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Graduation Rates and Accountability: Regressions versus Production Frontiers

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Abstract

This paper suggests an alternative to the standard practice of measuring the graduation rate performance using regression analysis. The alternative is production frontier analysis. Production frontier analysis is appealing because it compares an institution's graduation rate to the best performance instead of the average performance. The paper explains the differences between these two types of analysis and provides examples of their application using data for 187 national universities.

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I. Introduction

Students, parents, and state governments are paying increasing amounts for the services offered by colleges and universities. As the funds flowing to higher education have increased there has been an understandable increase in calls to hold colleges and universities accountable for the quality of the education they provide.[1] Those calling for increased accountability are not looking for testimonials. They are looking for simple quantitative measures of university performance.

The paucity of readily available measures of university performance has focused attention on graduation rates. The Federal Student Right-to-Know and Campus Security Act of 1991 mandates that colleges and universities publish data on graduation rates. For state governments graduation rates are the most frequently used performance measure for public colleges and universities.[2] The academic performance measures for athletes recently introduced by the National Collegiate Athletic Association are strongly influenced by graduation rates. And perhaps most important to some institutions, the rankings published annually by *US News and World Report* give a considerable weight to graduation rates.

The focus on graduation rates has been accompanied by calls for colleges and universities to improve their graduation rate performance. Clearly this is not always a good recommendation. As Charles Manski and David Wise (1983) emphasize, for some students the best unconstrained choice is to drop out of college because for them the returns to leaving exceed the returns to staying. Universities can always achieve a higher graduation rate by lowering curricular standards or by encouraging more grade inflation. And any institution could surely achieve higher graduation rates by restricting access to students who are sure bets to graduate. Raising graduation rates in these last two ways clearly is not socially useful since it would weaken the country's commitment to broad-based access and high quality programs.

These concerns about using raw graduation rates as an objective standard for comparing universities are not new. It is common practice to evaluate an institution's graduation rate by comparing it to the predicted graduation rate based on a regression equation controlling for factors that influence the graduation rate.[3] In 1997 *US News and World Report* introduced a factor they first called "value added" but eventually called "graduation rate performance." Graduation rate performance is calculated using the residuals from a regression equation in which the graduation rate is regressed on variables measuring entering student quality and expenditures per student. In January 2005 the Educational Trust created a web-based resource, *College Results Online*, which allows those interested in graduation rate performance to compare graduation rates of a particular institution to those of its peers.[4] Peers are determined by those institutions with similar performance in a regression including a considerably larger set of independent variables than those used by *US News*.

In this paper we argue that regression analysis may not be the best tool to assess the graduation performance of a college or university. We explore the hypothesis that graduation rates should be compared to best practice measured by a production frontier, not average practice measured by a regression equation. These two methods do not necessarily provide different results. If the regression line through the middle of the data is of the same shape as the production frontier through outer edge of the data, the two techniques will provide the same measures of graduation rate performance. This is a very unlikely outcome. Most likely there will be significant differences between these two measures. The purpose of this paper is to investigate the differences and to evaluate the advisability of using the production frontier technique.

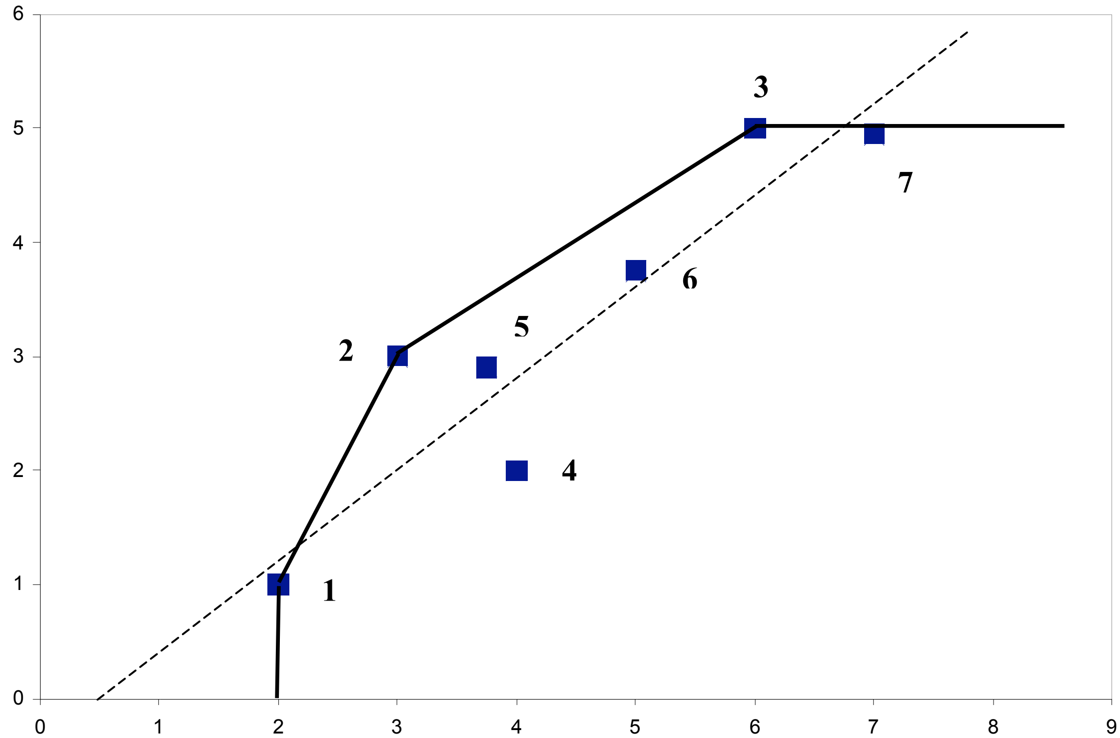
In section II of the paper we briefly discuss the choice between the estimation of production frontiers and regression analysis. The third section discusses data envelopment analysis, which is the procedure we use for determining the production frontier. The fourth section presents the results of production frontier calculation and regression estimates of graduation rates. The fifth section gives a detailed analysis of the differences between the production frontier and regression results. The sixth section discusses additional results from the analysis, and the final section provides a summary and some conclusions.

