Technical Change and Efficiency at US Land Grant Universities: Is There Any Fat Left to Cut?

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Summary:
This work uses non-parametric efficiency analysis and a unique panel data set to analyze efficiency and technical change at US universities from 1981-1998 with a special emphasis on Land Grant institutions. The analysis demonstrates that Land Grants are on average more efficient than their counterparts. While in the 1980s they had higher levels of technological change, in the 1990s that declined to levels similar to other types of universities. Identifying factors influencing efficiency and technological progress in university production provides key insights into the future of the Land Grant system.

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I. Introduction

It is well documented that federal and state funding in support of university research and development have played a vital role in generating long term social returns that are not available from private sector research (Alston and Pardey 1996; Chavas, Aliber, and Cox, 1997; Jones and Williams, 1998; Taylor, 2001). Yet, in recent years, as budget crises have beset virtually every state in the union, one of the first places state legislatures have looked to cut expenditures has been their Land Grant universities (LGUs) as well as other public universities. These cuts represent historic reductions in the long-term commitments of states to higher education and indirectly to public financing of research and development. In addition, it appears likely that federal funds at least for agricultural research and perhaps for public research in general are also likely to stagnate under the burden of mounting fiscal deficits, which would affect both public and private research-oriented universities. As a result, universities across the country find themselves in an austere era, searching for both alternative funding sources and ways to improve their efficiency. But, if they are already quite efficient, and there proves to be little in the way of "free" cost savings, cuts in state and federal funding could have profound long term effects on the economy. Alternatively, if efficiency improvements are possible, and/or technological progress is rapid, then universities might be able to mitigate if not substitute for declining state and federal resources.

This work uses non-parametric efficiency analysis and a unique panel data set on scientific research inputs and outputs at 96 U.S. universities from 1981-1998 to answer the following key questions:

- Are LGUs, other public, and private universities efficient in producing research outputs? How do they compare?

- What is the rate of technological progress at different types of universities?

- What are the factors influencing efficiency and technological progress in university production?

- What do the efficiency and technological progress estimates suggest for the capacity of universities to overcome declining public support for research?

- How does federal and state funding affect efficiency and rates of technological progress?

The analysis specifies the primal production problem of a university using the Luenberger (1995) shortage function. University scientific production outputs are measured by trained graduate and undergraduate students (doctorates and bachelor degrees), journal articles, and patent counts. These output measures are more complete than most previous analyses of university research production. Inputs to university scientific production are measured by numbers of faculty, doctoral students, and post-doctorates.[2] The shortage function approach measures technical efficiency by the number of faculty members that can be saved by moving to the current scientific production frontier. Technological progress, as exemplified by movements in the frontier, is measured for universities in terms of their change relative to a baseline technological frontier.

[2] This analysis focuses on variable inputs (faculty, post-docs, etc.). We make the implicit assumption that physical capital use such as lab space is in constant proportion to the variable inputs used as would be the case in a Leontief type production function. To the extent this assumption might be violated, the panel nature of the data does partially control for university specific differences in such labor to capital ratios.

This analysis is innovative in its use of the Luenberger shortage function which heretofore has been used almost entirely for theoretical explorations. As mentioned above, the approach also incorporates patent counts into an analysis of efficiency and technical change of university research production. In addition, the panel data allows not only for the creation of university-specific measures of technical efficiency and technological progress for each time period, but also for the specification of dynamic regression models that help to control for the inherent dynamics involved in university research efforts.

The key empirical steps of the paper are as follows. First is the non-parametric frontier analysis of the 1981-1998 input and output data to generate a panel of university-specific estimates of technical efficiency and technological progress. Second is a descriptive analysis of these estimates that helps to answer some basic questions on the degree of technical efficiency and rate of technological progress at different types of universities. Third is an econometric analysis of the determinants of efficiency and technological progress that combines the non-parametric estimates with supplementary panel data on university funding sources and other university-specific characteristics. As a lead-up to the empirical analysis, the next two sections describe the data and the shortage function approach.

II. Data

The panel dataset combines information on research inputs and outputs in the sciences and engineering for 98 top US universities, including 38 land grant universities, 26? other public universities, and 34 private universities from 1981-1998. The panel is complete and contains for all 98 universities the following data:

1) Total patent counts and patent citations from all science and engineering fields (U.S. Patent Office; and Hall et al. 2003),

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

3) Total number of doctorates and bachelor degrees granted in the sciences as well as the number of graduate students, faculty, and post-docs (NSF Webcaspar),

4) Levels of research funding from federal, state, industrial, and other institutional sources for the university (NSF Webcaspar), and,

5) Information on technology transfer offices (AUTM).

