University Licensing: Implications for Faculty Research

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I. Introduction

Licensing as a mechanism for university-industry technology transfer has increased dramatically in the last few decades. Since the early 1990s, this growth in the US has been tracked by annual surveys of the Association of University Technology Managers (AUTM). Their data show that not only have many universities recently established Technology Transfer Offices (TTO), but existing offices have expanded their patent licensing activities. Almost 50% of existing offices in the US were started after 1990. For the 109 US non-profit institutions responding to the AUTM survey in both 1996 and 2004, the number of inventions disclosed by faculty 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%). The number of license and option agreements executed rose 71.6% from an average of 18.7 to an average of 32.1. Along with this growth in disclosures, patents and licenses there has been substantial growth in income. Sixty-eight institutions reported income in both years; their income net of royalties paid to other institutions and net of legal fees rose 40.6% in real terms from an average of \$4.61mil to \$6.49mil.[2]

While many view this growth as evidence of the increasing role of universities in the national innovation system, others view it with skepticism, arguing that such commercial activity may 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. However, critics claim that publication would be sufficient for transfer, and more importantly, that potential financial returns from licensing may have diverted faculty from more basic to applied research.

We consider this question at a time when policy makers in the US are increasingly concerned about the health of the research environment for basic research. Universities produce the bulk of basic research, and since 2002 basic research conducted by universities has leveled off while their applied research is estimated to be growing (National Science Board 2008). As a result, the National Research Council has called for increased funding for basic research, while at the same time announcing a need for actions by industry, the academic sector, and professional organizations to encourage greater intellectual exchange between industry and academic (National Research Council 2008). This echoes the complex nature of the issues involved in our research question.

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[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] This includes sponsored research funds tied to licenses.

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 examine the impact of faculty engagement in licensing activity on the nature of their research. Our data include faculty who never disclosed inventions as well as those who did, which allows us to examine the likelihood that faculty members disclose inventions as a function of inputs and outputs of their research efforts, as well as other factors such as major program area, gender, age, and tenure. We take disclosure as our measure of faculty interest in commercial activity since it reflects only the faculty member's opinion that she has an invention with commercial potential. This is in contrast to patents which are also subject to the novelty and usefulness of the invention and unlike licenses which are subject to a firm's opinion of the commercial potential of an invention. Thus disclosure represents a necessary but not sufficient condition for licensing to have diverted faculty from basic research.

To explore whether commercial activity has influenced research we consider econometric models of the amounts of federal and industry research funding as a function of a set of regressors of individual characteristics including whether the faculty member disclosed an invention in the prior year. We also consider econometric models of publications, citations to those publications, "expected citations" and the number of "basic" publications.

By examining disclosures, as well as government and industry funding, we differ from prior studies that examine faculty patenting and its relation to research. An exception is Thursby and Thursby (2002) which constructs an intermediate input model of university licensing in which research funding is an input to invention disclosures, invention disclosures are inputs to patent applications, and both disclosures and patent applications are inputs to licenses executed. The model is estimated using data from 65 US universities for the period 1994-1998. An important result is that the primary factor behind the growth in licensing during that period was university administration decisions to patent, rather than the business climate or a change in the nature of faculty disclosure activity. A drawback of that paper is that it relies on university level data, rather than the individual level data used in this paper.[3]

Our analysis complements studies that examine individual level data on inventor patenting and the implications for research (see, for example, Azouley *et al.* (2006, 2007), Breschi *et al.* (2005), Jensen *et al.* (2008), Deng *et al.* (2006)).

II. Data

Our data are the research, demographic and disclosure profile of all faculty scientists and engineers at 11 major universities: Georgia Institute of Technology, California Institute of Technology, Uni-

[3] In Thursby and Thursby (2005, 2007a, 2007b) we consider individual data but the analysis is more limited in that it does not include funding data and deals only with a subset of the universities we consider here.

versity 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, 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 technology transfer office (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.[4] 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 also must exclude faculty who join the university after 1993 or who left the 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 inventions because they are unwilling to risk delaying publication during the patent and license process.[5] Faculty who specialize in basic research may not disclose because they are unwilling to spend time on the

[4] 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.

