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Incentives and Invention in Universities

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# Incentives and Invention in Universities

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## Abstract

Using data on U.S. universities, we show that universities that give higher royalty shares to faculty scientists generate greater license income, controlling for university size, academic quality, researchfunding and other factors. We use pre-sample data on university patenting to control for the potential endogeneity of royalty shares. We find that scientists respond both to cash royalties and to royalties used to support their research labs, suggesting both pecuniary and intrinsic (research) motivations. The incentive effects appear to be larger in private universities than in public ones, and we provide survey evidence indicating this may be related to differences in the use of performance pay, government constraints, and local development objectives of technology license offices. Royalty incentives work both by raising faculty effort and sorting scientists across universities. The effect of incentives works primarily by increasing the quality (value) rather than the quantity of inventions.

# 1 Introduction

Universities are an important source of technical change. By the end of the 1990's, they accounted for about 50 percent of basic research in the U.S. (National Science Board, 2000). Academic research has real effects by increasing productivity growth in the economy and stimulating greater private sector R&D through spillovers (Jaffe, 1989; Adams, 1990). In addition, university research contributes to the economy through the licensing of the resulting inventions to private firms.[1] Technology licensing activity has grown dramatically in the past two decades.[2] The number of U.S. patents awarded to university inventors increased from 500 in 1982 to more than 3,100 in 1998. The number of licenses more than tripled during the 1990's, and license revenues increased from $186 million to about $1.3 billion. It is important to understand what drives academic research and technology licensing activity. It is widely accepted in the literature that academics respond to non-pecuniary incentives, such as peer recognition and advancement of science (Dasgupta and David, 1987, 1994), but is it a purely intellectual pursuit, or do monetary incentives also matter?

In this paper we take a first step to answer this question by providing econometric evidence which suggests that high-powered, pecuniary incentives strongly affect university research and licensing outcomes. We examine how cash flow rights from university inventions (the share of license royalties received by academic inventors) affect the licensing income generated by universities. In the United States, university intellectual property policies always grant the university exclusive (first refusal) control rights over inventions, but the royalty income is shared between the inventor and the university according to specified royalty sharing schedules. We show that there is substantial variation in these royalty sharing arrangements

[1] There is substantial evidence of R&D spillovers (e.g., Jaffe, 1989; Jaffe and Trajtenberg, 2002; Adams, 1990). University research spillovers tend to be geographically localized as might be expected if direct knowledge transfers are important (Jaffe, Trajtenberg and Henderson, 1993; Audretsch and Stephan, 1996). There is also a growing empirical literature on university patenting and technology transfer (e.g., Henderson, Jaffe and Trajtenberg, 1998; Thursby and Kemp, 2002; Siegel, Waldman and Link, 2003) and university research productivity (Adams and Griliches, 1998).

[2] Part of this rapid growth in university innovation and licensing activity is due to the passage of the Bayh-Dole Act of 1980 (Patent and Trademarks Amendments Act, PL 965-17) which gave universities the right to patent and a mandate to license discoveries made with federally sponsored research to the private sector. By the year 2000, nearly all American research universities had established, or expanded, technology licensing offices and introduced explicit intellectual property policies and royalty sharing arrangements for academic scientists.

across universities, and use this cross-sectional variation to estimate the effect of royalty sharing arrangements on license income.

To address the potentially serious problem of endogeneity of royalty shares that can arise from unobserved heterogeneity across universities, we use pre-sample information on the university's patenting activity to proxy for the university's fixed effect (following the approach developed by Blundell, Griffith and van Reenen, 1999). It would be more convincing if we could control for fixed university effects, but there is not sufficient variation over time in the royalty sharing arrangements to permit this. While the pre-sample patent control is very significant and works in the expected direction, one cannot rule out the possibility that there is some remaining unobserved heterogeneity. It is important to recognise that there are some fundamental limitations to what can be said with the available data. To reach more definitive conclusions, we would need more time series variation in royalty shares than is available in our sample, or instrumental variables that affect royalty shares but not license income. We are not aware of the existence of such instruments and developing them would require a deeper institutional understanding of how universities determine their royalty sharing arrangements.

We develop a simple model in which a scientist makes three types of research effort: basic research, applied research devoted to starting new projects, and applied research to improve the quality of each project. Basic research generates scientific publications. The applied research efforts generate two types of outputs, projects with commercial value and scientific publications. This characterisation is based on the argument that scientific research is often dual-purpose, frequently referred to in the literature as 'Pasteur's Quadrant' (e.g. Stokes, 1992; Murry and Stern, 2006). Scientists value both publications and royalty income. We develop sufficient conditions under which (all three types of) efforts are increasing in the inventor royalty share. Thus the model predicts that a rise in the inventor royalty share of a university increases its license revenues. We also allow for royalty incentives to affect the sorting of more productive scientists to universities. This sorting mechanism predicts that a rise in the royalty shares of "competing universities" reduces the license revenue for the university.We test these predictions with university-level data from the Association of University Technology Managers, combined with information on the distribution of royalty shares which we collected from university websites.

There are three key empirical findings. First, royalty shares affect the level of license income generated by universities. Controlling for other factors, including university size, quality, R&D funding, scientific composition, and local demand conditions, universities with higher royalty shares generate higher levels of license income. This finding is important because it means that the design of intellectual property rights, and other forms of incentives, in academic institutions can have real effects on growth and productivity. Second, the incentive effects of royalty shares appear to work both through the effort and sorting channels. Third, the response to incentives is much stronger (and more significant) in private universities than in public ones.

Under a 'Betrand' assumption that universities do not expect a strategic reaction from their competitors, we find that in most private universities, and in about half the public ones, the incentive effect is strong enough to produce a Laffer effect, where raising the inventor's royalty share would increase the license revenue retained by the university (net of payments to inventors). However, if universities expect competitors to match changes in their royalty share, this Laffer effect holds for a much smaller subset of universities.

We also show that technology licensing offices (TLOs) are more productive in private universities, on average, suggesting that private institutions have more effective, commercially-oriented technology transfer activity. We argue that differences in TLO effectiveness help explain why there is a larger response to royalty incentives in private universities. Because universities retain the control rights over inventions, the TLO has exclusive rights to commercialize inventions disclosed by the faculty (unless expressly waived). As the "gatekeeper", the TLO's effectiveness in licensing activity directly affects the monetary returns to the faculty scientist. Raising the royalty share will have a smaller effect on incentives if the faculty scientist anticipates that the TLO will be ineffective at commercializing her inventions. We provide new survey evidence which shows that TLOs in private universities are more likely to use performance-based pay, are less constrained in their freedom of operation by state laws and regulations, and are more focused on generating license income rather than "social" objectives such as promoting local and regional development. The survey evidence is consistent with our findings that private university TLOs are more effective at generating license income, on average, and that royalty incentives have a larger impact in private universities.

We emphasize that this paper is not a normative analysis of university technology licensing activity. Greater commercialization has both benefits and costs. We show that private benefits to universities, in the form of license income, appear to be strongly affected by royalty incentives. The potential costs of commercialisation include the reallocation of scientists' effort from basic to more applied research and less "open science" in universities. While the public debate has focused heavily on such costs, economic research in this area is only just beginning.[3] We do not address these costs in this paper.

The paper is organized as follows. Section 2 describes the data. Section 3 presents a simple theoretical model of academic research that establishes a relationship between royalty incentives and scientists' research effort. In Section 4 we present the empirical specification and address the empirical issues that arise in testing the main theoretical implications. Section 5 presents the empirical results and their implications, as well as a variety of robustness checks. Brief concluding remarks follow.

## 2 Data

The data assembled for this project came from three main sources: 1) the Annual Licensing Surveys for the years 1991-1999 published by the Association of University Technology Managers (AUTM), 2) the 1993 National Survey of Graduate Faculty conducted by the National Research Council (NRC), and 3) royalty sharing arrangements downloaded from technology licensing offices' websites. Details of the variables and the sample selection are provided in Appendix 1.

The AUTM surveys provide information on licensing income, number of licenses, number of inventions reported to the TLO (invention disclosures), characteristics of the technology licensing office (TLO), and R&D funding from external sources in universities.

To control for differences across universities in faculty size (in the hard sciences) and scholarly quality, we use data from the 1993 NRC Survey. For each university we have information on faculty size and on three measures of quality for doctoral programs in twenty-three different fields of science, which we aggregate to the university level using faculty size weights.

[3] For an interesting theoretical analysis of the role for universities and private firms in basic and applied research, see Aghion, Dewatripont and Stein (2005). The available empirical studies on university patenting, applied research and open science give mixed results (Henderson, Jaffe and Trajtenberg, 1998; Agrawal and Henderson, 2002; Murray and Stern, 2004).

The primary quality measure we use is the number of citations per faculty during the period 1988-92.[4]

Table 1 reports descriptive statistics for private and public universities separately. The universities in our sample account for 68.1 percent of total license income in 1999, as reported by AUTM. These universities generate an average of $3.6 million of license income per year. Not surprisingly, this income is unevenly distributed across universities: the median license income is just $868,000 for private and $539,000 for public universities, but the top 10 percent of private universities earn over $11.5 million per year ($5.8 million for public). Normalizing by the number of active licenses (row 2) does not eliminate this variation. The median revenue per license is $28,000 for private and $17,000 for public universities, while the top 10 percent of universities have mean license income above $99,000 and $65,000, respectively. In short, the distribution of license income is very skewed: only a few universities produce very valuable inventions.

Citations per faculty reflect both the quantity and quality of publications and exhibits the highest dispersion across universities. The three measures of quality are highly correlated (with correlations above 0.76). Technology licensing offices at most universities are quite small, with a mean of about three full-time professionals. The average age of TLO's in 1999 was 16, reflecting the stimulus to commercialize university inventions given by the 1980 Bayh-Dole Act. Except for the quality measures – private universities are of higher quality on average – there are no statistically significant differences among the two groups in the other university characteristics.

Our third source of data was information on the distribution of licensing income between faculty scientists and the university, i.e., on the arrangements for sharing the royalties generated by the licensed inventions. This information was downloaded from the websites of individual technology licensing offices during the summer of 2001 and it constitutes the novel aspect of our data.

[4] We also experimented with two alternative university quality measures, the number of publications per faculty and a scholarly quality rating score between zero ("not sufficient for doctoral education") and five ("distinguished") to check the robustness of the results. Both of these other two measures are highly correlated with the citations measure we use, and the econometric results using the other measures are similar to those we report in Section 5.

The intellectual property policies of the universities usually state that a percentage of the net income received by the university from licensing an invention is retained by the inventor and the rest is allocated to the inventor's lab, department, college and to the university. The criterion we used for identifying the inventor share is that the inventor must gain either cash flow rights or direct control rights over the income. Thus, when the university's intellectual property policy states that the share accruing to the lab was under the control of the inventor, we added it to the inventor's share, but otherwise we did not. We call this the *inventor's royalty share*. In Section 5, we examine whether cash payments to the inventor and to her research lab have different incentive effects. This allows us to say something about the relative importance of monetary and intrinsic (research-oriented) motivations.

The observed royalty shares were those in effect (and posted on the web) in 2001. Because we study the impact of royalty shares on licensing outcomes during the period 1991-99, we wanted to identify any changes that occurred during these years. We sent an e-mail inquiry to the directors of the TLO's in the sample, and found that 70 percent of the universities did not change their royalty distribution during the sample period. In fact, in many cases the arrangements were set in the early 1980s and never changed. In the universities where royalty shares changed, and where the pre- and post-change levels were available, we assigned the reported values of the royalty shares to the relevant years.[5]

In 58 universities the inventor royalty share is a fixed percentage of the license income generated by an invention (hereafter, *linear* royalty schedules). Interestingly, in the other 44 universities these royalty shares vary with the level of license income generated by an invention (*non-linear* royalty schedules). Because the income intervals differ across universities, we divided the license income into seven intervals based on the most frequently observed structure (in US$): 0-10,000, 10,000-50,000, 50,000-100,000, 100,000-300,000, 300,000-0.5 million, 0.5-1.0 million, and over 1 million.[6] For these universities we compute an *expected royalty share* by

[5] In total, 53 universities responded to this query. Of the sixteen that reported a change in royalty shares during 1991-99, only eleven reported the pre- and post-change royalty sharing agreements. In these cases, we included the new royalty shares for the appropriate years. In the remaining five universities, we used the shares reported in 2001.

[6] In the many cases where our selected interval did not correspond to the interval chosen by the university, we recomputed royalty shares with the correct weights. For example, if a university reports a 50 percent share for income less than 5,000 and 40 percent share for income above 5,000, this would appear as an 45 percent share

weighting the average share in each income interval by the probability of observing license income in that interval. These probabilities were estimated non-parametrically from the distribution of license revenue per invention over all years in the AUTM sample. Let $v_{it}$ denote license income per invention disclosure in university $i$ in year $t$. We first estimated the density $f(v_{it})$ by kernel methods at these values. We then computed an average royalty share for each value of $v$, $\overline{s}(v)$, using the royalty schedule for each university, taking into account the varying marginal royalty rates.[7] The expected royalty share is then $s \equiv \Sigma_v \overline{s}(v)\widehat{f}(v)$.[8,9]

Table 2 summarizes the main features of the royalty share data. The average inventor share is 39 and 42 percent for private and public universities using linear royalty schedules, but there is substantial cross-sectional variation within each group. Average royalty shares in the universities with non-linear schedules is 51 percent, higher than for the linear schedules, and displaying even larger cross-sectional variation. The striking variation in inventor royalty

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in the first interval (0-10,000) and an 40 percent share in all the remaining intervals.

[7] For example, with three marginal rates the average share is

$$\overline{s}(v) = \frac{s_1 v}{v} I(0 \leq v \leq v_1) + \frac{s_1 v_1 + s_2(v - v_1)}{v} I(v_1 < v \leq v_2) + \frac{s_1 v_1 + s_2 v_2 + s_3(v - v_2) I(v > v_2)}{v}$$

where $I(\cdot)$ is an indicator function.