II. Efficiency Frontier Measurement and Regression Analysis

Figure 1 gives a simple example to illustrate the differences between regression analysis and efficiency frontier analysis. The dashed line is the regression line that minimizes the sum of the squared deviations for the seven observations for a one output one input case.[5] The production frontier is a piecewise linear function that goes through the input output combinations for firm one, firm two, and firm three. These firms are the efficient firms. They form the outer shell of the production surface.

Regression analysis would give the highest scores to firms two, three, five and six. These firms have positive residuals. Production frontier analysis would give the highest scores to firms one, two, three and seven. The first three are on the production frontier, and firm seven is very close to it. The two techniques agree in three of the seven

Figure 1. – Comparison between Regression and Frontier Analysis



cases: firm four has a negative residual, and it is below the production frontier, so it will be ranked poorly using either technique; firms two and three have positive residuals, and they are on the production frontier, so they will be highly ranked using either technique. The other four points present interesting cases. The cases in which the two techniques give contradictory messages deserve further scrutiny.

First, consider firm one and firm seven. They have extreme values for the level of input and output. Clearly, no firm, or convex combination of firms, could be found that produced firm 1's output level using fewer inputs, so firm 1 defines a portion of the production frontier. Firm seven represents a slightly different case. Firm three has the maximum output, but firm seven's output is just slightly below that output. The production frontier is horizontal at firm three's output, so firm seven is very close to being efficient. These extreme points illustrate important differences between the two techniques. Frontier analysis uses data in the neighborhood of the firm under consideration to determine the efficient boundary, and it does not impose a particular functional form on the production relationship.[6] Regression analysis uses all of the data and imposes a particular functional form. Which are we to believe? Confidence intervals around the estimated regression lines grow as the independent variable deviates from its mean, so we cannot have much confidence in what the regression forecasts say for firms with extreme values of the independent variable. By contrast, the production frontier analysis is clear. There is no firm that outperforms firm one in its neighborhood.[7] Although it is not on the efficient frontier, firm seven also will have a high technical efficiency score because its output is very close to the maximum output in the sample.[8]

The case of firms five and six is different. Here, two similar firms (firms two and three) were able to outperform the firms in question. In typical data there are few efficient firms, so there will be a large number of firms like four and five that are outperformed by the very best firms. While these two firms are inefficient, they are closer to the production frontier than, for example, firm 4. For firms in the middle of the data, such as firms five and six, the differences between the two types of analysis are not as striking as they are for firms on the edges of the data. Both types of analysis would rate these firms as relatively strong performers. Still, because firm five has a larger residual, regression analysis would rank firm five ahead of firm six. But, since firm six is closer to the production frontier than firm five, production frontier analysis would reverse the ranking of these two firms. Frontier analysis also captures the fact that these two firms are not best practice examples despite their positive regression residuals.

The case for using a frontier instead of a regression is strengthened by considering how the analysis would be affected by adding data. Suppose we include another data point in figure 1 inside the frontier. This will have no effect on the frontier itself, but it may cause the regression line to change. An existing data point that was above the regression line might now have a negative residual instead. Clearly, that firm has not changed its practices, but an observer relying on regression might view that firm less positively. On the other hand, adding a point beyond the frontier could shift the frontier substantially since a new best practice point has been found. Yet the regression line would move much less. Regression is concerned with central tendency, while frontier analysis is much more sensitive to data extremes that define boundaries. If we are concerned with best practice, or efficiency, frontier analysis offers a potentially better tool.

