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US universities' net returns from patenting and licensing: a quantile regression analysis

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Consistent with the rights and incentives provided by the Bayh–Dole Act of 1980, US universities have increased their involvement in patenting and licensing activities through their own technology transfer offices. Only a few US universities are obtaining large returns, however, whereas others are continuing with these activities despite negligible or negative returns. We assess the US universities' potential to generate returns from licensing activities by modeling and estimating quantiles of the distribution of net licensing returns conditional on some of their structural characteristics. We find limited prospects for public universities without a medical school everywhere in their distribution. Other groups of universities (private, and public with a medical school) can expect better but still fairly modest returns. These findings call into question the appropriateness of the revenue-generating motive for the aggressive rate of patenting and licensing by US universities.

Keywords: bayh–dole act; quantile regression; returns to innovation; skewed distributions; technology transfer; university patents

JEL Classification: C13; L31; L33; O31; O32

1. Introduction

Some critical policy shifts strengthening intellectual property rights (IPRs) in the United States have taken place over the last quarter century. These include the Bayh–Dole Act of 1980, which made it possible for universities to retain title to patents derived from federally funded research, as well as the establishment of the Court of Appeals for the Federal Circuit in 1982 and some critical US Supreme Court decisions. Concomitant with these pro-IPR policy shifts, more and more US universities have became directly involved in licensing activities. The number of universities with a technology transfer office (TTO) increased from 25 in 1980 to 200 in 1990, and by 2000 virtually every US university had such an office (Nelson 2001). A 15-fold increase in university patenting and a more than 5-fold increase in the number of universities granted patents were observed between 1965 and 1992 (Henderson et al. 1998). This trend in US universities' patenting and licensing activities has accelerated in the last decade (Sampat 2006). US patents issued to 69 US

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universities that are 9-year recurrent respondents to Association of University Technology Managers (AUTM) surveys increased 129% between 1993 and 2001. Licenses and options executed by 55 US universities that are 11-year recurrent respondents to AUTM surveys increased 139% between 1991 and 2001, and their gross license revenue increased 485% between 1991 and 2001. The aggregate gross license revenue obtained by all US universities approached $1 billion in FY 2002 (AUTM 2002).

This growth in university patenting and licensing activities has generated considerable attention in economic research (Jaffe 2000; Nelson 2001; Mazzoleni and Sampat 2002; Link et al. 2003; Mowery et al. 2004; Mazzoleni 2005; Sampat 2006). Issues considered include whether these activities have affected the traditional role of universities, typically understood to be the advancement of science and the dissemination of knowledge; whether Bayh–Dole was necessary to induce technology transfer and provided the right incentives for universities; and the social welfare implications of university patenting.

The underlying presumption of Bayh–Dole is that without (exclusive) licensing arrangements, firms would not undertake the follow-up investment to bring an invention to the marketplace as products or services. Mazzoleni (2005) showed that this presumption is too general and its validity depends on innovation-specific conditions. If the disclosure by universities does not prevent the downstream firms from patenting the developed product, licensing the invention could be welfare enhancing only if firms engage in socially excessive R&D under open access.[1] Although the Act was intended for inventions that would not be developed and commercialized without patenting and licensing, universities obviously can exploit their rights more generally for all patentable inventions. The Cohen–Bayer recombinant DNA technique (licensed by the University of California and Stanford University) and Richard Axel's co-transformation process (licensed by Columbia University) are examples of university inventions for which technology transfer would certainly have occurred absent patenting and licensing. University licensing in these cases has simply taxed industry, and ultimately consumers, for use of these technologies (Sampat 2006). Quite clearly, when it comes to patenting and licensing, universities are likely to behave based on their self-interest rather than the public interest. Beath et al. (2003) considered the possibility that universities, with reduced state and federal financial support, could provide incentives to faculty to engage in activities that can augment inventors' incomes. Furthermore, TTO managers as agents may have short-term horizons and give priority to monetary returns in their activities. In fact, based on a recent survey of 76 major US universities, the licensing income generated is found to be the most important criterion by which TTO offices measure their success (Thursby et al. 2001).