[8] The estimated density function of license income per invention disclosed (not shown) exhibits extreme dispersion and skewness. Such skewness is typical of distributions of the returns to innovation (e.g., Schankerman, 1998). In our case, nearly all of the weight is on the first two income intervals – 50.2 percent in the 0-$10,000 bracket and 46.1 in the $10,000-$50,000 bracket. Thus it would be highly inappropriate to use a simple average of sharing rates in a nonlinear schedule. In fact, for practical purposes a good approximation is simply to average the first two sharing rates.

Two other points should be noted. First, we also used yearly license income divided by the *cumulative* number of active licenses as a measure of $v$ and obtained essentially the same estimates of $s$. The two estimates differ by at most 1.7 percentage points, and the average difference is 0.7 percentage points. We normalized by disclosures because data on cumulative licenses is available only since 1995 resulting in a smaller number of observations. Second, one might want to estimate separate density functions for sub-categories of the pooled data, e.g., for different technology fields or universities of different quality levels. Since we do not have license revenue broken down by technology area, we cannot treat areas separately. However, we did estimate different kernel density functions for the lower, middle two, and upper quartiles of the quality distribution (using citations per faculty). The differences in the estimated kernel weights were negligible.

[9] The density estimates used to compute the expected royalty share are based on the observed distribution of license income per invention disclosed ($v$). However, if license income responds to royalty shares (as suggested by the theoretical model in Section 3) then the observed $\widehat{f}(v)$ depends on the royalty sharing schedule. This is an issue only for the universities with nonlinear schedules. To account for this circularity, we regressed license income per disclosure on $s$ (and other controls) and used the residuals to recompute the kernel density estimates and the expected royalty share. We found that the average difference in the computed expected royalty shares was only 1.3 percentage points, or about 2.5 percent of the mean royalty share (51 percent). Because this is a small difference and also because the final estimates (in Table 5) were essentially invariant to the two ways in which $s$ was computed, we decided to use the simpler, observed distribution of license income per disclosure in our computation of the expected royalty share.

shares is shown in Figure 1, where the histogram and a nonparametric estimate of the density of the expected royalty share are displayed for private and public universities separately. We exploit this cross-sectional variation to identify the effect of monetary incentives on license revenue from invention.

Another striking feature of Table 2 is that inventor royalty shares are either constant or decline in the level of license income per invention – royalty retention is regressive (i.e., the university 'tax' on inventors is progressive). On average, they start at 53 percent in the lowest interval and decline to 30 percent for inventions generating over $1 million. This feature holds in every quartile of the cross-sectional distribution and, in fact, it holds for *every* university in our sample with non-linear royalty schedules.[10]

In order to get some understanding of the determinants of the variation in royalty shares across universities, we split the sample into four quartiles defined by a variety of university characteristics and computed the mean royalty share in each quartile. Table 3 summarises the results, separately, for private and public universities. Royalty shares are not systematically related to faculty size, the number of citations per faculty (our measure of academic quality), the size of the TLO (measured by the number of TLO professionals per faculty), the age of the TLO, or the shares of the faculty in biomedical sciences and engineering. As the last row in the table shows, we cannot reject the hypothesis that the mean royalty rate is the same across the four quartiles of the distribution for each characteristic. Apparently there is no significant correlation between royalty shares and these university characteristics, taken individually.

These simple bivariate comparisons also hold in a regression context. In a regression of the royalty share on three binary indicators for each of the quartiles of the six characteristics (not reported for brevity), we find that these characteristics are not jointly significant (the p-values for significance of the regression are 0.59 and 0.17 for private and public universities,

[10] Regressive royalty sharing (i.e. progressive taxation of inventors) give inventors an incentive to focus on many low value inventions rather than on "big hits". Optimal taxation theory can generate progressive tax schedules when there is uncertainty to effort – when high income outcomes are largely due to luck rather than effort – together with risk aversion of the agents. In this case such taxes are essentially an insurance mechanism. This argument is relevant here if the scientist knows little about the quality of different research projects ex ante. In such cases, high payoff projects are basically due to good luck, and regressive royalty sharing may then be preferred by the inventor. But if the inventor has some ability to distinguish between low and high quality projects in making effort decisions, then optimal incentives are more likely to involve progressive royalty sharing in order to compensate for the higher marginal cost of producing higher-valued inventions. Of course, "fairness" and other considerations may affect how universities set royalty sharing.

respectively). We also cannot reject the hypothesis that each of the characteristics is individually insignificant. In addition, we ran a probit regression on the choice between linear and nonlinear royalty sharing against the same six characteristics. Again we do not reject the null that these characteristics are jointly insignificant (p-values are 0.30 and 0.94 for private and public universities, respectively). Finally, it is worth noting that the top quality and leading licensing performers are not the universities that offer the highest royalty shares. For example, the royalty shares are 33 percent for Stanford and MIT, 34 percent for Harvard, and 49 percent for Columbia and the University of California System. The overall mean royalty share in the sample is 45 percent.

To summarise, the two salient features of observed royalty sharing arrangements are their variability across universities and their regressiveness in the level of license income. Moreover, the evidence suggests that neither the form of the royalty sharing arrangement (linear versus nonlinear) nor the level of inventor royalty shares are significantly related to observed university characteristics. While it is important to study the determinants of royalty sharing arrangements in more detail, this would require information on the actual decision-making process at universities, which is beyond the scope of the present paper. As discussed in the next section, however, royalty shares may still be correlated with unobserved factors at the university level that also affect license income. We will address this potential endogeneity problem by using pre-sample information on university patenting.

# 3 Model

A scientist makes three types of research effort: basic research ($e$), applied research devoted to starting new projects ($z$), and applied research to improve the quality of each project ($q$). Basic research generates scientific publications. The applied research efforts generate two types of outputs, projects with commercial value and scientific publications. This characterisation is based on the argument that scientific research is often dual-purpose, frequently referred to in the literature as 'Pasteur's Quadrant' (e.g., Stokes, 1997).[11]

The production setup is as follows. First, the number of scientific publications is given

[11] In this specification, we are essentially *defining* purely basic research as any research that generates only publications.

by an increasing, concave production function $p(e, z, q)$. The assumption that this function is non-decreasing in $z$ and $q$ does not rule out a tradeoff between basic and applied research. The tradeoff enters here through the allocation of effort (and associated effort costs). Second, the number of new applied research projects is $n = n(z)$ where $n(z)$ is increasing and concave. Each invention has the same initial quality normalised at unity. By investing effort $q$ into a project, the inventor generates an invention of potential commercial value $v(q) = \psi(q)\varepsilon$ where $\psi(q) \geqslant 1$ is increasing and concave and $\varepsilon$ is a stochastic shock independent of $q$, with unit mean value and distribution function $G$. The shock $\varepsilon$ is observed after the scientist chooses effort levels. With no ex-ante differences among the $n$ inventions, the scientist sets the same level $q$ for each.[12]

Effort costs are given by the convex function $C(e, z, q)$. This should be interpreted as a reduced-form representation of a more complete model in which these effort costs reflect the university's valuation of different types of research. The university controls these shadow prices by setting promotion criteria and other rewards, including royalty shares.

The invention earns revenue $\theta v$ if it is licensed (zero otherwise), where $0 < \theta \leq 1$ reflects the effectiveness of the TLO. While $v$ is the invention's maximum potential commercial value, actual license income depends on how good the TLO is at identifying potential licensees and negotiating agreements.[13] These capabilities are likely to depend on institutional characteristics, such as whether the university is public or private (for more discussion, see Section 4.1). The TLO licenses an invention if expected income covers the fixed cost of licensing, $\underline{v}$. The selection rule $\theta v > \underline{v}$ implies that a proportion $1 - G\left(\frac{\underline{v}}{\theta\psi(q)}\right)$ of inventions is licensed.[14]

[12] An equivalent formulation is to allow the initial value of the idea to be random and unknown to the researcher when the decision on effort $q$ is made. We need some form of uncertainty in the model because otherwise the scientist would either set $q = 0$ or set $q$ at a level to ensure that any developed idea would pass the TLO selection rule (see below in the text). But this is not consistent with the data: the ratio of licenses executed to invention disclosures in a given year is about 30 percent, on average.

[13] As others have emphasised, apart from her role in doing the research that generates an invention, the university scientist also plays an important role in the commercialisation process, identifying potential licensees and transferring tacit knowledge. The royalty incentive can affect licensing revenue through both channels in practice, though we emphasise the invention channel in the model. For discussion of the optimal design of contracts for university technology transfer that recognises the scientist's post-invention role, see Jensen and Thursby (2001) and Macho-Stadler, Castrillo and Veugelers (forthcoming), and Agrawal (2006).

[14] This specification of the licensing decision is consistent with new survey data we gathered from TLOs, described briefly in Section 4.1.

Expected license revenue per faculty is

$$r(z,q) = \theta n(z)\psi(q)\int_{\frac{v}{\theta\psi(q)}}^{\infty} \varepsilon dG(\varepsilon) \tag{1}$$

Note that $r_z > 0$, $r_q > 0$, $r_{zq} > 0, r_{z\theta} > 0$ and $r_{q\theta} > 0$.[15] Quality effort' $q$ has two effects: it raises the expected value of the invention, which also increases the probability the TLO will license it.

The scientist derives utility from license income and publications, $V^*(e,z,q) = V(sr(z,q), p(e,z,q))$ where $V$ is increasing in both arguments and concave. We also assume that the utility function is separable in license income and publications, $V_{12} = 0$. The scientist's problem is

$$\max_{e,z,q} V(sr(z,q), p(e,z,q)) - C(e,z,q)$$

The first order conditions are

$$\begin{aligned} e &: V_2 p_e - C_e = 0 \\ z &: sV_1 r_z + V_2 p_z - C_z = 0 \\ q &: sV_1 r_q + V_2 p_q - C_q = 0 \end{aligned}$$

where subscripts denote partial derivatives with respect to the different arguments. The dual purpose role of applied research is reflected in the first order conditions for $z$ and $q$. In Appendix 2 we prove the following proposition.

**Proposition 1** *Higher inventor royalty rates and more effective technology licensing offices raise basic research and both the quantity and quality dimensions of applied research –* $\frac{\partial e}{\partial s} \geq$

[15]It should be noted that for $r_{q\theta} > 0$, we need the additional (sufficient) assumption that the density function $g(\varepsilon)$ is declining in $\varepsilon$ at $\frac{v}{\theta\psi(q)}$ where $q$ is the solution to the maximization problem. The expression is

$$r_{q\theta} = n(z)\psi'(q)\left(\int_{\frac{v}{\theta\psi(q)}}^{\infty} \varepsilon g(\varepsilon)d\varepsilon - \left(\frac{v}{\theta\psi(q)}\right)^3 g'\left(\frac{v}{\theta\psi(q)}\right)\right) \tag{2}$$

$0$, $\frac{\partial e}{\partial \theta} \geq 0$, $\frac{\partial z}{\partial s} \geq 0$, $\frac{\partial z}{\partial \theta} \geq 0$, $\frac{\partial q}{\partial s} \geq 0$ *and* $\frac{\partial q}{\partial \theta} \geq 0$ *– provided the following sufficient conditions hold:*

$$\begin{aligned} V_1 + s^2 V_{11} r &\geq 0 \\ \theta V_1 + s V_{11} r_\theta &\geq 0 \\ V_{22} p_e p_z + V_2 p_{ez} - C_{ez} &\geq 0 \\ V_{22} p_e p_q + V_2 p_{eq} - C_{eq} &\geq 0 \\ V_{22} p_z p_q + V_2 p_{zq} - C_{zq} &\geq 0 \end{aligned}$$

The first two conditions in the Proposition are satisfied if diminishing returns to income in the utility function are not 'too strong'. The last three conditions require that there be 'net complementarity' between the basic and applied research efforts, taking into account both the impact in the publications function and the effort cost function. That is, the marginal utility of each, net of effort cost, must be a non-decreasing function of the others. This is consistent with the recent empirical findings, based on panel data for university scientists, that publications and patenting appear to be complements rather than substitutes (e.g., Azoulay, Ding and Stuart, 2006).

One interesting special case is where there is no interaction between basic and applied research efforts, i.e., $V_{22} p_e p_z + V_2 p_{ez} - C_{ez} = 0$ and $V_{22} p_e p_q + V_2 p_{eq} - C_{eq} = 0$. This arises when applied research is not dual-purpose – i.e., $(z, q)$ do not generate publications – and where the marginal effort costs of applied and basic research are independent. Then we get $\frac{\partial e}{\partial s} = 0$ and $\frac{\partial e}{\partial \theta} = 0$, but even in that case we still get $\frac{\partial z}{\partial s} \geq 0$, $\frac{\partial z}{\partial \theta} \geq 0$, $\frac{\partial q}{\partial s} \geq 0$ and $\frac{\partial q}{\partial \theta} \geq 0$.

The key empirical implication of this simple model is that, under the stated conditions, optimal $(z, q)$ are increasing in the inventor royalty share, $s$, and TLO effectiveness, $\theta$. This implies that license revenue per faculty, $r(z(s, \theta), q(s, \theta)$, should increase in $(s, \theta)$. This is the implication we set out to test with data on university-level revenues, royalty rates, and proxies for $\theta$. Note that the model implies that both the number of projects, $n$ (innovations), and the average quality of projects, $v$, should increase in $(s, \theta)$.[16]

[16] The model also predicts a positive relationship between publications and royalty shares, under specific conditions, but this implication is not explored in this paper.