III. Data Envelopment Analysis

There are several production frontier estimation techniques. In this section, we explain our choice of technique and explain the outputs of this type of analysis. The literature on efficiency frontiers has evolved along two tracks. The first is data envelopment analysis (DEA), which uses non-parametric linear programming techniques. The alternative approach uses econometric methods to identify a stochastic frontier. Each approach has distinct advantages and disadvantages, but two reasons motivate us to use data envelopment analysis. First, linear programming techniques allow us to calculate simple and intuitive measures of relative technical efficiency. Second, DEA frees us from imposing any structure on the relationship between graduation rates and our inputs.[9]

Data envelopment analysis can be done using the assumption of constant returns to scale or allowing for variable returns to scale. Since we have no reason to suspect that all firms are operating at the optimal scale we have chosen the less restrictive variable returns to scale assumption.[10] Data envelopment analysis also can measure technical efficiency with respect to outputs or inputs. Input-oriented and output-oriented DEA identify the same efficient frontier. In other words, the same set of firms will be technically efficient. Because we are comparing our results to regression residuals which are a measure of output we use output oriented data envelopment analysis.

The linear program underlying variable returns to scale output-oriented data envelopment analysis is:

$\max_{\varphi,\lambda} \varphi$, subject to

(1) $-\varphi y_i + Y\lambda \geq 0$

(2) $x_i - X\lambda \geq 0$

(3) $\sum\lambda_i = 1$

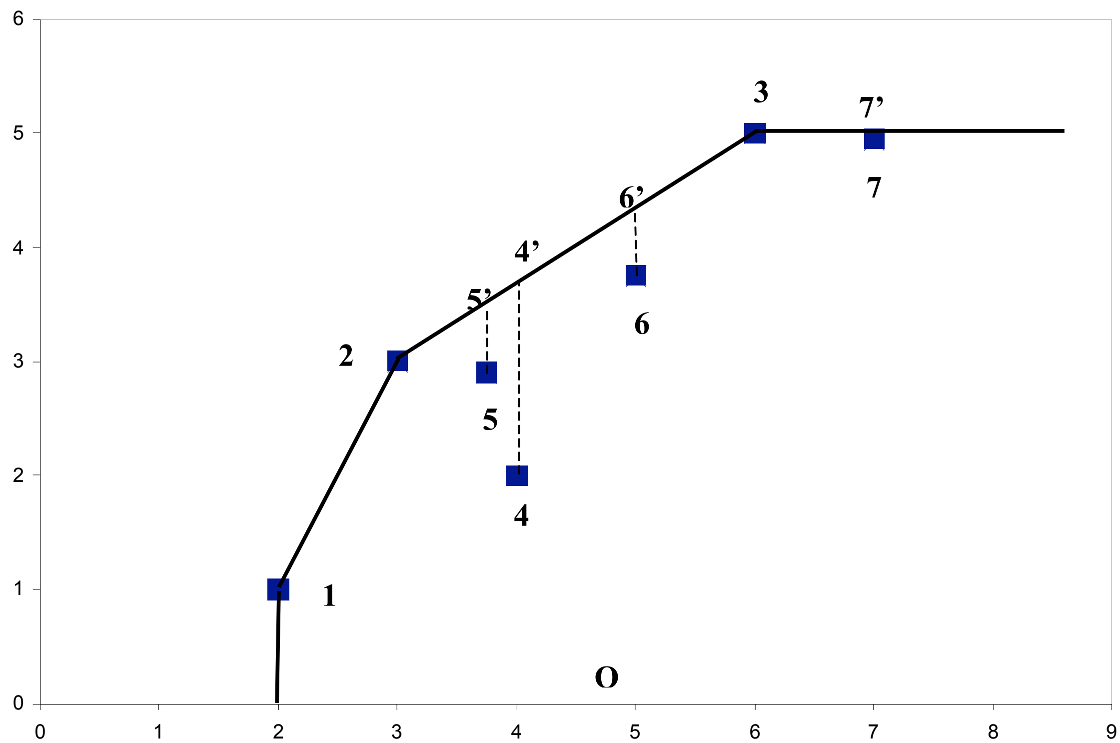
(4) $\lambda \geq 0$.

The vector y_i represents the outputs for the i^{th} firm, x_i is the vector of inputs, λ is an Nx1 vector of constants, N is the number of firms in the sample, and$1 \leq \varphi < \infty$. The proportional increase in output that the i^{th} firm could have obtained if it were on the efficient frontier is φ-1. The technical efficiency score is defined by $1/\varphi$, which varies between zero and one.

