CENTRE *for* ECONOMIC PERFORMANCE

CEP Discussion Paper No 729

June 2006

The Impact of Royalty Sharing Incentives on Technology Licensing 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 other factors including university size, quality, research funding, and local demand conditions. We use pre-sample data on university patenting to control for the endogeneity of royalty shares. The incentive effects are larger in private universities than in public ones, and we provide survey evidence on performance-based pay, government constraints and objectives of Technology License Offices that helps explain this finding. Royalty incentives work through two channels — raising faculty effort and sorting scientists across universities. The effect of incentives is mainly to increase the quality rather than the quantity of inventions.

Keywords: royalty incentives, invention, technology licensing
JEL Classifications: O31, O34, L2, L3

This paper was produced as part of the Centre's Productivity and Innovation Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

Acknowledgements

We are grateful to two referees for very constructive suggestions, and to James Adams, Bronwyn Hall, Adam Jaffe, Jenny Lanjouw, Imran Rasul, Len Waverman and Arvids Ziedonis for comments on earlier drafts of the paper. We thank Manuel Trajtenberg for his comments and for making available the university patent data, and Don Siegel for help with the AUTM data. We also thank seminar participants at Harvard, The Hebrew University, London School of Economics, San Fransisco Federal Reserve Bank, University of Chicago Graduate School of Business, and the NBER. Alan Paau, Director of the Technology Licensing Office at UCSD provided very helpful suggestions on the design of the TLO survey. Finally, we thank the Samuel Neaman Institute for Advanced Studies in Science and Technology Policy at the Technion (Israel) for encouragement and financial support in this research project.

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Published by
Centre for Economic Performance
London School of Economics and Political Science
Houghton Street
London WC2A 2AE

ISBN 0 7530 2025 4

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. Is it a purely intellectual pursuit, as many commentators claim, or do economic incentives matter?

In this paper we take a first step to answer this question by providing econometric evidence that incentives 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 across universities, and use this cross-sectional variation to estimate the effect of royalty sharing arrangements on license income.

We develop a simple empirical framework in which scientists allocate effort to start new

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[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; 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.

research projects and improve the quality of each project. Scientists value royalty income and publications. The model predicts that a rise in the inventor royalty share of university i increases research effort and thus 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 university i. 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. 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). We also show that technology licensing offices (TLOs) are more productive in private universities, suggesting that private institutions have more effective, commercially-oriented technology transfer activity.

One of the primary concerns is that this covariation between royalty shares and license income may arise from unobserved heterogeneity at the university level. In particular, there may be unobserved heterogeneity in research productivity or commercial orientation of faculty. If this heterogeneity is correlated with royalty shares , a potential endogeneity problem arises. For example, 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. Another possibility is that there are differences in institutional culture (or historical experience in technology transfer activity) across universities and that a strong culture of commercial innovation might lead both to greater inventor royalty shares and greater license revenue.

To address this endogeneity problem we adopt the approach recently developed by Blundell, Griffith and Van Reenen (1999). They show that, under certain assumptions, the pre-sample mean of the dependent variable is a consistent estimator of the unobserved, fixed heterogeneity, and thus it can be used as an additional regressor to control for such heterogeneity. Introducing this control does indeed reduce the estimated effect of royalty shares – by about 20 percent – but the central findings remain unchanged.

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 results help explain both why we find that private universities are more effective at generating license income and why 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, are strongly affected by royalty incentives. The potential costs include 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 develops

[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 are mixed (Henderson, Jaffe and Trajtenberg, 1998; Agrawal and Henderson, 2002; Murray and Stern, 2004).

the empirical framework. In Section 4 we present nonparametric evidence on the relationship between license income and inventor royalty shares as well as regression results. Their implications for revenue maximization and an assessment of the impact of incentives on the quality and quantity of invention are also discussed. Section 5 summarizes 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 the Appendix.

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 and scholarly quality, we use data from the 1993 NRC Survey. For each university we have information on faculty size and 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. The primary quality measure we use is the number of citations per faculty during the period 1988-92, but we also use 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. The NRC measures of size and quality do not vary over time.

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 sum, the distributions of licensing value 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 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.

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 IP 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*.

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, we updated the information when available.[4]

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.[5] For these universities we compute an *expected royalty share* by 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, $\bar{s}(v)$, using the royalty schedule for each university, taking into account the varying marginal royalty rates.[6] The expected royalty share is then $s \equiv \Sigma_v \bar{s}(v)\widehat{f}(v)$.[7]

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[4]In total, 53 universities responded to this query. Of the 16 that reported a change in royalty shares during 1991-99, only 11 reported the pre- and post-change royalty sharing agreements. In these cases, we updated the data according to the information received. In the remaining 5 universities, we used the shares reported in 2001.

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

[6]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.

[7]The estimated density function of license income per invention (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–but we do not have enough data to do this successfully.