# 4 Empirical Specification

We assume that observed university licence revenue equals its expected value $Fr(s, \theta)$ up to a multiplicative measurement error, $e^u$, where $F$ is faculty size,

$$R(s, \theta) = Fr(z(s, \theta), q(s, \theta))e^u$$

where $u$ is assumed to be stochastically independent of $s$ and $\theta$ with $E(e^u) = 1$.

Taking logs on both sides and linearizing we get

$$\log R = \log F + \delta s + \lambda \theta + \text{terms involving } G \text{ and } \underline{v} + u$$

where $u$ is independent of the main regressors $s$ and $\theta$.

Since $\theta$ in not observed, we use the size and experience (age) of the TLO as proxies in the empirical work. In addition to (log) faculty size, the regression equation includes variables that capture differences across universities in $G$ and $\underline{v}$ : specifically, the number of citations per faculty (academic quality), R&D funding, and the shares of faculty in each of six fields in the hard sciences to measure research orientation (see Appendix 1). Denoting all these proxies by the vector $x$, the basic model is

$$\log R = \delta s + x\beta + u \tag{3}$$

The parameter $\delta$ represents the incentive effect of royalty shares on (unobserved) research effort levels, including the effects of the TLO through their selection of inventions to commercialize, as equation (1) makes clear.

Despite our controls, there is likely to be unobserved heterogeneity in research productivity or commercial orientation of faculty. If this heterogeneity is correlated with $s$ and $\theta$ (or its proxies), a potential endogeneity problem arises. There are two main ways in which such correlation might arise: reverse causality and omitted variables (or sorting). The first is a "rent-seeking" argument about how royalty shares are set. Researchers with more commercial orientation or more valuable inventions may have been able to exploit their bargaining position to lobby their universities for more favorable royalty rates. In this case, estimating (3) by ordinary least squares would give an upward biased estimate of $\delta$.

Berkowitz and Feldman (2005) show that there are differences in institutional culture and historical experience in technology transfer activity across universities and that research culture has a strong effect on the propensity to commercialize university inventions. Such culture is likely to also influence royalty policy. Thus, a second way that endogeneity can arise is that universities with a more commercial orientation may attempt to attract more applied (innovation-oriented) faculty by offering a higher inventor royalty share or providing a more effective TLO (higher $\theta$). If successful, this "sorting policy" will also generate a positive correlation between $(s, \theta)$ and unobserved commercial or entrepreneurial quality: universities with higher $(s, \theta)$ will have more productive (innovation-oriented) faculty. This is essentially an omitted variable problem; we do have measures of academic quality but not of entrepreneurial quality or orientation and this will also bias upward the estimated $\delta$.[17]

There is, however, a subtle difference between the two cases. In the sorting example, the estimated $\delta$ would be an upward biased estimate of the *pure* effort component of the royalty incentive effect, but it would remain a consistent estimate of the overall incentive effect, which includes both the effort and sorting components. By contrast, in the reverse causality example we may find an incentive effect when, in fact, there is none. In the empirical section we address the potential problem of reverse causality by controlling for the pre-sample patenting activity of the university.

Sorting is essentially an issue of how to interpret the estimated incentive effect. Nonetheless, it is important to try to distinguish between the effort and sorting components because they have very different policy implications. The effort model implies that strengthening royalty incentives would increase aggregate inventive output (i.e., social gains as well as private ones), whereas a pure sorting model would imply that this would only redistribute inventive output across universities.

It is difficult to pin down the effects of these two mechanisms in the absence of data on

[17] Recall, however, that we include the shares of faculty by field in order to capture research orientation, which is likely to be correlated with commercial orientation. More generally, we recognise that some of the other controls may also be endogeneous, such as the size of the TLO and the level of R&D funding. This should be kept in mind in interpreting the estimated coefficients on these variables. However, we are particularly interested in the difference between the estimates for private and public universities (especially for TLO size), and there is no reason to believe that the direction of bias is different for the two types of universities.

individual inventors.[18] While the university-level data seriously limit what we can say about sorting, we can modify the empirical specification of the model to incorporate sorting effects. If sorting occurs, the ability of the university to attract entrepreneurial faculty depends both on its own royalty share and on the shares offered by the set of universities with which it competes. Let $\overline{s}_{ic}$ denotes the mean royalty share in the set of universities competing with university $i$. The impact of sorting on log license revenue of university $i$ is assumed to take the form $\phi(s_i, \overline{s}_{ic})$ where $\frac{\partial \phi}{\partial s_i} \geq 0$ and $\frac{\partial \phi}{\partial \overline{s}_{ic}} \leq 0$. We use a linear form $\phi(s_i, \overline{s}_{ic}) = \rho_1 s_i + \rho_2 \overline{s}_{ic}$ with $\rho_1 \geq 0$ and $\rho_2 \leq 0$. Using this, we can write the model incorporating both the effort and sorting mechanisms as follows

$$\log R_i = (\delta + \rho_1)\, s_i + \rho_2 \overline{s}_{ic} + x\beta + u \tag{4}$$

As before, $\delta$ captures the pure effort effect of royalty shares, while $\rho_1$ and $\rho_2$ capture the sorting effect. We emphasize that the total incentive effect of university $i's$ royalty share is given by the sum $\delta + \rho_1$. In this linear formulation, $\rho_1$ is not identified if there is also sorting. We can test the null hypothesis that there is no sorting, $H_0 : \rho_2 = 0$. If this is rejected, then the coefficient on $s_i$ captures both the effort and sorting effects of royalty shares.

To implement this approach, we need to measure $\overline{s}_{ic}$. To do this, we assume that faculty typically move among universities at similar quality levels.[19] We rank all universities (both private and public) according to the number of citations per faculty, and then define the set of competing universities as those within a specified window size around university $i$ in this ranking. Note that this procedure allows private and public universities to compete with each other in the relevant quality window. For example, a window of size one includes the nearest university above and below university $i$, and thus means that the scientist chooses among three universities (including his current location) when deciding whether to move.

[18] Lazear (2000) emphasises the different effects of performance based pay on effort and sorting in his study of the productivity gains of moving from hourly to piece-rate pay in a large auto glass company. He found that about half of the gains were due to increases in effort and the other half to “sorting or possibly other factors.”

[19] In the survey of TLO directors discussed in Section 4.1, we asked whether “staying in line with competing universities” was an important consideration in setting royalty sharing rates and, if so, how they would define that group. Academic quality was the most frequently listed criterion.

### 4.1 Gatekeeper Effect: Explaining Public-Private University Differences

All universities in our sample retain control rights over inventions so that the TLO effectively has exclusive rights (unless expressly waived) to commercialize the inventions. Because the TLO is the "gatekeeper," its effectiveness at finding licensees and negotiating agreements directly affects the monetary returns to the faculty scientist. As a consequence, raising the royalty share will have a smaller incentive effect if faculty scientists anticipate that the TLO will be ineffective at commercializing their inventions. We call this interaction between the incentive effect and the effectiveness of the TLO the *gatekeeper effect.* This interaction arises because the inventor's expected license income, $sr(\theta, s)$, depends directly on the product $s\theta$, as is clear from (1). Therefore, the marginal incentive effect of royalty sharing is rising in the TLO effectiveness parameter, $\theta$. In the extreme case where $\theta = 0$, the share apportioned to faculty will not matter at all.[20]

There are good reasons to believe that private universities may be more effective at generating license income than public ones, at least on average. University ownership may affect the constraints under which the TLO operates in selecting licensees and striking agreements. Public and private universities may also have different objectives – in particular, the former may be more concerned with local development than with license income maximization. And finally, university ownership may affect the ability or willingness of TLO's to adopt high-powered incentives for their staff. Unfortunately, there is almost no available information on the objectives, constraints and incentives within TLO's. For this purpose we developed a new survey questionnaire for TLO directors in public and private universities.[21]

[20] Using (1) we get

$$\frac{\partial R}{\partial s} = \theta F \left[ H(s,\theta)\{n(s,\theta)\psi' \frac{\partial q}{\partial s} + \psi(s,\theta)n' \frac{\partial z}{\partial s}\} + \psi(s,\theta)n(s,\theta)\frac{\partial H}{\partial s} \right]$$

where $H(s,\theta) \equiv \int_{\frac{v}{\theta\psi(q(s,\theta))}}^{\infty} \varepsilon dG(\varepsilon)$. The gatekeeper effect operates if $\frac{\partial^2 R}{\partial\theta\partial s} > 0$. If the TLO licenses all inventions ($H(s,\theta) = 1$), this property holds as long as diminishing returns in $n(z)$ and $\psi(q)$ are not too strong. The intuition is as follows: a rise in $\theta$ increases the marginal payoffs to $(z, q)$, raising their optimal levels. This direct effect increases the marginal payoff to $s$. But at the new, higher levels of $(z, q)$, the marginal returns to effort are lower due to diminishing returns, which reduces the marginal payoff to $s$. In order to get $\frac{\partial^2 R}{\partial\theta\partial s} > 0$, these diminishing returns must not dominate the direct effect. If invention quality affects the probability of being licensed ($H(s,\theta) < 1$), we also require that the density function $g(\varepsilon)$ not increase too much in $\varepsilon$.

[21] We sent the questionnaire to TLO directors in 198 public and private universities. They included both those used in the regression analysis an others. After considerable effort, we managed to get 101 responses, of which 57

Table 4 summarizes key results from the survey. First, faculty in both public and private universities are well-aware of monetary incentives from commercializing their inventions. Second, in the vast majority of cases in both public and private universities, faculty reward structures (salaries and promotion) do not give any significant weight to technology transfer outputs. Third, there are sharp differences between universities in the use of performance-based pay for TLO staff, and in the constraints and objectives of the TLO's. Private universities are significantly more likely to use performance-based pay (row 3), and are much less constrained by either formal government regulations or informal government pressure in each of the six categories of constraints we examine.[22] Interestingly, public and private universities share the objectives of increasing the number of licenses and license income, but public universities are much more likely to rank "promoting local or regional economic development" as an important objective.

These survey findings strongly suggest that the parameter $\theta$ is larger in private universities than in public ones, at least on average.[23] This finding has three testable predictions in the regression model: (1) because of the gatekeeper effect, the coefficient on the royalty share (the incentive effect) should be larger for private universities than for public ones, and (2) the coefficient on TLO size should be larger for private universities. Moreover, larger TLOs (relative to faculty size) should be more effective at commercialising university inventions. Thus a third implication is that, both for private and public universities, the incentive effect should be increasing in TLO size.

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were in the regression sample. The results of this survey are analysed more fully in Belenzon and Schankerman (2006).

[22] The survey question is: "Does the state government impose any significant constraints that limit the effectiveness of [your] TLO activity...either explicit forms - such as statutes, regulations, covenants of the university charter - or implicit forms such as pressure from political representatives or agencies."

[23] In a follow-up paper, Belenzon and Schankerman (2006) estimate the quantitative impacts of performance-based pay, local development objectives and government constraints on various dimensions of university technology transfer, including the number of licenses, revenue and start-ups.

# 5 Empirical Results

## 5.1 Nonparametric Evidence

We begin by abstracting from other determinants of license income and non-parametrically estimate the expectation of license income per faculty conditional on royalty shares, $E\left(\frac{R}{F}|s\right)$, using Fan's (1992) locally weighted regression smoother. Figure 2 plots estimates for the public and private universities separately.

$E\left(\frac{R}{F}|s\right)$ is clearly increasing in $s$ and somewhat non-linear: although license income is not very responsive to economic incentives at the low range of the royalty shares, this is strikingly reversed at shares above 40 percent. Also notice that the response to incentives is larger for privately owned universities as compared to public ones. To verify these nonparametric results and to quantify the relationships between license income and royalty incentives controlling for other university characteristics, we turn to regression analysis.

## 5.2 Baseline Econometric Evidence

The data form an unbalanced panel of 102 universities for the period 1991-1999. However, panel data estimation methods that allow for a correlation between the royalty share and unobserved, time-invariant determinants of license revenues – such as fixed effects or first differences – are of limited use here because the royalty share does not vary over time in 90 percent of the observations. The incentive effect is primarily identified from the cross-sectional variation, while controlling for unobserved heterogeneity by using pre-sample information on patenting by universities. We allow for arbitrary heteroskedasticity and serial correlation within universities (standard errors are clustered at the university level).

We allow for arbitrary heteroskedasticity and serial correlation within universities (standard errors are clustered at the university level) and attempt to control for unobserved heterogeneity by using pre-sample information on patenting by universities.

We first compare alternative specifications of the model, focusing on the estimated royalty incentive effect. Once we arrive at the "baseline specification", we discuss the full set of coefficients in more detail.

Table 5 presents estimates for equation (4) for private and public universities separately.

We strongly reject pooling of these two sub-samples (the test on the full set of 23 coefficients yields p-value $< 0.001$; this holds for other specifications as well). Columns (1) and (5) treat royalty shares as exogenous and ignore the (sorting) effect of competing universities (we set $\rho_2 = 0$). The OLS estimates indicate large and statistically significant incentive effects in both private and public universities. The point estimate of the incentive effect, however, is more than twice as large in private universities, and this difference will hold for all alternative specifications. We will test below whether this difference in statistically significant in the baseline regression, where we incorporate both sorting and the pre-sample patent control for unobserved heterogeneity.