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 is limited to scientific inputs and outputs, in part to focus the analysis on the parts of the university producing research that generates technological change and partially due to the difficulties of measuring output in the humanities. In addition our measures of scientific inputs and outputs relates well to one of the key research outputs of interest, patents which are almost entirely produced by the sciences.

In order to proceed with the empirical analysis we divide the university production process in the following way. Universities are measured as producing the following outputs: journal articles, patents, and trained students; using the following inputs: faculty, post-doctoral researchers, and PhD graduate students. Table 1 provides summary statistics across the data set years for the inputs and outputs. In the case of student training, we measure undergraduate bachelor's degrees in the sciences and the number of continuing graduate students. In dividing out which graduate students are inputs and which are outputs, we make the assumption that a graduate student is being trained (output) up until their final year at which point they become an input.[3] Thus we measure both continuing graduate students (outputs) and PhD's granted (inputs).

Table 1 Average Science Inputs and Outputs

Year	Patents	Articles	Faculty	Undergrads	PhD's	Grad stds	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 PhD's represents completed doctorates while "Grad stds" represents continuing graduate students.

A first look at the data reveals major increases in university scientific research production in spite of relatively minor changes in faculty numbers. Table 1 demonstrates

[3] Since graduate students are both inputs and outputs, we need to make some assumption in order to identify what is an input and what is an output. We assume that in their final year when we can measure their existence they are an input. 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 assumption reasonably closely matches the output data we have.

this burst in research production during the 1984-98 period by presenting the average output and faculty input levels for the universities in the sample for each year. 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 technical progress properties of the university production process. The empirical analysis pursued below builds on a non-parametric analysis of the production process, which is described next.

III. Shortage Function Theory

1. Introduction

One can think of a university as a single firm producing multiple outputs: patents, journal articles, trained students, etc. The standard method in the literature of analyzing multiple outputs from a single production process is to formulate the problem in terms of production possibility frontiers and firm expansion paths, *vis*. movements to higher production possibility frontiers (e.g. Baumol, Panzar, and Willig). Such an analysis of a multi-product production process allows one to investigate efficiency of production as well as technological progress.

The modeling strategy employed here is to specify the university production process using the shortage function suggested by Luenberger (1995), which is similar to the directional distance function of Chambers, Chung, and Fare (1996). The shortage function framework allows a description of the primal production problem with multiple outputs and avoids a number of the measurement problems associated with the dual, cost function, formulation (e.g., Gertler and Waldman, 1992).

2. The Model

Consider a production process involving 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 (where outputs are positive and inputs are taken to be negative), let $F \subset R^{n+m}$ represent the production possibility set, where $(-x, y) \in F$ means that outputs y can be produced from inputs x. Throughout, we assume that the set F is closed. Let $g \in R^n_+$, $g \neq 0$, be some reference input vector. And denote the prices for inputs x by $p \in R^n_+$. Consider the <u>shortage function</u>:

$$S(x, y, g, F) = \min_\beta \{\beta: (-x - \beta g, y) \in F\} \text{ if } (-x - \beta g, y) \in F \text{ for some scalar } \beta, \quad (1)$$

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

The shortage function S(x, y, g, F) in (1) measures how far the point (x, y) is from the frontier technology, expressed in units of the reference bundle g. The properties of the shortage function S(x, y, g, F) have been investigated by Luenburger. They are summarized next. First, $(-x, y) \in F$ implies $S(x, y, g, F) \leq 0$ (since $S(x, y, g, F) > 0$ implies $(-x, y) \notin F$). Second, if the set F is convex, the shortage function S(x, y, g, F) is convex in (x, y). Third, under free disposal (where $(-x, y) \in F$ and $(-x', y') \leq (-x, y)$

implies that $(-x', y') \in F$), the production possibility set F can be written as $F = \{(-x, y): S(x, y, g, F) \leq 0\}$ (Luenberger, p. 20). Then, the boundary of the production technology is represented by the implicit equation $S(x, y, g, F) = 0$.

3. Technical Efficiency

Under technology F, considering a firm observed to be at point (x, y). The shortage function S(x, y, g, F) in (1) provides a general way of assessing technical efficiency and productivity. And the choice of the reference bundle g in (1) provides some flexibility.