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 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.

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.[8]

In this paper we begin by taking the royalty shares as given and exploit their cross-sectional variation to identify whether they have an effect on inventive activity. As discussed in the next section, however, royalty shares may be correlated with unobserved heterogeneity at the university level. We address this potential endogeneity problem by using pre-sample information on university patenting. It is important to go further and study the determinants of royalty sharing arrangements, but this is beyond the scope of the present paper.

3 Empirical Framework

A scientist has a fixed amount of time (effort) to devote to research, T. She devotes effort z to starting new research projects, yielding $n = n(z)$ where $n(z)$ is increasing and concave. Each invention has the same initial quality v_0. By investing effort q into a project, she generates an invention potentially worth $v(q) = v_0\psi(q)\varepsilon$ where $\psi(q) \geqslant 1$ is increasing and concave and ε is

[8]Regressive royalty schedules 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 (i.e., when high income outcomes are largely due to luck rather than effort). This argument is relevant here if the scientist knows little about the quality of the project ex ante. But if the inventor can distinguish between low and high quality projects in making effort decisions, then optimal incentives involve a progressive inventor royalty to compensate for the higher marginal cost of producing high-valued inventions. Of course, "fairness" and other considerations may affect how universities set royalty sharing.

a stochastic shock independent of q, with unit mean value and distribution function G. The shock ε is observed after the scientist chooses (z, q). With no ex-ante differences among the n inventions, the scientist sets the same level q for each.[9] We assume that the effort constraint is binding, $z + n(z)q = T$. In addition to generating inventions, the research produces academic publications $p(z, q) = p(n(z), q)$. If there is a conflict between commercially-oriented and academic research, the partial derivatives of this function may not be positive at all points.

If licensed, the invention earns revenue θv (otherwise zero), where $0 < \theta \leq 1$ reflects the effectiveness of the TLO's licensing activities. While v is the maximum potential commercial value of the invention, actual license income depends on how good the TLO is at identifying potential licensees and negotiating agreements. These capabilities may depend on institutional features, such as whether the university is public or private (see Section 3.1 for survey evidence). The TLO licenses an invention if expected license income covers the fixed cost of licensing $\underline{v}$. The selection rule $\theta v > \underline{v}$ implies that a proportion $1 - G\left(\frac{\underline{v}}{\theta v_0 \psi(q)}\right)$ of all inventions is licensed.[10]

Expected license revenue per faculty is

$$r(z, q) = \theta n(z) v_0 \psi(q) \int_{\frac{\underline{v}}{\theta v_0 \psi(q)}}^{\infty} \varepsilon dG(\varepsilon) \tag{1}$$

Effort q has two effects: it raises the value of the invention and increases the probability the TLO will license it.

The scientist derives utility from license income and publications, $U(z, q) = V(sr, p)$, where $U(z, q)$ is assumed to be increasing in both arguments and concave in the neighborhood of the optimal choice. Let $C(z, q)$ be a convex effort cost function.[11] The scientist maximizes $U(z, q) - C(z, q)$, given the license revenue and publications functions, $r(z, q)$ and $p(z, q)$, and the time constraint $z + n(z)q = T$.

[9] 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.

[10] This specification of the licensing decision is consistent with new survey data we gathered from TLOs, described briefly in Section 3.1.

[11] In a more developed model, the inventor's effort cost function would reflect the university's valuation of research and teaching, as the university controls these shadow prices by setting promotion criteria and other rewards, including royalty shares.

It is straightforward to show that optimal research efforts is an increasing function of the inventor's royalty share, s, and the TLO effectiveness, θ. This implies that license revenue $r(z(s,\theta), q(s,\theta))$ also increases in (s,θ). This is the implication we set out to test with data on university-level revenues, royalty rates s, and proxies for θ.

Letting $R(s,\theta) = Fr(s,\theta)$ denote license revenue for the university (F is faculty size), taking logs of (1) and linearizing we get

$$\log R = \log F + \delta s + \lambda \log \theta + \text{terms involving } G, \underline{v} \text{ and } v_0$$

Since θ in not observed, we use the size and experience 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, $\underline{v}$ and v_0. We use the number of citations per faculty to capture initial quality (v_0), and differences in research orientation measured by the shares of faculty in each of six science fields (see Appendix) and the amount of R&D funding to the university, to capture differences in the distribution of quality shocks, G. Letting the vector x denote all these proxies, the basic model is

$$\log R = \delta s + x\beta + u \tag{2}$$

where u is the disturbance term. The parameter δ 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 may be unobserved heterogeneity in research productivity or commercial orientation of faculty. If this heterogeneity is correlated with s and θ (or its proxies), a potential endogeneity problem arises. There are two main ways in which such correlation might arise: reverse causality and 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. A broader possibility is that there are differences in institutional culture (or historical experience in technology transfer activity) across universities and that a strong culture of commercial innovation might lead both to greater inventor royalty shares and greater license revenue. In such cases of reverse causality, estimating (2) by OLS would give an upward biased estimate of δ.[12]

The second is that universities might attempt to attract more commercially productive faculty by offering a higher inventor royalty share or a more effective TLO (higher θ). If successful, this "sorting policy" will also generate a positive correlation between (s, θ) and unobserved faculty quality: universities with higher (s, θ) will have more productive faculty. This will also bias upward the estimated δ.