[5] 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 2008). The average delay is nearly 4 months, with some firms requiring as much as a year's delay.

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. In their interviews with MIT mechanical engineering faculty Agrawal and Henderson (2002) found that most conducted research with the primary goal of publishing.

We define three disclosure variables. The first is whether a faculty member discloses in a given year. $Disc_{it}$ 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 year t. It is our primary measure of commercial interest. Hereafter we use the term "disclosure observation" as one where $Disc_{it} = 1$. The second is an indicator of whether there was a disclosure in the prior year. $LagDisc_{it} = 1$ if faculty member i disclosed in year $t-1$. The final measure is the number of disclosures. $NumDisc_{it}$ is the number of disclosures made by faculty member i in year t. Note that $Disc_{it} = 1$ if $NumDisc_{it} > 0$.

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 received through 2003; the citation data is truncated. The citation information not only provides information about the importance of the research conducted in year t, but it also provides information on how fundamental is the work to the extent that fundamental research is likely to be cited more often than is applied research. In the ISI data are the average number of citations received by articles published in the same journal and in the same year; there is also truncation in the average citation data. $ExpCites_{it}$ is the average number of citations received by articles published in the same journals and for year t as $PubCount_{it}$. Average citations can be considered as the expected number of citations for each of the faculty publications. We consider it to be a measure of the nature of the faculty member's research in the sense that more fundamental publications are expected to receive more citations. Thus, journals with more citations can be considered to be journals that specialize in more fundamental research. $FirstAuthor_{it}$ 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 also 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. Each of these publication measures are converted to logarithms.

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. 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. 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. 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 number of basic publications made by faculty member *i* in year *t*. We calculate this figure by first finding the fraction of rated publications that are in the most basic category of the Narin classification. It is 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.

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. Most of our analysis is restricted to these 8 universities; the number of faculty 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. Funding is important to understanding disclosure behavior and its effects so that our econometric analysis will consider only the eight universities for which we have funding data. $FedFnd_{it}$ and $IndFnd_{it}$ are the amounts of federal and industry sponsored research funds received by faculty member *i* in year *t*. In the econometric analysis we measure these in logarithms.

Information on annual faculty activity is combined with information on age (Age_{it}) and year that the PhD was awarded ($PhDYear_i$) in the event there are PhD "cohort" effects. In many cases birth dates are unavailable; in such cases we assume birth dates are 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 PhD Whenever we include Age_{it} we also include its square ($AgeSq_{it}$). 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 there "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 the faculty member *i* has tenure in year *t* according to our algorithm. Our measure of tenure provides an undercount.

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 reflect faculty quality that is not reflected in individual specific research output measures such as numbers of publications; for example, faculty in high quality departments have undergone a more rigorous vetting process in being hired 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. If that is the case then the effect of department quality is unclear.

In each of our regressions we include indicator variables for the major program field of the faculty member. We define Eng_i = 1 if the inventor is in an engineering department and $PhySci_i$ =1 if the inventor is in a physical science department; the excluded field is biological sciences. 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 any annual effects not accounted for by our time varying regressors. The year effects will also mitigate to some extent the fact that $Cites_{it}$ and $ExpCites_{it}$ are truncated.

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, $Disc_{it}$ = 1).

Taking into account multiple disclosures in a year the total number of disclosures is 9,240; that is, 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 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 (not shown in the table). 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, $NumDisc_{it} = 2$) and for the remaining 84.7% there are more than two disclosures. Forty-five of the disclosure years are cases of 10 or more disclosures by a faculty member in a single year. The distribution of $Disc_{it}$ 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 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

As noted, we have for eight of the universities in our sample both federal and industry funding by researcher by year. This subsample includes 4,240 researchers and 51,951 person/year observations. Thirty-two percent in this group have no federal money in any years 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. Both sources of funds are observed in 9.4% of the sample.

Graphed in Figure 2 are annual average funding levels as a fraction of their average levels in 1983. Disclosure activity increased substantially over the period of our sample, and if this has come at the expense of faculty research funding, then it does not show up in the raw data. Relative to 1983, federal funding has increased almost six fold. 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 by 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 value of $Cites_{it}$ is 120.5. This is substantially larger that the 101.4 average for $ExpCites_{it}$ 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 to their work.

