U.S. Universities' Net Returns from Patenting and Licensing: A Quantile Regression Analysis

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Abstract

In line with the rights and incentives provided by the Bayh-Dole Act of 1980, U.S. universities have increased their involvement in patenting and licensing activities through their own technology transfer offices. Only a few U.S. universities are obtaining large returns, however, whereas others are continuing with these activities despite negligible or negative returns. We assess the U.S. 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 significant but still fairly modest returns only beyond the 0.9^{th} quantile. These findings call into question the appropriateness of the revenue-generating motive for the aggressive rate of patenting and licensing by U.S. universities.

Keywords: Bayh-Dole Act, quantile regression, returns to innovation, skewed distributions, technology transfer, university patents.

JEL numbers: 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 U.S. Supreme Court decisions. Concomitant with these pro-IPR policy shifts, more and more U.S. 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 U.S. 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, Jaffe and Trajtenberg, 1998). This trend in U.S. universities' patenting and licensing activities has accelerated in the last decade (Sampat, 2003). U.S. patents issued to 69 U.S. universities that are nine-year recurrent respondents to Association of University Technology Managers (AUTM) surveys increased 129% between 1993 and 2001. Licenses and options executed by 55 U.S. universities that are eleven-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 U.S. universities approached $1 billion in FY 2002 (AUTM, 2002).

This growth in university patenting and licensing activities has generated considerable attention in economic research (Mazzoleni, 2005; Sampat, 2003; Link, Scott and Siegel, 2003; Mazzoleni and Sampat, 2002; Nelson, 2001; Mowery et al., 2001; Jaffe, 2000). 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.[1] Thus, the Act was intended for inventions that would not be developed and commercialized without patenting and licensing, but 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, 2003). 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 U.S. universities, the licensing income generated is found to be the most important criterion by which TTO offices measure their success (Thursby, Jensen, and Thursby, 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 technology transfer offices, in million dollars) for 148 U.S. universities, averaged over the five-year period 1998 to 2002 (see the data section for details). It is apparent that only a few universities are earning large returns. In fact, the

[1] 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.

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 fraction 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 less than 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 break even. Obviously, these universities are hoping to do better in the future, an expectation perhaps predicated on the very asymmetric distribution of returns discussed earlier. 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 U.S. 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 technology transfer offices. Siegel, Waldman, and Link (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] 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%).

2. THE MODELING FRAMEWORK

In order to assess the potential of U.S. 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 over the conventional conditional mean analysis because the mean cannot adequately convey the potential for private returns to universities when, as is the case here, the distribution of net economic returns of U.S. universities is highly skewed. This skewness is apparent from the data reported in Table 2. Fifty percent of the U.S. 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 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.

[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.

2.1 Quantile regression

The basic quantile regression model 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, $\{(y_i, x_i) : i = 1,..., N\}$, 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 characteristicsthat 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. Based on the preceding two equations, error terms must satisfy the quantile restriction:

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

The parameter estimates for the τ^{th} sample quantile minimizes the weighted absolute deviations (the errors); that is,

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

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 (4) is as follows. Recall that the τ^{th} 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 $(1-\tau)$. For more discussion of estimation and inference with quantile estimation, see Buchinsky (1998).

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, Koenker, and Machado, 2002 and Yu, Lu, and Stander, 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 τ^{th} 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 τ^{th} quantile (VaR_τ) with $\hat{Q}_\tau(y\,|\,x)$. Then the relation of interest is

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

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 (5) with the method-of-moments approach as

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

Inserting (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 U.S. universities over the five-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, Waldman, and Link (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 to 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 to 2002.[6] Note that the cost items

[4] Pooling the observations over this time period yielded an initial sample of 173 U.S. universities. After adjusting for the missing observations on explanatory variables, we are left with the final sample of 148 observations from U.S. 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 (see AUTM, 2002).

[6] More details of our procedure are available upon request.

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:

(1) 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.

(2) Size of the university. This is measured by total research expenditures and averaged over the sample period 1998 to 2002. The data source is AUTM (1998-2002) surveys.

(3) Quality of the faculty. We proxy this variable by the total number of citations per faculty in technological departments.[7] 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 to 2002.

(4) State R&D intensity. We measure this variable as the share of state-level R&D within national R&D performance in order to measure ongoing R&D activity in that state. This is also averaged over the sample period 1998 to 2002. The data on state and national level R&D expenditures is obtained from the National Science Foundation's website.[8]

The characteristics captured by the dummy variables (1) have long been considered of interest. Because public universities are more vulnerable to budget crises (Link, Scott, and Siegel, 2003), they may license more aggressively. On the other hand, public universities may be less

[7] We normalize the citations received at each technological department by the number 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".