In columns (2) and (6) we add the average shares of "competing" universities to the regressions. This specification incorporates both the effort and sorting mechanisms into the model, as discussed in Section 4. We rank universities according to citations per faculty and define the set of competing universities as those closest to (above and below) university $i$ in this ranking. In defining the competing universities, we include both public and private universities, although we estimate the model separately for the two types. The results reported in the table are based on a window of size one, i.e. using a total of two competing universities. (Table 7 presents robustness results for windows of up to size four). It is very striking that the estimate of $\rho_2$ is negative for both private and public universities and, in the former case, quite large relative to the estimate of the "own royalty effect." In private universities, we can reject the hypothesis that there is no sorting ($\rho_2 = 0$). The estimated incentive effect - the coefficient of $s$ - captures both the effort and sorting effects of the 'own royalty share', $(\delta + \rho_1)$. But it is worth noting that this estimated incentive effect is not much changed by the inclusion of $\overline{s}_c$. For public universities, we find no evidence of sorting.[24]

Finally, using the specification with both effort and sorting, we attempt to control for correlation between royalty shares and unobserved heterogeneity. We adopt the approach devel-

[24]We cannot test the hypothesis that there is no effort effect ($\delta = 0$) without additional assumptions. In particular, if we make the assumption that $\phi(s_i, \overline{s}_{ic})$ is homogeneous of degree zero, then the hypothesis that there is no effort effect (pure sorting) implies that the coefficients on $s_i$ and $\overline{s}_{ic}$ should sum to zero. Because of the large standard we cannot formally reject the hypothesis $\delta + \rho_1 + \rho_2 = 0$ under the maintained hypothesis that $\rho_1 = -\rho_2$. However, given the associated standard error, we would also not reject the hypothesis that the effort effect equals the sorting effect, $\delta = \rho_1$ and $-\rho_2 = \rho_1$. In any case, there is no compelling theoretical basis for the assumption that the own incentive effect and the competing effect are equally important for license revenues.

oped by Blundell, Griffith and van Reenen (1999). They show that under the assumption that the unobserved fixed effect can be expressed as a linear function of the observable characteristics, the pre-sample mean of the dependent variable is a sufficient statistic for the unobserved fixed effect. Thus one can use this pre-sample mean as an additional regressor to control for such heterogeneity. In our context, this would involve using the pre-sample mean of license revenues to control for unobserved university effects. We do not have pre-sample information on license revenues, but we can use pre-sample information on patenting by the university (both patent counts and citations).[25] In Appendix 3 we show that pre-sample patent information can be used instead of pre-sample license revenues, provided we assume that patenting is also a linear function of the same unobserved heterogeneity that affects license revenues, which seems very reasonable (see Appendix 3 for technical details).

The results are presented in columns (3) and (7) in Table 5, and constitute our "baseline specification" of the model. The estimated coefficients of the pre-sample controls are positive and highly significant. As expected, adding the log of the mean number of citations to patents applied for between 1975 and 1990 to the regression reduces the estimated effects of royalty shares – by about 20 percent. With the pre-sample control, the estimated incentive effect remains statistically significant for private universities, but not for public ones. The fact that the estimated incentive effect falls when we include the pre-sample control indicates that there is some endogeneity at work. Of course, one can never entirely rule out the possibility that some unobserved, correlated heterogeneity remains, but that available data does not allow us to do more to address this issue.[26]

These results suggest that royalty shares have a positive incentive effect on license revenue for private, and possibly also for public, universities. The estimated effect is strongly significant and large in private universities, but smaller and less precisely estimated in public universities.

[25] We actually use the log of one plus the number of patent counts or citations so as not to discard universities with zero citations. The within-sample (1991-99) cross sectional correlation between patent counts (citations) and license revenue is very high, ranging between 0.65 and 0.79 for private universities and between 0.60 and 0.72 for public universities.

[26] Two points should be noted. First, we tried to instrument the royalty share with data on income tax rates in the state where the university is located, the percentage of the university faculty in hard sciences, and the size of the university endowment. These instruments proved to be too weak to produce sensible results. Second, the lack of correlation between royalty shares and our observed university characteristics means that we cannot use nonparametric matching methods (e.g., propensity scores) to estimate the royalty incentive effect.

The point estimate implies that a one percentage point increase in royalty share would increase license income by 4.5 percent in private institutions. This large incentive effect is one of the main empirical findings of this paper. It confirms the basic economic intuition that high-powered monetary incentives do matter for university research activity. In view of all the other determinants for which we control, it is encouraging that we can still find an empirical relationship between license income and royalty shares.

Furthermore, it appears that the incentive effect is larger in private institutions than in public universities. While it is difficult to be confident about whether these differences are statistically significant (as we discuss below, it depends on how general we make the specification for serial correlation), the results are consistent with the non-parametric evidence in suggesting that scientists in private universities exhibit a stronger response to royalty incentives than those in public universities. To our knowledge, this is the first empirical evidence on the impact of royalty incentives, and of how university ownership may affect faculty responsiveness to such incentives.

In order to test formally the null hypothesis that the incentive effects are the same in private and public universities, we pool the regressions (using the baseline model with sorting and the pre-sample control) and allow all coefficients to differ between private and public institutions. We then test the null hypothesis that the coefficients on the royalty share are the same. When we use standard errors that are robust to arbitrary heteroskedasticty and serial correlation (clustered at the university level), we cannot formally reject the null hypothesis (the $t-$statistic on the difference is 1.04). When we use a somewhat less demanding specification of serial correlation – an $AR(1)$ specification – the t-statistic is 1.47. If we adjust for arbitrary heteroskedasticity but do not allow for within-university serial correlation (i.e., using White standard errors), we strongly reject the equality of the incentive effects ($t-$statistic is 2.47). In summary, we get a large difference between the point estimates of the incentive effect in private and public universities and, while this difference is robust across specifications of the model, its statistical significance depends heavily on the error assumptions.

If we constrain the royalty share coefficient to be the same for private and public universities, but allow all other coefficients to differ in the baseline specification, we get an estimated incentive effect of 2.40 with a (clustered) standard error of 1.26. The corresponding estimate for the sorting coefficient is -1.60 with a standard error of 1.02. Thus, even if one takes the position that the incentive effect is not different in private and public universities, we still find a positive and significant royalty incentive effect overall, and some evidence for sorting.

The other striking finding in Table 5 concerns the productivity of the TLO. The estimated elasticity of TLO size on license income is positive and significant in private universities – a 10 percent increase in the number of TLO professionals (equivalent to one-third of a full time employee, at the sample mean) raises license income in private universities by 5.5 percent.[27] However, we find essentially no effect of TLO size on license income for public universities. It is important to recognise that these are average effects and do not imply that TLO size has no effect in any public university or, conversely, that the TLO is equally effective in all private ones. To understand the variations across universities and to assess how much, and why, these are tied to university ownership status is an important topic for future research.

We can use the estimated elasticity of TLO size for private universities to compute an implied marginal product and see how it compares to salaries in the TLO.[28] We find that the marginal product (evaluated at sample medians) is about three times greater than the median (chief officer's) salary, which suggests that private universities should substantially expand their size, if they are trying to maximise total license income, $R$. However, if they are trying to maximise license income that accrues to the university (i.e., excluding the inventor share), $(1-s)R$, the corresponding marginal product we estimate is only about 50 percent above the median salary. Thus whether private universities are leaving money on the table, and should expand their TLO activities, depends in part on what they are trying to maximise.[29]

In addition, the gains from experience are larger and are realized earlier in private universities. Using the coefficients on TLO age and its square, we find that, for private universities, an additional year of experience increases revenues by 10 percent when TLO age is 8

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[27] We use TLO per faculty since this is what is relevant for the scientist as a determinant of $\theta$. In this case, the coefficient of faculty size is capturing a pure size effect. The same comment holds for our use of R&D per faculty in the regression.

[28] We compute $\frac{\partial R}{\partial TLO}$ which equals the estimated coefficient of $\log\left(\frac{TLO\text{ Size}}{Faculty}\right)$ in the baseline regression times $\frac{R}{TLO\text{ Size}}$.

[29] Evaluated at medians (over universities and years) for private universities, we get $\frac{\partial R}{\partial TLO} = \$278,000$ and $\frac{\partial(1-s)R}{\partial TLO} = \$160,000$. As a rough comparison, the CUPA (2002) Survey of Administrative Personnel reports the median salary of $110,000 for 'chief technology transfer officers' in public *and* private universities.

and 7 percent at age 16. For public universities, the estimate is only 3.5 percent. Taken together, these findings on TLO size and age suggest that private institutions have more effective, commercially-oriented technology transfer activity, which is consistent with the survey evidence presented in Section 4.1.

The elasticity of license revenue with respect to faculty size is 0.74 in both private and public universities (but significant only in the latter). We cannot reject the null hypothesis that the size elasticity is unity. The coefficient on the quality measure - citations per faculty - is positive but, surprisingly, not significantly different from zero. The R&D variable includes funding from industry, government and non-profit sources. It has a significant effect only in public universities, with an elasticity of 0.63. The coefficient on the medical dummy is not significant.

We use a variable to control for differences in potential demand for licenses by private firms (density of high-tech activity). If demand is localized, e.g., due to information, universities in areas with more high-tech activity should license more inventions from a given pool of inventions and obtain more revenue. We use the 1995 Milken index of high-tech activity for each university's location (Friedman and Silberman, 2003). We assign each university to a quartile in the Milken index distribution, and then include dummy variables for the first and fourth quartiles (the reference level is the middle two quartiles).[30] High-tech density has a quantitatively large effect on the generation of license revenues but its effects are very different in private and public universities. Private universities appear to be more effective than public ones at exploiting the potential of being located in high-tech areas. The fact that local demand conditions matter at all suggests that either search or other transaction costs are lower when licensing within the local market. Given the global nature of technology markets, this is somewhat surprising and worthy of further investigation.

Finally, as controls for differences in research orientation, we use the fraction of the faculty in each of six technology fields (physical sciences is the reference group; results not reported for brevity). Surprisingly, we cannot reject the hypothesis that there are no technology field

[30] It is worth noting that royalty shares do not vary much with the Milken index of high-tech activity: the average shares in first, middle two, and last quartiles are 42, 47 and 43 percent, respectively. This suggests that royalty shares are not set in response to the value of outside options available locally to university scientists.

differences (p-value 0.52 and 0.46 in private and public universities, respectively), once we have controlled for R&D and other characteristics.

The parameter estimates from Table 5 suggest that raising the inventor's royalty share would increase total license income. The point estimates of $(\delta + \rho_1)$ imply that raising the inventor royalty share by ten percentage points would increase license income by 45 and 19 percent in private and public institutions, respectively. In fact, raising the inventor royalty share can actually increase license income retained by the university, $(1-s)\,R$. Since $\frac{d\log(1-s)R}{ds} = (\delta + \rho_1) - \frac{1}{1-s}$, there is a critical royalty share $s^* = 1 - (\delta + \rho_1)^{-1}$ such that universities below this threshold can actually increase their retained income by raising the royalty share (the 'Laffer effect'), while universities above the threshold can do so by reducing the royalty share. For private universities, $s^* = 0.78$, and the Laffer effect holds for most of them. For public universities, $s^* = 0.48$, which holds for about half of these universities.

Why would universities leave money on the table rather than change inventor royalty shares? Apart from not knowing this potential exists, there are two explanations. First, universities have multiple objectives and competing faculty interests in setting royalty shares, including incentives, fairness, and being competitive with other universities (sorting issues). The second explanation relates to the assumption the university makes about how competing universities might respond to a change in its own royalty share. The calculation above assumes that competing universities do not react by changing their royalty shares. But if a university believes that its competitors will fully match any changes it makes, the Laffer effect is much less likely to operate. Taking the competitive effect into account, the threshold for the Laffer effect becomes $s^* = 1 - (\delta + \rho_1 + \rho_2)^{-1}$. Using the point estimates, we get the implied threshold of 0.50 and -0.15 for private and public universities, respectively. This implies that no public universities are leaving any money on the table, though some private ones still appear to be doing so.[31] More generally, this discussion emphasises the importance of developing a more complete model of university competition and strategic interaction.

As explained in Section 4.1, the gatekeeper effect predicts that the royalty incentive effect

[31] Of course, even if a university is in the region where the Laffer effect does not hold, a university might want to raise the royalty share if it attaches weight to the license income for its faculty inventors (e.g., the university could reduce salaries in return for higher royalty shares).

should be an increasing function of the effectiveness of the TLO. Relevant determinants of this effectiveness include the size of the TLO (relative to faculty), the use of performance-based pay, government constraints and other factors that appear to differ between private and public universities (Table 4). Because of differences in university coverage, we cannot directly use the survey information in the regressions. However, as a first look at this prediction, we include in the baseline specification interaction terms between the inventor royalty share and dummy variables for the first and fourth quartiles of the size of the TLO relative to faculty (the reference point are the middle two quartiles). The results are given in columns (4) and (8) of Table 5. There is some support for the prediction of the gatekeeper effect in private universities, as shown by the positive and significant coefficient on the interaction term involving the fourth quartile. The point estimate implies that moving from the middle two quartiles to the upper quartile of TLO size would increase the responsiveness to royalty incentives in private universities from 3.97 to 5.60 (= 3.97+1.63). There is no such evidence for public universities, which suggests that size is not closely related to effectiveness in public university TLO's, on the average.

Finally, as explained in Section 2, in constructing the inventor royalty share we included both direct cash paid to the inventor and royalties used to support his research laboratory where he has direct control rights. This approach assumes that the inventor gives equal weight to both types of returns. Whether this assumption is reasonable depends on the importance of intrinsic (research) motivation and peer recognition for university scientists. Support for the research lab may be valued simply because the scientist values research activity for its own sake, and/or because he values peer recognition that comes from the resulting research output. If this is so, then royalties that finance the research lab should have an incentive effect, possibly even larger than the pecuniary incentives of cash royalties. If intrinsic motivation and/or peer recognition do not matter, then only the cash royalties should provide incentives.