To understand the results of this linear program note that a solution in which the vector λ has a one for a particular firm and zero's otherwise and $\varphi = 1$ will always satisfy all of the constraints. Call this the default solution. If no better solution can be found, the firm is said to be technically efficient. Such an outcome can be the result of two possibilities. First, there may be no other λ vector that satisfies constraints (1), (3) and (4). In this case there is no convex combination of other firms' outputs that is at least as large as this firm's output. Second, there may be a different λ vector that satisfies constraints (1), (3) and (4), but, given that λ vector, the $1/\varphi$ required to satisfy constraint (2) is greater than one. Such a solution is dominated by the default solution. Clearly, these two outcomes will not always occur. There will be firms that have feasible solutions for values of $1/\varphi$ less than one. These firms are below the production frontier; they are technically inefficient.

Figure 2 illustrates the estimation of a production frontier using output-oriented data envelopment analysis. Figure 2 uses the same data as Figure 1, but we have eliminated the regression line and added points 4', 5', 6', and 7', which are vertical extensions from points 4, 5, 6, and 7 to the production frontier. Firms 1, 2 and 3 are efficient points because in none of these cases is it possible to find a convex combination of the outputs of the other firms that exceeds the output of these firms, i.e. constraint 1 is only satisfied with a λ vector with a one for the firm in question and zeroes otherwise. On the other hand points 4', 5' and 6' represent convex combinations of the outputs of firms 2 and 3. The output for firms 4, 5, and 6 is less than the output for 4', 5', and 6' respectively, though the input usage is identical. In the language of data envelopment

Figure 2. – Measures of Technical Efficiency Using Data Envelopment Analysis



analysis, firms 2 and 3 are peers of firms 4, 5, and 6. The measure of technical efficiency from output-oriented data envelopment analysis is the vertical distance to the point representing the output of a firm over the vertical distance to the extension of that firm’s output to the production frontier. For example for firm 4, the measure of technical efficiency would be represented by the output at point 4 divided by the output at point 4’.

Firm 7 is different. Although it is not on the frontier, firm 3 is its only peer. Firm 3 produces more output than firm 7, and it does so using fewer inputs. The measure of technical efficiency would be given by the output for firm 7 divided by the output for firm 7’. Once projected to the frontier, however, a firm like 7 could further reduce its use of input with no loss of output. This illustrates input slack, which is another result of data envelopment analysis.[11]

IV. Data and Results

Our data are drawn in part from *America's Best Colleges* published by *US News and World Report.* We started with the 2003-04 6-year graduation rates for the institutions on the *US News and World Report* list of national universities. These data were for students who were in their first year in 1998-99. We chose four input variables for both of our analyses. Two of the variables measure student characteristics and two measure institutional effort. The student variables are: (1) the percentage of the incoming class that was in the top ten percent of their high school class and (2) the score that marks the 25th percentile for the SAT scores of the incoming students.[12] We pick that dividing line because the lowest quartile of the SAT distribution is more at risk of failing to graduate. Our measures of institutional effort are: (1) the percentage of the faculty that are full time and (2) the cost per undergraduate student. The percent full time was available from US News, and the cost per undergraduate student was computed from IPEDS using the technique described in Winston and Yen (1995). These costs include both operating costs and capital costs.[13]

Table 1. Means, Standard Deviations and Sources

Variable	Mean	Standard Deviation	Source
Graduation Rate (G)	.653	.157	*US News*
Percent in Top 10% of High School Class	.390	.253	*US News*
25th Percentile SAT	1048	126	*US News*
Percentage of Faculty Full Time	.907	.091	*US News*
Cost Per Undergraduate	$13,119	$6,689	IPEDS

There were 222 institutions in the original U.S. News list of national universities. The fact that some of the 2003-04 national universities were not included in the 1998-99 data combined with missing values reduced our final data set to 187 institutions. Table 1 contains descriptive statistics for the data.

Regression Analysis. The underlying data for graduation rates come from zero-one – graduate or not graduate – outcomes for individual students so our dependent variable is an example of grouped qualitative choice data. To estimate our model we transform graduation rate into the log of the odds of graduation.[14] The estimated equation with t-statistics based on robust standard errors is:

$$\ln[G/(1-G)] = \underset{(10.29)}{-31.2351} + \underset{(4.85)}{0.2573} \ln(\text{Top10}) + \underset{(9.10)}{4.1917} \ln(\text{SAT})$$

$$+ \underset{(5.07)}{1.7109} \ln(\text{Full Time}) + \underset{(4.08)}{0.3560} \ln(\text{Cost}),\ R^2 = .8432,\ n = 187$$

These results are in line with expectations. All of the variables are statistically significant at the 1% level. Universities whose students are more often in the top 10 percent of their high school classes and whose students have higher average SAT scores are more likely to have higher graduation rates. University effort also is significant. The greater the percentage of full-time faculty and the higher the cost per undergraduate, the higher will be the institution's graduation rate. The Appendix lists the residuals from our estimated regression for all the institutions in our sample.