[8] See the website at http://www.nsf.gov/sbe/srs/sepro/start.htm for more information.

flexible culturally and bureaucratically in interacting with private companies (Siegel, Waldman, and Link, 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 attracted the interest of industry, and this trend was present before the passage of the Bayh-Dole Act (Mowery et al., 2001). 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 size variable in (2) 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 (3) 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 (4) 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 five-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 U.S. 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 U.S. university (i.e., the average net return as a percent 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

Estimation was carried out by using the QUANTREG procedure in SAS (SAS Institute, 2003). To estimate standard errors in this procedure, we used the sparsity method (also called the direct method) under the assumption that observations are independently and identically distributed (i.i.d.). This method estimates the reciprocal of the underlying density at the quantile of interest, which is called the sparsity function. The precision of the estimates depends on how sparse (or dense) observations are near the quantile of interest. This method also requires a bandwidth choice. We used Hall and Sheater bandwidth based on the suggestion in Koenker (2005). We chose the simplex algorithm as the optimization method, which is the most stable one. Although the sparsity method is sensitive to the i.i.d. assumption, the estimated standard errors were also confirmed with the resampling estimation method available under the QUANTREG procedure of SAS. The resampling method uses a Markov-chain marginal bootstrap technique developed in He and Hu (2002) and was done for 200 repetitions.

4. RESULTS

Table 3 presents the estimations for the 0.25th, 0.5th, 0.75th, and 0.9th quantiles. The intercept and the explanatory variables size and faculty quality are significant in explaining these quantiles at conventional levels of significance. We recall that the base group to which the intercept applies is that of public universities without medical school. Private universities without medical school and public universities with medical school are not statistically different than this base group in all quantiles. Private universities with medical school obtain significantly higher returns than the base group around the 0.75th quantile of distribution, and this difference increases towards the upper end of distribution, as it is nearly \$10 million at the 0.9th quantile.

The estimated coefficient of the size variable, which expresses the return to an additional \$1 million of total research expenditure, is initially \$3.5 thousand (0.35%) at the 0.25th quantile; it increases towards higher quantiles, approaches \$20 thousand (2%) near the 0.75th quantile, and decreases slightly at further quantiles. The impact of an additional citation to publications in technology fields, a measure of faculty quality, is monotonically increasing with the level of quantiles. The impact of a single citation at the 0.9th quantile exceeds three times the value (\$3.2 thousand) at the median of the distribution. That is, the marginal value of faculty quality is higher for those universities that are already obtaining higher return. Finally, state R&D, the amount of R&D in the state of a given university vis-à-vis national R&D, becomes a significant factor (both economically and statistically) around the 0.75th quantile of the distribution. A one-percentage-point increase in the state R&D relative to the national level is associated with an increase in the licensing return for universities in that state by more than \$200 thousand.

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 and additional quantile points, Figure 3 plots the underlying distributions for the average university in each group.

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 0.9^{th} quantiles in Table 4 entails that there is a 90% chance that licensing returns will not exceed \$21.56 million for an average private university with a medical school, \$9.92 million for an average private university without a medical school, \$7.61 million for an average public university with a medical school, and \$3.27 million for an average public university without a medical school. These estimated values for the 0.9^{th} quantiles are 9.5%, 6.7%, 3.4%, and 3% of the corresponding average sizes, respectively.

We further estimate what the average university in each group can expect beyond the 0.9^{th} quantile, as described in equations (5) and (6). We report these values along with the sample mean for each group in the last two columns of Table 4. 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 10% 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 this estimate is to relate it to the estimated corresponding 0.9^{th} quantile. This ratio turns out to be 1.05, 2.56, 4.65, and 2.74, respectively, for the average university that is public without a medical school, private without a medical school, public with a medical school, and private with a medical school. Thus, an average public university without a medical school has an expected value beyond its 0.9^{th} quantile only slightly higher than the 0.9^{th} quantile. 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 10% of earners is highest for universities with a medical school. In any event, the expected returns of the top 10% 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 U.S. universities in generating economic returns from licensing activities, conditional on some of their characteristics. Recognizing that the underlying distribution is highly skewed, rather than modeling the conditional mean we model and estimate the select quantiles as linear functions of a set of characteristics of universities. Our finding that the estimated slope coefficients of characteristics are not constant over the quantile points supports this modeling choice.

