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Efficiency and Technological Change at U.S. Research Universities

By

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Efficiency and Technological Change at US Research Universities

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Abstract: This paper investigates the determinants of efficiency and technological progress at US research universities. It relies on a unique panel data set of multiple outputs and inputs from 92 universities covering the period 1981-1998. Over that time span, US universities experienced large increases in industry funding and in academic patenting activity. In this context, the directional distance function and a nonparametric representation of the underlying production technology are combined to obtain estimates of productivity growth and technical efficiency. A pooled-Tobit estimator is used to examine the determinants of technical efficiency and the rate of technological progress. The results show how changes in funding sources for U.S. research universities affects research performance.

JEL Codes: O3, O31, O33, C6, L31

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Efficiency and Technological Change at US Research Universities

1. Introduction

It is well documented that university research and development have played a vital role in generating long term social returns in the United States (e.g., Jaffe, 1989; Mansfield, 1995; Chavas, Aliber, and Cox, 1997; Jones and Williams, 1998). This R&D effort has been sponsored by a combination of public and industry funding support. Over the past two decades, universities have turned increasingly to industry sources to finance R&D activities, including sponsored research agreements with companies and various forms of commercialization of intellectual property rights (patent licensing, start-ups, etc.).

Increased commercialization of university research efforts has generated controversy about the effects on traditional outputs of universities: trained students, high quality research, and the pace, terms, and future use of scientific disclosures (see e.g., Bok, 2003; Ehrenberg Rizzo, & Jakubson, 2003; Atkinson et al., 2003; Kennedy, 2000). Blumenthal et al. (1996), for example, show that - in the life sciences - faculty with more than two-thirds of their research support from industry sources have lower rates of publication and write less influential articles than other faculty with less industry support. Yet universities are clearly identified as the source of exceptional regional entrepreneurial activities that have spurred the development of high technology (Jaffe, 1989; Bania, Eberts & Fogerty, 1993, Jensen and Thursby, 2001; Hall, Link, & Scott, 2003; Link and Scott, 2003). Leading private universities (e.g., Harvard, MIT, and Stanford) and some of the land-grant public universities (e.g., University of California and University of Wisconsin) are well known for their outstanding performance in technology transfer and licensing revenue generation. Indeed, since the Bayh-Dole act of 1980 allowed universities to patent their inventions, the last two decades have seen many research universities invest heavily in technology transfer offices. Overall, the literature on the production of university patents has shown mixed effects of this regulatory change on the quality of research, with some (Henderson, Jaffe, &Trajtenberg., 1998) showing declining quality and others (Sampat, Mowery, & Zeidonis, 2003) showing no effect. Another outcome potentially associated with increasing pressures to produce commercial outputs is the dramatic increase in the use of post-doctoral researchers in U.S. university labs (see Table 1), which has given rise over the past two decades to an 86% increase in the number of post-doctoral researchers while faculty numbers increased by about 10%. Universities clearly face some trade-offs between hiring post-doctoral researchers and expanding faculty or graduate student numbers, but do they increase their efficiency by having more post-doctoral researchers? At all three levels, increased industry funding, emphasis on technology transfer, and utilization of post-doctoral researchers, there is a need to examine how these and other factors have affected research performance at US universities.

This paper examines efficiency and technological change at U.S. research universities in order to explore how they are affected by the commercialization of university research outputs associated with the rise of academic patenting. This issue seems especially timely for two reasons. First, it has been more than two decades since the passage of the Bayh-Dole Act provided the institutional basis for a major expansion of academic patent activity. Second, US universities are in the midst of an era when both federal and state funds for research seem likely to stagnate under the burden of mounting fiscal deficits. As a result, most US research universities find themselves in an austere era, searching for alternative funding sources as well as ways to improve their efficiency. Knowing how commercialization in its different forms affects university research performance would be valuable to decision-makers at various levels.

This paper presents a refined analysis of a unique panel data set consisting of 92 top U.S. research universities from 1981 to 1998. We focus our attention on the estimation and determinants of technical efficiency and rates of technological change among universities during this period. The analysis is based on measurements reflecting traditional university outputs (trained graduate and undergraduate students, publications) as well as the growing importance of university patenting. The output measures are more complete than most previous analyses of university research production. They also take into account quality differences in university research outputs by adjusting counts with citation information. Inputs to university scientific production are measured by numbers of faculty, doctoral students, and post-doctorates.[1]

Our analysis of efficiency and technological change is based on the directional distance function (Chambers, Chung and Fare, 1996). The panel data allows for the estimation of university-specific measures of technical efficiency and technological progress for each time period. These estimates help answer some basic questions on trends in the degree of technical efficiency and rate of technological progress at different types of universities. Using a nonparametric representation of the university production process, we find that levels of efficiency and rates of technological change vary a great amount across different university types. We then conduct an econometric analysis investigating the factors influencing efficiency and technological change. This provides useful information on the

[1] The analysis focuses on the role of human capital (as measured by inputs such as faculty, post-docs, etc.) which is at the heart of the production of new knowledge by research universities.

effects of funding sources, university size, university type (e.g., public versus private), tech-transfer efforts, use of post-docs, and other university-specific characteristics.