Because increased revenue is one of the considerations motivating universities in this context, a relevant question concerns the extent of net returns that universities are collecting from these activities. Figure 1 presents the distribution of net license returns (license revenues received less the net legal fees paid and the operating cost of TTOs, in million dollars) for 148 US universities, averaged over the 5-year period 1998–2002 (see the data section for details). It is apparent that only a few universities are earning large returns. In fact, the top 20 universities obtain 83% of the aggregate net license returns generated, whereas most of the other universities earn negative or negligible net returns. Figure 2 presents the distribution of the net license returns as a percentage of the university's total research expenditures. This distribution is also highly skewed: the ratio is high for only a few universities, whereas it is <5% for the majority of them (90%).[2]

The overall picture is that of a few universities generating significant returns, whereas the majority of universities continue licensing activities even though they appear to earn negative net returns or just break even. Obviously, these universities are hoping to do better in

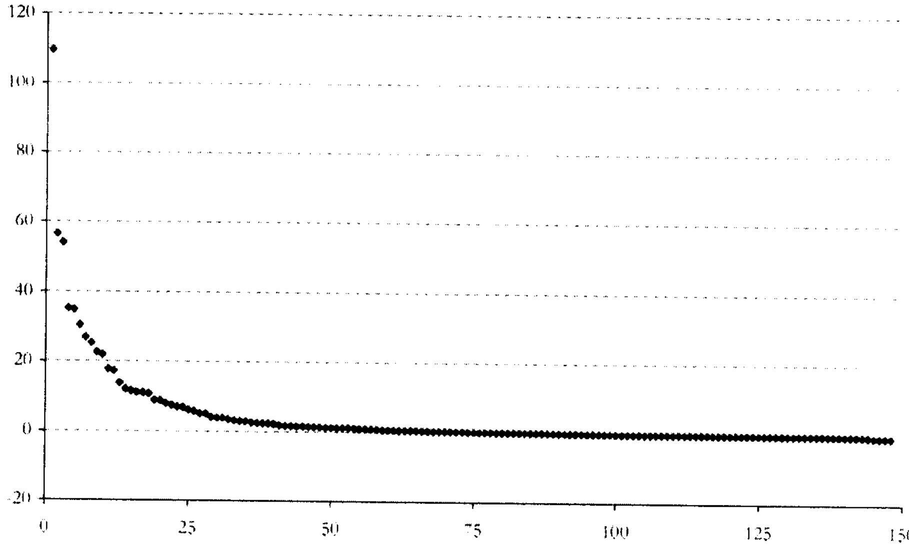

Figure 1. Net licensing returns of US universities, 1998–2002 (in million dollars).

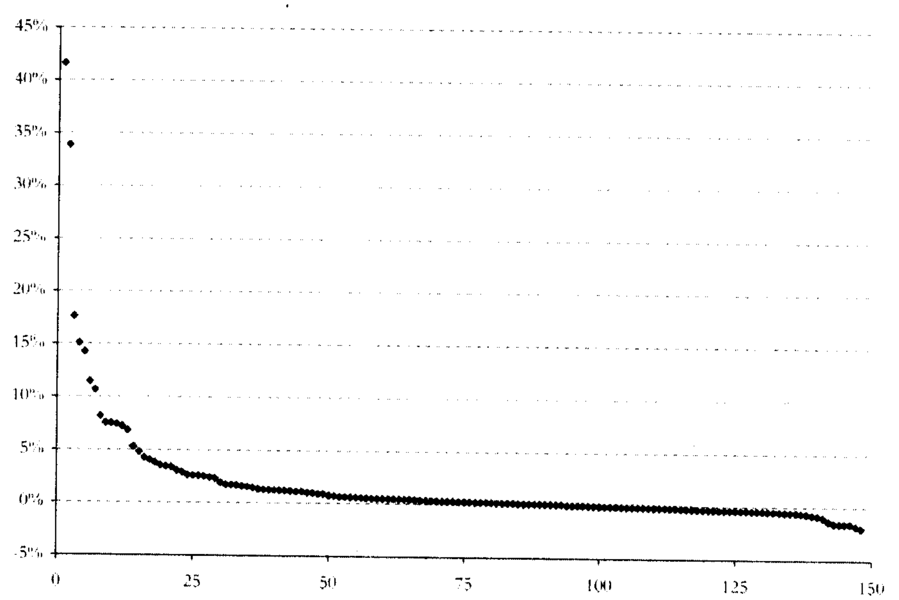

Figure 2. Net licensing returns as a fraction of total research expenditures of US universities, 1998–2002.

the future, an expectation perhaps predicated on the very asymmetric distribution of returns discussed earlier. As might be suggested by Jovanovic's (1982) theory of 'noisy' selection with incomplete information (wherein new entrants in any industry are likely to be less sure about their efficiencies and more likely to fail), new TTO offices are perhaps discovering their efficiency in generating net returns from licensing activities as they operate, and are likely to be (and perhaps remain) unprofitable.

Given the examples of big winners among universities, what can others, conditional on their characteristics, anticipate as the potential for generating economic return? This question has not been addressed in a coherent econometric study in the literature, and thus we wish to address it directly in what follows. Related existing work includes Trune (1996), who analyzed the licensing activities of US universities with the purpose of developing a 'national criterion' with which universities can measure their performance. Trune and Goslin (1998) calculated the profitability of technology transfer programs of universities and found that nearly 60% of the universities are earning negative profits from maintaining TTOs. Siegel et al. (2003) did a productivity analysis of TTO performance in terms of license revenues (taken as a proxy for technology transfer activities) by using the stochastic frontier estimation approach. Lach and Schankerman (2004) found that universities with higher royalty shares to inventors generated significantly higher license revenues.

