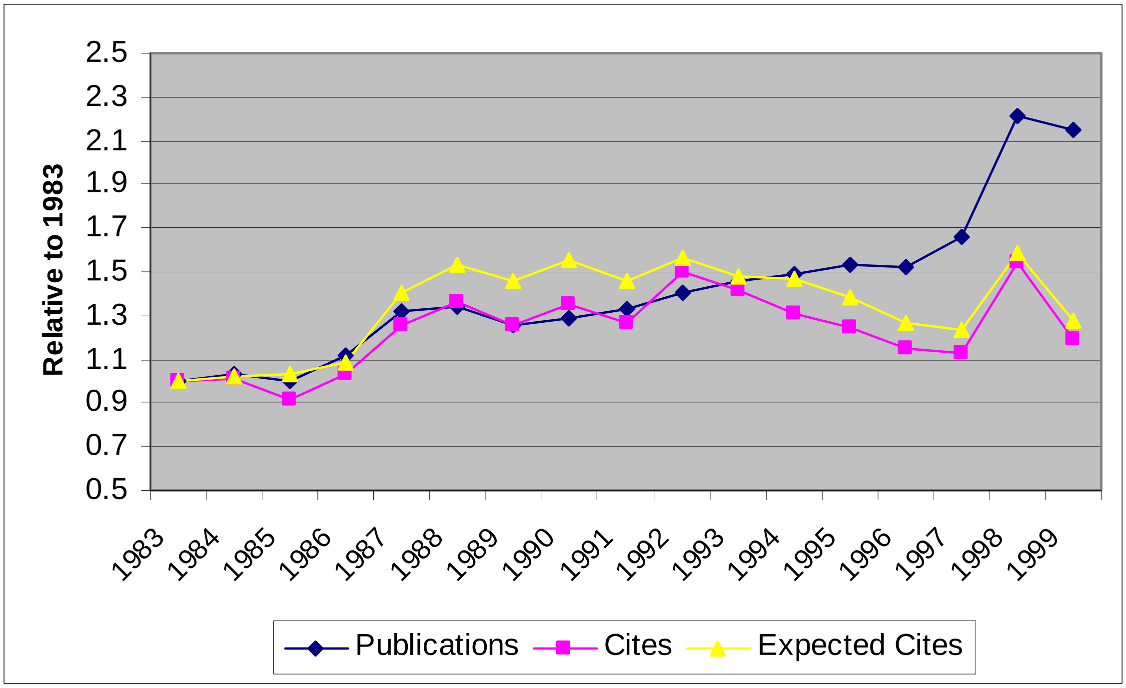


Figure 3. Average Publications, Citations and Expected Citations as a Fraction of 1983



Figures 4. Annual Average Basic Publications, Publications and Citations as a Fraction of 1983