To test this idea, we decompose the inventor royalty share into its two components: the cash royalty share and the laboratory share (with control rights). The two shares are separately entered into the baseline specification with sorting and the presample patents variable for unobserved heterogeneity. For private universities, the estimated coefficient on the cash royalty share is 4.15 with a standard error of 1.61, while the coefficient on the lab share is 8.08 with a standard error of 2.78. We strongly reject the hypothesis that only cash matters – scientists strongly respond also to research support, which points to an important role for intrinsic motivation. While the point estimate of the incentive effect of lab support is larger than for cash, we cannot statistically reject the hypothesis that they are equal (p-value of the t-test is 0.12). The results for public universities point in the same direction but are statistically weaker. The estimated coefficients on the cash royalty share and lab share are 2.03 (s.e. = 1.50) and 2.55 (s.e.= 2.34). This evidence that university scientists appear to be motivated by royalties used to support the inventor's research support, as well as cash royalties, is important for the design of university royalty sharing schemes.[32]

## 5.3 Analysis of Robustness

In this section we discuss the robustness of the empirical results for the baseline model, given in columns (3) and (7) in Table 5, to various specification changes. In each case, we focus attention on how the specification changes affect the coefficients on the key incentive variables; the coefficients of the other variables are suppressed for brevity.

### 5.3.1 'Outliers'

We begin with the concern that the results on the incentive effect may be driven by 'outliers' in the distribution of license income. Like most measures of the value of innovation (Schankerman, 1998; Harhoff, Narin, Scherer and Vopel, 1999; Hall, Jaffe and Trajtenberg, 2005), license income is highly skewed, with relatively few universities making large revenues from their technology transfer activities. The concern is that the appearance of a royalty incentive effect may simply be due to the fact that the top performing universities happen to have relatively high inventor royalty shares. This does not appear to be the case, however. The top technology transfer universities, measured in terms of average license revenue per faculty, do not have especially high inventor royalty shares. For example, the top two universities in average revenues per faculty are Columbia and Stanford, which have royalty shares of 49 and 33 percent, respectively, compared to the sample mean of 45 percent). The top decile of universities have mean royalty share of 47 percent.

[32] Of course, part of the value to the scientist of support for her research lab may come from future royalties on new inventions. Thus we may be overstating the importance of intrinsic motivation. More generally, this points to the difficulty in distinguishing between the two types of motivation.

A second concern is that the average incentive effect may be driven primarily by a small group, rather than the bulk, of universities. To address this concern, we re-estimate the baseline model using quantile regression to examine the incentive effects at different parts of the distribution of license income This method estimates the effect of royalty shares on the quantiles (rather than the mean) of the distribution of license income, conditional on all the control variables. Table 6 summarises the estimated incentive and sorting effects for the different quartiles. For private universities, the incentives effects are present and statistically significant for all three quartiles of the distribution, though they are larger in the higher quartiles. In public universities, the incentive effects are only statistically significant in the lowest quartile of the distribution and, as before, much smaller than for private universities. This evidence suggests that, while there are variations in the magnitude of the royalty incentive effect, it does not appear that the average incentive effects we estimated in the baseline model were simply due to strong effects at the top end of the distribution and no effects elsewhere.[33]

### 5.3.2 Alternative Specifications for Sorting

The baseline results in Table 5 were based on the assumption that a university competes for faculty with the two nearest neighbors in the quality ranking, one above and one below its own position in the distribution of average scientific publications per faculty. In Table 7 we examine the results for alternative assumptions – specifically, we let the number of competing universities vary from two (as in Table 5) to eight. For private universities, we find that increasing the number of competitors reduces the estimated royalty incentive effect by about 25 percent, but it remains large in absolute terms and generally statistically significant. In addition, the estimated impact of sorting (coefficient on the competitors' royalty rate) is reasonably robust, but it is not statistically significant for larger values of the number of competitors. For public universities, the point estimates of the incentive effect are nearly identical for different assumptions, but they remain statistically insignificant.

It is important to emphasise that we are almost surely measuring the mean royalty

[33] It is also worth noting that our earlier finding that the TLO is, on average, more effective in private than in public universities is confirmed by quantile regression. For private universities, the estimated elasticity of license income with respect to TLO size is 0.44, 0.47 and 0.62 for the first, second and third quartiles, respectively, and all are highly significant. For public universities, the estimates are either insignificant or negative.

incentive at competing universities with measurement error, which suggests that our estimates of $\rho_2$ are subject to attenuation bias. In part this measurement error arises because we are averaging over all fields when ranking universities by citations to scientific publications. It is likely that the rankings of universities are highly varied across fields, especially once one gets out of the top few universities. The appropriate method for identifying a given university's relevant competitors requires knowing how universities strategically set their royalty sharing arrangements (e.g. whether they target specific universities or faculties). This requires more detailed knowledge of the actual decision-making, and this may vary across universities. In this context, case study evidence could be very useful.

#### 5.3.3 Alternative Controls for Unobserved Heterogeneity

In the baseline regressions, we used the pre-sample mean of patent citations to control for unobserved heterogeneity (i.e., the mean number of citations until 2001 to all patents that were applied for in the period 1975-90 for each university). In Table 8 we examine robustness of the results to alternative specifications of the pre-sample control – specifically to using patent counts rather than citations, and to including dummy variables for cases of zero patent counts or citations. Columns (1) and (5) replicate the results of the baseline specification from Table 5. For private universities, we find that both the coefficients of royalty share and the sorting effect of competitors' royalty shares are robust to using pre-sample patent count data instead of patent citations and to including dummies for zero patent counts or cites. As before, the pre-sample controls are strongly significant. For public universities, the point estimates of the royalty incentive effects are also robust but, as before, not statistically significant. We also experimented with different pre-sample periods – 1980-90 and 1985-90 – and found that the results were qualitatively similar, if somewhat less strong (results not reported for brevity).

#### 5.3.4 Other checks

We performed three additional specification checks but, for the sake of brevity, we omit the regression results. First, the dependent variable in all the preceding regressions, licensing income, includes the cashed-in equity value of start-ups in which the university holds some stake. Since the sample period (1991-1999) includes several years during the period of 'irrational exuberance', we might get a distortion if private universities were more likely to endorse taking equity than their public counterparts and equity was 'hyper-valued'. To check for this possibility, we re-estimated the baseline specification using license income minus cashed-in equity as the dependent variable. This variable can only be constructed for the subperiod 1996-99, so we lose more than half the observations. For private universities, the estimated coefficient on the royalty share is 5.13 (s.e.=1.76) and the coefficient on the competitors' royalty share is -3.08 (s.e.=1.43). For public universities the estimated coefficients on these two royalty shares are 2.08 (s.e.=1.94) and -2.81 (s.e.=1.87), respectively. Thus our key empirical results are robust to excluding cashed-in equity value in licensing income.

Second, we used alternative measures of the quality of university faculty, specifically the NRC scholarly quality score, the number of publications per faculty, and the average faculty salary at the university. The estimates of the coefficient on the royalty share, as well as the other control variables, are very similar to those in the baseline specification using citations per faculty as the quality measure. For example, using the scholarly quality score the estimates of $(\delta + \rho_1)$ are 4.33 (s.e.=2.06) and 1.96 (s.e.=1.43) and the estimates of $\rho_2$ are -2.71 (s.e.=1.31) and -1.25 (s.e.=1.32) for private and public universities, respectively.

Third, we allowed for industry and publicly-funded R&D to have different effects on licensing income. The results show that publicly-funded R&D has a positive and significant effect on license revenue in public universities only, with an elasticity of about 0.6.[34] By contrast, industry-financed R&D has no significant effect on license income in either private or pubic universities. This is exactly what one would expect since the bulk of such funding comes from contract R&D with free licensing provisions (i.e., ex ante R&D funds are given in place of ex post licensing income). The estimated coefficients on the royalty shares, and on the other regressors, are nearly identical to the baseline case.

## 5.4 Incentive effects: Impact on the quantity and quality of inventions

License revenue per faculty depends both on the number of inventions and their value. As pointed out in Section 3, the model predicts that both the applied research effort directed at

[34] Payne and Siow (2003) analyze the effect of federal funding on university research. Using a sample of 68 research universities, they conclude that increasing federal research funding results in more, but not necessarily higher quality, research output.

the number of projects and the effort on the quality of projects should be increasing functions of the royalty share. The model allows us to distinguish between the quantity ($n$) and the quality ($v$) components of the royalty share effect on license revenue, even with university level data. Let $L$ be the the expected number of licenses obtained from $Fn$ inventions, $L = Fn(z(s,\theta))\left[1 - G\left(\frac{v}{\theta\psi(q(s,\theta))}\right)\right]$. Using (1) and observed revenues $R = Fre^u$, we can write

$$R = L \times \theta\psi(q(s,\theta))E\left(\varepsilon|\varepsilon > \frac{v}{\theta\psi(q(s,\theta))}\right)e^u \tag{5}$$

As this equation makes clear, if the royalty share affects the quality of inventions, it should affect license revenues even after controlling for the number of licenses. The elasticity of revenues with respect to licenses should be approximately one.

Table 9 presents results for a log version of equation (5). We measure $L$ by the stock of cumulative number of active licenses, which is reported by AUTM. This is the relevant measure since license income flows are generated by the existing stock of active licenses. Data on the latter are available from 1995 so, for purposes of comparison, columns (1) and (4) present the baseline specification for the same period 1995-99. Turning to the second column, when we control for $L$ the estimated effect of royalty shares on revenues declines but does not disappear.[35] This is particularly true in private universities, but less so in public ones where the incentive effect was not significantly different from zero to start with. Raising the royalty share at private universities by one percentage point will generate 4.3 percent more license revenue, given the same number of licenses. As the total effect of such a change in royalty shares is higher – about 5.0 percent in column (1)– it follows that the number of inventions is also affected by the royalty share. This is seen more directly in columns (3) and (6), which present the regressions of the (flow) number of licenses executed against royalty incentives and the various control variables. The royalty share has a significant effect on the flow number of licenses executed for private universities, but essentially no effect for public ones.

The main implication of this analysis is that the quality channel is more important than the quantity channel in private universities. In public universities, however, royalty share has an overall very weak effect because neither quantity nor quality seems to be affected by royalty

[35] The coefficient on $\log L$ is not very precisely estimated in private universities but one cannot reject the hypothesis that it equals one. Also notice that faculty size does not appear in equation (5) once $L$ is included.

incentives.

The use of quantity measures in these regression may introduce measurement error because of the possibility that faculty do not report all their inventions to the TLO. However, this is likely to bias the effect of royalty shares downward in the revenue regression.[36] Thus any possible non-reporting bias will reinforce our conclusion that the incentive effect of royalty sharing works predominantly by increasing the quality (commercial value) of inventions, rather than the number of inventions.

### 5.5 Incentive effects: Interactions with faculty quality and tenure

We next examine whether the incentive effect of royalty shares varies with faculty quality or with the extent to which faculty is tenured. First, as we discussed in Section 5.2, there is evidence in these data that intrinsic motivation/peer recognition do matter, as suggested by the fact that royalties for research lab support have an incentive effect. It is often argued that such motivation may be particularly strong for faculty at more prestigious institutions. In the model this takes the form of a lower marginal utility of license revenue in higher quality universities. To test this, we include in the baseline specification of the model interactions terms between the inventor royalty share and dummy variables for the lowest, the middle two, and the highest quartiles of the citations per faculty distribution.

Columns (1) and (3) of Table 10 summarise the results for the royalty incentive variables. In support of the popular view, we find that the incentive effect of royalty shares declines with university quality. For private universities, the estimated coefficient declines from 6.8 in the first quartile of the quality distribution to 4.5 in the fourth quartile. In public universities, we find a similar pattern: the universities in the bottom quality quartile are responsive to royalty incentives whereas higher quality public universities do not exhibit any significant response to royalties. This last finding is particularly interesting, since the baseline estimate of the incentive effect for public universities (with quality quartiles pooled) was not significantly different from

[36] Let $N^*$ and $N = N^*(1-\varphi)$ denote the true and observed number of disclosures, where $\varphi \in [0,1]$ is the rate of misreporting. When $\varphi = 0$ faculty reports all inventions to the TLO. Let $L^*$ and $L$ denote the true and observed number of licenses. They differ only because $N^*$and $N$ differ, so $L = L^*(1-\varphi)$. When $\log L$ is used instead of $\log L^*$ as a regressor, it adds $-\log(1-\varphi)$ to the error in the regression. If $Cov(\varphi, s) = 0$ there is no bias. However, if $Cov(\varphi, s) < 0$, i.e., misreporting decreases as the inventor's royalty share increases, then $s$ and -$\log(1-\varphi)$ are negatively correlated and we get a downward bias in the estimated coefficients of both $s$ and log $L$ in the regressions in columns (2) and (5) of Table 9.

zero (Table 5).

Second, if there is a trade-off between doing commercially-oriented research and generating academic publications, we would expect untenured faculty members to be less responsive to royalty shares than tenured members because the marginal cost of not publishing is higher for untenured faculty.[37] To test this, we include interactions terms between the inventor royalty share and dummy variables for the lowest, the middle two, and highest quartile of the tenure distribution (the percentage of tenured faculty at each university).[38] As columns (2) and (4) in Table 10 show, there is some support for the hypothesis in public universities. The incentive effect of royalty shares is significant and positive in the top quartile of the tenure distribution, but not in the lower three quartiles. However, we do not find any support for the hypothesis in private universities.

# 6 Concluding Remarks

This paper provides evidence that U.S. universities which give higher royalty shares to faculty scientists appear to generate greater license income, controlling for a variety of observed characteristics and using pre-sample data on university patenting to control for the potential endogeneity of royalty shares. We find that scientists respond both to royalties in the form of cash and research lab support, suggesting that both pecuniary and intrinsic (research) motivations play a role. The incentive effects appear to be larger in private universities than in public ones, and our survey evidence suggests this may be related to differences in the use of performance pay, government constraints and the importance of local development objectives in technology licensing offices. There is some evidence that royalty incentives work both by increasing faculty effort and by sorting scientists across universities.

This empirical evidence strongly suggests that royalty sharing arrangements and, more generally incentives within universities, have real effects. Universities are likely to consider a host of factors when choosing or changing these arrangements, but to our knowledge there

[37] Levin and Stephan (1991) make a related point regarding the effect of age on a researcher's academic productivity.