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.

III.4 Basic Publications

Basic publications are determined according to Narin et al.'s (1976) classification. As noted above we drop any person/year observations for which 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 slightly 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

In the above we consider changes in research inputs and outputs over time for the raw data. With the possible exception of the ratio of basic publications to total publications the raw data do not suggest that an increase in disclosure activity has been accompanied by a noticeable change in research. Those comparisons do not control for any other factors that might affect research inputs and outputs. In this section we consider econometric models of disclosures, 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.

IV.1 Dependent Variables

In Table 4 is a matrix summary of the models we consider. In the first panel columns show the dependent variables and rows show the regressors. In the second panel are our primary methods of estimation. For ease of discussion we categorized the dependent variables as follows.

- Disclosure measures
    - *Disc*
    - *NumDisc*
- Funding
    - *FedFnd*
    - *IndFnd*
- Research outputs
    - *PubCount*
    - *Cites*
- Research type
    - *ExpCites*
    - *Basic*

Research type refers to measures of how fundamental is the research. More fundamental research is expected to be published in journals that are cited more often. Both *ExpCites* and *Basic* are citation based measures of how basic is the research. Note that *Cites* is both an output and a measure of research type. The funding, research outputs and research type variables are all converted to logarithms.

IV.2 Independent Variables

In all of our regressions disclosing in the prior year is included. *LagDisc* is our regressor of greatest interest. If disclosure activity signals a change in research direction or interests it is likely that we will observe subsequent changes in the various measures of research. For example, if disclosures indicate a change in research then it should have an effect on current funding and current funding is based on research applications. Our priors are that a change in research toward a more commercial focus should lead to increased industry funding and decreased federal funding. Likewise, a change toward more applied research should show up through fewer citations and publications in journals that are less often cited and that are less basic in orientation. That is, *LagDisc* should have a negative coefficient in the equations for *Cites*, *ExpCites* and *Basic*. The effect on *PubCount* is unclear.

Federal and industry funding is included as a regressor in each equation either as the current year levels or the levels from the prior year. 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*. It is very likely that federal and industry sponsored research are simultaneously determined (see Jensen *et al.* (2008)). Thus, in the equation explaining federal funding we include the current level of industrial funding. Likewise, in the industry funding equation we include the current level of federal funding. Instrumental variables estimation is used and the instrument for *FedFnd* is *LagFedFnd*. Similarly, the instrument for *IndFnd* is *LagIndFnd*. 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). Lagged federal spending is included in the federal funding equation and lagged industry funding is included in the industry sponsored research funding equation since many of the research awards are multi-year awards (in addition there are other possible sources of inertia in funding). Their inclusion should also pick up any unobservable individual specific factors that are not captured by the publication data, major program area, etc. For example, the focus of a researcher's research interests should influence federal funding depending according to whether those interests are in line with federal initiatives. In each of the other regressions we include *LagFedFnd* and *LagIndFnd*.

PubCount is included in the disclosure equations as a measure of the current research activity of the faculty. It is also included in the *Cites*, *ExpCites* and *Basic* equations. *Cites* and *ExpCites* are counts of citations for this year's publications and *Basic* is the number of publications which are basic. The disclosure measures are functions not only of current research activity as measured by *PubCount* but also by the current year's citations and expected citations. *Cites* is a measure of the importance of the research, but it is also an indication of how fundamental is the research; hence *ExpCites* is also included. If one is first author more often then Inventors in larger labs will, in general, generate more publications per year, but they will be first author less often.