2. Methodology

Consider a university as a firm producing multiple outputs: patents, journal articles, and trained students. The production process involves the production of $y \in R_+^m$, a m-vector of outputs, using $x \in R_+^n$, a n-vector of inputs. Using netput notation, let $z \equiv (-x, y)$ where outputs are positive and inputs are taken to be negative. Let $F \subset R_-^n \times R_+^m$ represent a closed production possibility set, where $z \equiv (-x, y) \in F$ means that outputs y can be produced from inputs x. Let $g \in R_+^{n+m}$, $g \neq 0$, be some reference netput bundle. Following Chambers, Chung, and Fare (1996) and Luenberger (1995), consider the directional distance function:

$$D(z, g, F) = \max_\beta \{\beta: (z + \beta g) \in F\} \text{ if } (z - \beta g) \in F \text{ for some scalar } \beta, \quad (1)$$

$$= +\infty \text{ otherwise.}$$

The directional distance function D(z, g, F) in (1) measures how far the point $z \equiv (-x, y)$ is from the frontier technology, expressed in units of the reference bundle g. Note that D(z, g, F) in (1) is the negative of the shortage function discussed in Luenberger (1995). The properties of the directional distance function D(z, g, F) have been investigated by Chambers, Chung, and Fare (1996) and Luenberger (1995). They are summarized next. First, $z \in F$ implies $D(z, g, F) \geq 0$ (since $D(z, g, F) < 0$ implies $z \notin F$). Second, if the set F is convex, the directional distance function D(z, g, F) is concave in z. Third, under free disposal (where $z \in F$ and $z' \leq z$ implies that $z' \in F$), the production possibility set F can be written as $F = \{z: D(z, g, F) \geq 0\}$. Then, the boundary of the production technology is represented by the implicit equation D(z, g, F) = 0. Finally, the directional distance function satisfies the translation property where D(z - k g, g, F) = k + D(z, g, F).

2.1. Technical Efficiency

Under technology F, consider a firm observed to be at point z ≡ (-x, y). The directional distance function D(z, g, F) in (1) provides a general way of assessing technical efficiency and productivity. It is also intuitive: D(z, g, F) measures the quantity of inputs g that can be saved by moving to the frontier technology. In addition, for a given reference bundle g, this quantity can be meaningfully added across firms and/or across periods. It means that the directional distance function can be aggregated without undue complication.

Since D(z, g, F) $\geq$ 0 under feasibility, it follows that D(z, g, F) is a convenient measure of the distance to the frontier technology. If D(z, g, F) = 0, then point z is necessarily on the boundary of the production technology F. And finding D(z, g, F) > 0 implies that point z is technically inefficient as it is below the production frontier. It means the D(z, g, F) in (1) is a convenient <u>measure of technical inefficiency</u> for a firm that reflects the number of units of the netput bundle g needed to get to the frontier. In addition, consider the case where $p \in R^{n+m}_{++}$ is a vector of prices associated with netputs z. Noting that the point [z + D(z, g, F) g] is feasible, it follows that [D(z, g, F) p · g] provides a measure of profit increase that a firm choosing netputs z can attain by becoming technically efficient. In situations where prices p are normalized such that p · g = 1, then the directional distance function D(z, g, F) provides a measure of this profit increase.

Note that D(z, g, F) in (1) is closely related to three other measures of technical performance that have appeared in the literature. First, consider the case where g = (0, y).

Then, the directional distance function in (1) becomes $D(z, (0, y), F) = 1/D_O(z, F) - 1$, where $D_O(z, F) \equiv \inf_{\beta \geq 0} \{\beta: (-x, y/\beta) \in F\}$ is Shephard's output distance function (Shephard, 1970; Fare and Grosskopf, 2000). In this context, $D_O(z, F) \geq 1$ if z is feasible, and $D_O(z, F) = 1$ if z is on the upper boundary of the technology. Then $[D_O(z, F) – 1]$ measures the proportional change in outputs that can be obtained by moving to the production frontier.

Second, consider the case where $g = (x, 0)$. Then, the directional distance function in (1) becomes $D(z, (x, 0), F) = 1 – 1/D_I(z, F)$, where $D_I(z, F) \equiv \sup_{\beta \geq 0} \{\beta: (-x/\beta, y) \in F\}$ is Shephard's input distance function (Chambers, Chung, and Fare, 1996). A closely related concept is Farrell's (1957) input distance function $D_f(z, F) \equiv \inf_{\beta \geq 0} \{\beta: (-\beta\, x, y) \in F\} = 1/D_I(z, F)$ which satisfies $D(z, (x, 0), F) = 1 – D_f(z, F)$. In general, $D_f(z, F) \leq 1$ if z is feasible and $D_f(z, F) = 1$ if z is on the upper boundary of the technology. Much research has used Shepard's input distance function $D_I(z, F)$ and Farrell's input distance function $D_f(z, F)$ in the investigation of technical efficiency and productivity. For example, $[1 – D_f(z, F)]$ provides a measure of the proportional reduction in all inputs that can be obtained by moving to the frontier technology. This shows that $D(z, g, F)$ in (1) includes as special cases most measures of firm performance that have been proposed in the literature.

2.2. Productivity-Technological Progress

Consider a change in technology from F to F', where under technological progress, $F \subset F'$ as the feasible set expands. Since the directional distance function in (1) involves a maximization problem, this implies that $D(z, g, F') \geq D(z, g, F)$. Evaluated at point z, this suggests the following measure of technological progress

$$A(z, g, F, F') = D(z, g, F') - D(z, g, F). \quad (2)$$

A(z, g, F, F') in (2) has a simple and intuitive interpretation. First, A(z, g, F, F') = 0 in the absence of technological progress. Second, evaluated at point z, finding A(z, g, F, F') > 0 implies technological progress from F to F'. In this case, A(z, g, F, F') is the number of units of the netput bundle g that can be obtained by switching from technology F to F'. As noted above, for a given reference bundle g, this measure can be meaningfully summed across firms and/or across time periods. This additivity property makes A(z, g, F, F') a convenient measure in the investigation of technological change for a group of firms or for an aggregate industry. In addition, noting that [z + D(z, g, F) g] is a feasible point of the production frontier under technology F, the associated profit is [p · [z + D(z, g, F) g]]. It follows that the change in profit associated with switching from technology F to F' is [D(z, g, F') - D(z, g, F)] [p · g]. In the case where prices p are normalized such that p · g = 1, then [D(z, g, F') - D(z, g, F)] measures the benefit (in terms of profit increase) of technological progress from F to F'.

Below, we will use equations (1) and (2), respectively, to evaluate the technical efficiency and rate of technological change among US research universities.