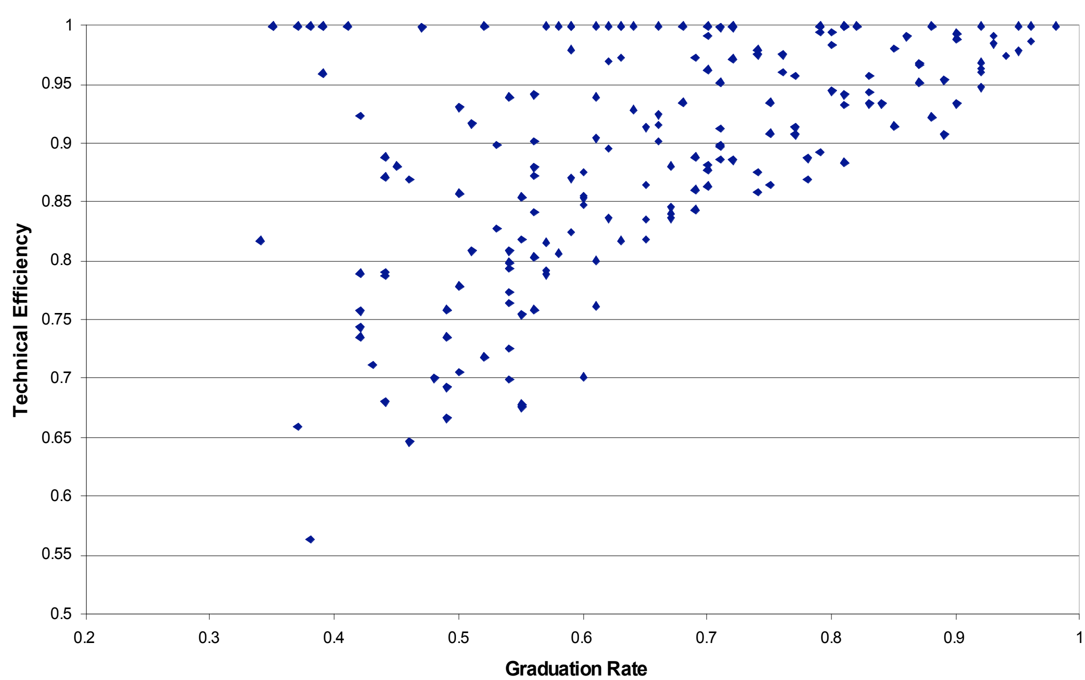
Our regression differs in a number of important ways from the one used by ***US News*** to measure graduation rate performance. Three of the explanatory variables (top ten percent, expenditure per student, and SAT scores) are common to both regressions.[15] We add a second effort variable (percent of the faculty who are full time). ***US News*** does not transform the graduation rate using the log of the odds ratio. But the most important difference is that ***US News*** includes a dummy equal to one if the institution is public. Since the coefficient of this dummy variable is significant in the ***US News*** regression, one might argue that we should have included it in our regression. We chose not to do this because there is no theoretical argument that, after correcting for student quality and university effort, public status should affect graduation rates. The fact that the coefficient on the variable is negative in the *US News* regressions means that their measure of graduation rate performance is biased against private colleges and universities. We see no reason to introduce such a bias in our analysis.[16]

<u>Production Frontier Analysis</u> As we described above, data envelopment analysis begins by identifying the efficient boundary and then computes for each university a measure of technical efficiency.[17] In our data, we found that thirty-five institutions defined the efficient frontier. The other 152 schools are to some degree inefficient in that they have lower graduation rates than do their peer institutions with similar inputs.[18] The Appendix lists the technical efficiency (TE) score for each of the institutions in our sample. An example might help with the interpretation of these scores. A score of .93, for instance, tells us that the school with a graduation rate of 70% could have achieved a graduation rate of 75.2% if it were operating on the efficient frontier as defined by its peers.

Figure 3 plots the VRS technical efficiency scores against the graduation rate. There is no reason a priori to expect that schools that define the efficient boundary would have high graduation rates and that is borne out by the data. The mean graduation rate of efficient schools and off-frontier schools both equal sixty-five percent. On the other hand, as Figure 3 shows, off-frontier schools with high graduation rates are much more likely to have high TE scores than schools with low graduation rates. This is because our production surface exhibits diminishing returns to scale in the neighborhood of every school with a graduation rate higher than .75. Lastly, thirty-nine percent of schools are on or within five percent of the frontier.[19]

The appendix gives the full ranking of institutions by their technical efficiency score. This technical efficiency score does not capture the full inefficiency for many universities because of the presence of input slack. To exist, slack requires input usage in

