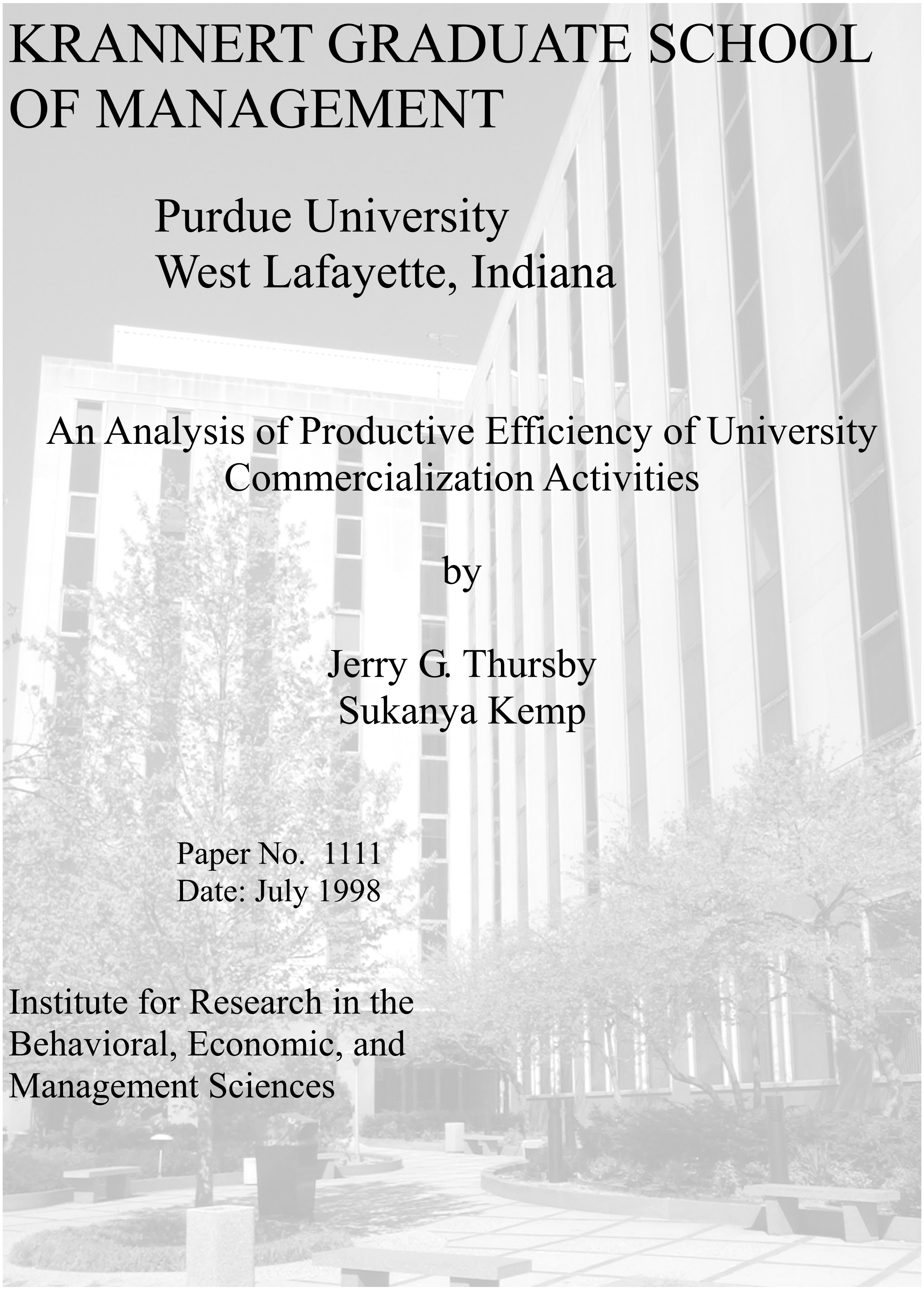

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An Analysis of Productive Efficiency of University Commercialization Activities

by

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AN ANALYSIS OF PRODUCTIVE EFFICIENCY OF UNIVERSITY COMMERCIALIZATION ACTIVITIES[a]

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INTRODUCTION

In this paper, we examine the productivity of commercial activity by U.S. universities in the past six years. While it is generally acknowledged that there has been a dramatic increase in university licensing and patenting, there is little understanding as to the extent to which this is the result of increased resources devoted to commercialization or to technical change in commercialization, where technical change has the standard definition of any increase in outputs that cannot be attributed to an increase in inputs. This paper employs data envelopment analysis (DEA) combined with regression analysis to examine the productivity of university commercial activity as well as changes in that productivity. DEA allows us to determine a commercialization frontier in order to evaluate overall productivity of universities in the sample, as well as to evaluate the technical efficiency of individual universities. We find that the commercialization frontier has moved out, indicating technical change in commercialization. That is, given input levels, universities are today more commercially productive than they were in the recent past; we propose several reasons for this shift. The regression analysis allows us to relate efficiency to university characteristics. We find that, ceteris paribus, private universities tend to be more efficient in commercialization than public, while universities with medical school are less likely to be efficient. The latter result is particularly interesting given that the majority of university licenses are related to biomedical inventions. We also examine efficiency as related to the size and quality of faculty in biological sciences, engineering, and physical sciences. Our measures of faculty input in biological sciences and engineering are significantly related to efficiency, while they are not for physical sciences; we propose reasons for this difference.

In our study of the commercialization of university intellectual property (IP) we consider the levels and changes in the levels of the "outputs"

- sponsored research agreements between universities and industry,
- license agreements which permit the use of university IP by private sector firms,
- royalty payments received by universities in exchange for the use of IP,
- disclosures by faculty to their central administration of potentially commercializable innovations, and
- university patent applications.

Each of these outputs is an integral part of a university's efforts to obtain commercial rewards from the creation of IP. While some of these outputs might be more properly regarded as intermediate inputs, we have settled on the above five outcomes as commercialization outputs based on interview and survey results reported in Thursby and Thursby (1998a). Each is viewed as an important criteria in measuring the success of a university's technology transfer. For want of better terms we use "commercialization," "commercial activity" and "licensing activity" as succinct ways of referring to the above five outcomes.

Why might such a study as this be of interest? Recent public policy has been aimed at increasing the commercial impact of universities. For reasons of greater U.S. "competitiveness," the federal government has encouraged greater interactions between universities and the private sector. The Bayh-Dole act of 1980 (P.L. 96-517, Patent and Trademark Act Amendments of 1980) changed the nature of ownership of inventions developed under federally funded programs. With passage of the act, universities could elect to retain title to such inventions, but they are required to file patent applications on those inventions. The Act also encourages the technology transfer activities of universities. The federal government has not been alone in encouraging university licensing activity. State governments have looked increasingly toward public universities as sources of economic development.

Whether in response to government incentives for commercial activity or whether it has followed from greater university needs/wants for revenues, the evidence suggests a shift in university goals toward greater commercialization. The Public Policy Center for Stanford Research International reported in 1986 that more than 90% of universities in their sample intended to increase interactions with industry. Morgan, Kannankutty and Strickland (1997) report survey results which show increasing responsiveness of engineering faculty to industry needs. Lee (1996) reports a similar finding based on his survey of engineering and science faculty. Finally, we note that university based "research parks" that are, in part, designed to facilitate commercialization of university technology are increasingly common.

Changing university goals has been accompanied by industry looking increasingly to universities for new technologies. Roessner and Wise (1994) report increasing industry participation in university research, and, based on interviews with industry licensing executives, Thursby and Thursby (1998b) report a similar finding.

Have the Bayh-Dole Act and state government efforts to increase commercialization made a difference? Have changing university and industry interests made a difference? The record suggests that the answers are yes. According to results reported in the *AUTM Licensing Survey* (Association of University Technology Managers, 1997), as well as AUTM press releases, university licensing activity has increased over the six year period during which AUTM has collected data. Using the sample of universities that participated in all years of the survey we find that the number of licenses agreements has risen by nearly 70% and the amount of royalties received (in real terms) has more than doubled between 1991 and 1996. Prior to 1980, fewer than 250 patents were awarded annually to universities; currently, over 1500 patents are awarded annually. The number of universities actively engaged in technology transfer has increased eightfold since 1980 to now more than 200.