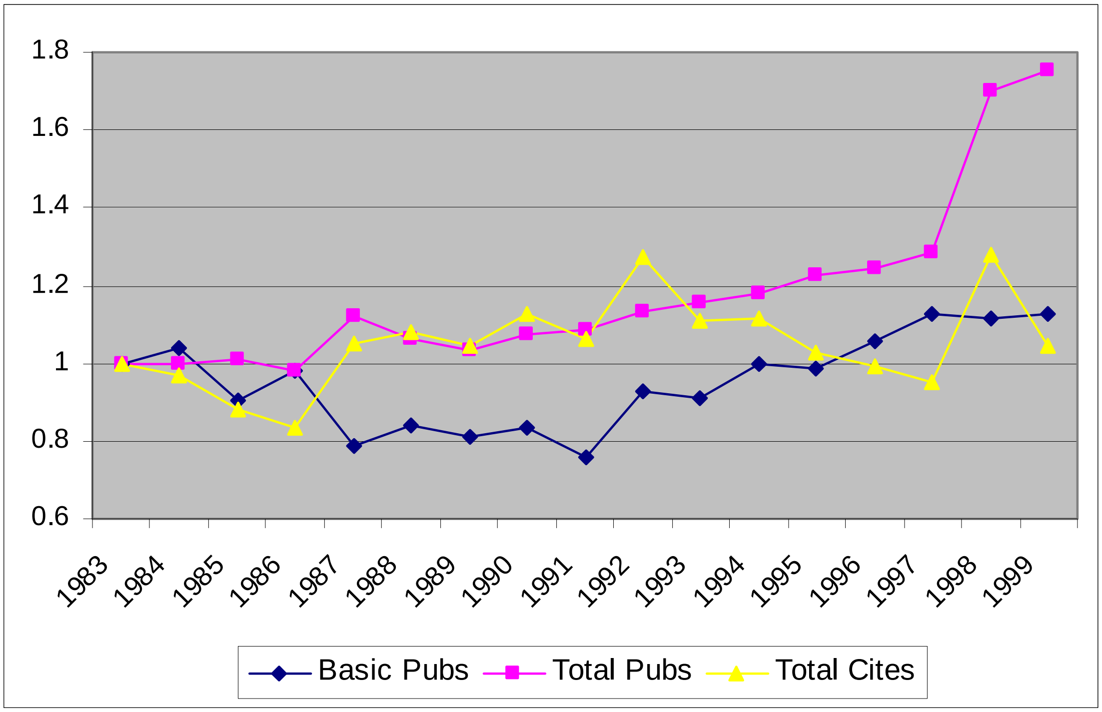


Table 4. Regression Results

	Federal Funding					
	Disclosure-Year			Disclosure-Number		
	Coef.	t-Stat		Coef.	t-Stat	
LagDiscYr	0.2921	2.56	***			
CumDiscYr	-0.0957	-3.29	***			
LagNumDisc				0.1327	2.99	***
CumDisc				-0.0209	-2.29	**
EverDisc	0.2976	4.17	***	0.2447	3.67	***
IndFnd	0.0276	2.52	**	0.0250	2.30	**
LagFedFnd	0.7619	78.32	***	0.7619	78.29	***
PubCount				0.4825	3.23	***
PubSq				-0.0693	-2.13	**
LagPubCount	0.4735	3.17	***			
LagPubSq	-0.0635	-1.96	**			
LagFirstAuthor	-0.0256	-0.46		-0.0224	-0.40	
LagCites	0.1329	3.36	***	0.1312	3.32	***
LagExpCites	0.0649	1.34		0.0662	1.37	
Age	0.1163	3.65	***	0.1178	3.70	***
AgeSq	-0.0014	-4.86	***	-0.0014	-4.89	***
PhDYear	-0.0276	-1.98	**	-0.0268	-1.93	*
Tenure	-0.3301	-3.84	***	-0.3376	-3.92	***
Male	-0.1419	-1.42		-0.1454	-1.45	
DeptQual	-0.0078	-0.29		-0.0052	-0.20	
Eng	-0.0872	-1.01		-0.0918	-1.06	
PhySci	0.2783	3.52	***	0.2800	3.54	***
Univ. Effects	YES			YES		
Year Effects	YES			YES		
Observations	33,596			33,596		
R-Square	NA			NA		

	Industry Funding					
	Disclosure-Year			Disclosure-Number		
	Coef.	t-Stat		Coef.	t-Stat	
LagDiscYr	1.1105	5.36	***			
CumDiscYr	-0.0535	-1.05				
LagNumDisc				0.1896	2.11	**
CumDisc				-0.0046	-0.34	
EverDisc	0.2254	1.46		0.3456	2.44	**
LagIndFnd	0.9284	73.53	***	0.9301	73.68	***
FedFnd	0.1284	5.71	***	0.1299	5.77	***
LagPubCount	0.6421	1.98	**	0.6630	2.04	**
LagPubSq	-0.0067	-0.09		-0.0072	-0.10	
LagFirstAuthor	-0.1629	-1.30		-0.1610	-1.28	
LagCites	-0.0042	-0.05		-0.0007	-0.01	
LagExpCites	-0.2456	-2.06	**	-0.2519	-2.10	**
Age	0.1781	2.89	***	0.1738	2.81	***
AgeSq	-0.0014	-2.35	**	-0.0013	-2.27	**
PhDYear	0.0496	3.14	***	0.0504	3.25	***
Tenure	-0.5262	-2.96	***	-0.5471	-3.08	***
Male	0.3528	1.48		0.3671	1.54	
DeptQual	0.1655	2.96	***	0.1649	2.96	***
Eng	0.2537	1.33		0.2644	1.38	
PhySci	-0.3621	-1.77	*	-0.3596	-1.76	*
Univ. Effects	YES			YES		
Year Effects	NO			NO		
Observations	17,457			17,457		
R-Square	NA			NA		

*** Significant at 1% ** Significant at 5% * Significant at 10%

Table 4. Regression Results (cont)

	Publications					
	Disclosure-Year			Disclosure-Number		
	Coef.	t-Stat		Coef.	t-Stat	
LagDiscYr	0.1450	6.98	***			
CumDiscYr	0.0612	6.37	***			
LagNumDisc				0.0563	5.78	***
CumDisc				0.0094	1.84	*
EverDisc	0.2736	10.51	***	0.3332	13.13	***
LagIndFnd	0.0097	4.99	***	0.0108	5.54	***
LagFedFnd	0.0381	24.56	***	0.0384	24.63	***
FirstAuthor	0.9053	68.37	***	0.9075	68.31	***
Age	0.0256	2.58	***	0.0257	2.58	***
AgeSq	-0.0005	-5.97	***	-0.0005	-5.94	***
PhDYear	-0.0225	-4.34	***	-0.0224	-4.30	***
Tenure	0.0082	0.34		0.0138	0.57	
Male	0.0770	2.05	**	0.0815	2.16	**
DeptQual	-0.0124	-0.95		-0.0144	-1.09	
Eng	-0.3236	-11.52	***	-0.3172	-11.25	***
PhySci	-0.1035	-3.38	***	-0.1022	-3.33	***
Univ. Effects	YES			YES		
Year Effects	YES			YES		
Observations	40,674			40,674		
R-Square	0.1626			0.1614		