Figure 3. Technical Efficiency Scores and Graduation Rates



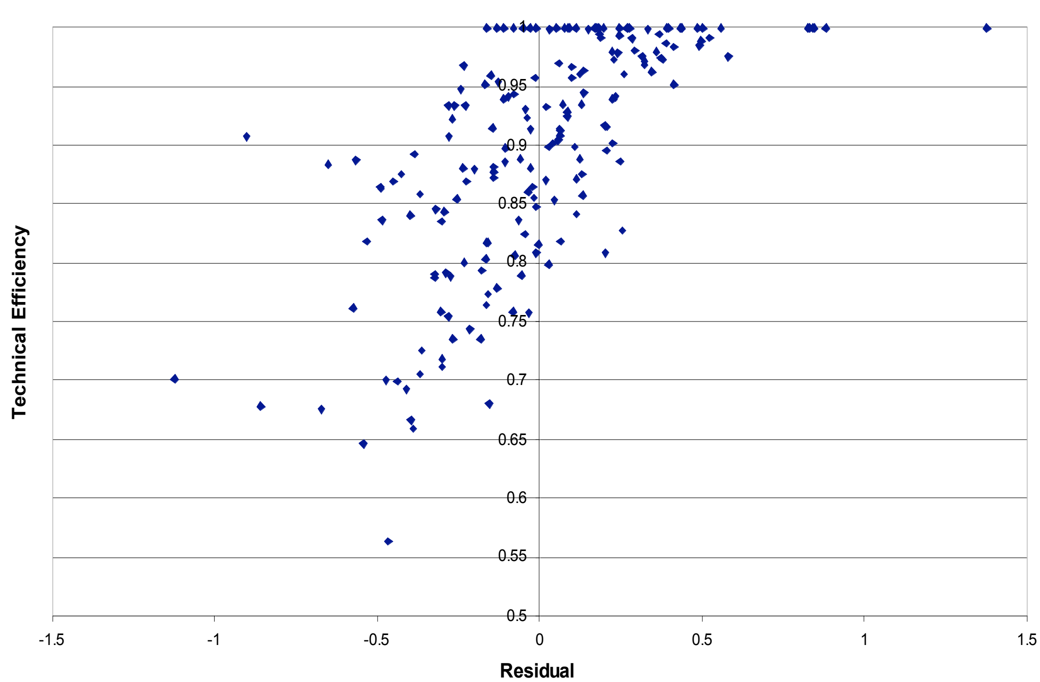
at least one dimension to be extremely large compared to that school's peers. Many inefficient institutions have no input slack. Nonetheless, in individual cases, the size of the slack can be quite large. Five schools – Cal Tech, Dartmouth, Wake Forest, Washington University, and Yale – all have input slack exceeding $14,000 of spending per full-time undergraduate. For some perspective, these input slacks alone exceed the mean level of spending per student in the data set as a whole. The appendix reports all input slacks, if any, for each university in the sample.

V. Comparison of Regression and Frontier Results

Figure 4 plots the residuals from the regression analysis against the technical efficiency scores from the data envelopment analysis. In any data the average residual is zero. In our sample, the average technical efficiency score is .896. As a result the lines at zero for the residual and a technical efficiency score of .9 divide the diagram into four quadrants.

An analysis of these four quadrants shows that results of the two types of analysis are similar for the vast majority of the institutions. The upper right-hand quadrant (above average by both measures) contains 79 institutions, and the lower left-hand quadrant (below average by both measures) contains 69 institutions. This means that the two types

Figure 4. Regression Residuals and Technical Efficiency Scores



of analysis agree 79 percent of the time. The anomalies are contained in the other two quadrants. The lower right-hand quadrant (above average residual but below average technical efficiency score) contains 12 institutions, and the upper left-hand quadrant (above average technical efficiency score but below average residual) contains 27 institutions.

Table 2 gives the means (with standard deviations in parentheses) of the data in the four quadrants defined by the mean residual and mean technical efficiency score. The institutions in the upper right-hand quadrant have above average graduation rates but their input levels are very close to the average. This puts them above average under either measure. The institutions in the lower left have poorer graduation rates, yet their inputs are also close to average. Thus they are below average using either measure.

The points in the lower right and upper left quadrants are the contradictory points we anticipated in the example illustrated in Figure 1. The institutions in the lower right quadrant correspond to the hypothetical firms five and six. They are inefficient relative to their peers but above the regression line. The institutions in the upper left quadrant are like firms one and seven in Figure 1. They have high technical efficiency scores but are below the regression line. A clear prediction from the discussion surrounding Figure 1 is that firms favored by production frontier analysis compared to regression analysis would be at the extremes of the data. In contrast, firms favored by regression analysis compared to production frontier analysis would be in the middle of the data. This prediction is consistent with the results presented in Table 2. The variances for the institutions in the upper left quadrant are consistently higher than the variances in the other quadrants, and the variances for the institutions in the lower right quadrant are consistently lower than the variances in the other quadrants.