It is clear that government, university, and industry goals are for greater involvement of universities in licensing activities, but, while evidence suggests an increase in such activity, the basis of those changes is not clear nor is there clear evidence on the relative productivity of universities with regard to commercial activities. In this paper we shed light on these issues by looking at relative university commercial productivity and factors related to levels of and changes in that productivity. In the next section we state more clearly the problem. Following that section we discuss the primary method of analysis, the data, and then present our detailed results.

THE PROBLEM

Universities are in the business of creation and dissemination of knowledge. This activity is generally divided into three interrelated (and hard to measure) outputs: teaching, service, and research. It is research that creates IP, and it is our purpose to study the management of that portion of IP with commercial potential. We have three specific goals. First, we wish to measure the productivity or efficiency of individual universities in the commercialization of their IP. Our measure of efficiency is based on a university's commercialization productivity relative to the productivity of other universities. Second, we seek to shed light on factors associated with different commercialization success across universities. Finally, we show that university commercialization activities have expanded substantially in the recent past. We consider whether that expansion in commercial activities has followed from a "catching" up by the lagging institutions or whether it stems from expanding activity of all institutions.

Commercial output can vary over time and across universities either because of changes in the amount of resources devoted to the creation and licensing of commercializable IP, or because of technological change which makes inputs more productive in the commercialization of university IP. There are two primary problems in analyzing university commercialization. First, there are multiple measures both of university licensing output and of the inputs used to produce commercializable output. These output and input measures cannot be easily aggregated due to the lack of prices for all outputs and inputs. We solve this technical problem by using DEA which is a linear programming approach to aggregating outputs and inputs and measuring productive efficiency. Second, and of substantially greater difficulty, is the fact that the inputs to university commercialization are also inputs to teaching, service, and non-commercializable research (i.e., basic research). While we can measure the number of faculty engaged in research and the funds available with which to conduct that research, we cannot measure the intensity of efforts directed toward teaching, basic research, etc. That is, we cannot distinguish between an increase in commercial output that follows from a reallocation of inputs away from, say, basic research toward commercializable (applied) research and an increase in output that follows from technical change.

Before proceeding it should be emphasized that the terms productivity, success and efficiency must be used guardedly as these terms might imply that an inefficient university is poorly run with respect to commercialization. This is, of course, not necessarily the case. As noted above, a university might specialize in basic over applied research, or it may have a greater preference for teaching over research vis-à-vis other institutions. If such specialization or preferences hold for some university, then it might fare poorly on measures of commercialization success because the showing follows, in part, from preferences and not from competencies.

University commercialization can be characterized with the following sequence: Research is conducted by faculty, though it is not necessarily conducted with the intent of creating a commercializable innovation or invention. This research may or may not have been sponsored by the private sector (industry sponsored research). If a faculty member believes that results of research are commercializable he or she undertakes a formal, confidential process of disclosure of the results to the university's Technology Transfer Office (TTO) which evaluates the innovation for patentable and commercial potential. If deemed commercializable, the TTO might seek patent protection and does seek to find private sector firms as licensees of the technology. If licensed, the university might receive royalties either in the form of upfront fees (a one time charge), milestone payments (fixed charges paid at specified points during commercial development), running royalties (a percent of revenues from sale or use of the IP) and/or equity. They might also seek sponsored research funds from an interested firm for further development of the IP, or for further undirected research; this further research may lead to other commercializable technologies.

While it might seem to the observer of this process that the ultimate objective is money either through sponsored research or royalties, this is not necessarily the case for every university. The private sector measures success via profits, but university obligations are more complex as universities – particularly public universities – are charged with the creation and dissemination of knowledge regardless of whether such activities are currently profitable in the private sector. Many universities view not only royalties and sponsored research as outputs of their commercialization activities, but also the number of patents and disclosures (measures of commercialization efforts) as well as the number of licenses (a measure of the dissemination of knowledge via new or improved products and processes). This is not to say that each of these commercialization outputs is equally important (they are not – see Thursby and Thursby (1998a)), but the fact that they are viewed as outputs by at least some universities makes the process of measuring commercialization activities difficult.

DATA ENVELOPMENT ANALYSIS AND EFFICIENCY MEASURES

In order to measure the relative productive efficiencies of universities in commercialization activities we must deal with multiple outputs (industry sponsored research, royalties, and numbers of disclosures, licenses, and patent applications).[1] Measuring efficiency is difficult when there are multiple outputs and the outputs do not all have prices so that they can be meaningfully aggregated and compared. Without prices how can we determine, for example, the relative importance of another invention disclosure compared to another license or dollar of royalties? To deal with this problem we use DEA. DEA is commonly used to evaluate the relative efficiency of a number of producers when there are multiple outputs (and/or inputs) and when the outputs cannot be meaningfully aggregated due to the lack of prices for at least some of the outputs. The output of DEA is an efficiency rating or score for each university.

Economists identify three types of inefficiency in production: technical, allocative and scale inefficiency. Allocative efficiency considers whether the producing unit is using the best mix of inputs given the prices that must be paid for inputs. As we do not have available input prices for all inputs we are unable to consider allocative efficiency. Scale efficiency deals with issues of size. A producing unit is said to be scale inefficient if a proportionate increase or decrease in inputs would lead to a fall in average costs. If such an increase in inputs leads to an increase (decrease) in average costs then the producing unit is said to be in a region of decreasing (increasing) returns to scale. Otherwise, the unit is said to produce in a region of constant returns to scale. It is not necessarily the case that it is better to produce in a region of constant returns. A profit maximizing firm may find that, based on market prices, the optimal output level occurs in a scale inefficient region of production. Likewise, scale efficient production for a university may not be optimal when all goals of the university are considered. In earlier analyses we considered whether universities were scale inefficient. We found about 45% of the universities in our sample to be scale inefficient; of these, about 60% are too large for efficient production and the rest are too small. Further analysis of the scale inefficient versus scale inefficient universities did not reveal any useful knowledge. For that reason and for reasons of brevity we do not present the scale results; we consider only models that allow for any scale effect.

A producing unit is said to be technically inefficient if it is possible to produce more output with the current level of inputs or, equivalently, it is possible to produce the same level of output with fewer inputs. It is our purpose to examine the technical efficiency of universities with regard to their licensing activities. We shall say that a technically inefficient (or, simply, inefficient) university is one that, when

[1] We do not include start-up companies as output. AUTM defines start-ups as new firms that are formed using a license from the university. As such, we do not view start-ups as output that is necessarily different from a license to an existing firm which then starts a new division or produces a new product based on that license.

compared to other universities with similar levels of inputs, could produce greater commercial output without increasing its level of input usage, or, equivalently, it is one that, when compared to other universities with similar levels of outputs, could produce the current levels of outputs with fewer inputs. Reasons for technical inefficiency include, among other things, the failure to take advantage of all commercializable IP as well as a greater preference for basic research over applied research.

To compare commercialization activities we use DEA.[2] DEA attempts to establish the shape of the frontier production function for, in our case, university commercialization activities when outputs are multiple (as are inputs) and where prices for some of the outputs are either missing or distorted. DEA is a mathematical programming method rather than a statistical tool; statistical approaches in the study of productive efficiency fit a single regression plane through the data while DEA calculates a discrete piecewise frontier determined by a set of efficient decision making units (DMUs). In this way a maximal performance for each DMU relative to all others is obtained such that each DMU either lies on or below the frontier. Units that lie on the surface are termed efficient and those not on the surface are said to be inefficient. In quantifying relative efficiencies, DEA weighs an inefficient DMU against a convex combination of the DMUs lying on the portion of the frontier closest to the inefficient DMU.

Consider the simple example. Let there be a single output and a single input for each of 6 DMUs whose outputs and inputs are depicted in Figure 1. The solid line which links DMUs 1 through 4 is the frontier in the presence of variable returns to scale. From the standpoint of technical efficiency, no one of DMUs 1 through 4 dominates the others; each successively uses more input and produces more output. These four determine the technical efficiency frontier and each is efficient in the sense that it is not dominated by another DMU. DMUs 5 and 6, on the other hand, are clearly dominated by the others; for example, DMU 2 uses less input and produces more output than DMU 5. DMUs 5 and 6 each lie below the technical efficiency frontier. There are no other DMUs with exactly the same input or output levels as 5 or 6. To measure the extent of inefficiency these DMUs are compared to the nearest facets linking efficient DMUs. For example, in considering how much less input DMU 5 could use to produce its current output, we compare it to a virtual DMU composed of the outputs and inputs of DMUs 1 and 2; these latter DMUs are referred to as the "peer" or "comparison" DMUs of unit 5.