First, consider the case where g = x. Then, the shortage function becomes $S(x, y, x, F) = D(x, y, F) - 1$, where $D(x, y, F) = \min_{\beta} \{\beta: (\beta x, y) \in F\}$ is the Farrell input distance function (Chambers, Chung, and Fare, 1996). In this context, $D(x, y, F) \leq 1$ if (x, y) is feasible, $D(x, y, F) = 1$ if (x, y) is on the upper boundary of the technology, and $[1 - D(x, y, F)]$ measures the proportional reduction in all inputs that can be obtained by moving to the frontier technology. Much research has used the Farrell input distance function D(x, y, F) as a measure of technical efficiency and productivity. A drawback of the Farrell distance function is that it cannot deal easily with aggregation across firms. The reason is that proportions cannot be meaningfully added across firms.

Second, the shortage function S(x, y, g, F) measures the quantity of inputs g that can be saved by moving to the frontier technology. When the same bundle g is used across all firms, this quantity can be meaningfully added across firms. It means that the shortage function can deal easily with aggregation issues. This is the main motivation for its use below in our analysis of technical efficiency and productivity.

We have seen that S(x, y, g, F) ≤ 0 under technological feasibility, and that S(x, y, g, F) = 0 implies that point (x, y) is necessarily on the frontier of the production technology F. It means that S(x, y, g, F) < 0 necessarily implies that point (x, y) is below the production frontier. In this case, outputs y could be produced by using inputs [x + S(x, y, g, F) g], i.e. with a cost reduction of [-S(x, y, g, F) p · g] (where p denote the price vector for inputs x).

This suggests the following measure of technical efficiency

$$E(x, y, g, F) = -S(x, y, g).$$

E(x, y, g, F) has a simple and intuitive interpretation. First, technical feasibility of point (x, y) implies that E(x, y, g, F) ≥ 0. Second, finding that E(x, y, g, F) = 0 means that point (x, y) is on the frontier of the production technology F. Third, finding E(x, y, g, F) > 0 implies the firm is technically inefficient at (x, y), i.e. that point (x, y) is below the frontier of technology F. In this case, E(x, y, g, F) is the number of units of the input bundle g that the firm can save by becoming technically efficient. 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 E(x, y, g, F) a convenient measure in the investigation of technical efficiency for a group of firms or for an aggregate industry.

4. Productivity-Technological Progress

Consider a change in technology from F to F'. Under technological progress, F ⊂ F' as the feasible set expands. Since the shortage function involves a minimization problem, this implies that S(x, y, g, F') ≤ S(x, y, g, F). Noting that the cost of producing outputs y under technology F is [p · [x + S(x, y, F) g]], it follows that the change in production cost from technology F to F' is [p · [S(x, y, F) - S(x, y, F')] g]. Thus, if positive, [p · [S(x, y, F) - S(x, y, F')] g] measures the benefit (in terms of reduction in production cost) of technological progress from F to F'. Evaluated at point (x, y), this suggests the following measure of technological progress

A(x, y, F, F') = S(x, y, F) - S(x, y, F').

A(x, y, F, F') has a simple and intuitive interpretation. First, A(x, y, F, F') = 0 in the absence of technological progress. Second, evaluated at point (x, y), finding A(x, y, F, F') > 0 implies technological progress from F to F'. In this case, A(x, y, F, F') is the number of units of the input bundle g that can be saved 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(x, y, F, F') a convenient measure in the investigation of technological change for a group of firms or for an aggregate industry.

5. Nonparametric Implementation

Estimating the Shortage Function

The shortage function is estimated with non-parametric programming methods that use input and output data to identify the frontier production technology and the distance that individual universities are from that frontier. University outputs are measured as research articles, patents, and doctoral students in labs, and bachelor degrees, while the inputs are measured as post-docs, doctorates in their final year of study, and faculty. Faculty numbers are used as the numeraire good, *g*, to provide a logical measure for the distance from the frontier: the number of faculty that could be saved if the university were fully efficient. A key strength of this approach, as opposed to a cost function approach, is that the major inputs and outputs of a university can be measured accurately.