3. Data

The dataset combines information on research inputs and outputs in the sciences and engineering for 92 US universities, including 61 public universities and 31 private universities for the period of 1981-1998. This dataset contains for all 92 universities the following data:

1) Total patent counts and citations from all science and engineering fields (U.S. Patent Office, 2004; Hall, Jaffe, &Tajtenberg, 2003),

2) Article counts and citations from all science and engineering fields (ISI Web of Science, 2004),

3) Total number of doctorates and bachelor degrees granted in the sciences as well as the number of graduate students, faculty, and post-docs (National Science Foundation, 2004).

Further details on the sources of the data and key choices in the construction of the dataset can be found in the appendix. One key aspect of the dataset warrants discussion here. The dataset focuses on scientific inputs and outputs, reflecting our interest in studying university production processes that include producing patents. We focus on the sciences because they are the disciplines which have experienced the greatest in-roads of industry funding and are most likely to be engaged in patenting.[2]

In order to proceed with the empirical analysis, we need a representation of the university production process. University research in the sciences produce outputs (articles, patents, and trained students) using primarily the following human capital inputs: faculty, post-doctoral researchers, and graduate student labor.

In the case of student training, we measure undergraduate bachelor's degrees in the sciences as university outputs. However, graduate students can be both inputs and outputs: they are outputs of the university educational function, but they are also inputs into the research process through their work in labs. To account for this dual function of graduate students, we assume that they are outputs until their final year, when they are treated as an input into the university research process. Since there is a one or two year delay between when research is done and when a graduate student worked on it, we think that this

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[2] Including the humanities and social sciences would have led to major measurement difficulties, since the outputs in many disciplines, such the arts, cannot be adequately measured by article and patent counts.

assumption reasonably closely matches the output data we have. Thus, we measure continuing graduate students as outputs, and PhDs granted as inputs. In this context, universities are involved in the production of four outputs (journal articles, patents, trained undergraduate students, and trained graduate students) using three inputs (faculty, post-doctoral researchers, and PhD graduate students).

To account for quality differentials, we use citations to quality-adjust the patent and article counts.[3] The quality adjustment measure used for each science article/patent is the deviation from the average citation rate of an article/patent in the same broad class/category published in the same year. For example, a 1995 biochemistry article with 10 citations is compared to the average level of citations of all biochemistry articles produced in that year. For a given year, the average quality article within a category has a citation rate of 1, with higher quality articles then having a measure greater than one and lower quality articles receiving a measure between zero and one. This relative citation approach minimizes a truncation bias that would be introduced by using an absolute citation count. Further details on the citation measure are available in the appendix.

Finally, the university research production process is dynamic: the process of scientific discovery is typically time-consuming. For example, lagged inputs can affect current outputs in the presence of production lags (e.g., it takes time for research to be published). And lagged outputs may affect current outputs in the presence of temporal synergies in production. We incorporate dynamics in the representation of the underlying technology by specifying and estimating a multi-period production technology over a four-

[3] The work presented here was also done using quantity measures without quality adjustments. The results showed relatively little difference. For brevity's sake we chose to only present the quality adjusted data. A summary of the quantity results are available from the authors upon request.

year period. Outputs for the current year are assumed to depend on inputs of the current year, as well as on inputs and outputs from the three previous years. The effects of lagged quantities are captured by a weighted average of the corresponding quantities, with weights equal to 0.5 for lag one-year, 0.37 for lag two-years, and 0.13 for lag three-years. As a result, our dynamic production process is represented by eight outputs (four current outputs and four lagged outputs) and six inputs (three current inputs, and three lagged inputs).

Some summary statistics of the data are presented in Table 1. Table 1 reveals major increases in U.S. university scientific research production between 1984 and 1998 in spite of relatively minor changes in faculty numbers. Patent production grew most over this fifteen-year time span with a 312% increase in the average annual level of production, followed by articles and doctorates with 60% and 47% increases, respectively. Meanwhile, the number of science faculty only grew by 10% over this time period. However, postdoctoral numbers grew by close to 86% over this same period. The fact that all of these scientific outputs grew much more substantively than faculty numbers may suggest the presence of major technological progress during this era, but it could also be true that the growing importance of postdoctoral inputs explains much of the increased research production. Little more can be said without a more careful analysis of the efficiency and technological progress properties of the university production process. The ensuing empirical analysis builds on a non-parametric representation of the production process to generate university-specific estimates of efficiency and technological change. This is followed by an econometric analysis of the determinants of these estimates.

4. Nonparametric Implementation

4.1. Estimating the Directional Distance Function

Estimating the directional distance function D(z, g, F) in (1) requires a representation of the technology F. This can be done either using parametric methods (involving a parametric specification followed by an econometric estimation of the parameters) or nonparametric methods. Below, we rely on a non-parametric approach for several reasons. First, it provides a flexible representation of the multi-output production frontier, and this does not require imposing a parametric structure on the problem. Second, when the number of netputs is large, it is not subject to multicollinearity problems. Finally, it does not require that each data point be on the frontier technology, which allows for technical inefficiencies.

Input and output data are used to recover an estimate of the underlying multi-output production technology for universities. As discussed above, university outputs are measured as research articles, patents, doctoral students in labs, and bachelor degrees, while the inputs are measured as post-docs, doctorates in their final year of study, and faculty. Following Afriat (1972), Varian (1984) and others, the non-parametric approach (also called data envelopment analysis or DEA) consists of representing the underlying technology by the smallest convex set that includes all the data. Consider a set of observations on S universities over T time periods. For the s-th university at time t, we observe netputs $z_s^t \equiv (-x_s^t, y_s^t)$, s = 1, …, S and t = 1, …, T. Assuming non-regressive technological change and variable returns to scale,[4] a nonparametric representation of the technology at time τ is

[4] Comparisons between variable returns to scale and constant returns to scale can also be used to investigate scale efficiency.