However, there is a subtle difference between the two cases. In the sorting example, the estimated δ 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 examples 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 individual inventors.[13] However, we can extend the empirical specification of the model to incorporate sorting effects. If sorting occurs, the type of faculty a university attracts should depend both on its own royalty share and on the shares offered by the set of universities with which it competes for faculty. Let $\overline{s}_{ic}$ denote the mean royalty share in the set of universities competing with university i. We represent sorting in a simple but intuitive way: the impact of

[12] Recall, however, that most royalty distribution schemes for universities in our sample were set before the start of the sample period (1991) and, in many cases, they were never changed since the foundation of the TLO.

[13] 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."

sorting on the (log) license revenues 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 $\frac{\partial \phi}{\partial \overline{s}_{ic}} \leq 0$. Using a linear form $\phi(s_i, \overline{s}_{ic}) = \rho_1 s_i + \rho_2 \overline{s}_{ic}$ with $\rho_1 \geq 0$ and $\rho_2 \leq 0$, we can write the expanded model which incorporates both the effort and sorting mechanisms as

$$\log R_i = (\delta + \rho_1)\, s_i + \rho_2 \overline{s}_{ic} + x\beta + u \tag{3}$$

As before, δ captures the pure effort effect of royalty shares, while ρ_1 and ρ_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, ρ_1 is not identified, but we can conduct a partial test of the "no-sorting hypothesis" by testing $\rho_2 = 0$. If this is rejected, then the coefficient on s_i captures both the effort and sorting effects of royalty shares.

To address the potential endogeneity of royalty shares arising from unobserved heterogeneity (e.g., the reverse causality issue mentioned above), we use pre-sample information on the patenting activity of universities. Blundell, Griffith and van Reenan (1999) show that the pre-sample mean of the dependent variable is a consistent estimator (in the time dimension) of the fixed effect in the regression. Thus adding the pre-sample mean as a regressor controls for any endogeneity arising from this unobserved heterogeneity. Since we do not have pre-sample information on license revenues, we use instead pre-sample data on patenting (both patent counts and citations).

Another possible bias arises from the researcher's choice between reporting the invention and sharing the license revenues with the university, or not reporting it and commercializing it outside (e.g., by forming a private start-up company). If this nonreporting error is negatively correlated with the royalty share (a reasonable assumption), then part of the observed rise in license revenue from an increase in the royalty share reflects inventors now reporting previously unreported inventions, and the estimator of $\delta + \rho_1$ would be biased upward. With the available data we cannot identify the magnitude of this misreporting bias but, because university faculty have a contractual obligation to report inventions to the TLO, the bias is unlikely to be large. Of course, from the financial perspective of the university, both the incentive effect and the reporting effect of royalty shares are relevant since they jointly determine how much license income the university actually earns.

3.1 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 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, θ. In the extreme case where $\theta = 0$, the share apportioned to faculty will not matter at all.[14]

There are good reasons to believe that private universities are 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.[15]

[14]Using (1) we get

$$\frac{\partial R}{\partial s} = \theta F v_0 \left[H(s,\theta)\{n(s,\theta)\psi' \frac{\partial q}{\partial s} + \psi(s,\theta)\frac{\partial n}{\partial s}\} + \psi(s,\theta)n(s,\theta)\frac{\partial H}{\partial s} \right]$$

where $H(s,\theta) \equiv \int_{\frac{v}{\theta v_0 \psi(q(s,\theta))}}^{\infty} \varepsilon dG(\varepsilon)$. 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 θ 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 $g(v)$ not increase too much in v.

[15]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

Table 3 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.[16] 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 support the hypothesis that the parameter θ is larger in private universities than in public ones, on average. This finding has two 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 coefficients on TLO size and age should be larger for private universities.

4 Empirical Results

4.1 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 income is not very responsive to economic incentives at the low range of the royalty shares, this is strikingly

57 were in the regression sample. The results of this survey will be analysed more fully in another paper.

[16] 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."

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.

4.2 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. We allow for arbitrary heteroskedasticity and serial correlation within universities (standard errors are clustered at the university level).[17]

We begin by comparing 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 4 presents estimates for equation (3) 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 estimated incentive effect, however, is more than twice as large in private universities, and this difference will hold for all alternative specifications.