The estimation of the non-parametric frontier, to be done using GAMS, finds the outer envelope of the production frontier and produces measures of the distance to that frontier. Estimation proceeds as follows. Consider a set of T observations on S universities. For the s-th university at time t, we observe the inputs-outputs (x_s^t, y_s^t), s = 1, …, S and t = 1, …, T. Assuming non-regressive technical change and variable returns to scale, a nonparametric representation of the technology at time τ is[4]

$$F_\tau^{v} = \{(-x, y): \sum_{s=1}^{S} \sum_{t=1}^{\tau} \lambda_s^t x_s^t \leq x, \sum_{s=1}^{S} \sum_{t=1}^{\tau} \lambda_s^t y_s^t \geq y, \sum_{s=1}^{S} \sum_{t=1}^{\tau} \lambda_s^t = 1, \lambda_s^t \geq 0,$$
$$s = 1, \ldots, S, \text{ and } t = 1, \ldots, T\}. \qquad (2)$$

Then, a nonparametric estimate of the shortage function is:

$$S^{v}(x, y, g, F_\tau) = \min_{\beta,\lambda} \{\beta: \sum_{s=1}^{S} \sum_{t=1}^{\tau} \lambda_s^t x_s^t \leq x + \beta g, \sum_{s=1}^{S} \sum_{t=1}^{\tau} \lambda_s^t y_s^t \geq y,$$
$$\sum_{s=1}^{S} \sum_{t=1}^{\tau} \lambda_s^t = 1, \lambda_s^t \geq 0, s = 1, \ldots, S, \text{ and } t = 1, \ldots, T\}. \qquad (3)$$

This is a straight forward linear programming problem in which the location of the frontier is estimated across all universities up to time τ. This allows measurements of technological progress (movements of the frontier overtime) and efficiency changes (university movements toward the frontier at a given time τ).

Estimating the Determinants of Efficiency and Technical Progress

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

The shortage function programs produce two measures of the production process at individual universities: 1) efficiency, $E(x,y,g,F_{\tau})$; and 2) university specific technological progress measured by, $A(x,y,g,F_{\tau},F_{\tau'})$. These measures are estimated for each university for each year in the data set, generating a panel that can be used to examine the levels, rates, and determinants of efficiency and technological progress.

In order to examine the determinants of these outcome measures (i.e., efficiency and technological progress), we specify a panel data econometric equation that describes them as a function of university characteristics and time specific measures. The estimation procedure will be complicated by censoring in both of the dependent variables. In the case of efficiency fully efficient universities will have $E(x,y,g,F_{\tau})=0$. In the case of technological change, in any given year a number of universities will not show any technological change from the baseline point, implying that $A(x,y,g,F_{\tau},F_{\tau'}) =0$. Such a censoring of the dependent variable suggests that a random effects Tobit model is appropriate. Rewriting all the right hand side variables as $\boldsymbol{z_{it}}$ the equation to be estimated becomes:

$$\pi_{it} = max(0, \boldsymbol{z_{it}}\delta + v_i + u_{it}),$$

where u_{it} is, conditional on π_{it}, v_i and $\boldsymbol{z_i}$, distributed $N(0, \sigma_u^2)$. The above equation can be estimated using a likelihood function given in Wooldridge (2002). The procedure is run in STATA, which uses the Gauss-Hermite quadrature procedure to approximate the double integral.

The university characteristics hypothesized to influence these outcomes will include: total number of science faculty, percent of funding from federal and industry sources, whether they have an office of technology transfer, whether they have a medical school. In order to capture interaction effects we also include the cross-product term between percent federal and percent industry funding. The technology transfer office variable is measured with two dummy variables one designating whether the university had a technology transfer office before the Bayh-Dole act in 1980 (tto_1980) and the other for whether they had a technology transfer office with more than 0.5 of an FTE working there. In addition we include dummy variables for public universities and for land grant universities. We also include a time trend variable along with its square to capture secular time trends.