We find that the net returns from patenting and licensing by U.S. universities are, on average, quite modest. Regarding the marginal impacts of the characteristics along the quantiles, we found that the marginal "rate of return" of research funds does not exceed 2% in any quantile we considered. The value of additional research dollars is highest and the state R&D, a measure of local economic conditions, appears particularly important around the 0.75^{th} quantile of the distribution. The impact of faculty quality, on the other hand, appears monotonically increasing for the quantiles we considered.

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.

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 10% 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 return but qualifies the argument for medical school impact.

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 to disseminate knowledge.

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Table 1: Description of Variables

Variable	Description
Net Returns (y)	Licensing return in a given university (averaged over the sample period 1998 to 2002 and in million dollars).
Public & 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 & 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 & Medical (x_3)	Dummy variable, which takes value of 1 if university is public and has medical school, and 0 otherwise.
Private & Medical (x_4)	Dummy variable, which takes value of 1 if university is private and has medical school, and 0 otherwise.
Size (x_5)	The average total research expenditures (in million dollars) over the sample period 1998 to 2002.
Faculty Quality (x_6)	Total number of citations received per faculty in technology departments in a given university (evaluated in 1993).
State R&D (x_7)	The ratio of total R&D performance level in a given state to the national R&D performance level (averaged over the sample period 1998 to 2002).

Table 2: Data on U.S. Universities, 1998-2002: Descriptive Statistics

U.S. Universities	N	Variables	Min	Median	Max	Mean	Std. Dev.
All	148	Net Returns	-0.80	0.31	109.59	4.42	12.53
		Size	9.7	116.9	2,079.2	183.7	224.7
		Quality	0.6	318	2,691	485	519
		State R&D	0.0003	0.021	0.209	0.031	0.036
Public & 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
		State R&D	0.0003	0.013	0.070	0.018	0.019
Private & 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
		State R&D	0.0063	0.056	0.209	0.060	0.053
Public & Medical School	59	Net Returns	-0.80	0.31	56.50	4.58	11.28
		Size	9.7	163.4	2,079.2	222.8	284.3
		Quality	3	325	1,882	469	407
		State R&D	0.0013	0.021	0.209	0.030	0.031
Private & Medical School	33	Net Returns	-0.29	1.65	109.59	9.61	20.46
		Size	25.0	184.7	1,120.0	226.1	210.3
		Quality	29	627	2,691	794	674
		State R&D	0.0019	0.036	0.209	0.043	0.047

Source: see text. Note: “N” is the number of observations; “Net Returns” and “Size” are measured in million of dollars.

Table 3: Parameter Estimates for Select Quantiles (Dependent variable: Net return measured in $ million)

Explanatory Variables	**Q-25**	**Q-50**	**Q-75**	**Q-90**
Intercept	-0.5087 ***	-0.9717 ***	-1.8780 ***	-0.7431
Private & No Medical	-0.0625	-0.8500	-0.9498	1.1376
Public & Medical	-0.1838	-0.2400	-0.2647	-0.1016
Private & Medical	0.1839	-0.0343	4.8790 ***	9.9398 **
Size	0.0035 **	0.0065 ***	0.0196 ***	0.0182 *
Faculty Quality	0.0009 ***	0.0032 ***	0.0057 ***	0.0099 *
State R&D	-2.57	6.14	22.33 *	-7.52

Note: ***, **, * indicate significance at 1%, 5%, and 10%, respectively, based on the largest of p-values of Wald and likelihood ratio statistics.

Table 4: Select Predicted Quantiles at the Mean Values of Characteristics, and Sample Estimates of Expected Values (in million dollars)

U.S. Universities	Q-0.25	Q-0.5	Q-0.75	Q-0.9	Estimated Expected Value	Estimated Expected Value Beyond Q-0.9
Public without medical school	0.032	0.552	1.936	3.272	0.474	3.438
Private without medical school	0.481	1.855	5.616	9.925	4.123	25.417
Public with medical school	0.446	1.913	5.560	7.610	4.582	35.379
Private with medical school	1.605	4.223	14.792	21.562	9.608	59.121

Figure 1: Net Licensing Returns of U.S. Universities, 1998-2002 (in million dollars)