The idea behind DEA is that, if DMU i produces y_i units of output with x_i inputs, then it should be the case that any other DMU j should also be able to do at least as well in the following sense. If j has an amount x_i of inputs then j should be able to produce at least y_i output, otherwise j is inefficient. If j produces more than y_i using x_i amount of inputs, then i is inefficient. If j produces an amount y_i of output then j should be using no more than x_i of inputs, otherwise j is inefficient. If j uses less than x_i of inputs to produce y_i then i is inefficient. Schematically, we have:

Let i use x_i and produce y_i, then

if j uses x_i then: $y_j < y_i \Rightarrow$ j is inefficient

$y_j > y_i \Rightarrow$ i is inefficient

$y_j = y_i \Rightarrow$ no evidence that i or j is inefficient.

if j produces y_i then: $x_j > x_i \Rightarrow$ j is inefficient

$x_j < x_i \Rightarrow$ i is inefficient

$y_j = y_i \Rightarrow$ no evidence that i or j is inefficient

DEA compares each DMU's inputs and outputs with every other DMU's inputs and outputs. When there are multiple inputs and outputs, it is unlikely to find another DMU with exactly the same amounts of inputs in order that a comparison of outputs can be made to determine which of the DMUs is more productive. Even if another DMU is found with exactly the same amount of inputs, the presence of multiple outputs makes it difficult to compare efficiency. For example, if i and j use the same amounts of inputs and i produces 2 units of output y_1 and 4 units of y_2 while j produces one less unit of y_1 and one more unit of y_2, which DMU is more efficient? Without output prices, the answer is not obvious. Alternatively, even if we find two DMUs producing the same amounts of each output, the presence of multiple inputs makes efficiency comparisons difficult. Essentially, DEA avoids this problem by considering, for each DMU i, a combination of other DMUs that forms a "virtual" DMU that can be used to ask whether i is or is not efficient.

DEA is formulated as a linear program to find the "best" virtual DMU for each real DMU i. If the virtual DMU produces more outputs with the same inputs or the same outputs with less inputs, then i is inefficient, otherwise, we have no evidence that i is inefficient. There are a number of formulations of DEA, but the basic problem can be presented as follows. Let there be n DMUs each with vectors of outputs y_i and vectors of inputs x_i, i=1, …, n. To determine productive efficiency of DMU i, DEA involves the solution of the problem

$$
\begin{aligned}
&\max_{u,v}\ u'y_i/v'x_i \\
\text{st}\quad & u'y_j/v'x_j \le 1,\ j = 1, \ldots, n \\
& u,v \ge 0.
\end{aligned}
$$

Since there are an infinite number of solutions to this problem, we add the further constraint $v'x_i = 1$. If

[2] For discussions of DEA, see, for example, Seiford and Thrall (1990), Charnes, Cooper, Lewin, and Seiford (1994), Ali and Seiford (1993), or Fare, Grosskopf and Lovell (1994). Introductory accounts can be found in Norman and Stoker (1991) and Ganley and Cubbin (1992).

no combination of DMUs (virtual DMU) has a larger ratio than DMU i, then i is efficient. This problem is solved for each of the n DMUs. To understand more clearly the DEA approach, consider a simple case where each DMU produces a single output using a single input. In such a situation one determine efficiency by looking at the ratio of output to input. In the multiple input, multiple output setting, DEA produces a composite or "virtual" output $u'y_i$ which is compared to the virtual input $v'x_i$.

One can also solve the equivalent envelopment form (following duality in linear programming)

$$\begin{aligned} &\max_{\phi,\lambda} \phi \\ \text{st} \quad & -\phi y_i + Y\lambda \geq 0, \\ & x_i - X\lambda \geq 0, \\ & \lambda \geq 0, \end{aligned}$$

where Y and X are matrices of outputs and inputs for all universities and $1 \leq \phi \leq \infty$. If $\phi = 1$ we have no evidence that DMU i is inefficient, whereas ϕ-1 is the proportionate increase in output that could be achieved if the DMU were to become efficient.

Researchers typically use either a constant or variable (VRS) returns to scale models. The VRS model is less restrictive in that it allows for any scale effect, and, for that reason, it is increasingly the choice for researchers. For the VRS model we add the constraint $\mathbf{1}'\lambda = 1$ where $\mathbf{1}$ is an n×1 vector of ones (that is, the λ's sum to one). Additionally, a DEA model can have either an input or output orientation; in the input (output) orientation the focus is on the optimal reduction in inputs (outputs) that would follow if an inefficient DMU were to move to efficiency. Given either type of envelopment surface and any type of orientation, DEA involves the solution of a linear programming model for each DMU. In this paper we consider an output orientation and the VRS model. The above envelopment form is the output oriented form of DEA. In the results section we report the value of ϕ, the efficiency score for each university in our sample.

Before turning to data and results, there are several points which need to be emphasized. First, it is standard to say that a DMU which lies on the frontier is efficient. However, this is not to say that units on the frontier are efficient, only that, if a unit is on the frontier, we do not observe another unit that is more efficient given the mix of outputs and inputs. If a unit lies on the frontier, we can only say that we do not have evidence that it is inefficient. We have the further caveat with respect to the commercialization problem that inefficient units may be deemed inefficient simply because of preferences (or, perhaps, distractions) for other activities over commercialization. Standard DEA analysis deals only with production efficiencies, here we have the further confounding problem that a university may not lie on the frontier because of preferences in the use of inputs or the value of outputs. The actual level of input usage in commercialization activity is not necessarily equal to our measured inputs (even if we have correctly identified all possible inputs) since many of our inputs are used in conjunction with outputs not associated with commercialization (teaching, basic research, etc.). If an output has no value to a university then DEA is not strictly appropriate for that institution. For example, in their survey of TTOs, Thursby and Thursby (1998a) found that some universities do not apply for patents until a licensor is found; for such universities, patents are a subset of licensing activity rather than a separate activity.

Second, we note that care should be used with the terms outputs and inputs. For some of the data, the terms may seem to be misleading. For example, industry sponsored research is both an output and an input. Universities use resources to attract industry funding, but that funding is then an input to further research output and, possibly, disclosures, patent applications, etc. Sponsored research is, in part, an "intermediate good" as well as a "final product."[3] For the purposes of DEA, we can think of an output as simply something of which the university wants more and inputs are those resources that are used (and used up in some cases) in getting more of the outputs. Commercialization outputs consist of those activities that reflect the commercialization of a university while the inputs consist of those resources that are important in producing the outputs, but that themselves are not measures of commercial activity.

DATA

The AUTM licensing survey has data on the technology transfer programs of many U.S. and Canadian institutions. The survey includes public and private universities, hospitals and health care institutions as well as patent management firms. Information from 1991 through 1996 is currently available. The survey is the source for all output information; outputs are the number of licenses executed (LCEXEC), the amount of industry sponsored research (INDSUP), the number of new patent applications (NPTAPP), the number of invention disclosures (INVDIS), and the amount of royalties received (ROYREC). The survey provides two input measures; it provides the amount of federal support the university receives (FEDSUP) and the number of full time equivalent professionals employed in the technology transfer office (PTTFTE). It is clear that the number of professionals engaged in licensing activity is important for licensing activity, but the role of federal support as a technology transfer enabler is not as clear. It has been suggested that industry money tends to flow to universities with large federal support. Presumably, the reason is that federal support is believed to leverage industry support thereby reducing industry research costs. All dollar denominated measures are adjusted to 1996 dollar values.

The remainder of the input data are from the National Research Council's (NRC) *Research-*

[3] Industry sponsored research may also have elements of altruism. However, it is the case that sponsored research agreements are almost always either for the further development of a licensed technology, or they include options for

Doctorate Programs in the United States Data Set (1993) which is based on the NRC's 1992 survey of all Ph.D. granting departments in the U.S. No information is provided for departments that do not grant the Ph.D. degree. It is plausible to assume that substantial research programs have difficulty existing in the sciences and engineering – the departments from which the bulk of commercial activity originate -- without the presence of Ph.D. students. Research faculty are drawn, in part, to such departments because of research aid provided by graduate students. As the Ph.D. degree in the sciences is primarily a research degree, Ph.D. students are drawn to departments with substantial research programs. This implies the reasonable proposition that science and engineering departments that do not grant the Ph.D. are not strong research departments and, hence, provide less inventive input to a university's commercial activities. The AUTM data for those universities without science and engineering Ph.D. programs supports the position that such universities have small levels of commercial activity.