2. The modeling framework

In order to assess the potential of US universities in generating economic returns from licensing activities given their characteristics, we model and estimate the select quantiles as linear functions of a set of characteristics of universities. We take this route because the conventional conditional mean analysis may not adequately convey the potential for private returns to universities when, as is the case here, the distribution of net economic returns of US universities is highly skewed. This skewness is apparent from the data reported in Table 2. Fifty percent of the US university population earns less than \$0.31 million, whereas the average net return is \$4.42 million.[3] The standard deviation is large; 75% of the population obtains less than half of the mean, which implies that the mean is strongly influenced by the upper 10% of the population.

In addition, the quantile regression helps us to describe the entire conditional distribution. By taking this approach, we can look at the impacts of covariates at different points in the distribution. We are interested in how the marginal impacts of covariates vary with the ranking of universities in terms of generating licensing return (in the case of the conditional mean estimation the slope coefficients are forced to be the same at all quantiles). Assuming a particular skewed distribution and parameterizing its mean does not seem to be a promising avenue either. There is no consensus over a specific distribution governing the innovation process *per se*. Based on various data on citation and value measures of patent significance, which includes license revenue data of Harvard University, Silverberg and Verspagen (2004) find that overall fit of the distribution resembles log normal, whereas the Pareto distribution fits the tails better. They note the implication that the second and even the first moments of underlying distributions may not even exist. With quantile regression, the existence of moments is not a concern because the focus is on quantiles, and every distribution has quantiles.

2.1. *Quantile regression*

The basic quantile regression model (Koenker and Hallock 2001) assumes that the conditional quantiles are linear functions of the explanatory variables. Assume that we have a sample of N observations from a population, that is, $\{(y_i, x_i) : i = 1, \ldots, N\}$, where the subscript i indexes each observation, y_i is the licensing return, and x_i is the $K \times 1$ vector of explanatory variables (a set of characteristics), which can include the intercept term. Moreover, let $\tau \in (0, 1)$ define the quantile of interest; let $\beta(\tau)$ be the corresponding parameter vector for the vector of characteristics that vary with quantiles; and let $Q_\tau(.)$ be the quantile function, which is defined as the inverse function of $F(.)$, the underlying conditional (on x_i) cumulative distribution function for y_i. Then the quantile of interest is written as a linear function of a set of characteristics as

$$y_i = x_i'\beta(\tau) + u_i(\tau) \tag{1}$$

$$Q_\tau(y_i|x_i) = x_i'\beta(\tau) \tag{2}$$

where $u_i(\tau)$ denotes the error term, which is also a function of the quantile of interest (Buchinsky 1998; Koenker 2005). Based on the preceding two equations, error terms must satisfy the quantile restriction

$$Q_\tau(u_i(\tau)|x_i) = 0 \tag{3}$$

The parameter estimates for the τth sample quantile minimizes the weighted absolute deviations (the errors); that is

$$\underset{\beta \in \mathbb{R}^K}{\mathrm{Min}} \left[\sum_{i \in \{i: y_i < x_i\beta\}} \tau |y_i - x_i\beta| + \sum_{i \in \{i: y_i \geq x_i\beta\}} (1-\tau)|y_i - x_i\beta| \right] \tag{4}$$

where $|.|$ is the absolute value operator and the other notation as defined before. For $\tau = 0.5$, one would weigh deviations equally, which is known as median regression. Weights differ for other quantiles, such as $\tau = 0.75$; one would weight positive deviations with 0.25 whereas one would weight negative deviations with 0.75. The rationale for the suggested weights in Equation (4) is as follows. Recall that the τth quantile denotes the maximum value that y_i can take with given probability τ. Then, the probability to observe a value less than the quantile is τ, whereas the probability to observe a value beyond that quantile is $(1 - \tau)$.

Quantile regression has emerged as a comprehensive method and found applications in various fields of economics, including labor economics, wealth distribution, and various disciplines such as finance, medicine, demographics, and environmental modeling (see Fitzenberger et al. 2002; Yu et al. 2003). In particular, quantile regression has found use in the finance literature via the notions of value at risk (VaR_τ) and conditional value at risk (CVaR_τ) (Uryasev and Trindade 2004). Based on a given loss distribution, VaR_τ is the maximum amount one can lose at a given probability τ, i.e., the τth quantile. CVaR_τ is defined as the expected value of loss beyond a VaR_τ. Rockafellar and Uryasev (2000) show that CVaR_τ has better properties as a measure of risk.