IV. Empirical Results

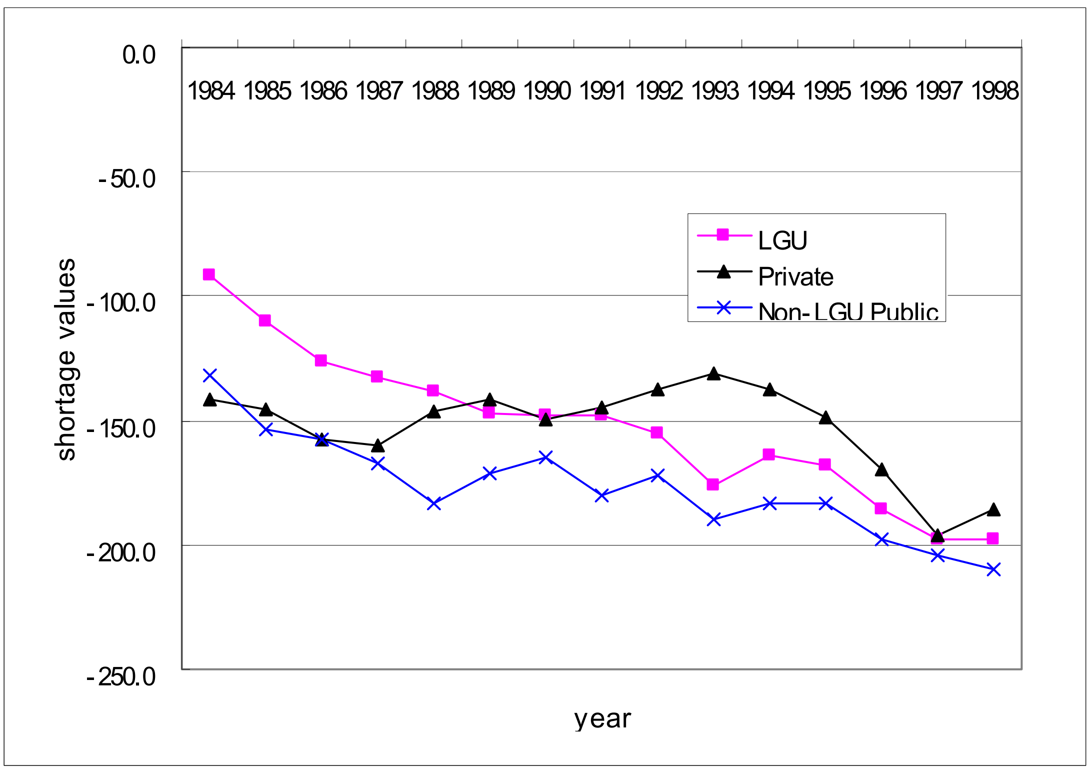
A. Descriptive statistics from the shortage function output.

Technical efficiency of U.S. Universities

One way of examining the technical efficiency of U.S. universities is to identify which ones tend most often to be at the frontier of the scientific research production process. In general Land Grant universities are more likely to be at the frontier than non-LGUs, with 36% of all the LGU observations at the frontier compared to 25% of the other universities. Among the 38 LGUs, there are four (Texas A&M, UC-Berkeley, U. of Minnesota, and U. of Wisconsin) which are estimated to be at the frontier in every time period, and five that are at the frontier in all but one time period. However, two these latter LGUs (U. of Alaska and U. of New Hampshire) help to define the frontier of the technology at very low levels of science research output, while the others (Penn State, U. of Florida, and U. of Illinois) are at higher levels.

A second way of examining the technical efficiency is shown in Figure 1 which shows the average distance from the frontier across different university types. In the 1980's Land Grant universities were significantly more efficient than either private or non-Land Grant public universities. This situation changed in the late 1980's with the rise in average efficiency of private universities, although by the end of the 1990's the average efficiency level of all university types had converged to similar values.

Figure 1: Average Efficiency Across University Types



Describing Technological Change

In order to describe technological change we measure the resources that could be saved in subsequent years producing our baseline year's (1984) outputs over the actual inputs used. We fix the inputs used and the outputs produced at our baseline year (1984) level, then measure how many fewer resources would be needed in a subsequent year to produce those outputs. Since we have designated science faculty as our numeraire good, all measurements are made in the number of faculty members that could be saved.

We measure technological change over two periods: from 1984 to 1989 and from 1990 to 1998. These time periods allow us to focus on the differences between universities rather than the time series aspect of the data. Table 2 shows technological change across the two time periods with universities divided by type: Land Grant, Public non-LGU, and Private. Overall technological change was much faster in the 1980s and especially so at public universities, both Land Grants and non-LGUs. By the 1990s both types of public universities had levels of technological change that were just about half of what they had been in the previous decade.

Table 2: Technology Change by University Type (1980s vs. 1990s)

	LGU	Private	Non-LGU Public	MEAN
1980s	76.6	57.2	62.3	65.9
1990s	34.5	48.7	36.5	40.0

Table 3 shows the top 5 universities in each time period. Especially noteworthy is that in the 1980s, 4 of the top 5 were public of which 3 were Land Grant universities. However, by the 1990’s only one of the top 5 was a Land Grant university and only one other was a non-LGU public university.

Figure 2 shows a histogram and kernel density distribution for the two time periods showing the dispersion of technological change across universities. One of the key differences is the much higher portion of universities in the 1990s that saw no technological change during that period.