The input data from the NRC survey include the number of faculty in each Ph.D. granting department as well as a faculty quality rating obtained from a 1992 peer evaluation survey. Our units of analysis are the three major program areas biological sciences, engineering and physical sciences/mathematics. Input variables are TOTFACi and QUALi for total faculty and faculty quality rating in the research departments of program area i (i=2 for biological sciences, i=3 for engineering and i = 4 for physical sciences/mathematics – the numbering system follows the NRC system).

The AUTM and NRC data cover a heterogeneous group of institutions. To reduce heterogeneity we consider a subset of surveyed institutions. Any university which does not have a Ph.D. program in any of the three major program areas is eliminated. We also exclude Canadian institutions, patent management firms and institutions that are solely hospitals or health care institutions; thus we focus solely on U.S. universities with at least one Ph.D. program in the sciences and engineering. This provides data on 112 universities. Of these, 57 provide complete information in each of the six survey years.

Initial computations are based on the full sample of 112 institutions. For these computations we use averages of the annual values reported in the AUTM survey. Not every university has participated each year so that our measures are the average values for the years in which a university participates. Using averages allows us not only to expand the sample beyond the 57 institutions appearing in each year, but it also reduces some of the year to year noise in the AUTM data (particularly for schools with little commercial activity). Table 1 gives summary statistics. INDSUP, FEDSUP, and ROYREC are each measured in millions of (constant) dollars and QUALi (i=2,3,4) are measured on a scale of 0 to 5 with 5 indicating a distinguished program. Entries in Table 1 are averages over the five years of the sur-

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the grantor firm to license any commercializable innovation resulting from the sponsored research (Thursby and Thursby, 1998b).

vey so, for example, the minimum of 0.67 for INVDIS tells us that the minimum *average* number of disclosures across the 112 universities is 0.67. After consideration of the full sample of universities, we turn to computations of year to year changes in productivity. For an analysis of year to year changes it is necessary to include in the sample only those institutions that appear in every year of the AUTM survey.

A weakness of our approach is that some actions that lead to current output may be actions that originated in earlier years. For example, current royalties are based upon research conducted in the past and, to some extent, on licenses executed in the past. Thus, we are mixing inputs and outputs from different points in time. Our analysis implicitly assumes concurrent events. To the extent that there are lags involved, our results must be considered with caution. However, it is the case that for some of our data, the year-to-year variation is small. This is certainly true for faculty size and quality and is true to some extent for sponsored research. Also, results for the full set of universities are based on averages of outputs and inputs which should reduce error from time lags.

DEA RESULTS

A. FULL SAMPLE EFFICIENCY SCORES

DEA results for the full sample of 112 universities are found in Table 2 which lists each of the universities and their efficiency ratings (scores). Universities are listed alphabetically by state and then alphabetically by institution. Before examining the scores, we reiterate two important points. First, universities with scores less than one are not necessarily poorly run institutions as their preferences may not include some or all of the outputs we measure. From interviews with university technology transfer professionals (Thursby and Thursby, 1998a), it is clear that valuation of commercialization outputs varies substantially. For example, few universities value new patent applications as highly as, say, new licenses; indeed, some universities do not value new patent applications as outputs. Further, if a university specializes in basic rather than applied research, then the result can be a lower, less efficient commercialization score. Second, universities deemed efficient are measured as such because no other combination of universities is found to do better; this does not necessarily imply that no institution could do better. We cannot conclude that a university with an efficiency score of one is efficient, only that we cannot provide evidence that it is inefficient.

Turning to Table 2, if a university has an efficiency score of one then it lies on the frontier and we have no evidence that it is inefficient. A score greater than one indicates the proportionate increase in commercial output that could be produced if the university were to move to the frontier (become efficient). For example, Alabama, Birmingham has an efficiency score of one, hence we have no evidence that it is technically inefficient. On the other hand, Auburn's score of 2.07 suggests that, based on its level of inputs and the performance of the efficient universities, it could more than double its commercial output and the shortfall in output is due to technical inefficiency. There is bunching of scores on the surface (multiple scores of one). Such bunching is common in DEA analysis. For intuition, consider again Figure 1 in which we are unable to differentiate among five of the eight DMUs. We have evidence that 58 of the 112 universities exhibit some degree of technical inefficiency.

The list of universities that make up the comparison sets for each technically inefficient institution is found in the final columns of Table 2. Peer universities are the efficient universities that form the section of the frontier closest to the inefficient university. For example, Alabama at Huntsville is inefficient and its level of inefficiency is determined by comparing it to its peer institutions University of New Orleans, Florida Atlantic, Boston University, and Central Florida. In examining peer institutions, keep in mind that we are dealing with comparisons across *thirteen* dimensions (five outputs and eight inputs).

While of interest, a listing of efficiency or productivity scores is incomplete. DEA produces an aggregate of a university's inputs and outputs as a single efficiency score. It does not provide evidence on the statistical significance of the various inputs and outputs in producing that score. In the following sections we conduct two separate analyses in an effort to understand the pattern of efficiency scores. We begin with two-way tabulations of inputs or outputs and whether a university is efficient. These tabulations, and companion statistical tests, do not require distributional assumptions about the efficiency scores. Following the contingency table comparisons we consider regressions with efficiency scores as dependent variables and inputs and outputs as independent variables. That analysis will allow us to consider effects on efficiency of changes in each of the inputs and outputs, holding constant the values of the remainder of the inputs and outputs. The validity of the statistical tests used in the regression analysis rests on distributional assumptions regarding the efficiency scores.

Rather than use the scores in Table 2 we use an indicator variable for whether the university is efficient. We do this for the following reason. DEA finds the same sets of efficient and inefficient DMUs regardless of whether one uses an input or an output orientation. However, for inefficient institutions, the relative inefficiency will vary depending on the orientation. In Figure 1, the input oriented inefficiency of, say, DMU 6 is based upon the horizontal distance from the efficiency frontier to 6 whereas the output oriented inefficiency of 6 is based upon the vertical distance from the frontier to DMU 6. We have greater confidence in the separation of universities into efficient versus inefficient than we do in the score of the inefficient universities. The technical efficiency indicator variable is IEFF where IEFF = 1 if the university is technically efficient and IEFF = 0 if the university is technically inefficient.

B. TWO-WAY COMPARISONS

The formation of two-way contingency tables allows us to ask whether there are associations or meaningful patterns between efficiency and values of the inputs and outputs. The input and output observations are divided (approximately) into quintiles. We then count the number of efficient or inefficient universities in each of the quintiles. Pearson χ^2 tests are used to test for association. Note that, unlike the regression analysis in the next section, no distributional assumptions are necessary for the χ^2 tests. To reduce the number of tables to a manageable number we aggregate the counts of faculty into a single total faculty number (TOTFAC) and the faculty quality measures into an weighted average quality rating (QUAL) where the weights are faculty size. The number of full time TTO professionals (PTTFTE) is the only input measure that relates solely to a university's licensing efforts. The remainder of the inputs are related to other goals in addition to commercialization (teaching, service, etc.). As an added measure of a university's licensing efforts we form a new variable, PTTFAC, which is the ratio of PTTFTE per 100 research faculty (TOTFAC). We also consider the importance of two "environmental" variables that could serve to influence a university's efficiency. The first indicates whether a university has a medical school (MEDSCH = 1 if the university has a medical school, 0 otherwise), and the second indicates whether the university is private (PRIVATE = 1 if the university is private, 0 otherwise).

Medical schools are heavily subsidized by the federal government and have a substantial service component. In addition, since clinical trials are conducted in medical schools, universities with medical schools have the leverage to engage in late stage development of such products. Private universities are able to specialize to a greater extent than are public universities which have greater service commitments and often more substantial teaching duties. As the sample is restricted to research universities, we may have a sample of private universities that value research highly, which, if they specialize, will devote less of their effort to teaching and service. As these latter activities absorb resources (money and faculty time), then it may be the case that private, research universities are more research productive.

Table 3 presents the contingency tables. The values under the input or output names are the bound values of the input or output. Unless otherwise noted, each of these entries is the upper bound on the value for the row. The table entries give counts of universities that fall into the efficient (IEFF = 1) or inefficient (IEFF = 0) categories. The table also gives the p-values for the χ^2 tests (or level at which the test of independence between an efficiency measure and input or output is significant). For example, the tabulation of IEFF versus ROYREC reveals that, among universities with \$320,000 to \$750,000 of royalty income, 16 are inefficient and 6 efficient. The test of independence between ROYREC and IEFF is significant at a significance level of 3.2% or smaller.