LagPubCount, *LagFirstAuthor*, *LagCites* and *LagExpCites* are each in the funding equation since current funding is based on past applications and those applications are based on research performance in the recent past. We include the number of times the researcher is first author on papers for two reasons. The more often one is first author then we can expect that the researcher has fewer co-authors. This could follow from being in a small lab so *LagFirstAuthor* can be argued to control for lab size

There are four life cycle variables – *Age, AgeSq, PhDYear* and *Tenure*. Each is included in all equations. Thursby *et al.* (2007) provide theoretical evidence that licensing activity is associated with age and that the age effects are non-linear. Levin and Stephan (1991) and Thursby *et al.* (2007) offer evidence of life cycle effects in research output. Thus, we include both the age of the inventor at the time of the disclosure *Age* and the square of age *AgeSq*. *PhDYear* is included to pick up any PhD "cohort" effects not captured by age. 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 PhD that is not captured by age. For example, attitudes toward commercial activity might have changed over time and the year of the PhD might capture such changes.[6] Stephan *et al.* (2002) find that faculty who are not tenured are more likely to patent. Our measure of interest in licensing is clearly much broader than their measure, nonetheless there is expected to be a relation between tenure and disclosure (see also Thursby *et al.* (2007)).

Gender is included as a regressor in all equations. Thursby and Thursby (2005) find significant gender differences in faculty propensity to engage in licensing activities and Azoulay *et al.* (2007) find significant gender effects on faculty patent activity.

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[6] An industry licensing executive claimed to one of the authors that more recent vintage PhD's in university biological science departments were more accepting of licensing to industry.

Indicator variables *Eng* and *PhySci* are included to capture field effects. We also include the department quality score *DeptQual*. Universities differ in license policies via different as inventor shares of income or outreach programs to encourage disclosures. To account for that heterogeneity (much of which we cannot observe) we include the university indicator variables. Finally, we include year indicators to capture annual effects not accounted for by our time varying regressors. The year effects will also mitigate the truncation in *Cites* and *ExpCites*. We do not present the detailed results on the university and year indicator variables which show in all cases significant year and university heterogeneity.

IV.3 Estimators

We use a logit probability model for *Disc.* A negative binomial counts model was initially attempted *NumDisc* but the process did not converge. In its place we use a negative binomial counts model where the count consists only of zero, one, two, and three or more disclosures in a year.

All other models are estimated using a Tobit estimator given the very large numbers of zero observations. As noted above, instrumental variables estimation is used for the funding dependent variables since *FedFnd* is on the right hand side of the industrial funding equation and *IndFnd* is on the right hand side of the federal funding equation. The instrument for *FedFnd* is *LagFedFnd*. Similarly, the instrument for $IndFnd_{it}$ is $LagIndFnd_{it}$. 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). We do not use a counts model is not used since the number of publications is often large. For example, the average number of publications for person/years in which there is a publication is 5.34 and the maximum is 130. In addition we encountered convergence problems.

There is very likely measurement error in *FedFnd* and *IndFnd* since we were forced to assume that all principal investigators and co-principal investigators expensed awards equally and that award were expensed equally over time. As a robustness check we defined an indicator variable $DumFed_{it}$ which is equal to 1 if researcher *i* received funding in year *t*. Similarly, we defined $DumInd_{it}$ to be an indicator variable for the presence of industry funding. Instrumental variable probit models were used with lagged indicator variables as instruments. The industry funding model did not converge. Results when *DumFed* is the dependent variable are quite similar to the Tobit results so we do not present the detailed results.

Ten of the person/year observations have federal funding of more than $6Mil with two observations in excess of $30Mil. The effects of these outliers are mitigated through our use of logarithms. However, we considered these regressions after discarding the 10 largest federal funding observations. Results are almost identical to what is reported in Table 6 so we do not report the details.

It was noted earlier that citations and expected citations are truncated after 2003. Year indicator variables will pick up some of the truncation bias. As an alternative we dropped the last four years of data and reran both the citation and the expected citation models on the remaining 31,394 observations. The results are very similar and details are not presented.

Table 4 provides a summary of the regressors used to explain the levels of the eight dependent variables as well as the estimation strategies.

IV.4 Disclosure Equation Results

The logit results for disclosures in terms of the odds ratios are in the first panel of Table 5. $LagFedFnd_{it}$, $LagIndFnd_{it}$, $PubCount_{it}$, $Cites_{it}$ and $ExpCites_{it}$ are converted to logarithms. There are 47,279 observations and all coefficients are significantly different from zero at least at a 5% level. The negative binomial results (incident rate ratios) are in the second panel of Table 5 and the results very close to the logit results with the exception that *AgeSq* is no longer significant and tenure is now significant. The pseudo R^2 is also smaller. We concentrate on the logit results since our main interest is in whether or not the faculty member has shown an interest in licensing in a given year.