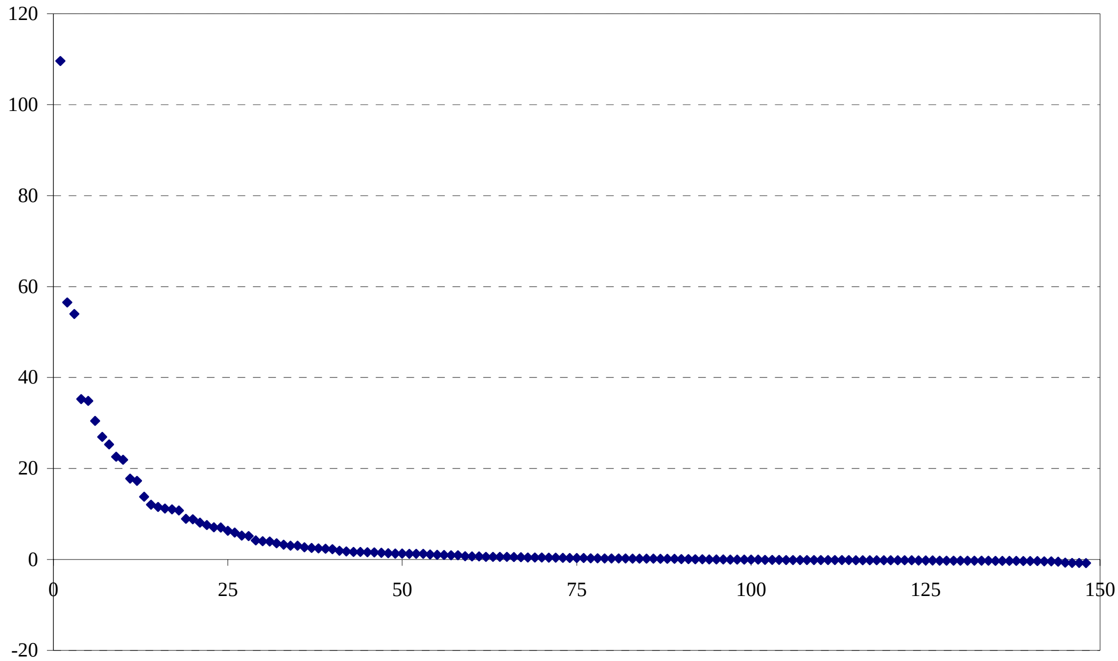

Figure 2: Net Licensing Returns as a Fraction of Total Research Expenditures of U.S. Universities, 1998-2002

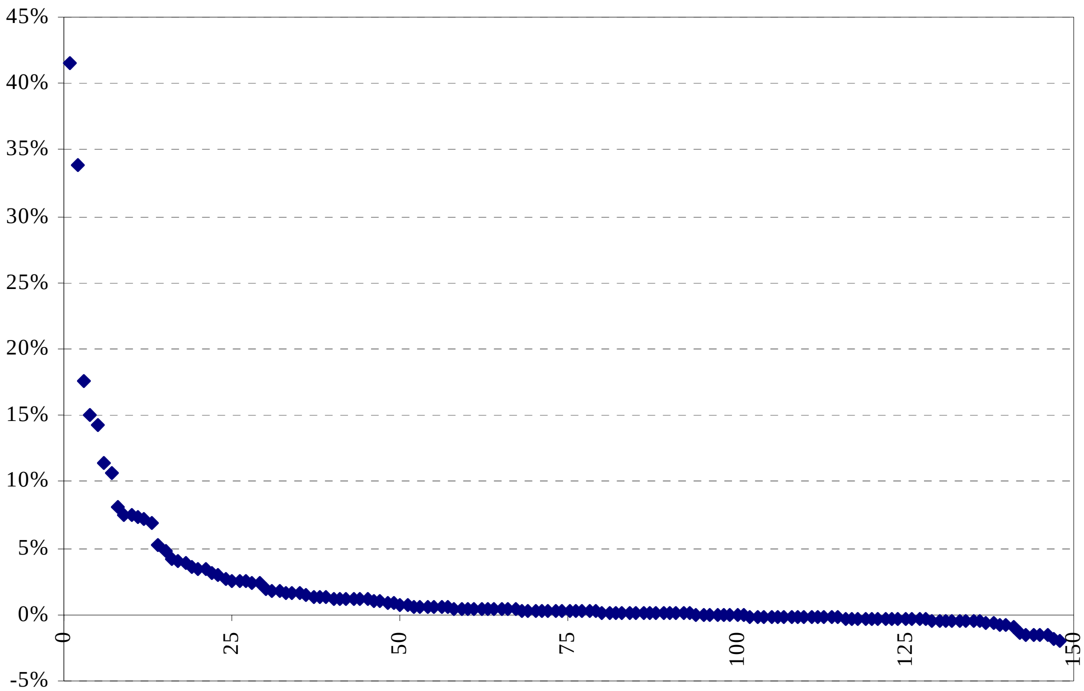

Figure 3: Predicted Quantiles (at the mean characteristics, in million dollars)