F_τ = {z: $\sum_{s=1}^{S} \sum_{t=1}^{\tau} \lambda_s^t\ z_s^t \geq z$, $\sum_{s=1}^{S} \sum_{t=1}^{\tau} \lambda_s^t = 1, \lambda_s^t \geq 0$, s = 1, …, S, and t = 1, …, τ}.(3)

Given F_τ in (3), the directional distance function in (1) can be obtained as follows

$$D(z, g, F_\tau) = \max_{\beta,\lambda} \{\beta: \sum_{s=1}^{S} \sum_{t=1}^{\tau} \lambda_s^t\ z_s^t \geq z + \beta\ g, \sum_{s=1}^{S} \sum_{t=1}^{\tau} \lambda_s^t = 1, \lambda_s^t \geq 0, s = 1, \ldots, S, \text{ and } t = 1, \ldots, \tau \}. \quad (4)$$

This is a straightforward linear programming problem which implicitly estimates the multi-output production frontier across all universities up to time τ. This allows measurements of efficiency changes (university movements toward the frontier at a given time τ) as well as the analysis of technological progress (movements of the frontier overtime) using (2). We implement this approach using GAMS software to analyze university performance. We choose the reference bundle g to represent "one faculty unit": g = $(g_1, \ldots, g_{n+m})$ where $g_i = 1$ when i corresponds to faculty input, and $g_i = 0$ otherwise. In this context, given university netputs z, $D(z, g, F_\tau)$ in (1) gives the distance to the frontier measured by the number of faculty that could be saved if the university could move to the boundary of the technology F_τ. Similarly, from (2) and given university netputs z, $A(z, g, F_\tau, F_{\tau'})$ measures the magnitude of technological progress by the number of faculty that could be saved by switching from technology F_τ to technology $F_{\tau'}$ for τ' > τ.

4.2. Estimating the Determinants of Efficiency and Technological Progress

The empirical implementation of (4) yields two measures of interest for individual universities: 1) technical inefficiency $D(z, g, F_\tau)$; and 2) university-specific technological progress between period τ and τ' as measured by $A(z, g, F_\tau, F_{\tau'})$ from (2). These measures are estimated for each university for each year in the data set, and provide the data that we use to examine the levels of efficiency and rates of technological progress. Summary statistics for these estimates are presented first to show how they differ across types of universities and across time. Then, with these estimates, we pursue an econometric analysis of efficiency and technological change, thus generating insights on the determinants of university performance.

The econometric model describes the dependent variables (i.e., inefficiency and technological progress) as a function of university characteristics and time specific measures. Note that university netputs z being feasible implies that $D(z, g, F_\tau) \geq 0$. Thus, our measurement of university inefficiency is censored at 0. Similarly, for $\tau' > \tau$, non-regressive technological progress implies that $A(z, g, F_\tau, F_{\tau'}) \geq 0$. Again, our measurement of technological progress is censored at zero. This implies that the econometric analysis of university performance must deal with the censored nature of the data. As noted by Wooldridge (2002), estimating censored models with panel data can be challenging. We estimate Tobit models using partial maximum likelihood estimation, because as shown by Wooldridge (2002, p. 402) they have desirable asymptotic properties: for fixed T and $S \to \infty$, they give parameter estimates that are consistent and asymptotically normal. This applies under fairly general conditions: it does not require strict exogeneity of the explanatory variables; and it allows the error terms to be serially correlated. However, the presence of serial correlation affects the computation of asymptotic standard errors and requires appropriate adjustments (Wooldridge, 2002, p. 406). Below, we implement such an approach to the analysis of university performance.

Let $Y_{it} \geq$ be the dependent variable for the i-th university at time t (either technical inefficiency or technological progress). And denote by X_{it} the corresponding vector of explanatory variables. The associated Tobit model is $Y_{it} = \max(0, X_{it}\beta + u_{it})$ where $u_{it}| X_{it}$ is distributed $N(0, \sigma^2)$. Following Wooldridge (2002, p. 539), the partial maximum likelihood estimator is the pooled Tobit estimator that maximizes the partial log-likelihood function $\sum_i \sum_t l_{it}(\beta, \sigma^2)$, where

$$l_{it}(\beta, \sigma^2) = 1[Y_{it} = 0] \log[1 - \Phi(X_{it}\beta/\sigma)] + 1[Y_{it} > 0] \{\log \phi[(Y_{it} - X_{it}\beta)/\sigma] - \log(\sigma^2/2\},$$

where $1[\cdot]$ is an indicator variable, and $\Phi(\cdot)$ and $\phi(\cdot)$ are, respectively, the distribution function and the density function for the standard normal distribution. As just noted, this gives consistent parameter estimates. The standard error estimation accounts for the possibility of serial correlation. This provides a basis for obtaining robust standard errors and conducting statistical inferences on the determinants of university performance.

5. Empirical Results

5.1. Technical Efficiency Estimates for U.S. Universities

Based on empirical estimates of $D(z, g, F_\tau)$ in (4), summary measures of technical inefficiency of U.S. universities are presented in Figure 1 as the average of 100*D/Faculty for three university types: private universities, public land grant universities (LGU), and public non-LGU. Here, 100*D/Faculty measures the percent of faculty that can be saved by moving to the frontier. On average, private universities are found to be relatively more inefficient than public universities, but that over the last decade the gap has narrowed significantly as public universities have become less efficient. Figure 1 also shows that technical inefficiency has increased over the sample period, with 100*D/Faculty at the average university rising from 10.6 percent in 1984 to 20.4 percent in 1998. One finds a similar trend in all university types, although public universities (both land grant and non-LGU) have on average become relatively less efficient, thus narrowing the gap between public and private universities.

The general increase in inefficiency reflected in Figure 1 can be decomposed further into three groups of universities; those that were:

- On the frontier in the initial and ending period (24 of the 92 in the sample)
- On the frontier in the initial period but not the ending period (25 of the 92)
- Not on the frontier in the initial or ending period (42 of the 92)

Several empirical regularities emerge from that exercise. First, the frontier universities consist of three groups that are not surprising: the top tier private universities, such as Harvard, MIT, Cal Tech, Johns Hopkins, and Stanford; leading public universities, such as five of the eight University of California campuses, University of Minnesota, University of Texas-Austin, Texas A&M University, University of Washington, and University of Wisconsin-Madison; and several mid-range public universities, such as Penn State University and Florida State University. Second, the universities on the frontier in the initial period but not in the final period were, on average, 42 percent closer to the frontier in the final period than was the third group, while the efficiency gap between those on the frontier and those that were never on the frontier was more than 35 percent on average. Thus, the trend toward more inefficiency shown in Figure 1 masks a process within which a group of "winners" has pulled further way from the rest of the sample, and especially from the third group. It is noteworthy that this increase in inefficiency for two-thirds of the sample occurred during the period of increased commercialization. The econometric analysis presented below sheds additional light on this issue.