Consider the four variables associated with stages of the life cycle: *Age, AgeSq, Tenure* and *PhDYear*. *Age* has a negative effect on disclosure but the effect of *AgeSq* is positive. The marginal effect of another year is declining with age though the net effect of another year is always negative. More recent PhD's (that is, the larger is *PhdYear*) are less likely to disclose. For example, a 40 year old who received his/her degree in 1980 is less likely to disclose than a 40 year old who received his degree in 1970. As time passes, a faculty member is less likely to disclose because she is getting older but this effect is mitigated by the fact that the PhD was further in the past. The final time variable, *Tenure*, is a measure of where the faculty member is with respect to their professional career. Those with tenure are less likely to disclose but this is significant only in the *NumDisc* regression.

Funding is positively associated with disclosure. While the positive effect of industrial funding is expected, the effect of federal funding is not clear *a priori*. Federal funding is generally thought to be aimed more toward more fundamental work and fundamental work is generally less readily for commercialization. This latter point is supported by the fact that *LagIndFnd* is larger than *LagFedFnd* and these are significantly different (p-value = 0.000).

There is a substantial difference in the disclosure rates of men and women. Men are about 35% more likely to disclose than females, all else equal. Holding constant the research output of the faculty member, those in higher quality departments are less likely to disclose. This result may be due to greater internal rewards to commercial activity in lower quality departments. Jensen et al. (2003) provide evidence that higher quality universities (as measured by the NRC survey rankings of PhD granting departments) provide lower royalty shares for licensed inventions.

The omitted major program area is biological sciences. Those in engineering are most likely to disclose, followed by faculty in the biological sciences. Physical science faculty are least likely to disclose. Faculty at the eight universities have very different probabilities of disclosure (results are not shown). Faculty in the university that is most likely to have faculty disclose are about 2.7 times as likely to disclose as are faculty university in the university that are least likely to disclose.

With respect to year effects the raw data show an almost 4.5 fold increase in disclosure activity from 1983 until the late 1990's. In our logit regression this effect continues to hold (detailed results not shown in the table). In other words, the increase in disclosure activity over time has been independent of changes in faculty profiles with respect to research productivity, funding and life cycle effects.

IV.5 Funding, Output and Type Results

Results for the remaining dependent variables are in Table 6. A summary of results are in Table 7 where "+" and "-" denote significant positive and negative results. Insignificant results are blank.

IV.5.a Lagged Disclosure Regressor

The main focus of this paper is an examination of possible effects of an interest in commercialization as evidenced by the act of disclosing an invention in some year. $LagDisc_{it}$ is equal to 1 if researcher *i* disclosed an invention in year *t-1*; it is zero otherwise. We are looking at whether we can find effects on year *t* funding, research outputs and research type for researcher *i* from an interest in commercialization the prior year. In each of the six regressions we find a significant effect of lagged disclosures. In both the federal and industry funding equations higher levels of funding occur in the years following disclosures. If disclosure indicates a change in orientation toward less fundamental research then we would expect the positive relationship between lagged disclosures and industry funding. However, we would expect a negative relationship with federal funding. Higher publication counts are also observed following a disclosure. However, those publications receive fewer citations and are published in journals that on average receive fewer citations and in journals that are rated as being less basic. The effects on citations, expected citations and fewer basic publications are consistent with a change in research orientation.

IV.5.b Industry and Federal Funding Regressors

Current industry funding and lagged federal funding are included as regressors in the federal funding equation. Likewise, current federal funding and lagged industry funding are included in the industry funding equation. Results are in the first two panels of Table 6. In both regressions the other source of funds is positively and significantly different from zero, though the elasticities are very small. That is, *IndFnd* is positive and significant in the federal funding equation and *FedFnd* is positive and significant in the industrial funding equation suggesting that federal and industrial funding are complements rather than substitutes. There does not appear to be crowding out of either type of funding by the other. The coefficient of industrial funding in the federal equation is slightly larger that the coefficient of federal funding in the industrial equation. In a study of funding Jensen *et al.* (2007) also found that different sources of funding were complements. However, they found that federal funding had a larger effect on industrial funding that industrial funding had on federal funding. Their study differs from ours in that they only consider faculty in years in which an ultimately successful application for a patent had been made. Past research funding is significantly and positively related to current funding though the coefficient (elasticity) of *LagFedFnd* in the federal funding equation is only 0.086 while the coefficient of *LagIndFnd* is 0.674. Thus there is inertia in funding. The larger elasticity of *LagIndFnd* most likely follows from the fact that most industry funding values (about 86%) are zero.