Table 2 – Averages and Standard Deviations for Each Quadrant in Figure 4

Variable	Upper Right	Lower Right	Lower Left	Upper Left	Total Sample
n	79	12	69	27	187
Grad. Rate	.73 (.14)	.57 (.08)	.57 (.12)	.69 (.21)	.653 (.16)
Top 10	.43 (.28)	.21 (.07)	.32 (.17)	.53 (.31)	.390 (.25)
SAT	1064 (134)	955 (60)	1020 (93)	1114 (158)	1048 (126)
Full Time	.91 (.06)	.87 (.05)	.88 (.06)	.92 (.08)	.907 (.07)
Cost	13.65 (7.13)	10.94 (3.60)	11.87 (3.58)	15.73 (10.74)	13.12 (6.69)

These results point to the advantages of production frontier analysis. Using regression analysis, the institutions in the lower right quadrant might well be satisfied. Their graduation rate performance is rated above average. Yet the production frontier analysis suggests that they are far below best practice. As opposed to being satisfied with being above average, these institutions should be taking a look at how their peer institutions are performing so much better than they are. In contrast, using regression analysis the institutions in the upper left quadrant might be displeased. Their graduation rate performance is rated below average. The vast majority of the institutions in this quadrant fit into one of two groups. A large number of them have very high graduation rates, placing them very close to the production frontier that is bounded above by .98, which is the highest graduation rate in the sample (Harvard). It is quite possible for the regression analysis to compare these schools' results to higher graduation rates than actually have been achieved. This kind of out of sample extrapolation can be very inaccurate. A somewhat smaller group has very low graduation rates. The regression analysis tells them they should be doing better. But the production frontier analysis indicates that they are on or very close to the production frontier. Given their inputs, they are doing very well.

VI. Additional Results

Public vs. Private. The data profile for public and private schools contains some meaningful differences. The graduation rate achieved at private institutions is significantly higher, but so are their students' SAT scores and their annual spending per full time undergraduate. There are also differences in the regression residuals between public and private institutions. As we mentioned above, *US News and World Report's* regressions include a dummy variable equal to one for public institutions. The estimated coefficient for this variable is negative. Therefore, using the residuals from this equation, *US News* biases its measure of graduation rate performance in favor of public institutions. We did not use this kind of dummy variable, because we could find no clear causal link for this in the literature. It is, however, interesting to average our results for the two groups of institutions. Consistent with what we would expect from the US News results, our average regression residual for public institutions is -.0225, while the average regression residual for private institutions is .0044. Also, the average technical efficiency score is lower for public institutions, .8830, than it is for private institutions, .9216.

Before we conclude that private institutions have better graduation rate performance, we should also consider input slacks. The public-private differences are particularly striking for the cost slack, which is the amount that spending could be reduced without any decrease in graduation rate. For off-frontier private institutions cost slack averages $2,717, which is significantly higher than the $200 average for off-frontier public institutions. Five private institutions have cost slack that exceeds $14,000. Five more have slack that exceeds $4,000. The largest cost slack at a public university is $2,105 (SUNY Buffalo).

Institutes of Technology Our analysis did discover a bias in both regression analysis and production frontier analysis. Rankings based on either analysis are biased against what we call "tech schools." To investigate the tech school phenomena we created a new variable. Using data from IPEDS on first major of students completing a bachelor's degree, we computed the percentage of each institution's graduates in the fields of Biology, Chemistry, Computer Science, Engineering, and Physics. There was a clear break in these data at fifty percent. We focused on the fourteen institutions with fifty percent or more of their graduates in these fields as our tech schools. Table 3 lists these schools, their logistic residuals and technical efficiency scores.

Table 3. - Institutes of Technology

Institution	Percent Technical Degrees	Logistic Residual	Technical Efficiency Score
Carnegie Mellon U	52.6	-0.6535	.884
Case Western Reserve U	56.2	-0.4535	.870
New Jersey Inst. Tech.	56.3	-0.3984	.667
Clarkson U	59.6	-0.4904	.864
Florida Inst. Tech	66.2	-0.1665	.765
Rensselear Poly. Inst.	75.4	-0.0977	.942
Michigan Tech. U	77.7	-0.5772	.762
Massachusetts Inst. Tech.	78.5	-0.2447	.948
Illinois Int. Tech	81.9	-0.4875	.837
Stevens Inst. Tech	90.3	-0.2959	.844
Worcester Poly. Inst.	90.4	-0.2816	.908
Polytechnic U	90.6	-0.6754	.676
California Inst. Tech.	92.8	-0.9048	.908
U of Missouri - Rolla	93.7	-1.1263	.702

Regression analysis indicates that all of these institutions are below average; they have negative residuals. The average rank of these institutions using regression analysis is 165.3 (out of 187 institutions). Four of the fourteen institutions – Rensselaer Polytechnic Institute, Massachusetts Institute of Technology, Worcester Polytechnic Institute, and California Institute of Technology – do better than average using production frontier analysis. Still, the average rank of these institutions using production frontier analysis (132.9) is only a little higher than the average rank using regression analysis. In general, both regression and frontier analysis suggest that these institutions have poor graduation rate performance.