Table 3: Technological Change: The Top 5 Universities

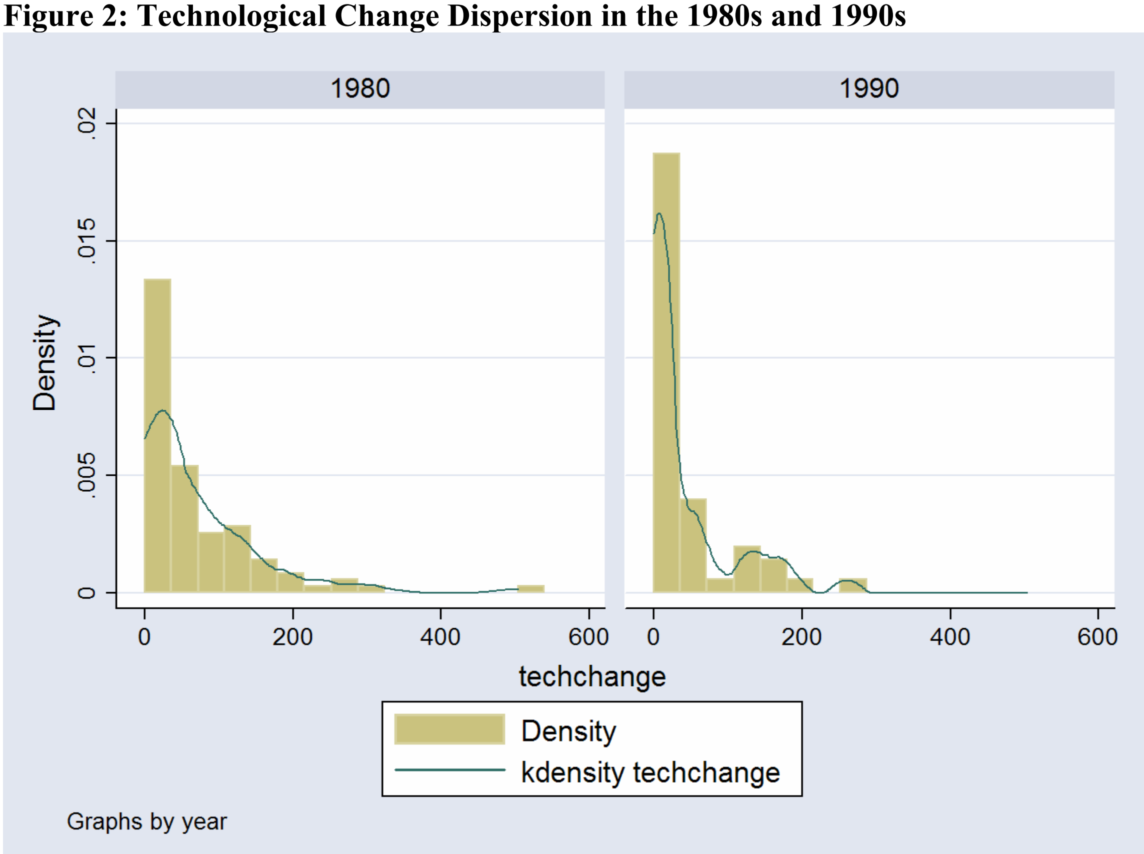
1980s

University	Land Grant	Public	Private	Technology Change
U. of Illinois	1	1	0	228.6
U. of Washington	0	1	0	271.0
Virginia Tech	1	1	0	282.7
MIT	0	0	1	315.8
U. of Florida	1	1	0	503.5

1990s

University	Land Grant	Public	Private	Technology Change
Harvard	0	0	1	176.3
U. of Washington	0	1	0	185.0
Cornell	1	1	0	188.5
Stanford	0	0	1	257.3
MIT	0	0	1	263.3

Figure 2: Technological Change Dispersion in the 1980s and 1990s



B. Determinants of Efficiency and Technological Progress

In order to understand the determinants of efficiency and technological progress we specify them as functions of some key variables hypothesized to make a difference to efficiency and technological progress. A panel data Tobit model is estimated using the measure of distance from the frontier, E(x, y, g, F), normalized on a per faculty member basis as the dependent variable. The second regression estimates a Tobit model using the measure of technological progress, A(x, y, F, F'), as a dependent variable. In this case since there are only two periods, 1984-1989 and 1990-1998, we estimate a pooled regression model. 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 the sources of research funding and the pressures for certain types of work that come with that funding. We measure some of these differences using dummy variables for public versus private universities and for Land Grant universities versus non-Land Grants. We hypothesize that the additional outreach missions of public universities, especially Land Grant universities, would make them less efficient and result in slower technological progress than the default value of private universities.