With the exception of NPTAPP and LCEXEC, we reject the hypothesis of independence between

IEFF and the outputs at a significance level of 15% or lower. The count pattern for INDSUP, ROYREC, and INVDIS suggests that a school in the largest or smallest quintile of royalties has a higher probability of being efficient than does a school in any of the three middle quintiles. That is, for these three outputs, the probability of efficiency first falls and then rises as output increases; schools with the smallest outputs and with the largest outputs appear to be more likely to be efficient than are midrange schools.

Efficiency and the inputs FEDSUP, TOTFAC, QUAL, and PTTFTE are significantly related. The count [4]pattern suggests that schools with the smallest levels of inputs are more likely to be efficient than are schools in the middle quintiles. For QUAL and PTTFTE there is a suggestion that, as is the case with the output measures, the schools in the largest quintile are also more likely to be efficient than are schools in the middle quintiles. We find interesting the suggestion that schools with the lowest quality rating are the most likely to be efficient. This may be due to tendencies for the highest quality faculty to specialize in basic research which, in general, results in less inventive activity. When we consider the number of technology managers per 100 faculty members (PTTFAC), we find that it is the schools in the largest quintile that tend to be efficient. To the extent that PTTFAC measures a university's relative intensity of effort for commercialization, this result is not surprising.

Comparisons between efficiency and the environmental variables reveals significant relationships only between IEFF and PRIVATE. As expected, we find that the likelihood of efficiency is greater for the private schools.

The above results must be qualified with the observation that nothing is held constant in a two-way comparison. Failure to control for other effects may not only mask relationships, but it can also suggest relationships between variables when the variables are unrelated, but each is related to a third variable. For example, we note above that TOTFAC and QUAL are related to efficiency. Since these two variables have a moderately high correlation (0.72), it may be that, for example, only TOTFAC is actually related to efficiency but QUAL appears to be related to efficiency simply because of its correlation with TOTFAC, a correlation that may have nothing to do with efficiency. This need for a measure of effects holding constant levels of other factors naturally leads us to regression analysis.

C. REGRESSION RESULTS

We consider logit regressions with the indicator variable IEFF as the dependent variable. The relevance of logit regression rests on probabilities generated by a logistic distribution and it is strictly appropriate only under the following conditions. In our discussion we emphasized that a university can

[4] On a related note, Mansfield and Lee (1996) report that industry sponsored basic research tends to be biased toward higher quality departments, while there is no bias in industry sponsored applied research.

be inefficient in the sense of lying below the true but unobserved production frontier, but nonetheless it can have an efficiency score of one; a score of one only implies that we cannot find a set of universities that do better. In other words, for many universities with scores of one, the true efficiency score is unobserved and has been replaced with the value one. Our logit analysis implicitly assumes that the efficiency scores of one are in place of the true and unobserved efficiency scores.[5]

Table 4 presents results for two logit models. IEFF is considered first in a regression with outputs and inputs only and then in a regression with outputs, inputs and the two environmental variables. Logit coefficients are interpretable only when used in the logistic probability function to calculate effects on the probability that the indicator variable is equal to one or zero. For that reason we do not present the logit coefficients, rather, with the exception of MEDSCH and PRIVATE, the entries in the table are the elasticities of the probability that the indicator variable equals one with respect to each of the regressors.[6] For example, the value of 0.815 for INDSUP in the first IEFF column means that a 1% increase in industry support will increase the probability by .815% that a university is technically efficient. Elasticities have the added value in allowing a comparison of the importance of various outputs and inputs in determining efficiency. The significance levels refer to the levels for whether the associated coefficient is equal to zero. Since MEDSCH and PRIVATE are indicator variables, elasticities calculations are meaningless. For these two regressors we present the odds ratio for a change in MEDSCH or PRIVATE from 0 to 1. For example, the value of 4.438 for PRIVATE in the second IEFF column implies that the probability of efficiency for a private school is more than 4 times that of a public school, all other factors held constant.

Consider the regression with only outputs and inputs (column 2). In interpreting the results it is important to bear in mind that the coefficients are partial effects holding constant *all* other inputs and *all* other outputs. Thus, we expect that each output will have a positive elasticity since, holding constant all inputs, an increase in an output will clearly be a move toward efficiency. Likewise, input elasticities should be negative as an increase in an input, holding output constant, is a move away from efficiency.

All output elasticities are positive, and, with the exception of INVDIS, each associated coefficient is significant. LCEXEC, with an elasticity of 1.273, has the greatest impact on efficiency scores. The importance of licenses executed follows, we believe, from its central role in the commercialization process. Faculty disclose IP that they wish to have licensed, patents are to protect IP that is licensed or believed licensable, royalties flow from licensed IP, and industry support is either for further develop-

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[5] Alternatively, we can view the unobserved scores as "super efficiency" or "modified DEA" scores wherein a DMU is omitted from its own reference set . See Anderson and Petersen (1993), Lovell, Walters, and Wood (1994), and McCarty and Yaisawarng (1993).

ment of a licensed technology or the sponsoring firm retains some rights to license any commercializable IP. The smallest elasticity is the one associated with royalties. We believe this finding stems from two factors. First, the royalty data are skewed toward a few institutions and it tends to be associated with only a few licenses. In their survey of TTOs, Thursby and Thursby (1998a) find that 76% of royalty income comes from only the top five income licenses. In other words, substantial royalty income from a specific license has a very low probability. Second, some, but not all, universities are willing to forego royalty income for sponsored research funds. In other words, preferences for royalty income are highly varied across universities.

The insignificant INVDIS coefficient can be taken to imply a substantial number of inefficient universities with large numbers of invention disclosures and/or a substantial number of efficient universities with small numbers of invention disclosures. It is perhaps not surprising that invention disclosures might have greater variation across institutions regardless of efficiency. Of the five outputs, only INVDIS and NPTAPP are completely within the discretion of university personnel, the others require agreements with industry and, hence, are possibly more clearly related to commercialization. Of the two discretionary outputs, INVDIS has low cost in comparison to NPTAPP (the patent process can cost from five to ten thousand dollars per patent). Further, based on interviews with technology transfer professionals, Thursby and Thursby (1998a) found that some universities informally evaluate or pre-screen new technologies with regard to their commercial appeal; those judged likely to have such appeal go through the formal disclosure process. Pre-screening by a subset of universities implies that INVDIS is counted differently at those universities compared to those that do not pre-screen; that is, INVDIS is potentially subject to greater measurement error than are the other inputs.

All inputs have the expected negative elasticities, but only the number of TTO professionals (PTTFTE), the number of research faculty in the biological sciences (TOTFAC2), and the quality of the research engineering faculty (QUAL3) are significant. The lack of significance of so many inputs most likely follows from the use of these inputs to produce other university outputs such as teaching and basic research. In other words, our measure of inputs are imperfect measures of the effort expended in licensing activity. The largest elasticities are for QUAL3 (-1.94) and PTTFTE (–1.642). PTTFTE is the only input solely associated with licensing activity so that a large elasticity is expected. Since engineering is a more applied field than the biological and physical sciences, it is not surprising to find that it appears to be important in creating commercializable IP, but we are somewhat surprised at the magnitude of the elasticity and the fact that the total number of engineering faculty is apparently of less importance.

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[6] Since the logit regression involves a nonlinear relation between probability and the regressors, we follow the standard practice of presenting the average of the elasticities calculated at each point in the data.

We find the opposite with biological sciences for whom quality is apparently not important but the total number of faculty is important. It has been noted to us that the university market for biological science IP has tended to be a seller's market whereas the market for engineering and physical science IP has tended to be a buyer's market.[7] In such settings, we expect universities to do relatively better with finding licensees and extracting rents in biological sciences. Further, in interviews with university technology transfer professionals (Thursby and Thursby (1998a)) several interviewees volunteered the observation that researchers in biotechnology tend to have a culture that that is more encouraging of commercial activity whereas the culture in physical sciences tends to be less oriented toward commercialization. Data collected by AUTM support these differences in markets and cultures. In 1996, AUTM collected license information split by life sciences versus physical sciences. For our sample of universities, aggregate royalties from life science licenses is around four times that of the physical sciences. Further, royalties per active life science license is around 2.5 times that of the physical sciences. The relative importance of TOTFAC2 is in keeping with this difference in markets and cultures, but the quality results are not. Our finding of importance only of total faculty in the biological sciences and quality of the engineering faculty remains something of a puzzle that merits further investigation.