[38] Source: NSF WebCASPAR Database System (http://caspar.nsf.gov/webcaspar). The information of tenure refers to all faculty rather than just to those in hard sciences, which is what we would like to measure.

is no economics literature on these issues. We need to understand the multiple objectives in universities and TLOs, the trade-offs among them, and the way in which university governance and other constraints affect the use of high-powered incentives to achieve their goals. At the same time, we need to develop a more complete model of university competition and strategic interaction. It would help in building such a model to have case study evidence on the actual decision-making process in universities for setting royalty shares and other non-pecuniary incentives.

We found that being in a high-tech area is associated with better licensing performance, and that private universities appear to be more effective than public ones at exploiting this potential. That local demand conditions matter at all is somewhat surprising given the global nature of technology markets. Understanding the factors underlying this finding is worthy of further investigation, because they are likely to relate to how university technology transfer should best be organised. For example, in the U.S. one striking feature of the "technology transfer industry" is the lack of specialisation and competition. Currently, each university TLO has exclusive rights to commercialise all inventions generated by the university. But TLOs could specialize by technology area and serve multiple universities across geographic markets, and there could be elements of either ex ante or ex post competition. The benefits of such alternative structures will depend on the strength of local (high tech) demand effects, as well as on the strength of economies of scale and scope.

Finally, we want to emphasise that there are natural limits to what aggregate data can deliver. Micro data on academic scientists have the potential to allow us to separate the effort and sorting effects of royalty sharing. This is important because, as pointed out earlier, if higher royalties work only through a sorting effect then there are no aggregate gains (apart from those associated with better matching), whereas if higher royalty sharing leads scientists to exert more effort then social, as well as private, gains are increased.

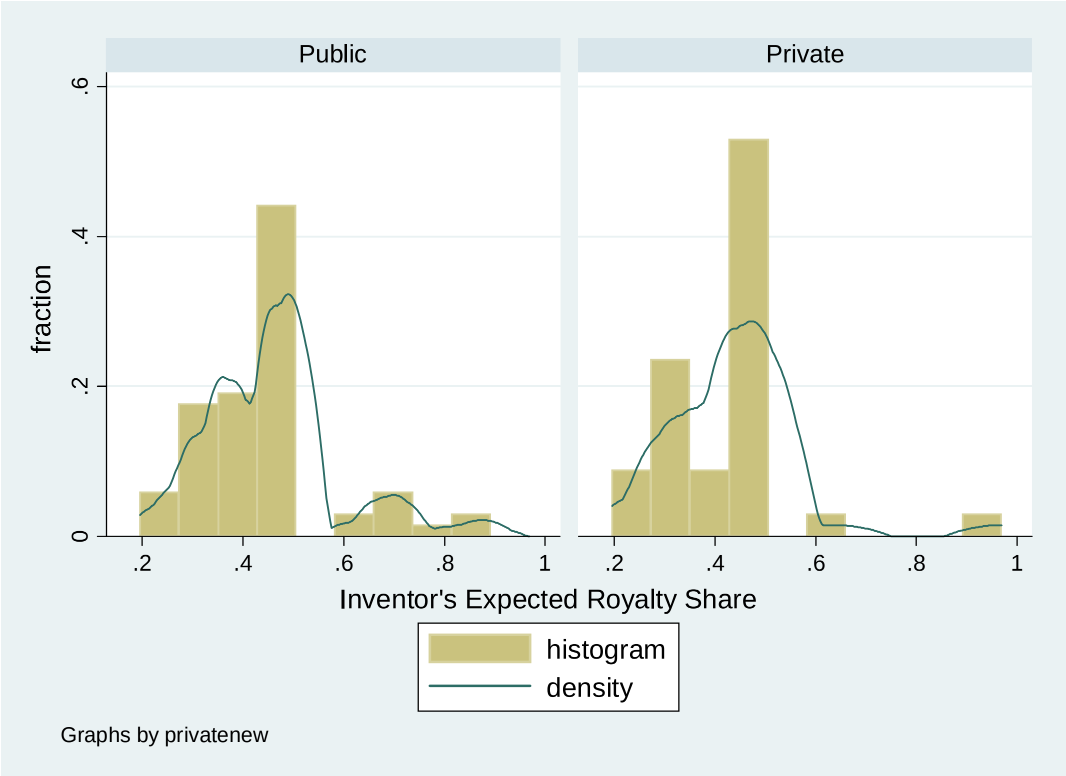


Figure 1: Distribution of Expected Inventor's Royalty Share

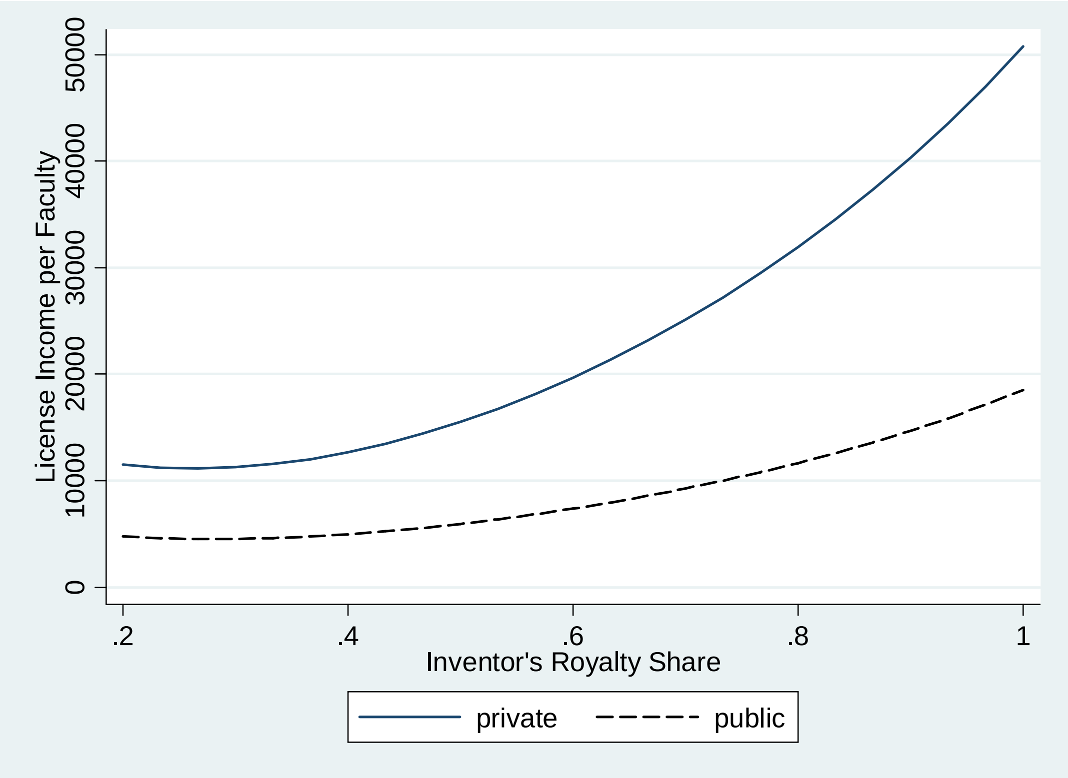


Figure 2: Plot of $E\left(\frac{R}{F} \mid s\right)$

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Appendix 1: Data

# A Variable Definitions

## A.1 Data from AUTM Licensing Surveys 1991-99.

1. *Licensing income* includes license issue fees, payments under options, annual minimums, running royalties, termination payments, the amount of equity received when cashed-in, and software and biological material end-user license fees equal to $1,000 or more. License income includes net transfers of license income from other institutions.

2. *TLO Size* is the number of person(s) employed in the $TLO$ whose duties are specifically involved with the licensing and patenting processes in either full or fractional allocation. Because this information is not available for 1991, we used the data for 1992 to measure size in 1991. The change in the point estimates is minimal but their precision increases due to the larger number of observations.

3. *TLO Age* is measured using the year when then TLO was established as reported by the AUTM surveys. When the foundation year was on 1991 or later we recoded the foundation year to be the first year when the TLO size was larger than 0.5–one half full-time equivalent professional employed.

4. *R&D funding* includes the total amount of research support committed to the university that was related to license/options agreements.

## A.2 Data from 1993 National Survey of Graduate Faculty

The Survey provides data on doctoral programs that participated in the 1993 National Research Council (NRC) National Survey of Graduate Faculty (appendix K on engineering programs, appendix L on life science programs, and appendix N on biological sciences).

1. *Science Fields:* 23 doctoral programs were aggregated into 6 science fields. We used the shares of faculty employed in each field to proxy for the research orientation of the university. The fields are:

(a) *Biomedical and Genetics* - biochemical/molecular biology, cell and development biology, biomedical engineering and molecular and general genetics

(b) *Other Biological Sciences* - neurosciences, pharmacology, physiology and ecology/evolution and behavior

(c) *Computer Science* includes only the department of computer sciences

(d) *Chemical Science* - chemistry and chemical engineering

(e) *Engineering* - aerospace, civil engineering, electrical engineering, industrial engineering, material science, and mechanical engineering

(f) *Physical Sciences* - astrophysics/astronomy, geosciences, mathematics, oceanography, physics, and statistics/biomedical statistics.

2. *Faculty Size* is the total number of faculty in the 23 doctoral programs as reported in the Survey.

3. *Quality measures*:

(a) *Citations per faculty*: ratio of total number of program citations in the period 1988-92 to the number of program faculty.

(b) *Publications per faculty:* ratio of total number of program publications in the period 1988-92 to the number of program faculty.

(c) *Scholarly quality index* of program faculty is the trimmed mean of the responses received in the Survey for each doctoral program. Scores were converted to a scale of 0 to 5, with 0 denoting "Not sufficient for doctoral education" and 5 denoting five "Distinguished".

All these quality measures were aggregated to the university level using faculty weights. In some instances, a university appears more than once in the NRC file because the NRC has information on two or even three units of the same *department*, e.g., statistics and biostatistics or meteorology and geology (in geosciences). In these instances we averaged their quality measures weighting each unit by its share in the total faculty number of both units combined. In other instances, a university appears more than once in the NRC file because the NRC has information on two or more *campuses* (e.g., California, Rutgers, etc.). In these instances we averaged their quality measures weighting each campus by its share in the total faculty number of all campuses combined.

### A.3 Data from TLO's Websites

*Inventor's royalty share.* This information was downloaded from the websites of each university technology licensing offices during the summer of 2001. The net income received by the university from licensing an invention is distributed between the inventor and the university. The university allocates its share to various units such as the inventor's laboratory, department or college. The criterion we use for identifying the inventor share is that the inventor must gain either cash flow rights or direct control rights over the income. Thus, when the university intellectual property policy states that the share accruing to the lab was under the control of the inventor, we added it to the inventor's share, but otherwise we did not. Royalty shares were computed out of *net license income* after deducting direct licensing expenses from gross income. We also made an adjustment for the TLO's overhead rate, when it was reported.

## B Data Selection Process

Starting with the nine files containing the Association of University Technology Managers' (AUTM) Annual Licensing Surveys for 1991-99 we compiled a list of 209 institutions with licensing income and disclosure data for all or part of the 1991-99 period. These institutions include American and Canadian universities, medical research institutes and patent management firms. The size and quality measures from the 1993 National Survey of Graduate Faculty conducted by the National Research Council (NRC) are available for universities with doctoral programs only. This reduces the sample of institutions with AUTM and NRC data to 146. Merging with the royalty share distribution data further reduced the number of institutions with AUTM, NRC and royalty share data to 102.

## C Structure of the Data

We have panel data on 102 universities with non-missing license income data ranging from $T = 1$ to $T = 9$ years. We start with a total of 749 university-year observations with non-missing license income data. Tables 1–3 rely on the full sample of 102 universities but the sample used in Tables 5-10 is smaller because of missing data on some of the regressors and observations with zero license income (we use the log of license income). This sample comprises 96 universities (31 private and 65 public) and 708 observations. Assigning a zero value to the dependent variable of the universities with zero license revenue, and including them in the regression, did not change the parameter estimates.