A large literature on university research production has also shown the importance of federal funding to the research process (see e.g., Alston and Pardey) and at the same time worried about the influence of industry funding (see e.g., ???). The literature suggests and we hypothesize that higher percentages of federal funds in the university budget will increase both efficiency and technological progress. At the same time the literature worries and we hypothesize that a higher percent of industry funding will divert resources away from the typical university outputs we measure and lead to lower levels of efficiency. We also include a cross product term for these funding percentages to capture any interaction effect between them.

In order to capture any scale effects we also include a measure of the number of science faculty at the university. We hypothesize that, having controlled for other effects, larger universities will be less efficient and have lower rates of technological change.

Since the existence and experience of a technology transfer office will influence the production of one of our measured outputs, patents, we also include two variables to measure the level of technology transfer infrastructure at the universities. We use two dummy variables; the first measures whether or not they have 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 technology transfer. It is hypothesized that having a technology transfer office will increase efficiency. A technology transfer office's existence as an initial condition is thought to reduce technological progress since most universities that did not have one would have added one in the sample period and therefore gotten a technological boost. 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 two variables to control for what we think are important differences between universities. One measures whether the university has a medical school (0 – 1) and the other measures the number of post-doctoral researchers per faculty. We expect universities with more post-docs per faculty to have higher efficiency levels.

Table 4 Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Pct. Federal Funds	0.610	0.15	0.24	0.96
Pct. Industry Fund	0.066	0.05	0.00	0.29
Pct. Fed X Pct. Ind	0.039	0.03	0.00	0.16
Public University	0.646	0.48	0.00	1.00
Land Grant U.	0.365	0.48	0.00	1.00
Science Faculty	501.432	249.38	98.50	2162.21
Tech Transfer Y/N	0.751	0.43	0.00	1.00
Tech Transfer 1980	0.292	0.45	0.00	1.00
Medical School Y/N	0.645	0.48	0.00	1.00
Postdoc / faculty	0.522	0.58	0.00	5.30
E(x, y, g, F) per faculty	0.369	0.30	0.00	0.91

The estimation results from the panel data tobit on efficiency are reported in Table 5. As a reminder, efficiency, E(x, y, g, F), is measured as the distance from the frontier, so that a negative coefficient estimate indicates a variable that helps to increase efficiency, while a positive estimate reflects the opposite. For example, then, the descriptive finding above that efficiency fell in the 1990s relative to the 1980s is reflected in the positive and significant coefficient estimate on the time trend variable.

All but one of the estimates on the explanatory variables is statistically significant. Only the coefficient estimate on the percent of funds coming from federal sources is insignificant. We highlight the following results from Table 5:

- Land Grant Universities are more efficient than other public and private universities in terms of science research production.

- Other public universities are less efficient than private universities in terms of science research production.
- More science faculty and more post-docs per faculty member are associated with increased efficiency. Both of these results suggest the presence of agglomeration, with higher efficiency resulting from more faculty and more post-docs per faculty member. This latter result is consistent with work by Buccola and Xia.
- Contrary to the main hypotheses in the literature, a higher percent of research funds coming from industry sources is significantly associated with more efficient science research production relative to other sources of funding, while a higher percent of research funds from federal sources is not significantly associated with higher efficiency. Perhaps most striking is the negative and significant impact on efficiency of universities that are more highly dependent on both federal and industry funding.
- Universities that have had a technological transfer office since 1980 are more efficient than those that added tech transfer offices later. Surprisingly, the presence of a technological transfer office appears to have a negative impact on the efficiency of scientific research production.

Table 5 Efficiency Regressions: Panel Data Tobit
Dep. Var. = E(x, y, g, F) per faculty

Variables	coeff.	std. err.	Z
Constant	0.445	0.057	7.740
Time	0.010	0.005	1.980
Time^2	-0. 00005	0. 0003	-0.160
Pct. Federal Funds	-0.069	0.077	-0.900
Pct. Industry Fund	-1.092	0.550	-1.980
Pct. Fed X Pct. Ind	2.947	0.902	3.270
Public University	0.040	0.023	1.740
Land Grant U.	-0.128	0.018	-6.960
Science Faculty	-0.00023	0.00003	-8.140
Tech Transfer Y/N	0.068	0.016	4.190
Tech Transfer 1980	-0.158	0.025	-6.440
Medical School Y/N	0.038	0.013	2.820
Postdoc / faculty	-0.094	0.015	-6.140
sigma_u	0.268	0.006	41.380
sigma_e	0.157	0.004	42.000
rho	0.743	0.011	