Instead of loss distribution typically used in VaR_τ and CVaR_τ literature, here we work with gain distribution. Estimating a given quantile then shows the maximum amount a university can gain at a given level of probability. In order to estimate the expected value beyond a given quantile (CVaR_τ), we use the relations derived in Uryasev and Trindade (2004). First, define functions $[.]^+$as $[v]^+ \equiv \max\{v, 0\}$ for generic variable $v \in \mathbb{R}$, and denote the estimated τth quantile (VaR_τ) with $\hat{Q}_\tau(y|x)$. Then the relation of interest is

$$E(y|y \geq \hat{Q}_\tau(y|x)) = \hat{Q}_\tau(y|x) + \frac{1}{(1-\tau)} E([y - \hat{Q}_\tau(y|x)]^+) \tag{5}$$

For a sample of N observations from a population, y_i for $i = 1, \ldots, N$, one can estimate the expectation on the right-hand side of Equation (5) with the method-of-moments approach as

$$E([y - Q_\tau(y|x)]^+) = \frac{1}{N} \sum_{i=1}^{N} [y_i - \hat{Q}_\tau(y|x)]^+ \tag{6}$$

Inserting Equation (6) into (5) yields the desired estimate.

2.2. Data

Table 1 lists the variables that we use in our analysis, along with their brief descriptions, and Table 2 provides summary statistics. Our data pertain to 148 US universities over the 5-year period from 1998 to 2002 and are aggregated at the university level.[4] We compute the annual averages of the time-varying variables (both dependent and explanatory variables) over the sample period. This approach is also adopted in Siegel et al. (2003).

The dependent variable of our model is the net licensing return for each university. This is calculated as the total license revenue less the cost of patenting and licensing activities. The cost is measured as the sum of net legal fee expenditures (legal fees expended less legal fees reimbursed) and operating expenditures of TTOs (salary expenses plus benefits to the employees and overhead cost).[5] The net licensing return variable is averaged over the sample period 1998–2002. The source for the license revenue and legal fees reimbursed and expended is AUTM (1998–2002) surveys. To compute the cost of operating expenditures of TTOs, we relied on employment data from AUTM surveys and used salary data from College and University Personnel Association (CUPA) administrative compensation surveys. CUPA surveys provide data for the top two positions in TTOs for the period 1998–2002. Note that the cost items considered here do not include the opportunity cost of time of faculty who are involved in patent and licensing activities, and therefore the real cost to universities of their patenting and licensing activities is underestimated.

The explanatory variables that we use in our model are meant to capture some basic structural characteristic that, at least in the short run, may be considered as exogenous. These variables are as follows:

(a) *Whether a university is public or private, and whether or not it has a medical school.* These are dummy variables constructed from information provided by AUTM surveys.
(b) *Log of size of the university.* Natural logarithm of size of the university, whereby size of the university is measured by total research expenditures and averaged over the sample period 1998–2002. The data source is AUTM (1998–2002) surveys.

Table 1. Description of variables.

Variable	Description
Net returns (y)	Licensing return in a given university (averaged over the sample period 1998–2002 and in million dollars)
Public and no medical (x_1)	Dummy variable, which takes value of 1 if university is public and does not have medical school, and 0 otherwise (base case)
Private and no medical (x_2)	Dummy variable, which takes value of 1 if university is private and does not have medical school, and 0 otherwise
Public and medical (x_3)	Dummy variable, which takes value of 1 if university is public and has medical school, and 0 otherwise
Private and medical (x_4)	Dummy variable, which takes value of 1 if university is private and has medical school, and 0 otherwise
Log of size (x_5)	Natural logarithm of the average total research expenditures (in million dollars) over the sample period 1998–2002
Log of faculty quality (x_6)	Natural logarithm of total number of citations received per faculty in technology departments in a given university (evaluated in 1993)
Local industrial R&D (x_7)	Industry-performed R&D as share (%) of private industry output in the state of a given university (average of 1998 and 2000)

Table 2. Data on US universities, 1998-2002: descriptive statistics.