In columns (2) and (6) we add the average shares of "competing" universities to the

[17]There is one estimation issue that arises from the computation of the expected royalty share for universities with nonlinear royalty schedules. The density estimates used to compute the expected royalty share are based on the observed unconditional distribution of license income per disclosure. However, the model says that the distribution of license income per disclosure depends on the control variables s and x. To account for this, we used an iterative procedure whereby we use the residuals from an initial license income per disclosure (i.e., v) regression to recompute the kernel density estimates and the expected royalty shares. We found that after one iteration the average difference in the computed royalty shares for the nonlinear schedules was only 1.3 percentage points, or about 2.8 percent of the mean royalty share, and the estimated coefficients were very close to those obtained using the expected royalty shares based on the unconditional distribution of v. We report the parameter estimates based on the unconditional distribution.

regressions. This specification incorporates both the effort and sorting mechanisms into the model, as discussed in Section 3. 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.[18] 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 groups of two competing universities (Table 7 presents robustness results for groups of four competitors). It is very striking that the estimate of ρ_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_i - 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.[19]

These large effects are not driven by the skewness of the license income distribution discussed in Section 2. Columns (3) and (7) present the estimates obtained by using median regression to account for outliers. For private universities we get similar, large incentive and sorting effects, while the median regression substantially reduces the point estimate of the incentive effect for public universities. As an alternative way to address outliers, we re-estimated the model dropping the top license income earners: Stanford and Columbia Universities in the private university sample, and the University of California System in the public sample (not reported for brevity). The estimated incentive effects were 4.2 (s.e.=2.35) and 2.3 (s.e.=1.35) in the private and public regressions, respectively.

Finally, in columns (4) and (8) we present estimates, for the model with both effort

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[18]In the survey of TLO directors discussed in Section 3.1, 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.

[19]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.

and sorting, using pre-sample information on university patenting to control for the correlation between royalty shares and unobserved heterogeneity.[20] We adopt the approach developed by Blundell, Griffith and van Reenen (1999). They show that, under certain assumptions, the pre-sample mean of the dependent variable is a consistent estimator of the unobserved, fixed heterogeneity, and thus it can be used as an additional regressor to control for such heterogeneity. In our context, this means using the pre-sample mean of license revenues as a way to control for the endogeneity arising from unobserved, fixed university effects. Since we do not have pre-sample information on license revenues, we use instead pre-sample data on patenting (both patent counts and citations).[21] Since patents are an intermediate output of the invention process, which then generate license income, it is reasonable to assume that they are determined by the same factors generating license income. As a check on this we examined the cross-sectional correlation between patent counts (citations) and license revenue within the sample period (1991-99) and found that it is, in fact, very high, ranging between 0.65 and 0.79 for private universities and between 0.60 and 0.72 for public universities.

The 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 – and makes the estimated incentive effect in public universities not significantly different from zero.

It is clear from these results that royalty shares have a positive incentive effect on license revenue both for private and public universities. The estimated effect is strongly significant in private universities, but less precisely estimated in public universities. 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 sizeable 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 inventive activity. In view of all the other determinants for

[20] 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 very weak, resulting in nonsensical 2SLS estimates.

[21] We actually use the log of one plus the number of patent counts or citations so as not to discard universities with zero citations (see Section 5).

which we control, it is striking that we can still pin down an empirical relationship between license income and royalty shares. Furthermore, the incentive effect is more than twice as large in private institutions than in public universities. These results confirm the non-parametric findings 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 affects faculty responsiveness to such incentives.

The other striking finding concerns the effectiveness of the TLO. The estimated elasticity of TLO size on license income is much larger in private universities than in public ones. 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 almost 6 percent increases but has no significant effect in public universities.[22] 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 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 3.1.

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, once we control for pre-sample patenting activity (without this control for endogeneity, the medical dummy is significantly positive for both private and public universities).

We use a variable to control for differences in potential demand for licenses by private

[22] We use TLO per faculty since this is what is relevant for the scientist as a determinant of θ. 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.

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).[23] 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. This finding is consistent with our survey evidence that TLO's are more free from government constraints in private universities. Of course, the fact that local demand conditions matter at all indicates the importance of structuring technology transfer institutions so that they can more effectively exploit demand for inventions in non-local areas. For this purpose, specialization of TLO's by university (the current arrangement) may be inferior to alternatives such as having TLO's that specialize by technology area and serve multiple universities.

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). Surprisingly, we cannot reject the hypothesis that there are no technology field differences (p-value 0.52 and 0.46 in private and public universities), once we have controlled for R&D and other characteristics.

The parameter estimates from Table 4 imply 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 public and private institutions, respectively. In fact, raising the royalty share for inventors 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 will such a 'Laffer effect' for universities with sufficiently low royalty rates, in particular when $s < s^* \equiv 1 - (\delta + \rho_1)^{-1}$. For private universities, $s^* = 0.78$, and the Laffer effect holds for most of them. For public universities, $s^* = 0.48$, which holds for

[23] 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.

about half of these universities. This finding raises an important question of why universities do not exploit the Laffer effect by increasing inventor royalty shares. Apart from not knowing this potential exists, universities may have other objectives and constraints, among them fairness, entrenched interests, and remaining competitive with other universities.[24] An analysis of these issues is beyond the scope of this paper.