## Appendix 2: Comnparative Statics

The scientist's problem is

$$\max_{e,z,q} V(sr(z,q), p(e,z,q)) - C(e,z,q)$$

We also assume that the utility function is separable in license income and publications, $V_{12} = 0$. The first order conditions are

$$\begin{aligned} e &: V_2 p_e - C_e = 0 \\ z &: sV_1 r_z + V_2 p_z - C_z = 0 \\ q &: sV_1 r_q + V_2 p_q - C_q = 0 \end{aligned}$$

where subscripts denote partial derivatives with respect to the different arguments. Differentiating totally yields

$$\begin{bmatrix} \Omega_{ee} & \Omega_{ez} & \Omega_{eq} \\ \Omega_{ez} & \Omega_{zz} & \Omega_{zq} \\ \Omega_{eq} & \Omega_{zq} & \Omega_{qq} \end{bmatrix} \begin{bmatrix} de \\ dz \\ dq \end{bmatrix} = - \begin{bmatrix} 0 & 0 \\ \Omega_{zs} & \Omega_{z\theta} \\ \Omega_{qs} & \Omega_{q\theta} \end{bmatrix} \begin{bmatrix} ds \\ d\theta \end{bmatrix}$$

where

$$\begin{aligned} \Omega_{ee} &= V_{22} p_e^2 + V_2 p_{ee} - C_{ee} \\ \Omega_{zz} &= sV_1 r_{zz} + s^2 V_{11} r_z^2 + V_{22} p_z^2 + V_2 p_{zz} - C_{zz} \\ \Omega_{qq} &= sV_1 r_{qq} + s^2 V_{11} r_q^2 + V_{22} p_q^2 + V_2 p_{qq} - C_{qq} \\ \Omega_{ez} &= V_{22} p_e p_z + V_2 p_{ez} - C_{ez} \\ \Omega_{eq} &= V_{22} p_e p_q + V_2 p_{eq} - C_{eq} \\ \Omega_{zq} &= V_{22} p_z p_q + V_2 p_{zq} - C_{zq} \\ \Omega_{zs} &= V_1 r_z + s^2 V_{11} r r_\theta \\ \Omega_{z\theta} &= sV_1 r_{z\theta} + s^2 V_{11} r_z r_\theta \\ \Omega_{qs} &= V_1 r_q + s^2 V_{11} r r_q \\ \Omega_{q\theta} &= sV_1 r_{q\theta} + s^2 V_{11} r_q r_\theta \end{aligned}$$

Second order conditions imply $\Omega_{ii} < 0$, $\Omega_{ii}\Omega_{jj} - \Omega_{ij}^2 > 0$ for $i \neq j \in (e, z, q)$ and $\det\Omega < 0$. Solving we get the following comparative statics results:

$$\frac{\partial e}{\partial s} = \frac{1}{\det\Omega}\{(V_1 r_z + s^2 V_{11} r r_z)(\Omega_{ez}\Omega_{qq} - \Omega_{zq}\Omega_{ez}) - (V_1 r_q + s^2 V_{11} r r_q)(\Omega_{ez}\Omega_{zq} - \Omega_{zz}\Omega_{eq})\}$$

$$\frac{\partial e}{\partial \theta} = \frac{1}{\det\Omega}\{(sV_1 r_{z\theta} + s^2 V_{11} r_z r_\theta)(\Omega_{ez}\Omega_{qq} - \Omega_{zq}\Omega_{eq}) - (sV_1 r_{q\theta} + s^2 V_{11} r_q r_\theta)(\Omega_{ez}\Omega_{zq} - \Omega_{zz}\Omega_{eq})\}$$

$$\frac{\partial z}{\partial s} = \frac{1}{\det\Omega}\{(V_1 r_z + s^2 V_{11} r r_z)(\Omega_{eq}^2 - \Omega_{ee}\Omega_{qq}) + (V_1 r_q + s^2 V_{11} r r_q)(\Omega_{ee}\Omega_{zq} - \Omega_{ez}\Omega_{eq})\}$$

$$\frac{\partial z}{\partial \theta} = \frac{1}{\det\Omega}\{(sV_1 r_{z\theta} + s^2 V_{11} r_z r_\theta)(\Omega_{eq}^2 - \Omega_{ee}\Omega_{qq}) + (sV_1 r_{q\theta} + s^2 V_{11} r_q r_\theta)(\Omega_{ee}\Omega_{zq} - \Omega_{ez}\Omega_{eq})\}$$

$$\frac{\partial q}{\partial s} = \frac{1}{\det\Omega}\{(V_1 r_z + s^2 V_{11} r r_z)(\Omega_{ee}\Omega_{zq} - \Omega_{ez}\Omega_{eq}) - (V_1 r_q + s^2 V_{11} r r_q)(\Omega_{ee}\Omega_{zz} - \Omega_{ez}^2)\}$$

$$\frac{\partial q}{\partial \theta} = \frac{1}{\det\Omega}\{(V_1 r_z + s^2 V_{11} r r_z)(\Omega_{ez}\Omega_{qq} - \Omega_{zq}\Omega_{ez}) - (V_1 r_q + s^2 V_{11} r r_q)(\Omega_{ez}\Omega_{zq} - \Omega_{zz}\Omega_{eq})\}$$

## Appendix 3: Adaptation of Pre-sample Scaling Method

The model is

$$y_{it} = x_{it}\beta + \eta_i + u_{it}$$

where $i = 1, ..., N$, $t = 1, ..., T$, $y$ is the logarithm of license income, $x$ includes both time varying and invariant regressors (the latter includes, for most universities, the royalty share), and we only assume $E(u_{it}|x_{it}, x_{it-1}, ..., \eta_i) = 0$ for all $t$. The unobserved heterogeneity $\eta_i$ may be correlated with royalty share and other variables. We use the 'pre-sample scaling method' developed by Blundell, Griffith and van Reenen (1999), which amounts to constructing a sufficient statistic for $\eta_i$ based on pre-sample information on the dependent variable and then directly controlling for it in the regression.[39] They develop the method for a (nonlinear) patent count model. Below we sketch how the method works in our context and how we must adapt it for our purposes.

Let $J$ denote the number of pre-sample observations. Then

$$p\lim\left(\frac{1}{J+1}\sum_{t=0}^{-J} y_{it}\right) = p\lim\left(\frac{1}{J+1}\sum_{t=0}^{-J}(x_{it}\beta + \eta_i + u_{it})\right) = \underset{J\to\infty}{p\lim}\left(\frac{1}{J+1}\sum_{t=0}^{-J} x_{it}\beta\right) + \eta_i$$

The left-hand-side of this equation is the limit of the pre-sample mean of license income for university $i$.

Using a linear projection argument, we can express each of the observable regressors $x_j$ as a linear function of the unobservable $\eta_i$ and an error $c_{ijt}$ uncorrelated with $\eta_i$ :

$$x_{ijt} = \alpha_0 + \phi_j\eta_i + c_{ijt}, \qquad j = 1, \ldots, k$$

with $E(c_{ijt}) = 0$ and $E(\eta_i c_{ijt}) = 0$.

Note that if all the $\phi_j' s$ are zero then there is no endogeneity problem. Thus, if $x_{ijt}$ is endogenous at least one of the $\phi_j$'s is non-zero. We assume that the projection parameters are

[39] They also show that one can use pre-sample information on the regressors, but we do not have such information.

constant over time.[40] This representation implies

$$\begin{aligned}\frac{1}{J+1}\sum_{t=0}^{-J}x_{it}\beta &= \frac{1}{J+1}\sum_{t=0}^{-J}\sum_{j=1}^{k}x_{ijt}\beta \\ &= \alpha_0\sum_{j=1}^{k}\beta_j+\eta_i\left(\sum_{j=1}^{k}\phi_j\beta_j\right)+\frac{1}{J+1}\sum_{t=0}^{-J}\sum_{j=1}^{k}c_{ijt}\beta_j\end{aligned}$$

Provided a law of large numbers apply to $\frac{1}{J+1}\sum_{t=0}^{-J}c_{ijt}$ so that $\underset{J\to\infty}{p\lim}\frac{1}{J+1}\sum_{t=0}^{-J}c_{ijt}=0$, we get

$$\begin{aligned}\underset{J\to\infty}{p\lim}\frac{1}{J+1}\sum_{t=0}^{-J}x_{it}\beta &= \alpha_0\sum_{j=1}^{k}\beta_j+\alpha_1\eta_i+\underset{J\to\infty}{p\lim}\frac{1}{J+1}\sum_{t=0}^{-J}c_{ijt}\beta_j \\ &= \alpha_0\sum_{j=1}^{k}\beta_j+\alpha_1\eta_i\end{aligned}$$

where $\alpha_1=\sum_{j=1}^{k}\phi_j\beta_j$.[41]

We can then write

$$m_{yi}\equiv\underset{J\to\infty}{p\lim}\left(\frac{1}{J+1}\sum_{t=0}^{-J}y_{it}\right)=\alpha_0\sum_{j=1}^{k}\beta_j+(1+\alpha_1)\,\eta_i$$

and solving for $\eta_i$,

$$\eta_i=-\frac{\alpha_0\sum_{j=1}^{k}\beta_j}{1+\alpha_1}+\frac{1}{1+\alpha_1}m_{yi}$$

This equation says that the pre-sample mean of log license income is a sufficient statistic for $\eta_i$. Substituting into the original model we get the estimating equation

$$y_{it}=x_{it}\beta+\frac{1}{1+\alpha_1}m_{yi}+u_{it}$$

where the constant term $-\frac{\alpha_0\sum_{j=1}^{k}\beta_j}{1+\alpha_1}$ is absorbed into the constant term of the original model. In the actual estimation the pre-sample mean of $y$ is used instead of its probability limit $m_{yi}$.

The problem in our context is that we do not have pre-sample information on license income. However, we do have pre-sample information on the patenting activity for each university. In order to use pre-sample patents instead of pre-sample license income we make the

[40] This assumption is made to simplify the exposition and it will hold if the $x's$ are drawn from the same distribution at every $t$. The method can be extended to time-varying coefficients under an additional convergence assumption.

[41] Note that there are no time-invariant components in $c_{ijt}$ – they are captured by $\eta_i$ – and that some weak serial dependency is possible as long as a law of large numbers can be applied.

additional assumption that patenting is also a linear function of the unobserved heterogeneity, $\eta$. That is, we assume

$$p_{it} = z_{it}\lambda + \sigma\eta_i + v_{it}$$

where $p$ is the log of patents (or patent citations) and the regressors $z$ may have common components with $x$. Since the decision by the TLO to patent an invention is based on expected returns from commercialising the invention, this assumption that patenting depends on $\eta$ seems very reasonable.

Retracing the previous steps but using $p$ instead of $y$, using tildes to denote coefficients in this derivation for patents, and letting $m_{p_i} = p\lim_{J\to\infty} \frac{1}{J+1}\sum_{t=0}^{-J} p_{it}$, we have

$$\eta_i = -\frac{\widetilde{\alpha}_0 \sum_{j=1}^{k} \lambda_j}{\sigma + \widetilde{\alpha}_1} + \frac{1}{\sigma + \widetilde{\alpha}_1} m_{pi}$$

and substituting into the original model, we get the estimable equation

$$y_{it} = x_{it}\beta + \frac{1}{\sigma + \widetilde{\alpha}_1} m_{pi} + u_{it}$$

where the constant term $-\frac{\widetilde{\alpha}_0 \sum_{j=1}^{k} \lambda_j}{\sigma + \widetilde{\alpha}_1}$ is absorbed into the constant term of the original model.

This is the equation we estimate in the paper, using the pre-sample mean of patents (or patent citations) instead of its probability limit $m_{pi}$ to control for the correlation with unobserved heterogeneity.

**Table 1. Descriptive Statistics[1]**

| | Private Universities (n=34) | | | | | |
|---|---|---|---|---|---|---|
| | Mean | 10% | 25% | 50% | 75% | 90% |
| Licensing income ('000s) | 4,940 | 63 | 463 | 868 | 4,029 | 11,500 |
| Licensing income ('000s) per license[2] | 41 | 6 | 12 | 28 | 51 | 99 |
| Faculty size | 320 | 89 | 134 | 276 | 479 | 576 |
| Citations per faculty[3] | 74 | 20 | 32 | 68 | 114 | 134 |
| Publications per faculty[3] | 9 | 3 | 6 | 9 | 10 | 13 |
| Scholarly quality (0-5) | 3.4 | 2.2 | 2.7 | 3.5 | 4.0 | 4.5 |
| Average size of TLO | 3.2 | 0.4 | 1.2 | 2.1 | 4.0 | 8.3 |
| Age of TLO in 1999 (years) | 16 | 7 | 11 | 15 | 18 | 23 |

| | Public Universities (n=68) | | | | | |
|---|---|---|---|---|---|---|
| | Mean | 10% | 25% | 50% | 75% | 90% |
| Licensing income ('000s) | 2,905 | 45 | 155 | 539 | 2,206 | 5,768 |
| Licensing income ('000s) per license[2] | 55 | 5 | 10 | 17 | 31 | 65 |
| Faculty size | 380 | 53 | 145 | 289 | 514 | 756 |
| Citations per faculty[3] | 36 | 9 | 18 | 28 | 47 | 62 |
| Publications per faculty[3] | 7 | 3 | 5 | 7 | 8 | 10 |
| Scholarly quality (0-5) | 2.8 | 1.9 | 2.3 | 2.9 | 3.3 | 3.8 |
| Average size of TLO | 3.1 | 0.6 | 1.0 | 1.7 | 3.1 | 6.5 |
| Age of TLO in 1999 (years) | 16 | 7 | 8 | 12 | 17 | 30 |

Notes:

[1] Statistics computed on the time-averaged data for each of university. Constant 2000 dollars, using GDP deflator.

[2] Licensing income in year t divided by the cumulative number of active licenses through year t.

[3] During 1988-92.

**Table 2. Distribution of Inventor Royalty Shares (percentage)[1]**

| | Mean | 10% | 50% | 90% | Min | Max |
|---|---|---|---|---|---|---|
| Linear Schedules (n=58) | | | | | | |
| Private Universities | 39 | 25 | 40 | 50 | 21 | 50 |
| Public Universities | 42 | 30 | 40 | 50 | 25 | 65 |
| Nonlinear Schedules (n=44)[2] | | | | | | |
| Private Universities | 51 | 34 | 49 | 64 | 34 | 97 |
| Public Universities | 51 | 38 | 49 | 70 | 20 | 89 |
| by Income Interval (Private and Public): | | | | | | |
| 0-10,000 | 53 | 40 | 50 | 75 | 20 | 100 |
| 10,000-50,000 | 45 | 25 | 50 | 50 | 20 | 93 |
| 50,000-100,000 | 41 | 25 | 44 | 50 | 20 | 85 |
| 100,000-300,000 | 35 | 25 | 33 | 43 | 20 | 85 |
| 300,000-500,000 | 33 | 25 | 30 | 40 | 20 | 85 |
| 500,000-1 million | 32 | 21 | 30 | 40 | 20 | 85 |
| Over 1 million | 30 | 20 | 30 | 40 | 15 | 85 |

Notes:

[1]Time-averaged royalty shares are used for the 11 universities that changed their shares during 1991-99.

[2] Expected royalty shares for nonlinear schedules are computed using kernel density weights, as described in the text.