Finally, note that the level of federal support is unrelated to the efficiency score. This is surprising given that the Bayh-Dole Act encourages commercialization activity related to federal research money, and, in particular, it requires that patent applications be made for any commercializable IP if that invention was sponsored by federal dollars. We suggest that the insignificance of FEDSUP may come from the preponderance of federal money which is directed toward basic research; as such it would be hard to detect a relation between commercialization and federal support.

In the second IEFF column of Table 4 are the elasticities and odds ratios when the environmental variables are included as regressors. Both environmental variables are significant at a 10% level. Universities with medical schools are less likely to be efficient and private schools are more likely to be efficient. The result on private schools is expected. We are somewhat surprised at the medical school results since the majority of university licenses are related to biomedical inventions and the ease of conducting clinical trials when a medical school is present. It may well be that heavy service commitments of medical schools serves to reduce commercialization efficiency. All output and input elasticities remain similar to their values in the regression which excludes MEDSCH and PRIVATE with the exception that the number of engineering faculty is now significant with a fairly large elasticity and FEDSUP is now significant albeit with a small elasticity.

[7] We are indebted to Dan Massing of Cornell Research Foundation for this interpretation.

D. YEAR TO YEAR PRODUCTIVITY CHANGES

Year to year efficiency changes can be examined for universities that appear in each of the six survey years. Fifty-seven of the 112 universities provide data for every survey year. We begin with a measure of the potential increase in output that would have occurred for each of the five outputs if each university had been technically efficient. The experiment is as follows: We conduct a single DEA analysis which includes each of the six years and each of the 57 universities. That is, we conduct an experiment that implicitly assumes that there are 342 universities (57 schools by 6 years). We are looking for "best practice" across 6 years and 57 universities. A simple count of the number of efficient institutions by year and averages of the scores by years provides information on whether efficiency has changed over time. We also use the scores to compute the potential outputs that would have occurred if each university had been efficient. That is, if the efficiency score is ϕ and the actual level of some output is A, then potential output is $A\phi$. We then compute aggregate potential outputs them to actual outputs.

Table 5 presents, for each year, the number of efficient universities, the average efficiency score and the percentage increase in each of the five outputs that would be expected under efficiency. The evidence clearly indicates increasing efficiency over time. Universities in each year are generally closer to the frontier than they were in the preceding year. The change in efficiency is particularly striking when ones consider the shortfall from potential output. In 1991, the universities could have been producing about 55% more commercial output had each university been efficient whereas in 1996 they could only have produced about 17% more commercial output. Note that the potential gain in royalties is smaller in each year than the potential gain in any of the other inputs. We interpret this result as suggesting that inefficient universities tend to be closer to efficient universities in royalties received than in any other dimension of output; in other words, inefficient universities do relatively "best" with royalties received.

The results in Table 5 suggests productivity improvements over time. Since those results are based on a single frontier, they do not reveal whether the production frontier has shifted over time (technical change), whether the frontier has been stable and the inefficient universities are closer to the frontier, or whether the frontier has shifted as well as a relative improvement in efficiency has occurred. To address this issue we use DEA linear programs and a Malmquist total factor productivity (TFP) index to measure changes in productivity. Fare, et.al. (1994) suggest as a measure of TFP the geometric mean of two Malmquist indices, one of which is based on technology in period t and the other on technology in period t+1, or

$$m(y_{t+1}, x_{t+1}, y_t, x_t) = \left[\frac{d^t(x_{t+1}, y_{t+1})}{d^t(x_t, y_t)} \times \frac{d^{t+1}(x_{t+1}, y_{t+1})}{d^{t+1}(x_t, y_t)} \right]^{1/2}$$

where, for k=t or t+1,

$$[d^k(x_k, y_k)]^{-1} = \max_{\phi,\lambda} \phi$$

st $\quad -\phi y_{ik} + Y_k\lambda \geq 0,$

$x_i - X\lambda \geq 0,$

$\lambda \geq 0,$

and

$$[d^t(x_{t+1}, y_{t+1})]^{-1} = \max_{\phi,\lambda} \phi$$

st $\quad -\phi y_{i,t+1} + Y_t\lambda \geq 0,$

$x_{i,t+1} - X_t\lambda \geq 0,$

$\lambda \geq 0,$

and $\quad [d^{t+1}(x_t, y_t)]^{-1} = \max_{\phi,\lambda} \phi$

st $\quad -\phi y_{i,t} + Y_{t+1}\lambda \geq 0,$

$x_{i,t} - X_{t+1}\lambda \geq 0,$

$\lambda \geq 0.$

A value of m greater than one indicates TFP growth between periods t and t+1; a value of m of, say, 1.1 implies 10% factor productivity growth. As we have a panel of 57 universities for a 6 year period we calculate 6 x 57 values of m.

In Table 6 are listed geometric means of m for each of the 57 universities. The geometric mean for all universities is 1.079 which indicates an average annual growth in TFP of 7.9% over the period 1991-96; that is, if input levels had been held constant over the 1991-96 period, there would still have been a growth in commercialization output of 7.9% annually. Only 13 (23%) of the universities do not appear to have experienced productivity growth.

The aggregate figure for TFP can be decomposed into the product of two separate measures of growth: productivity growth due to movements of inefficient universities toward the frontier and expansion of the frontier itself (see Fare, et. al., 1994). Changes in relative efficiency of inefficient institutions is a sort of "catching up." Our computations suggest that inefficient universities have been catching up to efficient universities at an annual rate of 0.4%. The bulk of the TFP growth, however, follows from expansion of the frontier. The annual growth in the frontier over the 6 years is calculated to be 7.5%. It would appear that, in general, universities are increasingly involved in commercialization, but this increasing commercialization stems largely from an expansion of the production frontier rather than from a catching up by the inefficient institutions. The frontier is expanding and most institutions are "chasing" that frontier.

Standard usage of the term "technological change" refers to any change in outputs that does not follow from a change in inputs. As discussed earlier, it is difficult to measure the actual inputs used in commercialization because those inputs are used to produce other university outputs such as basic research and teaching. What we are calling technological change may well be a reallocation of inputs from another activity toward commercialization so that, while we might observe constant *aggregate* levels of university inputs, more of them are involved in commercialization. We suggest that the expansion of the frontier (technological change) stems from a change in the environment for university commercialization that involves both a reallocation of inputs, a change in market demand for university IP, and increasingly experienced, knowledgeable and demanding TTOs.

The introduction cites sources that suggest a change in both university preferences for commercialization activities and a change in industry demand for university technologies. If acted upon, the change in university preferences implies a shift of resources away from other activities toward activities with potential commercial appeal. This change in preferences would also imply that more commercially viable IP is being disclosed by faculty to university TTOs. In interviews with technology transfer officers, Thursby and Thursby (1998a) asked about the potentially commercializable innovations that are not disclosed. While reluctant to offer numbers, several interviewees suggested that they would not be surprised if they were seeing substantially less than half of such innovations, though several noted an increasing willingness of faculty (particularly younger faculty) to disclose. The increase in demand for university technologies can be expected to improve the matching of university technologies with firms that can exploit the commercial potential of the technology. University technology transfer officers suggest that a major problem in licensing a technology is simply finding a firm that is suited for and interested in the technology (Thursby and Thursby, 1998a); it is sufficiently difficult that bidding for a technology is rare. Increased industry interests in university inventions would serve to improve this matching process and both reduce the costs of searching for a licensee and increase the probability of a match. Finally, from interviews with both industry and university licensing personnel (Thursby and Thursby, 1998a and 1998b), it is clear that university TTOs are becoming increasingly sophisticated and demanding in their license dealings with industry.

CONCLUSION

The federal and state governments have encouraged universities to increase their commercialization activities. Universities espouse an increasing willingness to engage in commercial activities and private sector firms are looking more carefully at university intellectual property. In this paper we examine university commercialization activities in order to shed light on the activities of individual universities as well as the overall direction of such activities. Commercial activities include industry sponsored research and royalties as well as numbers of invention disclosures, licenses executed and new patent applications. University productivity or efficiency with regard to such activities varies not only according to the capabilities of the faculty and staff with regard to such efforts, but also according to university preferences for the use of their resources. We use data envelopment analysis to measure the relative efficiency of each university in our sample. Both contingency table analyses and regressions are used to relate the scores to the levels of all commercial outputs as well as to the level of inputs. We also examine the changes in productivity of university commercial activity over time.