4.3 Incentive effects on the quantity and quality of inventions

License revenue per faculty depends both on the number of inventions and their value. Even with the available data at the university level, we are able to distinguish between the quantity (n) and the quality (v) components of the royalty share effect on license revenue. Let L be the the number of licenses obtained from Fn inventions, $L = Fn(z(s,\theta))\left[1 - G\left(\frac{v}{\theta v_0 \psi(q(s,\theta))}\right)\right]$. Using (1) and $R = Fr$ we can write

$$R = L \times \theta v_0 \psi(q(s,\theta)) E\left(\varepsilon | \varepsilon > \frac{v}{\theta v_0 \psi(q(s,\theta))}\right) \tag{4}$$

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 5 presents results for a log version of equation (4). We measure L by the 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.[25] 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

[24] Of course, if a university believes that its competitors will follow suit the Laffer effect is diminished. Taking the competitive effect into account, the threshold for the Laffer effect is $s^* = 1 - (\delta + \rho_1 + \rho_2)^{-1}$. This is reduced to 0.50 and 0.15 for private and public universities, respectively. Even without a Laffer effect, 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).

[25] 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 (4) once L is included.

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 – 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 number of licenses against royalty incentives and the various control variables.

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 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.[26] 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.

4.4 Incentive effects: Interactions with faculty quality and tenure

In this section we examine whether the incentive effect of royalty shares varies with faculty quality or with the extent to which faculty is tenured. First, it is often argued that faculty at more prestigious institutions are likely to be motivated mainly by scientific recognition and status rather than by monetary rewards. In the model this takes the form of a lower marginal utility of license revenue in higher quality universities. To test this, we include interactions terms between the inventor royalty share and dummy variables for the lowest, the middle two, and highest quartiles of the citations per faculty distributions (columns (1) and (3), Table 6). In support of the popular view, we find that the incentive effects of royalty shares declines with university quality. For private universities, the estimated coefficient declines from 6.8 in the

[26]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 5.

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 s. This is particularly interesting, since the baseline estimate of the incentive effect for public universities was not significantly different from zero (Table 4).

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.[27] 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).[28] As columns (2) and (4) in Table 6 show, the hypothesis is confirmed for 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. There is no support for the hypothesis in private universities.

5 Robustness Checks

In this section we discuss the robustness of the empirical results for the baseline model to various specification changes. The top panel in Table 7 shows that the estimated incentive effects are robust to using pre-sample patent count data to control for endogeneity of royalty shares, instead of pre-sample patent citations. Column (1) replicates the results of the baseline specification (column (4) in Table 4). As before, the pre-sample controls are strongly significant. The incentive effects are somewhat larger and more precisely estimated when we use patent counts rather than citations. Introducing a dummy variable for universities that had zero pre-sample patents or citations does not change this conclusion.

The bottom panel of the table is based on using a set of four competing universities in the specification for sorting (i.e., two universities on each side of university i in the distribution

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

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

of citations per faculty). This reduces the estimated incentive effect in private universities by about 20 percent, but it remains large in absolute terms and statistically significant. In addition, the competition effect in private universities is now increased. In public universities there is a smaller change in the point estimates, but they remain not significant.

Both panels corroborate the conclusions reached from Table 4. First, royalty shares have a positive and significant effect in private universities, about twice as strong as in public universities. Second, the incentives offered by competing universities reduce license revenues. Third, pre-sample patent data is important for controlling unobserved heterogeneity.

We performed two additional specification checks but, for the sake of brevity, we omit the regression results. First, 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 ρ_2 are -2.71 (s.e.=1.31) and -1.25 (s.e.=1.32) for private and public universities, respectively.

Second, 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.[29] 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.

[29] 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.

6 Concluding Remarks

In this paper we exploit cross-university variation in the share of license royalties received by academic scientists in order to estimate the effect of monetary incentives on license income generated by the inventions. There are three main findings. First, universities that give higher royalty shares to academic scientists generate greater license income, controlling for other factors including university size, quality, research funding, and local demand conditions. This finding is robust to pre-sample patent data used to control for the endogeneity of royalty shares. This finding is important because it implies that the design of intellectual property rights in academic institutions, and presumably other forms of incentives, can have real effects. Second, we find that these incentive effects appear to work both by increasing effort and by sorting of scientists across universities. We also show that the incentive effects work primarily by increasing the quality, rather than the quantity of inventions.