	Citations					
	Disclosure-Year			Disclosure-Number		
	Coef.	t-Stat		Coef.	t-Stat	
LagDiscYr	*LagDiscY*	2.79	***			
CumDiscYr	0.0091	1.31				
LagNumDisc				0.0307	3.44	***
CumDisc				0.0016	0.89	
EverDisc	0.0030	0.17		0.0109	0.68	
LagIndFnd	0.0048	3.80	***	0.0048	3.82	***
LagFedFnd	0.0005	0.48		0.0005	0.46	
PubCount	1.1055	30.95	***	1.1079	30.93	***
PubSq	-0.2367	-25.77	***	-0.2374	-25.71	***
ExpCites	1.0426	130.28	***	1.0426	130.29	***
Age	0.0031	0.44		0.0032	0.46	
AgeSq	0.0000	-0.42		0.0000	-0.41	
PhDYear	0.0077	2.38	**	0.0079	2.43	**
Tenure	-0.0144	-0.81		-0.0135	-0.76	
Male	-0.0040	-0.16		-0.0034	-0.14	
DeptQual	-0.0003	-0.03		-0.0004	-0.04	
Eng	0.0566	2.77	***	0.0581	2.84	***
PhySci	0.0606	3.05	***	0.0613	3.08	***
Univ. Effects	YES			YES		
Year Effects	YES			YES		
Observations	40,674			40,674		
R-Square	0.545			0.545		

*** Significant at 1% ** Significant at 5% * Significant at 10%

Table 4. Regression Results (cont)

	Expected Citations					
	Disclosure-Year			Disclosure-Number		
	Coef.	**t-Stat**		**Coef.**	**t-Stat**	
LagDiscYr	-0.0042	-0.20				
CumDiscYr	0.0128	1.62				
LagNumDisc				0.006	0.64	
CumDisc				0.004	1.83	*
EverDisc		-0.58		-0.008	-0.41	
LagIndFnd	-0.0082	-5.42	***	-0.008	-5.41	***
LagFedFnd	0.0130	9.69	***	0.013	9.67	***
PubCount	4.4810	87.83	***	4.482	87.62	***
PubSq	-0.7356	-37.84	***	-0.736	-37.77	***
Age	-0.0240	-2.78	***	-0.024	-2.77	***
AgeSq	0.0000	0.37		0.000	0.38	
PhDYear	-0.0190	-3.96	***	-0.019	-3.94	***
Tenure	-0.0956	-4.48	***	-0.094	-4.43	***
Male	-0.0124	-0.33		-0.012	-0.32	
DeptQual	-0.0596	-5.27	***	-0.060	-5.25	***
Eng	-0.6097	-24.41	***	-0.609	-24.41	***
PhySci	-0.2144	-8.14	***	-0.214	-8.12	***
Univ. Effects	YES			YES		
Year Effects	YES			YES		
Observations	40,674			40,674		
R-Square	0.479			0.480		

	Basic Publications					
	Disclosure-Year			Disclosure-Number		
	Coef.	**t-Stat**		**Coef.**	**t-Stat**	
LagDiscYr	-0.0428	-0.25				
CumDiscYr	0.0994	1.55				
LagNumDisc				-0.0019	-0.03	
CumDisc				0.0492	2.83	***
EverDisc	-0.3782	-1.91	*	-0.3644	-1.96	**
LagIndFnd	-0.0741	-4.93	***	-0.0750	-5.01	***
LagFedFnd	0.0645	5.89	***	0.0641	5.85	***
PubCount	7.1293	22.23	***	7.1364	22.29	***
PubSq	-1.4491	-15.15	***	-1.4509	-15.22	***
Age	-0.1788	-2.49	**	-0.1783	-2.48	**
AgeSq	0.0006	0.98		0.0006	1	
PhDYear	-0.1299	-3.11	***	-0.1289	-3.08	***
Tenure	-0.5860	-3.24	***	-0.5861	-3.24	***
Male	-0.1187	-0.41		-0.1209	-0.42	
DeptQual	-0.0901	-1.14		-0.0883	-1.11	
Eng	-3.2182	-11.96	***	-3.2179	-11.97	***
PhySci	0.5115	2.8	***	0.5187	2.84	***
Univ. Effects	YES			YES		
Year Effects	YES			YES		
Observations	11,552			11,552		
R-Square	0.086			0.086		

*** Significant at 1% ** Significant at 5% * Significant at 10%