5.2. Technological Change

Our analysis of technological change is based on $A(z, g, F_\tau, F_{\tau'})$ in equation (2). For a given z and for $\tau' > \tau$, this measures the amount of faculty that can be saved by switching from technology F_τ to $F_{\tau'}$. To facilitate interpretation, we report 100*A/Fac, i.e. the percentage of faculty that can be saved due to technological progress.

We evaluate technological change over two periods: from 1984 to 1989 and from 1990 to 1998. For each period, we evaluate $A(z_i, g, F_\tau, F_{\tau'})$ where z_i is the netput vector of the i-th university during the first year of each period (1984 and 1990). Then, we obtain 100* $A(z_i, g, F_\tau, F_{\tau'})/Fac_i$ and convert this into an annualized rate of change for each university over the selected period. A summary of the results are reported in Table 2.

Table 2 shows that technological change across the two time periods by university type, where technological change is measured by the yearly percent change in the number of faculty saved by using the new technology rather than the old. It shows technological change across all types of universities of just under 1 percent per year, with the change slightly faster in the 1990's. That there is not a more rapid pace of technological progress in the 1990's is perhaps surprising given the major improvements in information technology during that decade. In terms of university types, private universities also show higher technological change with Land Grant universities showing the lowest rate in the 1990s.

Figure 2 shows a histogram for the two time periods showing the distribution of technological change across all universities. One of the key differences is the much higher portion of universities in the 1980s that saw zero or very low levels of technological change during that period. Universities in the 1990s were more likely to experience some technological change overall, although both distributions show the majority of universities with less than 1 percent change per year.

6. Determinants of Efficiency and Technological Progress

In order to understand the determinants of efficiency and technological progress, we specify an econometric model of university performance as a function of key variables hypothesized to make a difference to efficiency and technological progress. To examine technical efficiency, a Tobit model is estimated using the relative measure of distance from the frontier, D(z, g, F)/Fac, as the dependent variable. To investigate technological progress, a Tobit model is estimated using the annualized rate (measured from $A(z, g, F_{\tau}, F_{\tau'})$ in (2)) as a dependent variable for the two periods: 1984-1989 and 1990-1998. We use the same basic set of explanatory variables in both regressions. The variables and their hypothesized effects are described below and their descriptive statistics are shown in Table 4.

First among the independent variables describing efficiency and technological progress are control variables that capture university type. We use dummy variables for public versus private universities and for Land Grant universities versus non-Land Grants.[5] This allows us to investigate whether the additional outreach missions of public universities, especially Land Grant universities, would make them less efficient in research production

[5] Note that Cornell university is both public and private, and part land grant part non-land grant. We decided to categorize Cornell as a public land grant university. None of the results presented below were affected to any measurable degree by changing this classification.

and perhaps result in slower technological progress than private universities (McDowell, 2001).

In order to control for scale effects in the influence of funding on efficiency and technological change, we include a measure of the total amount of research funding at the university. We also include a measure of the number of science faculty at the university as another measure of scale effects. We investigate whether larger universities (as measured by faculty numbers or research funding) will be equally efficient and have similar rates of technological change than smaller universities. Since these size effects may be different depending on the university's type, we include interaction variables between faculty size and our measures of university type.

In terms of commercialization variables, we draw from previous literature on university research production that has shown the importance of funding sources to the research process (see e.g., Campbell and Blumenthal, 2000). The literature suggests and we hypothesize that higher percentages of federal funds in the university budget increases both efficiency and technological progress. At the same time we investigate whether a higher percent of industry funding diverts resources away from the typical university outputs and possibly lead to lower levels of efficiency. We include a cross product term for these funding percentages to capture any interaction effect between them.

Since the existence and experience of a technology transfer office will influence the production of one of our measured outputs, patents, we also include variables to measure the level of technology transfer infrastructure at the universities. We use two dummy variables: the first measures whether or not the university has more than 0.5 of an FTE working in their technology transfer office; the second measures whether the university had a technology transfer office before 1980, which is the date of the Bayh-Dole act that changed the institutional framework governing university intellectual property right ownership and commercialized technology transfer.[6] It is hypothesized that having a technology transfer office will increase the measured efficiency by increasing patent production. The existence of a technology transfer office is thought to stimulate technological progress as it facilitates the process of patent production. We hypothesize similar effects for having a technology transfer office before 1980 which we see as a proxy for the experience or quality of the technology transfer office.

We also include variables to control for what we think are important differences between universities in their response to increased commercialization efforts. The first measures the number of post-doctoral researchers per faculty, and the second whether the university has a medical school. Potentially, post-docs can be very productive in the research process. However, if more post-docs reflect a move toward more commercialization, this could also reduce the efficiency of producing more traditional university outputs. To examine this issue, the variable "post-doc" is included in the model, with a squared effect to account for possible non-linearity. The presence of a medical school should be thought as more of a control variable than a commercialization effort measure, but it is also an activity that stretches beyond the classic research and teaching missions to include treatment of patients and other health care provision services.

6.1. Determinants of Technical Inefficiency

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[6] Between 1984 and 1998, more than half (55%) of the universities in our sample added a technology transfer office. Most of the additions occurred in the late 1980s and early 1990s.