Third, the response to royalty incentives, and the effectiveness of technology licensing offices, are much larger in private universities than in public ones. We argue that this is due to a "gatekeeper effect": TLO's in private universities are more effective at commercializing inventions than in public universities. Because the inventor must go through the university TLO to commercialize the invention (unless expressly waived), this difference in TLO effectiveness translates into a higher incentive effect of higher royalty shares at private universities. We provide survey evidence on the incentives, constraints and objectives within TLO's in public and private universities that are consistent with this claim.

There are many possible avenues for further research in this area. One is to extend the empirical analysis to universities in other countries, but to our knowledge there is no counterpart to the AUTM so this effort will involve a major data construction effort. A second important avenue is to model university behavior and the academic labour market, incorporating pecuniary incentives (salaries and royalties), multi-tasking and career concerns. Such a model could be used as the basis for more detailed studies of incentives and university research using micro-data on academic scientists.

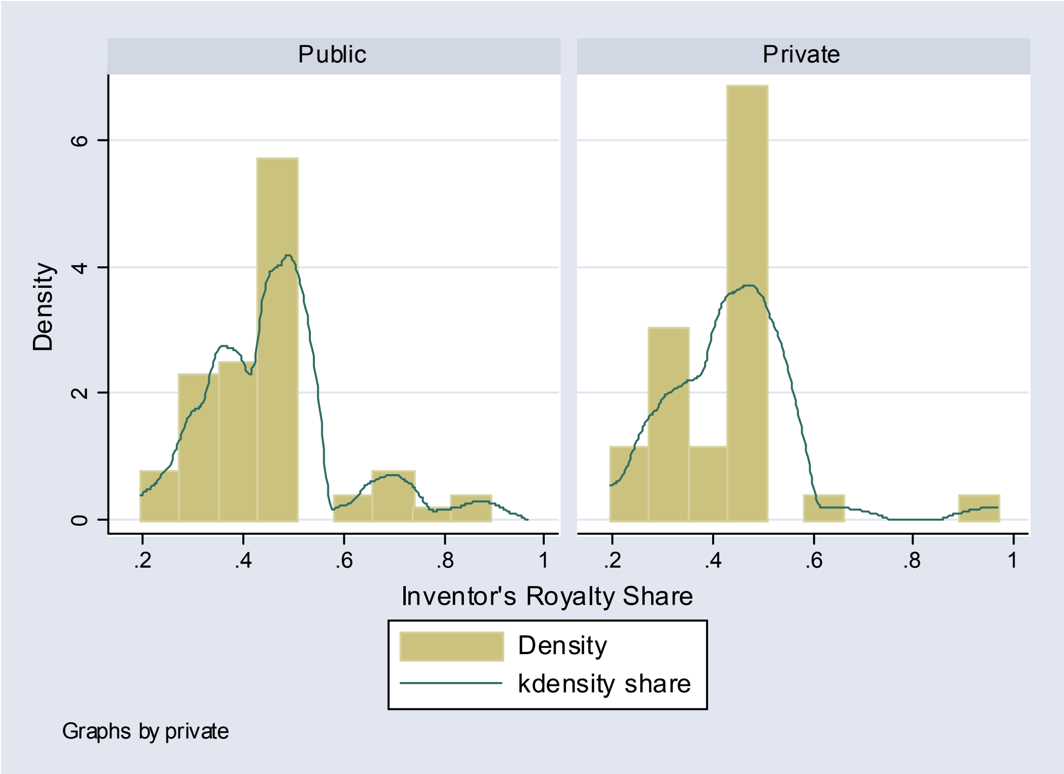

Figure 1: Distribution of Expected Inventor's Royalty Share

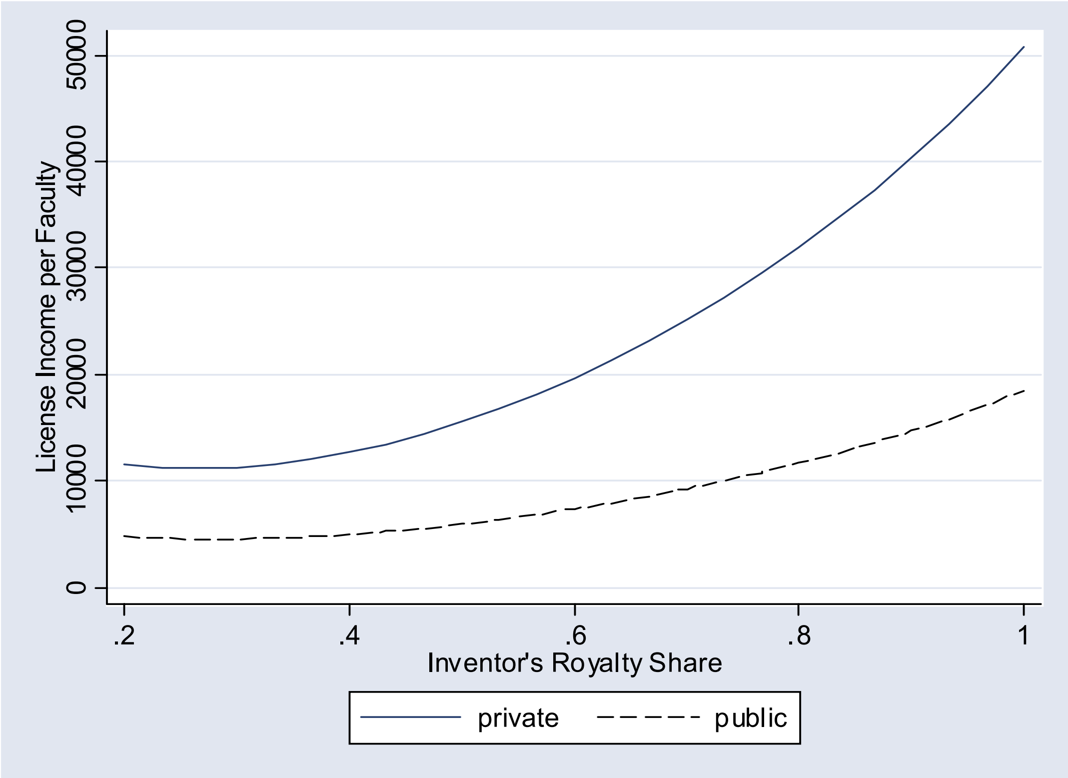

Figure 2: Plot of $E\left(\frac{R}{F} \mid s\right)$

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[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. Incentives, Constraints and Objectives in Public and Private 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 4 . License Revenue Equation (eq.(3)): Baseline Specifications

	Private Universities				Public Universities			
Determinants of Incentives	1	2	3	4	5	6	7	8
Royalty Share	5.84***	5.26***	5.30***	4.52**	2.30*	2.32*	1.39**	1.93
	2.16	1.98	1.69	2.04	1.35	1.36	0.66	1.46