US universities	*N*	Variables	Minimum	Median	Maximum	Mean	Standard deviation
All	148	Net returns	−0.80	0.31	109.59	4.42	12.53
		Size	9.7	116.9	2079.2	183.7	224.7
		Quality	0.6	318	2,691	485	519
		Local industry R&D	0.20	1.63	5.14	1.91	1.24
Public and no medical school	45	Net returns	−0.39	−0.03	4.02	0.47	1.06
		Size	17.9	67.1	426.4	110.2	96.5
		Quality	0.6	169	780	218	196
		Local industry R&D	0.20	1.46	5.14	1.62	1.24
Private and no medical school	11	Net returns	−0.77	0.24	26.97	4.12	8.23
		Size	16.9	44.5	780.3	147.4	224.9
		Quality	179	385	2,362	740	817
		Local industry R&D	1.59	2.33	4.54	2.91	1.28
Public and medical school	59	Net returns	−0.80	0.31	56.50	4.58	11.28
		Size	9.7	163.4	2079.2	222.8	284.3
		Quality	3	325	1,882	469	407
		Local industry R&D	0.24	1.59	5.14	1.85	1.20
Private and medical school	33	Net returns	−0.29	1.65	109.59	9.61	20.46
		Size	25.0	184.7	1120.0	226.1	210.3
		Quality	29	627	2,691	794	674
		Local industry R&D	0.33	1.76	4.54	2.10	1.17

Source: see text.
Note: '*N*' is the number of observations; 'net returns' and 'size' are measured in million dollars.

(c) *Log of quality of the faculty*. Natural logarithm of quality of the faculty, whereby we proxy quality of the faculty by the total number of citations per faculty in technological departments.[6] This is obtained from the National Survey of Graduate Faculty completed in 1993 (National Research Council 1995). Note that this variable is thus predetermined given the sample period we covered, which is 1998–2002.

(d) *Local industrial R&D intensity*. We measure this variable as the share of industry-performed R&D in private-industry output in the state of a given university. It is the average of available years (1998 and 2000) in the period of interest, expressed as a percentage. The data are obtained from the National Science Foundation.[7]

The characteristics captured by the dummy variables in Equation (a) have long been considered of interest. Because public universities are more vulnerable to budget crises (Link et al. 2003), they may license more aggressively. On the other hand, public universities may be less flexible culturally and bureaucratically in interacting with private companies (Siegel et al. 2003); therefore, *ceteris paribus*, they may have a lower licensing rate. Lach and Schankerman (2004) found that private universities are more effective in terms of generating licensing income compared to public universities and warranted future research on the determinants of this observation.

Regarding the medical school effect, we note that biomedical research has emerged as a productive field whose research output has attracted the interest of industry, and this trend was present before the passage of the Bayh–Dole Act (Mowery et al. 2004). Hence, having a medical school is expected to provide a significant advantage in terms of generating return from licensing activities. In fact, top university licenses by revenue generation are biomedical (Eisenstein and Resnick 2001).

The variable in Equation (b) captures the quantitative side of the research potential of a given university. The interest is on the value of additional research dollars, and how it varies with the rank of universities in terms of licensing return, that is, across quantiles. The variable in Equation (c) captures the qualitative side of a university's research potential. The quality of inventions obviously matters in assessing the inventions' revenue-generating potential, and the quality of inventions can be presumed to be positively associated with the quality of faculty. Finally, the variable in Equation (d) is meant to determine if the revenue-generating abilities of a university is affected by its location—the local economic conditions that are mostly outside of a university's control.

Before proceeding to the econometric analysis, it is worth commenting briefly on the net returns of Table 2. The average net return from patenting and licensing—across all 148 institutions and over the 5-year period of our sample—is \$4.42 million. This is certainly not an inconspicuous amount and underscores the extent of the activities being undertaken by TTOs in US universities. But these net returns still represent a fairly small amount when considered within the scope of the R&D efforts undertaken. Over the period considered, the average annual total research expenditures at these universities was \$183.7 million. Thus, if one were to focus exclusively on the commercial licensing outcome, the 'yield' for the average US university (i.e., the average net return as a percentage of the average research expenditures) would be a paltry 2.41%. This percent return is quite variable for the structural groups that are identified in Table 2. For public universities it is 2.06% if they have a medical school and 0.43% if they do not have a medical school; for private universities the percent return is 4.25% if they have a medical school and 2.80% if they do not have a medical school.

3. Estimation procedure

Quantile regression estimation was carried out by using the QUANTREG package in *R*, an open source software project.[8] A brief introductory tutorial on quantile regression with *R* is provided in Koenker (2007). To estimate the standard errors, we used the *xy*-pair bootstrapping technique. This technique resamples from the joint empirical distribution of *y* and *x*. Buchinsky (1995) shows through Monte Carlo simulations that the design matrix bootstrap technique performs well under heteroskedastic errors, for relatively small sample sizes, and it is robust to changes in the bootstrap sample size relative to sample size. The resampling in our study was done for 5000 repetitions to ensure stability in standard errors (we followed a procedure similar to that of Canarella and Pollard, 2004, in setting the number of repetitions). Finally, ordinary least squares (OLS) estimation of conditional mean models is done by using SAS (SAS Institute 2003).