The estimation results from the pooled Tobit model on inefficiency are reported in Table 4. Many of the coefficients are found to be statistically significant.[7] Recall that D(z, g, F) measures inefficiency as the distance from the frontier, so that a positive coefficient estimate indicates a variable that increases inefficiency. For example, the finding reported above that inefficiency increased in the 1990s relative to the 1980s is reflected by the positive and significant coefficient estimate on the time trend variable. This suggests a secular trend toward more inefficiency in university production during an era of increased commercialization orientation.

The effects of overall funding and funding sources on the efficiency of university science production are of special interest. Table 4 shows that higher overall levels of funding significantly reduce inefficiency (i.e., increases efficiency). After controlling for the scale of funding, having higher percentages of federal funding always lowers inefficiency. This highlights the importance of federal funding in the efficient operations of universities. However, the effects of industry funding are more complex. For a given total funding, the marginal effect of industry funding on inefficiency is: 3.346 – 0.06229 * (Pct. Federal funds).[8] It follows that a relative increase in industry funding makes the production process more efficient whenever a university gets more than 53.7% of its funding from federal government sources. This shows that a relative increase in industry funding can contribute to improved university efficiency. However, this applies only when the majority of funding comes from federal sources. Our results suggest the presence of a possible "crowding-out

[7] Note that the analysis was also conducted without correcting for quality differences in research outputs. In general, the econometric results were found to be similar, leading to the same qualitative findings.
[8] Note that these results based on ratios of coefficients are the same whether they are presented using the coefficients themselves or the marginal effects conditional on the censoring. For ease of exposition we chose to present them based on the coefficients themselves.

effect" of industry funding (as suggested by Blumenthal et al. (1996) for the life sciences), whereby extensive industry funding of university research that replaces rather than complements federal funding can contribute to increasing university inefficiency.

The technology transfer variables provide some surprising evidence on the efficiency effects of having a technology transfer office. Universities that have long-standing technology transfer offices established before the Bayh-Dole act of 1980 (e.g., MIT, Stanford, University of Wisconsin) are more efficient at producing research outputs (patents, articles, and students). On the other hand, late-comers to the patent and technology transfer process do not get an efficiency increase from having a technology transfer office. This result is especially strong since we are not accounting for any of the costs of a technology transfer office in our estimates, but we are measuring their major output, patents. This suggests that increased commercialization efforts associated with technology transfer may take time and experience to prove effective. It also raises the question of whether latecomers will be able to accomplish the same research productivity gains as those of early tech transfer entrants.

The coefficient estimates in Table 4 show that the marginal effect of "post-doc/Fac" on inefficiency is: 0.361 – 0.372 (post-doc/Fac). It follows that the effect of increasing post-docs per faculty member reduces efficiency when (post-doc/Fac) < 0.97. This suggests that an increase in a post-doc/Fac ratio tends to reduce inefficiency only when (post-doc/Fac) > 0.97.. Since universities with a post-doc/fac ratio higher than 1 represent only 10 percent of the sample, our estimates suggest that a relative increase in post-docs tends to increase inefficiency for most universities. We also find that universities with medical schools are less efficient. This may be a direct result of having more faculty with clinical and non-research responsibilities, which are not adequately reflected in our output measures.

In terms of university types, the results in Table 4 show that public universities are more efficient than private universities. Larger universities are significantly more inefficient than smaller universities. The performance of Land Grant universities (LGU) is more complex. The marginal effect of LGU on inefficiency is: 0.168 - 0.197 * (science fac). This means that this effect is negative when (science fac) > 0.852, and positive otherwise. Since the sample mean for (science fac) is 0.583, or 583 faculty members, it follows that small LGUs are less efficient than non-LGU universities. Alternatively, Table 4 indicates that, ceteris paribus, larger LGU are relatively more efficient than non-LGU universities.

6.2. Determinants of Technological Progress

The econometric estimates of the determinants of technological progress are reported in Table 5. Note that very few of the parameters are significant. This indicates that the process of technological progress for universities does not follow obvious patterns. In other words, this process appears to be for the most part unrelated to the characteristics of the universities and their commercial orientation, a result that is consistent with the lack of variation in rates of technological progress over time or across university type found in Table 2 above. The estimates in Table 5 do show a statistically significant effect of post-doctoral researchers on technological change. The marginal effect is: 3.082 – 1.255 * (postdoc/fac). It is positive as long as "postdoc/fac" is less than 2.455. This indicates that, for most all universities, postdocs do contribute positively to technological progress. Table 4 also shows that universities with technology transfer offices in 1980 experienced lower technological change than the late comers to the technology transfer process. This result may partially mitigate the efficiency advantage that the early innovators showed in the previous regressions.

7. Conclusions

This paper has estimated a production frontier for the university research process for science articles, patents, and students and examined the determinants of efficiency and technological change using a panel of 92 US universities over 18 years. The analysis made use of the directional distance function estimated using nonparametric methods, which in a multi-output framework enables recovery of university-level estimates of efficiency and technological change. These estimates were in turn used to examine the temporal trends in these measures and to identify econometrically significant determinants of university performance. This analysis seems particularly important given recent changes in US research universities. These changes include a takeoff in academic patenting, the commercialization of research efforts, and increasing fiscal constraints in federal and state financing for academic institutions.

The results show that U.S. research universities have become somewhat less efficient in this recent era of increasing commercialization. However, we found that this general trend masks an increasing efficiency gap between a significant set of top tier private and public universities and the rest of the sample. The econometric analysis show that many factors affect university efficiency. We found that total research funding tends to increase efficiency. Perhaps more importantly, we uncovered evidence on the role of funding sources. We found that, while federal funding always increases efficiency, a relative increase of industry funding can improve efficiency but only when federal funding remains dominant. This has three significant implications. First, it stresses the importance of federal funding of university research, which is primarily distributed on a competitive basis. Second, it identifies the presence of synergies between public and industry funding. Third, it shows that these synergies remain present only when federal funding is dominant. Thus, our results show that, while the commercialization of universities can generate efficiency gains, it does so only in consort with continued strong federal funding of university activities.