Competitors' Royalty Share	--	-3.37**	-3.35**	-2.54*	--	-0.52	0.25	-1.06
		1.38	1.29	1.35		1.51	0.77	1.42
Log (TLO/Faculty)	0.56**	0.61***	0.61***	0.55**	-0.09	-0.10	-0.03	-0.24
	0.26	0.23	0.24	0.22	0.15	0.16	0.11	0.16
Age TLO	0.17***	0.19***	0.21***	0.13***	0.03	0.03	0.02	0.04
	0.05	0.05	0.04	0.05	0.03	0.03	0.02	0.03
Age TLO squared	-0.002**	-0.003***	-0.003***	-0.002***	-0.0001	-0.0001	0.0001	-0.0002
	0.001	0.001	0.001	0.001	0.0004	0.0004	0.0002	0.0004
Pre-sample Control								
Log (Average Patent Cites)	--	--	--	0.53**	--	--	--	0.41***
				0.24				0.12
Other Controls								
Log (Faculty Size)	0.65	0.89*	0.44	0.74	1.25***	1.26***	1.07***	0.74***
	0.58	0.46	0.46	0.48	0.18	0.19	0.13	0.23
Publication Cites/ Faculty	0.01	0.01	0.008**	0.00	0.00	0.00	0.010**	0.00
	0.01	0.01	0.004	0.01	0.01	0.01	0.005	0.01
Log (R&D/Faculty)	0.15	0.02	0.07	0.04	0.53**	0.53**	0.36*	0.63***
	0.36	0.31	0.23	0.27	0.21	0.22	0.19	0.22
Medical School Dummy	1.81*	1.17	1.69**	0.55	0.24	0.24	0.53***	0.11
	0.94	0.80	0.77	0.93	0.37	0.38	0.20	0.35
High-Tech, first quartile	-0.39	-0.27	-0.83	0.36	0.54	0.56	0.34*	0.75**
	0.56	0.58	0.51	0.72	0.36	0.37	0.21	0.35
High-Tech, fourth quartile	0.69*	0.75**	0.60**	0.64*	0.31	0.32	0.49*	0.40
	0.39	0.31	0.25	0.33	0.34	0.34	0.27	0.39
Share Biomedical	0.0004	0.0110	0.0141	0.0112	0.0078	0.0091	-0.0084	0.0170
	0.0202	0.0187	0.0155	0.0197	0.0148	0.0144	0.0124	0.0142
Share Other Biological	-0.0066	0.0175	0.0032	0.0243	-0.0118	-0.0121	-0.015**	-0.0007
	0.0288	0.0278	0.0264	0.0291	0.0135	0.0133	0.0071	0.0134
Share Computer Science	-0.0025	0.0256	0.0087	0.0234	0.0130	0.0143	0.0053	0.0257
	0.0698	0.0611	0.0573	0.0587	0.0219	0.0213	0.0223	0.0196
Share Chemical Science	0.1166*	0.1111**	.1611***	0.0686	0.0049	0.0077	-0.0082	0.0108
	0.0627	0.0470	0.0459	0.0468	0.0160	0.0162	0.0109	0.0140
Share Engineering	0.0466**	0.0506***	0.0463	0.0294*	0.0120	0.0123	0.0050	0.0160
	0.0200	0.0186	0.0144	0.0174	0.0168	0.0165	0.0101	0.0163
R^2	0.75	--	0.78	0.79	0.62	--	0.66	0.66
Number of Observations	246	246	246	246	462	462	462	462