Lagged federal and industry funding have the expected results in the *PubCount*, *Cites*, *ExpCites* and *Basic* regressions. More of each type of funding increases publications. Increased federal funding, which is tied to fundamental research, increases citations, expected citations and basic publications. Increased industrial funding, on the other hand, reduces each of these.

IV.5.b Publications, Citations, Expected Citations and First Author in the Funding Regressions

Not surprisingly, more publications, since they indicate greater research productivity, are associated with higher levels of both industry and federal funding. More citations and expected citations, holding constant publications, should lead to greater federal funding and lower industry funding to the extent that more citations and expected citations are indicative of more fundamental research. To the extent that they measure greater productivity they should be associated with greater levels of both types of funding. *LagCites* has a positive coefficient in both the federal and the industry funding equations but it is significant only in the federal equation. *LagExpCites* is positive but not significant in the federal equation and negative and significant in the industry equation. *LagFirstAuthor* is expected to reflect the size of the researcher's lab since researchers in large labs are expected to have more publications but to be first author less often. The results in both funding equations supports this argument since the more often one is a first author, holding total publications constant,, the less federal and industry funding the researcher receives.

IV.5.c Life Cycle Regressors

Our prior is that there should be a positive relation between age and funding but that the effect should decline as the faculty member ages so that an additional year initially has a positive effect but the marginal effect eventually becomes negative. Older researchers at major research universities such as those in our sample are expected to have more established and substantial research records. In the early years when those records are being established we should expect another year of age to increase the availability of sponsored research funding. However, to the extent that research productivity declines over the life cycle (see, for example, Levin and Stephan (1991), Thursby et al. (2007) and our results below), another year should eventually begin to have a negative partial effect. Thus our expectation is that *Age* should be positive while *AgeSq* should be negative. This is the case for both funding equations (*Age* and *AgeSq* are jointly different from zero in both equations at the 1% level). The marginal effect of an additional year (the coefficient of *Age* plus twice the coefficient of *AgeSq* times the age of the faculty member) is negative beginning with age 41 in the federal funding equation and age 52 in the industry funding equation. The earlier age for the maximum level of federal funding is possibly due to the more fundamental purpose of federal funding and that younger researchers are more oriented towards fundamental research. The implied overall decline in federal funding, all else equal, between the ages of 40 (when federal funding is a maximum) and 60 is about 26%; this is significantly different from zero at a 1% level. The implied overall decline in industry funding between the ages of 51 (when industry funding is a maximum) and 60 is about 1.3%; this is not significantly different from zero at conventional levels.

Publications increase at a decreasing rate with age. This effect was expected. A similar result is reported by Levin and Stephan (1994) based on both theoretical and empirical models. Thursby *et al.* (2007) report a similar theoretical result. The effects of *Age* and *AgeSq* are similar in the citations, expected citations and basic publications regressions. *Age* has a negative effect but *AgeSq* is positive.

More recent PhD's receive less federal funding but there is no statistically significant effect on industry funding. Newer PhD's have fewer publications, expected citations and basic publications. *Tenure* has a negative effect on federal funding (significant at the 5% level) but it is not significant in the industry funding equation. *Tenure* has not effect on the number of publications but it does have a negative effect on citations, expected citations and basic publications. Tenure appears to be associated with a change in orientation to less fundamental research.

Males receive significantly more of both types of funding; the coefficient is significant at the 5% level in the federal equation but it is only significant at the 10% level in the industry equation. Men also have larger numbers of publications, but there is no other difference in research profile between men and women.

When department quality is significant it has a negative effect. We had expected department quality to pick up measures of individual research output that is not captured by other regressors, hence this negative effect is puzzling.

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