4. Results

Table 3 presents the OLS estimation of the conditional mean and quantile regression estimations of the 0.10th , 0.25th, 0.5th, 0.75th, 0.9th , and 0.95th quantiles. By using ANOVA function in the QUANTREG package, we find that the null hypothesis of equality of slope parameters across the quantiles (an implication of conditional mean modeling) is strongly rejected (p-value of < 0.0001) based on the Wald test statistic distributed χ-square with one degree of freedom. The results in this table show that conditional quantile modeling does not make much difference in terms of statistical significance, but it does matter in terms of the economic significance of the variables considered. The magnitudes of estimated coefficients are much higher at the upper and much lower at the lower quantiles than in the

Table 3. Parameter estimates for select quantiles (dependent variable: net return measured in million dollars).

Explanatory variables	OLS	Q–10	Q–25	Q–50	Q–75	Q–90	Q–95
Intercept	−19.6257***	−0.8813**	−1.6026**	−3.6361***	−7.9347*	−19.3644***	−25.4474***
Private & no medical	2.2464	−0.4490	0.0684	−0.0036	3.3503	1.7739	2.7648
Public & medical	1.2117	−0.1211	−0.0713	−0.1048	1.0916	1.7386	4.1075
Private & medical	5.2210*	0.2212	0.3860*	0.5660	4.8820	13.8377	14.9195
Log of size	3.5871***	0.1027	0.2796*	0.7148**	1.8565*	4.5444***	6.4452***
Log of faculty quality	0.8326	0.0339	0.0419	0.1450	0.2938	0.5547	0.9206
Local industrial R&D	0.3023	0.0323	0.0541	0.1057	0.1712	2.1991	1.0955

Notes: ***, **, * indicate significance at 1%, 5%, and 10%, respectively, based on the t-statistics using heterosckedasticity-robust standard errors for OLS and bootstrapped standard errors for the quantiles (based on 5000 repetitions).

conditional mean model. Comparing the estimated coefficients of conditional median and mean models, the latter is clearly influenced by upper quantiles and may not adequately reflect the performance of a typical university in the population. The conditional mean model also under-predicts the net returns of universities positioned in upper quantiles.

Looking at the results of the quantile regression in more detail, the intercept is statistically significant at conventional levels in all quantiles. We recall that the base group to which the intercept applies is that of public universities without a medical school. Private universities without a medical school and public universities with a medical school are not statistically different than this base group. Nevertheless, in upper quantiles of the distribution, starting with the 0.75th quantile, these two groups of universities have positive and mostly increasing coefficients; that is, their difference over the base group is much more accentuated in the upper quantiles of the distribution. Private universities with a medical school obtain significantly higher returns than the base group at the 0.25th quantile and their coefficient is positive in all quantiles and monotonically increases toward the upper end of distribution (it is nearly $15 million at the 0.95th quantile).

The signs of the other variables are positive in all quantiles, as perhaps should be expected. The log of size variable is statistically significant at conventional levels in all quantiles above the 0.10th quantile. The return to an additional 1% increase in total research expenditures (which is obtained directly from the estimated coefficient of the size variable, upon dividing by 100) is initially $1027 at the 0.1th quantile, is monotonically increasing toward higher quantiles, and becomes $64,452 at the 0.95th quantile. Despite more than a 60-fold difference in the values of additional research expenditures between the two tails of the distribution, the impact is still very small, even at the 0.95th quantile, when compared with the size of research expenditures (which, as reported in Table 2, is $183.4 million for the average university).

Similarly, the coefficient of log of faculty quality, upon dividing by 100, shows the impact of a 1% increase in faculty productivity (as proxied here by citations received to publications in technology fields). The impact of 1% increase in the quality of faculty at the 10th quantile of the distribution is merely $339, whereas its value at the 0.95th quantile ($9206) is nearly six times the value ($1450) at the median. Thus, the marginal value of an increase in faculty quality is higher for those universities that are already obtaining high net returns from licensing.

Finally, the impact of the local industrial R&D variable (industrial R&D as the share of industry output in the state of a given university) has a positive sign everywhere and increases with the quantiles of the distribution (except at the very upper end of the distribution). To interpret the estimated coefficient, recall that this variable is measured in percent terms and that its sample average is 1.91%. Hence, a unit increase in this variable corresponds to more than a 50% increase in the amount of industry R&D (holding industrial output constant). With such a big change in the amount of industry-performed R&D, the resulting synergy (in the form of net licensing returns) is predicted to be nearly $2.2 million for universities positioned around the 0.9th quantile, whereas the same impact is only about $107,000 at the median (and smaller still at lower quantiles). Therefore, local industry R&D intensity appears to matter mostly for universities positioned at the very high end of the net returns distribution.