Wald chi2(12) = 460.94
Log likelihood = 97.998943 Prob > chi2 = 0.0000
Observation summary: 941 uncensored observations
405 left-censored observations
0 right-censored observations

The determinants of technological progress are reported in Table 6. A Tobit model is estimated which analyzes technological change in the 1990 across universities as a function of the independent variables described above using their 1990 values. We chose to focus on the 1990's in order to be able to capture persistence effects.[5] We add

[5] We ran the technological change Tobit using the technological change data from both 1980 and 1990 and found only two significant parameters to describe the rate of technological change. The dummy variable for the 1990's was negative and significant demonstrating lower technological change in the 1990s and the parameter for the number of science faculty was positive and significant suggesting that larger universities have higher rates of technological change. Results are available from the authors.

two additional variables: the lagged technological change from the 1980s and the measure of university efficiency E(x, y, g, F). The first of these measures persistence in technological change while the second measures the relationship between technological change and efficiency as a way to measure whether "inefficient" universities can catch up through faster technological change.

The regression results show significant persistence in technological change between periods with universities that experienced high technological change in the 1980s also experiencing it in the 1990s. In addition universities that were more efficient, closer to the frontier, in 1990 tend to experience greater technological change in the decade. Taken together these results suggest a great deal of persistence and little opportunity for less efficient universities to catch up with their more efficient and technologically advanced counterparts.

The regressions also show that larger universities (as measured by the number of faculty) have higher technological growth rates than smaller ones. The coefficient on the public university dummy variable is negative and significant at a 10% level suggesting that they had lower rates of technological change, although no significant effect is observed in either direction for Land Grant universities. Universities with long established technology transfer offices had higher rates of technological growth. In addition, just as having more post-docs per faculty raised efficiency, it also had the effect of increasing technological change.

Table 6 Technological Change in the 1990s, Tobit Regression

Variable	coeff.	std. err.	t-value
Constant	-27.72	0.07	-0.63
tech_change_lag	0.29	0.03	4.25
E(x, y, g, F)	-0.07	58.81	-2.13
Pct. Federal Funds	34.19	430.29	0.58
Pct. Industry Fund	-139.96	697.54	-0.33
Pct. Fed X Pct. Ind	187.72	13.64	0.27
Public University	-24.12	13.33	-1.77
Land Grant U.	-7.47	0.02	-0.56
Science Faculty	0.11	12.55	4.45
Tech Transfer Y/N	-3.74	12.29	-0.30
Tech Transfer 1980	27.76	10.47	2.26
Medical School Y/N	-11.29	7.80	-1.08
Postdoc / faculty	15.07	43.84	1.93

Obs. summary: 12 left-censored observations at techch~e<=0
78 uncensored observations
LR chi2(12) = 75.51
Prob > chi2 = 0.0000
Log likelihood = -413.44735

Conclusions

This work has estimated a production frontier for the university research process for science articles, patents, and students and then estimated the determinants of efficiency and technological change using a panel of 98 universities over 15 years. The shortage function methodology allows a calibration of the primal production problem in a multi-output world. Estimates of efficiency and technological change were then regressed on some potential determinants to demonstrate what contributes to differences between universities.

The results show that LGUs across the size spectrum operate more efficiently than the overall sample of universities even when one controls for other effects. Among the large LGUs efficient in all the study years are U. of Wisconsin and U. of California-Berkeley, while the U. of Alaska appears to be one of the efficient small universities. Given that LGUs are already relatively more efficient, one has to wonder whether the current round of budget cuts at LGUs will have a negative effect. While in the 1980s LGUs also had higher levels of technological change than other universities, in the 1990s the fell back to the same level as other universities potentially due to budget cuts in the early 1990s.

This analysis demonstrates the success of the Land Grant system in being an efficient and cutting edge institution for generating research and development. The results, however, also suggest that state budget cuts in the 1990s and potentially those happening currently at LGUs may have a significantly negative effect on the research outputs (journal articles, trained students, and patents) of US Land Grant universities. The combination of already efficient production, but declining rates of technological change at LGUs does not bode well for a future with significant budget cuts.

This line of investigation can be extended in several ways. First, our analysis can produce more conclusive implications if quality-adjusted data are used in the estimation. It has been documented elsewhere that in the investigation of university production, both outputs and inputs can be adjusted using appropriate quality adjustment factors. Second, by measuring additional mission of the Land Grant system, i.e., extension of technology and research, a future study can increase the quality of analysis on the dynamics of efficiency and technical change in Land Grant universities compared to private and non-Land Grant pubic universities.

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