Notes: Columns (3) and (7) are median regressions. Year dummies included in all regressions. Standard errors clustered by university in small numerals except in the median regressions where they are bootstrapped.
*** , **, * significant at the 1, 5, and 10 % level, respectively.

Table 5 . Incentive Effect on Invention: Quantity vs Quality

	Private Universities			Public Universities		
	1	2	3	4	5	6
Dep. Variable	Log Revenues		Log Licenses	Log Revenues		Log Licenses
Determinants of Incentives						
Log (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
Log (TLO/Faculty)	0.95***	0.50**	0.49***	-0.27	-0.50***	0.17**
	0.24	0.22	0.13	0.21	0.20	0.10
Age TLO	0.16***	0.07	0.11**	0.03	0.02	0.03*
	0.05	0.07	0.04	0.03	0.03	0.01
Age TLO squared	-0.003***	-0.001	-0.002***	-0.000	-0.000	-0.000
	0.001	0.001	0.001	0.0002	0.0004	0.0002
Pre-sample Control						
Log (Average Patent Cites)	0.40	0.50	0.09	0.40***	0.37***	0.20*
	0.27	0.31	0.17	0.12	0.13	0.07
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 4 are included in all regressions but are not reported, 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 6. Quality and Tenure Interactions with Incentive Effects

	Private Universities		Public Universities	
	1	2	3	4
	Quality quartiles	Tenure quartiles	Quality quartiles	Tenure quartiles
Determinants of Incentives				
Royalty Share (1st quartile dummy)	6.84**	5.08**	3.65**	1.80
	2.99	2.01	1.85	1.76
Royalty Share (2nd & 3rd quartile dummy)	4.81**	4.31**	1.62	1.21
	2.10	1.74	1.03	1.20
Royalty Share (4th quartile dummy)	4.505**	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
Log(TLO/Faculty)	0.55***	0.49**	-0.27*	-0.15
	0.21	0.19	0.16	0.15
Age TLO	0.14***	0.17***	0.03	0.02
	0.05	0.06	0.03	0.03
Age TLO squared	-0.002***	-0.002***	-0.000	-0.000
	0.001	0.001	0.000	0.000
Pre-sample Control				
Log Average Patent Cites	0.54**	0.36	0.41***	0.42***
	0.23	0.28	0.11	0.11
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 4 are included in all regressions but are not reported.
Standard errors clustered by university in small numerals.
*** , **, * significant at the 1, 5, and 10 % level, respectively.

Table 7 . Robustness to Pre-sample Controls and Competitors' Groups

Sorting Based on 2 Competing Universities	Private Universities				Public Universities			
	1	2	3	4	5	6	7	8
Determinants of Incentives								
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
Pre-sample Controls								
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

Sorting Based on 4 Competing Universities	Private Universities				Public Universities			
	1	2	3	4	5	6	7	8
Determinants of Incentives								
Royalty Share	3.61*	3.49*	4.07**	3.83**	1.91	1.90	2.22	2.25
	2.09	2.05	2.11	2.07	1.47	1.42	1.54	1.53
Competitors' Royalty Share	-3.24	-3.57	-4.38**	-4.40**	-1.33	-1.34	-0.85	-1.05
	2.42	2.42	2.34	2.33	1.7	1.64	1.52	1.5
Pre-sample Controls								
Log (Average Patent Cites)	0.55**	0.43*			0.40***	0.53***		
	0.24	0.26			0.13	0.13		
Dummy for Zero Cites	--	-3.10***			--	1.28**		
		0.92				0.54		
Log (Average Patents)	--	--	0.4	0.36	--	--	0.59***	0.61***
			0.39	0.39			0.23	0.23
Dummy for Zero Patents				-3.91***				0.86
				0.80				0.86
R^2	0.78	0.79	0.77	0.79	0.66	0.67	0.66	0.66
Number of Observations	246	246	246	246	462	462	462	462

Notes:Competing universities defined by their ranking of publication citations per faculty.
All other control variables appearing in Table 4 are included in all the regressions but are not reported.
Standard errors clustered by university in small numerals.
*** , **, * significant at the 1, 5, and 10 % level, respectively.

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Appendix: Description of the 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 the 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 IP 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 4-7 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.

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