Based on the estimates in Table 3, we predict select quantiles for the structural groups of universities that we have identified (public and private, and with and without a medical school) at the mean characteristics of each group. Table 4 presents the predicted values for select quantiles. Based on these estimates, Figure 3 plots the underlying distributions for the average university in each group.

Table 4. Select predicted quantiles at the mean values of characteristics, and sample estimates of expected values (in million dollars).

US universities	Q–0.1	Q–0.25	Q–0.5	Q–0.75	Q–0.9	Q–0.95	Estimated expected value	Estimated expected value beyond Q–0.95
Public without medical school	−0.164	0.025	0.677	2.653	8.547	11.586	0.474	NA
Private without medical school	−0.499	0.296	1.195	7.124	15.157	18.766	4.123	33.676
Public with medical school	−0.179	0.196	1.211	5.317	14.416	21.191	4.582	54.223
Private with medical school	0.191	0.693	1.995	9.332	27.426	32.857	9.608	82.044

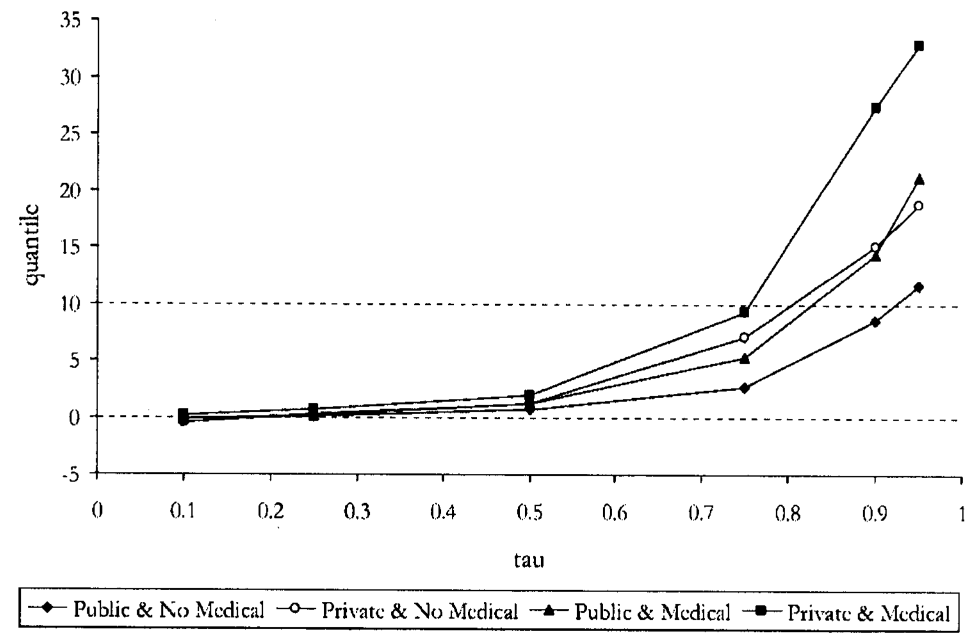

Figure 3. Predicted quantiles (at the mean characteristics, in million dollars).

From Figure 3, we observe that the average private university with a medical school ranks highest in terms of generating licensing return in all quantiles, whereas the average public university without a medical school is dominated by others in all quantiles in that regard. These structural differences are increasing with the level of quantiles. The average private university without a medical school and the average public university with a medical school appear to have similar distributions. This suggests that they may have close expected values but may differ in terms of dispersion of licensing returns.

The estimates of the 0.95th quantiles in Table 4 show that there is a 95% chance that licensing returns will not exceed \$32.9 million for an average private university with a medical school, \$21.19 million for an average public university with a medical school, \$18.77 million for an average private university without a medical school, and \$11.59 million for an average public university without a medical school. These estimated values for the 0.95th quantiles are 14.53%, 9.51%, 12.73%, and 10.51% of the corresponding average sizes, respectively.

We further estimate what the average university in each group can expect beyond the 0.95th quantile, as described in Equations (5) and (6). Note that the group public universities without a medical school does not have a single realized observation beyond the predicted value of 0.95th quantile during the sample period covered here, which is consistent with the limited prospects for this group that emerges from our analysis. For this reason, the expected value beyond the 0.95th quantile for the average public university without a medical school is not estimated. For the other groups, Table 4 reports the estimated expected net returns beyond the 0.95th quantile, along with the overall estimated expected net returns. Specifically, the last column of Table 4 can be interpreted as the expected value of net returns conditional on a university being in the top 5% of earners of its group (as identified by the characteristics of being public or private, and of whether or not the university possesses a medical school). One way to gauge the information in the last column of Table 4 is to relate it to the corresponding estimated 0.95th quantile. This ratio turns out to be 1.79, 2.56, and 2.5, respectively, for the average university that is private without a medical school, public with a medical school, and private with a medical school.