Our analysis also documents how technology transfer offices and hiring of more post-docs affect university efficiency. Technology transfer offices appear to contribute positively to efficiency for those universities that have had them for a long time but not for latecomers to the technology transfer arena. In addition, we find that increasing reliance on post-docs does not improve research efficiency. In terms of some of the control variables, we uncovered evidence of performance differences across university types. For example, our results indicate that, on average, large public Land Grant universities exhibit higher levels of technical efficiency.

Finally, we investigated technological progress in university activities. We found evidence of significant productivity growth associated with an outward shift in the university frontier technology. However, explaining the determinants of technological progress proved more difficult. This may reflect the fact that technological progress for universities may well be driven by factors exogenous to the university such as general improvements in computational speed, which are available to and adopted by major research universities simultaneously.

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Table 1: Average Inputs and Outputs for US Research Universities*

Year	Patents	Articles	Faculty	Undergrads	PhD's	Graduate students	Postdoc
1984	5.7	1326	471.9	1360	148.8	1482	177.6
1985	5.7	1413	480.1	1388	150.1	1508	185.6
1986	6.4	1465	476.4	1376	152.9	1564	198.2
1987	8.3	1503	474.4	1354	156.3	1574	205.8
1988	10.0	1549	467.8	1321	165.1	1596	216.3
1989	11.1	1617	470.7	1325	171.8	1633	232.2
1990	11.9	1674	474.8	1364	177.0	1681	246.4
1991	12.1	1771	488.2	1374	187.7	1729	257.8
1992	14.5	1892	475.3	1434	192.0	1811	272.5
1993	17.1	1893	494.1	1480	196.6	1839	285.4
1994	21.6	1976	502.9	1510	204.0	1824	302.9
1995	28.3	2082	514.3	1529	206.0	1786	301.1
1996	22.6	2082	531.4	1547	210.0	1753	309.3
1997	24.9	2100	528.9	1537	208.7	1721	320.2
1998	23.5	2132	518.7	1568	209.6	1720	329.9
Average	14.9	1765	491.3	1431	182.4	1681	256.1

* Note that "PhD's" represents completed doctorates while "Graduate students" represents continuing graduate students.

Table 2: Rate of Technological Change (as measured by annualized 100*A/fac)* by University Type (1980s and 1990s)

	LGU	Private	Non-LGU Public	Average
1980s	0.71	1.09	0.82	0.87
1990s	0.67	1.07	1.06	0.92

* This is the percentage of faculty saved per year due to technological progress.

Table 3: Descriptive Statistics

Variables	Number of observations	Mean	Std. Dev.	Min	Max
Research Funding ($million)	1257	148.365	111.830	7.078	825.631
Pct. Federal Funds	1257	60.994	15.5572	23.8272	96.0457
Pct. Industry Funds	1257	6.3209	4.0551	0	27.1062
Pct. Fed X Pct. Ind	1257	378.02	261.46	0	1569.31
Private University	1257	0.307876	0.461799	0	1
Land Grant U.	1257	0.393795	0.488785	0	1
Science Faculty (1,000)	1257	0.519	0.239	0.125	1.327
Tech Transfer Y/N	1257	0.747812	0.434441	0	1
Tech Transfer 1980	1257	0.295943	0.456647	0	1
Medical School Y/N	1257	0.630072	0.482977	0	1
Postdoc/fac	1257	0.490902	0.450179	0	4.39428
100*D/fac	1257	14.8826	15.9573	0	57.8012
Annualized 100*A/fac	184	0.895	0.9471	0	5.782

Table 4: Inefficiency Estimates: Tobit Model*

Dependent Variable = 100*D(z, g, F)/Fac

Variables	Estimate
Time Trend	1.062
	(5.99)**
Research Funding ($million)	-0.109
	(4.96)**
Pct. Federal Funds	-0.053
	(0.60)
Pct. Industry Funds	3.346
	(4.93)**
Pct. Fed X Pct. Ind	-0.06229
	(5.38)**
Private University	13.89
	(3.07)**
LGU	16.76
	(4.27)**
Science Faculty (1,000)	22.998
	(2.86)**
Private* Science Faculty	2.84
	(0.29)
LGU* Science Faculty	-19.72
	(3.02)**
Tech Transfer Y/N	3.90
	(2.29)*
Tech Transfer 1980	-12.22
	(6.63)**
Medical School Y/N	8.03
	(6.03)**
Postdoc / faculty	36.06
	(5.96)**
$(\text{Postdoc / faculty})^2$	-18.61
	(7.12)**
Constant	-10.97
	(1.71)
Sigma	20.17
std. error of sigma	(0.511)**
Log Likelihood	-3653.7
Observations	1257

* Robust z statistics are presented in parentheses: * = significant at 5% level; ** = significant at 1% level.