**Table 3. Inventor Royalty Shares (percentage) by University Characteristics[1]**

| | **Private Universities** | | | | | |
|---|---|---|---|---|---|---|
| | Faculty Size | Citations per Faculty | TLO Size per Faculty | TLO Age | Faculty Share in Bio-medicine[2] | Faculty Share in Engineering[3] |
| First Quartile | 46 | 50 | 44 | 46 | 48 | 47 |
| Second Quartile | 48 | 45 | 43 | 43 | 41 | 46 |
| Third Quartile | 41 | 42 | 43 | 47 | 41 | 39 |
| Fourth Quartile | 41 | 38 | 49 | 37 | 44 | 43 |
| F test (p-value) | 0.6 | 0.31 | 0.82 | 0.51 | 0.76 | 0.7 |

| | **Public Universities** | | | | | |
|---|---|---|---|---|---|---|
| | Faculty Size | Citations per Faculty | TLO Size per Faculty | TLO Age | Faculty Share in Bio-medicine[2] | Faculty Share in Engineering[3] |
| First Quartile | 48 | 44 | 40 | 46 | 44 | 49 |
| Second Quartile | 45 | 49 | 51 | 47 | 40 | 43 |
| Third Quartile | 45 | 44 | 45 | 49 | 48 | 44 |
| Fourth Quartile | 46 | 47 | 45 | 41 | 51 | 46 |
| F test (p-value) | 0.89 | 0.76 | 0.22 | 0.45 | 0.22 | 0.78 |

Notes:

[1] Using 1996 data for time-varying variables.

[2] Bio-medicine includes biochemical/molecular biology, cell and development biology, biomedical engineering and molecular and general genetics

[3] Engineering includes aerospace, civil engineering, electrical engineering, industrial engineering, material science, and mechanical engineering

**Table 4. Incentives, Constraints and Objectives in Private and Public TLO's[1]**

| | Private Universities | Public Universities | P-value of Equality of Means Test |
|---|---|---|---|
| **1. Faculty Awareness of Incentives** | | | |
| % responding "yes" | 96.4 | 91.7 | 0.41 |
| **2. University Rewards Technology Transfer** | | | |
| % responding "yes" | 15.4 | 9.4 | 0.42 |
| **3. Performace-based Pay (merit or bonuses)** | | | |
| % responding "yes" | 79 | 49 | 0.007 |
| **4. Government constraints on:** | | | |
| % reporting "important" or "very important" | | | |
| Choice of license partners | 0 | 23 | < 0.001 |
| Setting license contract terms | 0 | 19 | < 0.001 |
| License confidentiality | 0 | 27 | < 0.001 |
| Use of equity stakes | 3.5 | 23 | 0.024 |
| University liability/indemnification | 18 | 75 | 0.050 |
| Dispute resolution mechanisms | 3.6 | 49 | 0.038 |
| **5. Objectives** | | | |
| % reporting "important" or "very important" | | | |
| Number of licenses | 100 | 97 | 0.380 |
| License income | 93 | 88 | 0.440 |
| Promoting local/regional development | 57 | 88 | 0.001 |

Notes:
[1]Based on survey conducted by the authors. Numbers of public and private universities are 73 and 28, respectively.

**Table 5 . License Revenue Equation (eq.(3)): Baseline Specifications**

| | Dependent variable: log license income | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Private Universities | | | | Public Universities | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Royalty Share | 5.84*** | 5.26*** | 4.52** | 3.97** | 2.30* | 2.32* | 1.93 | 1.75 |
| | 2.16 | 1.98 | 2.04 | 1.97 | 1.35 | 1.36 | 1.46 | 1.41 |
| Competitors' Royalty Share | -- | -3.37** | -2.54* | -2.02* | -- | -0.52 | -1.06 | -1.18 |
| | | 1.38 | 1.35 | 1.21 | | 1.51 | 1.42 | 1.42 |
| Royalty Share x Dummy for 1st Quartlile of TLO /faculty | | | | -0.23 | | | | 0.95 |
| | | | | 0.94 | | | | 1.06 |
| Royalty Share x Dummy for 4st Quartlile of TLO /faculty | | | | 1.63** | | | | -0.54 |
| | | | | 0.80 | | | | 0.82 |
| Log (Average Patent Cites) | -- | -- | 0.53** | 0.52** | -- | -- | 0.41*** | 0.44*** |
| | | | 0.24 | 0.25 | | | 0.12 | 0.12 |
| Log (TLO/Faculty) | 0.56** | 0.61*** | 0.55** | 0.28 | -0.09 | -0.10 | -0.24 | -0.08 |
| | 0.26 | 0.23 | 0.22 | 0.21 | 0.15 | 0.16 | 0.16 | 0.16 |
| Age TLO | 0.17*** | 0.19*** | 0.13*** | 0.13*** | 0.03 | 0.03 | 0.04 | 0.04 |
| | 0.05 | 0.05 | 0.05 | 0.05 | 0.03 | 0.03 | 0.03 | 0.03 |
| Age TLO squared | -0.002** | -0.003*** | -0.002*** | -0.002*** | -0.0001 | -0.0001 | -0.0002 | -0.0002 |
| | 0.001 | 0.001 | 0.001 | 0.001 | 0.0004 | 0.0004 | 0.0004 | 0.0004 |
| Log (Faculty Size) | 0.65 | 0.89* | 0.74 | 0.89* | 1.25*** | 1.26*** | 0.74*** | 0.64*** |
| | 0.58 | 0.46 | 0.48 | 0.52 | 0.18 | 0.19 | 0.23 | 0.23 |
| Publication Cites/ Faculty | 0.01 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |
| | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| Log (R&D/Faculty) | 0.15 | 0.02 | 0.04 | -0.05 | 0.53** | 0.53** | 0.63*** | 0.67*** |
| | 0.36 | 0.31 | 0.27 | 0.29 | 0.21 | 0.22 | 0.22 | 0.24 |
| Medical School Dummy | 1.81* | 1.17 | 0.55 | 0.33 | 0.24 | 0.24 | 0.11 | 0.18 |
| | 0.94 | 0.80 | 0.93 | 0.85 | 0.37 | 0.38 | 0.35 | 0.33 |
| High-Tech, first quartile | -0.39 | -0.27 | 0.36 | 0.62 | 0.54 | 0.56 | 0.75** | 0.825** |
| | 0.56 | 0.58 | 0.72 | 0.66 | 0.36 | 0.37 | 0.35 | 0.34 |
| High-Tech, fourth quartile | 0.69* | 0.75** | 0.64* | 0.57* | 0.31 | 0.32 | 0.40 | 0.53 |
| | 0.39 | 0.31 | 0.33 | 0.32 | 0.34 | 0.34 | 0.39 | 0.57 |
| $R^2$ | 0.75 | 0.77 | 0.79 | 0.80 | 0.62 | 0.62 | 0.66 | 0.67 |
| Number of Observations | 246 | 246 | 246 | 246 | 462 | 462 | 462 | 462 |

Notes: Year dummies and faculty shares in six fields are included in all regressions. Standard errors clustered by university in small numerals.

*** , **, * significant at the 1, 5, and 10 % level, respectively.

**Table 6 . Robustness to "Outliers"**

| | Dependent variable: log license income | | | | | |
|---|---|---|---|---|---|---|
| | Private Universities | | | Public Universities | | |
| | 1 | 2 | 3 | 5 | 6 | 7 |
| **Quartile** | $Q_{25}$ | $Q_{50}$ | $Q_{75}$ | $Q_{25}$ | $Q_{50}$ | $Q_{75}$ |
| Royalty Share | 3.88*** | 4.06*** | 8.24*** | 1.34* | 0.31 | 0.80 |
| | 0.98 | 1.33 | 2.20 | 0.68 | 0.66 | 0.79 |
| Competitors' Royalty Share | -2.79*** | -1.95 | 0.39 | -0.68 | -0.64 | -1.24 |
| | 0.91 | 1.28 | 1.91 | 0.88 | 0.67 | 1.08 |
| $R^2$ | 0.63 | 0.58 | 0.57 | 0.48 | 0.46 | 0.46 |
| Number of Observations | 246 | 246 | 246 | 462 | 462 | 462 |

Notes: All other control variables appearing inTable 5 are included in all regressions, but their coefficients are not reported for brevity.
Bootstrapped standard errors in small numerals.
*** , **, * significant at the 1, 5, and 10 % level, respectively.

**Table 7 . Robustness to Number of Competing Universities in Sorting**

| | Dependent variable: log license income | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Private Universities | | | | Public Universities | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| **Number of Competing Universities** | 2 | 4 | 6 | 8 | 2 | 4 | 6 | 8 |
| Royalty Share | 4.52** | 3.61* | 3.36 | 3.94* | 1.93 | 1.91 | 1.97 | 1.93 |
| | 2.04 | 2.09 | 2.36 | 2.38 | 1.46 | 1.47 | 1.48 | 1.47 |
| Competitors' Royalty Share | -2.54* | -3.24 | -4.80 | -3.09 | -1.06 | -1.33 | 1.52 | 0.70 |
| | 1.35 | 2.42 | 3.54 | 5.23 | 1.42 | 1.70 | 2.46 | 2.55 |
| $R^2$ | 0.79 | 0.78 | 0.79 | 0.78 | 0.66 | 0.66 | 0.66 | 0.66 |
| Number of Observations | 246 | 246 | 246 | 246 | 462 | 462 | 462 | 462 |

Notes: Competing universities are defined by their ranking of publication citations per faculty.
All other control variables appearing inTable 5 are included in all regressions, but their coefficients are not reported for brevity.
Standard errors clustered by unviersity in small numerals.
*** , **, * significant at the 1, 5, and 10 % level,  respectively.

**Table 8 . Robustness to Alterntive Pre-sample Controls**

| | Dependent variable: log license income | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Private Universities | | | | Public Universities | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Royalty Share | 4.52** | 4.50** | 5.28*** | 5.05*** | 1.93 | 1.92 | 2.24 | 2.27 |
| | 2.04 | 2.03 | 1.95 | 1.94 | 1.46 | 1.43 | 1.55 | 1.55 |
| Competitors' Royalty Share | -2.54* | -2.69* | -3.19** | -3.16** | -1.06 | -0.73 | -0.85 | -0.98 |
| | 1.35 | 1.36 | 1.39 | 1.38 | 1.42 | 1.43 | 1.4 | 1.43 |
| Log (Average Patent Cites) | 0.53** | 0.41 | | | 0.41*** | 0.52*** | | |
| | 0.24 | 0.26 | | | 0.12 | 0.12 | | |
| Dummy for Zero Cites | -- | -3.09*** | | | -- | 1.22** | | |
| | | 0.82 | | | | 0.56 | | |
| Log (Average Patents) | -- | -- | 0.41 | 0.38 | -- | -- | 0.60*** | 0.61*** |
| | | | 0.36 | 0.36 | | | 0.23 | 0.22 |
| Dummy for Zero Patents | | | | -3.84*** | | | | 0.87 |
| | | | | 0.70 | | | | 0.88 |
| $R^2$ | 0.79 | 0.80 | 0.78 | 0.79 | 0.66 | 0.67 | 0.66 | 0.66 |
| Number of Observations | 246 | 246 | 246 | 246 | 462 | 462 | 462 | 462 |

Notes: Competing universities are defined by their ranking of publication citations per faculty.
All other control variables appearing inTable 5 are included in all regressions, but their coefficients are not reported for brevity.
Standard errors clustered by unviersity in small numerals.
*** , **, * significant at the 1, 5, and 10 % level,  respectively.

**Table 9 . Incentive Effects on the Quantity vs Quality of Invention**

| | Private Universities | | | Public Universities | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| **Dep. Variable** | Log Revenues | | Log Licenses | Log Revenues | | Log Licenses |
| Log (Stock of Licences) | -- | 0.46 | -- | -- | 0.57*** | -- |
| | | 0.30 | | | 0.18 | |
| Royalty Share | 5.05** | 4.31* | 2.20** | 2.24 | 2.06 | 0.42 |
| | 2.21 | 2.31 | 1.06 | 1.63 | 1.70 | 0.55 |
| Competitors' Royalty Share | -4.27*** | -2.33 | -2.39*** | -2.51 | -2.36 | -0.28 |
| | 1.34 | 1.77 | 0.81 | 1.62 | 1.58 | 0.50 |
| $R^2$ | 0.81 | 0.79 | 0.86 | 0.65 | 0.66 | 0.81 |
| Number of Observations | 137 | 137 | 137 | 265 | 265 | 265 |

Notes: All other control variables appearing in Table 5 are included in all regressions but their coefficients are not reported for brevity except for regressions 2 and 5 which exclude Log (Faculty Size).
Standard errors clustered by university in small numerals.
*** , **, * significant at the 1, 5, and 10 % level, respectively.

**Table 10. Interactions between Incentives Effects and the Quality and Tenure of University Faculty**

| | Private Universities | | Public Universities | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| | Quality quartiles | Tenure quartiles | Quality quartiles | Tenure quartiles |
| **Determinants of Incentives** | | | | |
| Royalty Share (in 1st quartile ) | 6.84** | 5.08** | 3.65** | 1.80 |
| | 2.99 | 2.01 | 1.85 | 1.76 |
| Royalty Share (in 2nd & 3rd quartiles) | 4.81** | 4.31** | 1.62 | 1.21 |
| | 2.10 | 1.74 | 1.03 | 1.20 |
| Royalty Share (4th quartile) | 4.51** | 3.22 | 0.23 | 3.15** |
| | 2.00 | 1.96 | 1.19 | 1.62 |
| Competitors' Royalty Share | -2.41* | -1.09 | -0.08 | -0.38 |
| | 1.40 | 1.65 | 1.26 | 1.12 |
| $R^2$ | 0.79 | 0.81 | 0.68 | 0.69 |
| Number of Observations | 246 | 246 | 462 | 462 |

Notes: All other control variables appearing in Table 5 are included in all regressions but their coefficients are not reported for brevity.
Standard errors clustered by university in small numerals.
*** , **, * significant at the 1, 5, and 10 % level, respectively.

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