Our major results are as follows. First, we find substantial evidence of inefficiencies. As we note, this inefficiency may well stem simply from university preferences for or specialization in outputs unrelated to licensing activity (such as basic research and teaching) rather than from competencies in licensing. Second, there has been substantial growth in commercialization activities of U.S universities. We attribute this to both a changing environment within universities regarding commercialization activity as well as an increasing desire of industry for university technologies. Third, this growth in commercialization has stemmed primarily from a growth in commercialization by all universities rather than a "catching up" by the inefficient institutions. Fourth, we find that biological sciences and engineering are more important to licensing activity than are the physical sciences. This we attribute to the more applied nature of engineering and the better market opportunities and orientation toward markets of biological sciences. Fifth, we find that, on a number of dimensions, the smallest schools tend to be more like the largest schools than the mid-range schools. Finally, we find that private universities are more likely to be efficient and universities with medical schools are less likely to be efficient.

It has been suggested in a number of venues that university resources are not fully exploited as a source of economic growth and competitiveness (see, for example, Gray, et. al. (1986), Public Policy Center for Stanford Research International (1986), Geisler and Rubenstein (1989), National Academy of Sciences (1992), National Science Board (1993)). Our results clearly show that this criticism is decreasing in its relevance.

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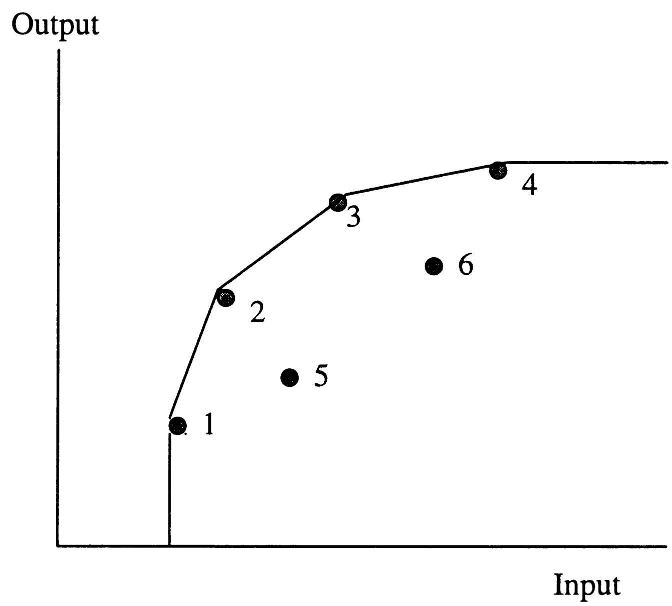

Figure 1

TABLE 1: SUMMARY STATISTICS

VARIABLE	MEAN	MIN	MAX
OUTPUTS			
INDSUP	10.83	0.85	67.80
ROYREC	1.91	0.00	35.91
INVDIS	53.43	0.67	307.83
LCEXEC	15.05	0.00	122.67
NPTAPP	16.85	0.00	91.83
INPUTS			
PTTFTE	2.50	0.00	11.57
FEDSUP	90.81	1.86	753.59
TOTFAC2	151.79	0.00	643.00
TOTFAC3	83.41	0.00	390.00
TOTFAC4	119.99	0.00	406.00
QUAL2	2.59	0.00	4.50
QUAL3	2.20	0.00	4.60
QUAL4	2.63	0.00	4.70

TABLE 2. EFFICIENCY SCORES AND PEER UNIVERSITIES

UNIVERSITY	CODE	SCORE	PEERS									
Auburn	AL1	2.070	MA5	NC2	IA1	OK1	UT1	FL3	UT2			
Ala./Huntsville	AL2	1.274	LA3	FL1	MA1	FL3						
Ala./Birmingham	AL3	1	AL3									
South Alabama	AL4	1	AL4									
Ark./Fayetteville	AR1	1.335	UT1	CA1	IL2	FL6	FL3	MI1				
Arizona State	AZ1	1.927	NC2	MI1	MA5	IA1	CA1	UT1				
Arizona	AZ2	1.506	CO1	MA1	MA4	CA1	UT2	PA3	IN2			
CALTECH	CA1	1	CA1									
Stanford	CA2	1	CA2									
Southern Cal	CA3	1.656	GA1	NY2	ND1	CO1	CA1	OR2	MA1	CA2		
Colorado State	CO1	1	CO1									
Colorado	CO2	1.639	CA1	NY2	MI1	MA4	MA1	PA3	CO1	AL4		
Denver	CO3	1	CO3									
Connecticut	CT1	1.739	FL6	UT2	CA1	NY2	MA5	CO1	MI1	PA3	FL3	AL4
Yale	CT2	1.101	MD1	CA2	MA1	CO1	NY2	CA1				
Georgetown	DC1	1	DC1									
Delaware	DE1	1.873	FL6	UT2	MA4	FL3	CA2					
Florida Atlantic	FL1	1	FL1									
Florida State	FL2	1	FL2									
Central Florida	FL3	1	FL3									
Florida	FL4	1.088	FL6	MA4	UT2	CA2	MI1	NC2	FL1	IL2	PA3	
Miami	FL5	1.647	CO1	GA3	GA1	AL4	IL2	MA1	FL6	CA2		
South Florida	FL6	1	FL6									
Emory	GA1	1	GA1									
Georgia Tech	GA2	1	GA2									
Georgia	GA3	1	GA3									
Hawaii	HI1	1.736	PA4	MA1	ND1							
Iowa State	IA1	1	IA1									
Iowa	IA2	1.543	MA4	AL3	MD2	CA1	CO1	MD1	FL6	CA2		
Illinois Inst. of Tech.	IL1	1	IL1									
Illinois State	IL2	1	IL2									
Northern Illinois	IL3	1	IL3									
Northwestern	IL4	1.418	NY2	CA1	CO1	MI1	PA3	GA2	MA5			
Chicago	IL5	1	IL5									
IL/Chicago	IL6	2.710	MI1	PA4	IA1	CA1	FL6	MA4	NC2	UT2		
IL/Urbana-Cham	IL7	1	IL7									
Ball State	IN1	1	IN1									
Indiana	IN2	1	IN2									
Purdue	IN3	1.019	OH5	CA1	IA1	FL3	UT2	NC2	FL6	MA4		
Kansas State	KS1	1.466	IA1	ND1	CA1	MA5	OH5	FL6				
Kansas	KS2	1.709	IL2	FL3	IA1	UT2	CA1	FL6				
Kentucky	KY1	1	KY1									
Louisiana State	LA1	1.075	IL2	FL6	MI1	FL3	NC2	MA5	UT1	CA1		
Tulane	LA2	1	LA2									
New Orleans	LA3	1	LA3									
Boston U.	MA1	1	MA1									
Brandeis	MA2	1.058	ND1	GA3	OH2	OR2	LA3					
Harvard	MA3	1	MA3									
MIT	MA4	1	MA4									
Northeastern	MA5	1	MA5									
Tufts	MA6	1.068	MD2	GA1	DC1	IL5	MA1	ND1	GA3			
Johns Hopkins	MD1	1	MD1									
MD/Baltimore	MD2	1	MD2									
MD/College Park	MD3	1.340	FL3	MA4	CA2	IA1	UT2					
Maine	ME1	1	ME1									
Michigan State	MI1	1	MI1									
Michigan Tech.	MI2	1.065	MA1	FL3	FL1	OH5						
Michigan	MI3	1.585	MA4	NY2	PA3	AL4						
Wayne State	M4	1.645	FL6	UT2	UT1	NC2	OH2	IL2	FL3			
Minnesota	MN1	1.144	UT2	CA2	FL1	AL4	MA4	CA1				
Washington	MO1	1	MO1									
Mississippi State	MS1	2.165	CA1	NJ1	FL6	CA2	FL1	MA1	MA4	FL3	AL4	
Montana State	MT1	1.247	MD2	FL3	NC4	FL1	FL6	IL2	IA1			