In summary, there was no evidence of a fatter tail for an average public university without a medical school. For all other groups, on the other hand, the right tail of the distribution of returns is fatter. In particular, the gains in relative returns associated with being in the top 5% of earners is highest for universities with a medical school. In any event, the expected returns of the top 5% of earners remain a relatively small fraction of the total research expenditure of the universities.

5. Conclusion

In this paper, we have assessed the potential of US universities in generating economic returns from licensing activities, conditional on some of their characteristics. Recognizing that the underlying distribution is highly skewed, we model and estimate the select quantiles as linear functions of a set of characteristics of universities, and also provide OLS estimation of the conditional mean model as a benchmark. Our statistical finding that the estimated slope coefficients of characteristics are not constant over the quantile points supports the modeling of the quantiles of net licensing returns distribution.

We found that the economic impacts of explanatory variables log of size of research dollars and log of faculty quality (measured as the citations received in technology fields) and industrial R&D (a measure of local economic conditions) are positive and monotonically increasing in almost all quantiles. Regarding the marginal impacts of the characteristics along the quantiles, we found that the marginal 'rate of return' of research funds for an average-size university does not exceed 0.5% in any quantile we considered. Similarly, the impact of faculty quality remains modest. Even in the hypothetical case in which the research productivity doubles, the change in net licensing returns would not exceed 13% of the average net licensing returns in any quantiles. The economic impact of the industrial R&D variable indicates synergies between industry-performed R&D intensity and university net licensing returns at the state level. Nevertheless, these synergies may not spill over uniformly and appear important only for universities that are at the very high end of the distribution of net returns.

We also found structural differences in the licensing return distributions of groups of universities depending on whether they are private or public and on whether or not they have a medical school. In terms of generating licensing returns after controlling for other factors, private universities with a medical school appear to have an institutional advantage over other groups. Public universities with a medical school and private universities without a medical school are close at the distributional points. Public universities without a medical school are dominated by other groups at all quantile points.

We find that the net returns from patenting and licensing by US universities are, on average, quite modest. A rationalization that is sometimes proffered as to why universities should continue with their patenting and licensing activities, even when they are making negligible or negative returns, relies on the marked skewness of the returns distribution, i.e., on the notion of 'waiting for the big one.' Our estimate of the expected net licensing returns, conditional on a university being in the top 5% of earners of its group, helps to quantify this scenario. The expected payoff for being a winner is highest for universities with a medical school and for private universities. This is in line with the argument in Lach and Schankerman (2004) that private universities are more efficient in terms of generating licensing returns, although our results emphasize the impact of having a medical school.

Based on the estimated marginal effects and the structural differences among the group of universities, we would argue that universities should form a more realistic perspective of the possible economic returns from patenting and licensing activities. The potential in terms of generating returns appears particularly limited for public universities without a medical school. The fairly modest overall expected licensing returns, especially when compared with the investment in university research expenditures, suggest that the increased emphasis on university patenting and licensing that has emerged in the United States in the last quarter century should perhaps be reconsidered, especially when attempts to privatize some of the returns of university research appear to conflict with the traditional public research objectives of fostering basic research and disseminating knowledge.

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Notes

1. On the other hand, Jensen and Thursby (2001) suggest that Bayh–Dole may have a further enabling effect because the resulting license contracts can be designed to induce collaboration between faculty inventors and licensee firms in developing typically 'embryonic' university inventions.
2. Note also that the big earners in Figure 1 are not necessarily those with high ratios in Figure 2. For example, the University of California System has the third-largest net license return but that is only 2.6% of its total research budget. Moreover, Columbia University earns the highest net license return ($109.6 million), whereas Florida State University receives the highest net return relative to its research budget (41.6%).
3. To put this mean net return into perspective, we note that it is only 2.41% of the average research budget (total research expenditures) of universities.
4. Pooling the observations over this time period yielded an initial sample of 173 US universities. After adjusting for the missing observations on explanatory variables, we are left with the final sample of 148 observations from US universities.
5. Legal fees expended are the expenditures of an institution on external legal fees, which include prosecuting, maintenance, and interference costs of patents and copyrights. They also include minor litigation costs. Legal fees reimbursed are the legal fee expenditures reimbursed to the institution by licensees (AUTM 2002).
6. We normalize the citations received at each technological department by the number of faculty in that department and sum over these departments in order to obtain total number of citations per faculty in technological departments in a given university. Alternative indexes for faculty quality can be 'scholarly quality of faculty (ratings) in technological departments' and the 'number of publications per faculty in technological departments.'
7. See the website at http://www.nsf.gov/statistics/seind06/c8/c8.cfm for more information.
8. The program is available from the CRAN website: http://cran.r-project.org.

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