Table 5: Technological Change Estimates: Tobit Model*

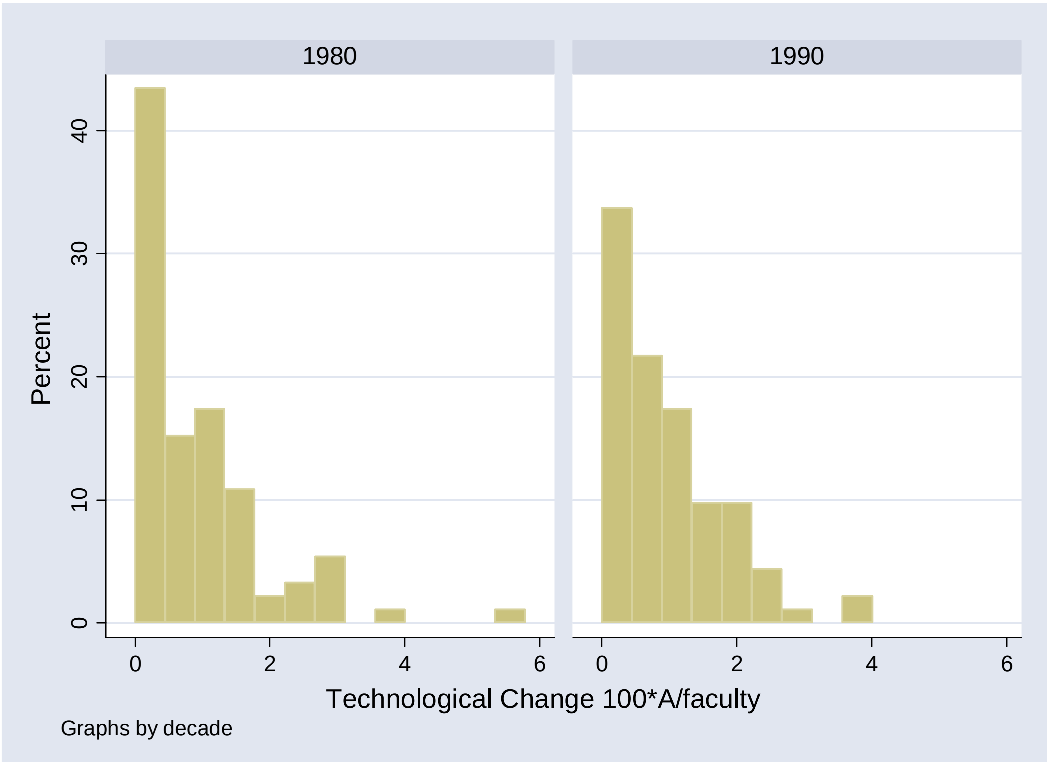
Dependent variable = annualized 100*A/Fac

Variables	Estimates
Time (1990's = 1)	-0.037
	(0.16)
Research Funding ($million)	-0.003
	(1.28)
Pct. Federal Funds	-0.012
	(1.25)
Pct. Industry Funds	0.0052
	(0.06)
Pct. Fed X Pct. Ind	-0.00007
	(0.05)
Private University	-0.787
	(1.07)
LGU	0.257
	(0.52)
Science Faculty (1,000)	0.831
	(0.98)
Private* Science Faculty	2.546
	(1.44)
LGU* Science Faculty	-0.648
	(0.80)
Tech Transfer Y/N	0.281
	(1.21)
Tech Transfer 1980	-0.789
	(2.78)**
Medical School Y/N	0.317
	(1.56)
Postdoc / faculty	3.082
	(3.81)**
$(\text{Postdoc / faculty})^2$	-1.255
	(3.48)**
Constant	0.411
	(0.63)
Sigma	1.141
std. error of sigma	(0.094)**
Log Likelihood	224.84
Observations	168

* Absolute value of t statistics are presented in parentheses: * = significant at 5% level; ** = significant at 1% level.

Figure 1: Average Inefficiency by University Types

Figure 2: Distribution of Technological Change (measured by annualized 100*(A/fac)) in the 1980s and 1990s



Appendix

Patents

Patent data were culled from the NBER patent database, where they were identified as having a university assignee. Patents assigned to the University of California system were associated with a campus (Berkeley, Davis, Los Angeles, etc.) by the location of their authors through searches of campus directories. Relative citations for patents were generated by year and by patent class comparing each individual patent to the universe of all patents in that class (whether owned by universities or not). A university's patent count for that year is then adjusted by the ratio of number of citations received to the expected citations for that portfolio:

$$Quality\ Adjusted\ Patents = \#\ patents \times \frac{\#\ citations\ received}{E(citations)}$$

where the number of expected citations, *E(citations)* is calculated as the number of citations that same portfolio of patents would receive if each patent received the average citation rate for its US patent class for that year.

Articles

Article data were culled from the ISI-Web of Science database based on universities included in their "University Science Indicators" and categories established in that same document. The Web of Science includes only the major journals in a field as identified by impact factors, such that our article measures necessarily cut out articles written for lesser journals. In addition the citation measures are only for citations in other major journals. This truncation, we believe serves our purposes of adding a subtle quality measure even to our quantity measures. Articles listed in all science disciplines were chosen.

Relative citations for articles were generated by category compared to citations of other articles assigned to the universities in the sample, rather than to all articles, and these measures were constructed annually. The same techniques of generating relative citations used for patents were used for articles.

Universities included in the sample: (universities in italics were not included in the regressions due to missing technology transfer office data (7 of them) or post-doc data (Georgia Inst. of Technology).

Arizona State U., Boston U., Brandeis U., Brown U., Caltech, Carnegie Mellon U., Case Western Reserve U., Colorado State U., Cornell U., Dartmouth College, Emory U., Florida State U., *Georgetown U., Georgia Inst. of Technology*., Harvard U., Indiana U., Iowa State U., Johns Hopkins U., *Lehigh U.*, *Loyola U.*, Michigan State U., MIT, N Carolina State U., New Mexico State U., *Northwestern U.*, Ohio State U., Oregon State U., Penn State U., Princeton U., Purdue U., Rice U., Stanford U., Syracuse U., Texas A&M U., Tufts U., U. Alabama, *U. Alaska,* U. Arizona, U. C. Berkeley, U. C. Davis, U. C. Irvine, U. C. Los Angeles, U. C. Riverside, U. C. San Diego, U. C. Santa Barbara, U. C. Santa Cruz, U. Chicago, U. Cincinnati, U. Colorado, U. Connecticut, U. Delaware, U. Florida, U. Georgia, U. Hawaii, U. of Illinois Chicago, U. Illinois Urbana, U. Iowa, U. Kansas, U. Kentucky, U. Maryland Baltimore, U. Maryland College Park, U. Miami, U. Michigan, U. Minnesota, U. Missouri, U. N. Carolina Chapel Hill, U. Nebraska, U. New Hampshire, U. New Mexico, U. Oregon, U. Penn, U. Pittsburgh, U. Rochester, U. So Calif, U. Tennessee, U. Texas Austin, U. Texas Houston, U. Utah, U. Vermont, U. Virginia, U. Washington, U. Wisconsin Madison, Utah State U., Vanderbilt U., Virginia Polytech Inst, W. Virginia U., Wake Forest U., *Washington State U.*, Washington U., Wayne State U., Yale U., *Yeshiva U.*