TABLE 2 (Cont.). EFFICIENCY SCORES AND PEER UNIVERSITIES

UNIVERSITY	CODE	SCORE	PEERS										
Duke	NC1	1	NC1										
North Carolina State	NC2	1	NC2										
NC/Chapel Hill	NC3	1.183	FL6	CA1	MA1	NY2	MD1	CA2	CO1				
Wake Forest	NC4	1	NC4										
North Dakota State	ND1	1	ND1										
Nebraska-Lincoln	NE1	1.621	MA5	CA1	FL6	IA1	OH5	ND1					
Dartmouth College	NH1	1.565	GA1	OH2	GA3	CO1	CA2	ND1	OR2				
New Hampshire	NH2	1	NH2										
NJ Inst. of Tech.	NJ1	1	NJ1										
Princeton	NJ2	1	NJ2										
Rutgers	NJ3	1.290	MI1	IA1	MA4	CA1	FL6	NC2					
Stevens Inst. of Tech.	NJ4	1.912	OH5	FL3	IL1	IL3	FL1						
New Mexico State	NM1	1.650	GA2	CA1	NY2	OH2	OK1	CO1	UT2	CO3			
Columbia	NY1	1	NY1										
Cornell	NY2	1	NY2										
Syracuse	NY3	2.882	UT1	FL6	UT2	OH5	FL3	CA1					
Rochester	NY4	1.295	MI1	CA1	CO1	GA2	MA5	NY2	OH2				
Case Western	OH1	1.795	OH7	MA1	CA2	UT2	CO1	FL3					
Miami	OH2	1	OH2										
Ohio State	OH3	1.560	MI1	NY2	PA3	GA2	MA5	UT2	OK1				
Ohio	OH4	1	OH4										
Akron	OH5	1	OH5										
Cincinnati	OH6	1.631	GA2	CA2	UT2	MA5	CA1	CO1	MI1	NY2	OK1	FL3	ND1
Dayton	OH7	1	OH7										
Tulsa	OK1	1	OK1										
Oregon State	OR1	2.288	CA2	CO1	CA1	NY2	ND1	OH2	GA1				
Oregon	OR2	1	OR2										
Carnegie Mellon	PA1	1	PA1										
Drexel	PA2	1.003	IL1	UT2	UT1	CO1							
Penn State	PA3	1	PA3										
Temple	PA4	1	PA4										
Pennsylvania	PA5	1.086	NY2	AL4	MA1	MD1							
Pittsburgh	PA6	1.055	AL4	MA1	GA2	CA1	NY2	CO1	CO3	PA3			
Brown	RI1	2.049	MI1	CA1	NY2	FL3	ND1	FL6	UT2	CO1			
Rhode Island	RI2	1.189	MA1	CO3	OH5								
Clemson	SC1	1.015	IL2	LA3	MI1	FL3	FL6	CO1	IL1				
South Carolina	SC2	2.463	MI1	CO1	IL2	FL3	FL6	CA1					
Tennessee	TN1	1.403	PA3	FL6	MA4	CA1	MI1	CO1	UT2	IN1	LA3	FL3	
Vanderbilt	TN2	1.028	CA2	CO1	FL1	OK1	UT2	FL3					
Rice	TX1	1.425	ME1	GA2	CO1	CO3							
Texas A&M	TX2	1.095	FL3	PA3	MA4	LA3	IA1	GA2	UT2				
Texas at Austin	TX3	1.527	IL7	UT2	GA2	PA3	CA2						
Brigham Young	UT1	1	UT1										
Utah	UT2	1	UT2										
Virginia	VA1	1.012	MI1	NY2	IL7	CA2	GA2	CO1	OH2				
Virginia Tech	VA2	1.140	GA2	CA1	UT2	FL6	IA1	MA5	NC2	NY2	FL3		
Washington	WA1	1.302	CA2	MA4	MA3	CA1	MD2						
Washington State	WA2	2.020	NY2	IL7	MA5	IA1	OH2	UT2	OK1				
Wisconsin-Madison	WI1	1.170	AL4	CA2	MA1	NY2	IA1	CA1	MA4				

TABLE 3: CONTINGENCY TABLES

INDSUP	IEFF 0	IEFF 1
≤3.25	5	15
5.5	15	8
9.75	13	10
17	14	8
>17	11	13
p-VALUE		0.056

FEDSUP	IEFF 0	IEFF 1
≤19.5	4	18
46	17	6
83	13	8
140	11	12
>140	13	10
p-VALUE		0.003

ROYREC	0	1
≤0.1	6	14
0.32	14	9
0.75	16	6
2	13	10
>2	9	15
p-VALUE		0.032

TOTFAC	0	1
≤100	3	17
235	14	11
350	12	8
550	13	10
>575	16	8
p-VALUE		0.008

INVDIS	0	1
≤13	8	14
28	14	9
45	12	8
82	15	8
>82	9	15
p-VALUE		0.135

QUAL	0	1
≤2.1	6	17
2.55	10	10
3	16	6
3.5	15	8
>3.5	11	13
p-VALUE		0.018

NPTAPP	0	1
≤4.5	10	12
9	12	10
14.75	15	9
25	11	9
>25	10	14
p-VALUE		0.628

PTTFTE	0	1
≤.92	7	16
1.4	15	6
2	10	11
3.5	16	9
>3.5	10	12
p-VALUE		0.051

LCEXEC	0	1
≤2.75	8	13
5.5	13	10
11.5	13	9
22	13	9
>22	11	13
p-VALUE		0.547

PTTFAC	0	1
≤.325	12	10
0.55	16	7
0.8	13	9
1.3	11	9
>1.3	6	19
p-VALUE		0.024

MEDSCH	0	1
0	26	30
1	32	24
p-VALUE		0.257

PRIVATE	0	1
0	42	31
1	16	23
p-VALUE		0.096

TABLE 4: LOGIT REGRESSION RESULTS

	IEFF		IEFF	
INDSUP	0.815	***	1.119	***
ROYREC	0.156	***	0.189	***
INVDIS	0.378		0.735	
NPTAPP	0.878	*	0.871	*
LCEXEC	1.273	***	1.257	***
PTTFTE	-1.642	***	-1.810	***
FEDGOV	-0.327		-0.445	*
TOTFAC2	-0.662	*	-0.508	*
TOTFAC3	-0.657		-1.076	**
TOTFAC4	-0.435		0.128	
QUAL2	-0.664		-0.654	
QUAL3	-1.940	***	-2.109	***
QUAL4	-0.150		-0.802	
MEDSCH			0.145	**
PRIVATE			4.438	**
R-SQUARE	0.482		0.530	

*** Significant at 5% level
** Significant at 10% level
* Significant at 15% level

TABLE 5. YEAR TO YEAR EFFICIENCY COMPARISONS

			Potential % Increase in Outputs				
Year	Number Inefficient	Average Score	INDSUP	ROYREC	INVDIS	LCEXEC	NPTAPP
1991	48	0.664	57.2	45.5	56.5	53.3	57.9
1992	40	0.735	42.1	28.8	37.5	33.4	38.9
1993	45	0.731	40.4	25.5	39.5	37.0	39.3
1994	40	0.771	28.0	17.1	30.8	27.9	30.3
1995	37	0.802	25.1	14.3	26.0	21.3	23.6
1996	28	0.832	19.9	9.4	19.9	14.9	18.8

TABLE 6: TOTAL FACTOR PRODUCTIVITY

University	TFP AVG.	University	TFP AVG.
Alabama/Birmingham	1.168	Minnesota	1.076
Arkansas/Fayetteville	0.977	North Carolina/Chapel Hill	0.962
Arizona	1.049	Wake Forest	1.175
CALTECH	0.953	Dartmouth College	1.208
Stanford	1.085	New Jersey Inst. of Tech.	1.278
Southern California	1.262	Princeton	1.068
Colorado State	0.916	Rutgers	1.121
Colorado	1.350	Columbia	1.221
Connecticut	0.987	Syracuse	0.843
Yale	1.075	Rochester	1.074
Delaware	0.943	Case Western	0.872
Florida State	1.163	Ohio State	1.119
Emory	1.144	Ohio	1.066
Georgia Tech.	1.078	Akron	1.245
Northern Illinois	1.232	Cincinnati	1.025
Northwestern	1.232	Dayton	1.040
Chicago	1.041	Oregon State	0.971
Illinois/UC	0.759	Oregon	1.135
Indiana	1.060	Penn State	1.153
Tulane	0.994	Temple	0.913
New Orleans	1.115	Pennsylvania	1.026
Harvard	1.142	Clemson	1.071
MIT	1.037	Vanderbilt	0.993
Johns Hopkins	1.092	Brigham Young	1.200
Maryland/Baltimore	1.191	Utah	1.026
Maryland/College Park	1.219	Virginia	1.185
Michigan State	1.048	U. ofOFWashington	1.133
Washington	1.054	Washington State	1.148
Michigan	1.120		
Geometric Mean	**1.079**		

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