The tech school case brings up an important point. Institutions that do poorly on measures of graduation rate performance will be inclined to object that graduation rates represent the percentage of entering students that clear a hurdle, and that their graduates soar over the hurdle while the graduates of other institutions barely skim the hurdle. This is a claim about value added. In some cases this is no doubt true. The challenge for institutions making such a claim is to demonstrate that they provide more value added using data as well as argumentation and anecdote. The tech school case is different. Institutes of Technology could claim that they are producing a different product, a science graduate, and that this product is more difficult to produce than the standard graduate.[20] The data in Table 5 give some support to this notion. It illustrates that one should be very careful when comparing institutions with very different missions.

Ranking Efficient Schools - One of the difficulties of using production frontier analysis is that it generates a large group of efficient institutions with identical technical efficiency scores of 1.00. This leaves us unable to produce a ranking among efficient schools or make any efficiency comparisons among them. In our case 35 schools would be ranked as number one. The notion of "super efficiency scores" has been designed as a partial solution to this problem.

Andersen and Petersen (1993) developed super efficiency scores as a measure of how much the efficient boundary is moved because a particular firm is present in the data. It is easy to illustrate the calculation of super efficiency scores by using the example in Figure 2. If we eliminated firm 3, the production frontier would contain a segment between firm 2 and firm 7. The measure of super efficiency for firm 3 would be firm 3's output over the output for firm 3's inputs on the altered production frontier. If we eliminated firm 2, firm 5 would become efficient, and the super efficiency score for firm 2 would be its output over the output for its inputs on the new segment of the altered production frontier between the points for firm 1 and firm 5. Point 1 presents a problem. If we eliminate firm 1, the new production frontier will be vertical at the input of firm 2. There is no way to project firm 1's output on to this altered production frontier, and as a result it is impossible to define a super efficiency score in this case.

Table 4 gives the super efficiency scores for the efficient institutions with the institutions with undefined super efficiency scores in alphabetical order followed by the other in order of their super efficiency scores. The institutions with undefined super efficiency scores have an average graduation rate of 41.7 percent, well below the average. Those for which we could calculate super efficiency scores have much more varied graduation rates, which are generally higher. It is not surprising that St. Johns University and Fordham University, two institutions that are frequent peers of institutions in the lower right quadrant of Figure 3 also have very high super efficiency scores. These two institutions push out the production frontier more than do most of the other efficient institutions.

Table 4. - Super Efficiency Scores for Efficient Institutions

Institution	**Super Efficiency Score**	**Instituton**	**Super Efficiency Score**
Indiana State U	undefined	U of Illinois	1.052
Lousiana Tech U	undefined	Harvard U	1.043
Texas A&M Commerce	undefined	SUNY - Albany	1.041
U of Akron	undefined	Oklahoma State U	1.040
U of Colorado Denver	undefined	U of New Hampshire	1.037
U of Louisville	undefined	Pace U	1.028
U of Missouri – St. Louis	undefined	Louisiana State U	1.023
U of Wisconsin - Milwaukee	undefined	U of Vermont	1.021
New School U	undefined	U of California - Irvine	1.021
Howard U	1.392	U of Notre Dame	1.016
St. Johns U	1.340	U of California - Davis	1.016
Johns Hopkins U	1.198	Syracuse U	1.013
Fordham U	1.198	Pennsylvania State U	1.012
Florida State U	1.197	U of Georgia	1.011
Auburn U	1.184	Indiana U	1.010
Mississippi State	1.167	Illinois Sate U	1.005
U of Virginia	1.100	Brown	1.001
Bowling Green State U	1.073		

VII. Policy Analysis and Conclusions

Universities are multi-product firms. They produce value added in the classroom, research activity, and public service to name a few. The graduation rate is a very imperfect proxy for what colleges and universities produce. Unfortunately there exist no good alternative measures of value added from higher education that can be used to evaluate and compare performance across universities.[21] For that reason, as the accountability movement gathers steam graduation rates will assume increasing importance to state legislatures, Congress, private donors, and to students themselves. The reliance on this performance measure makes universities uncomfortable, especially given the difficulties in evaluating graduation rates that we have discussed. Yet the alternative – qualitative discussion of how each university is special – no matter how attractive it is to colleges and universities, is very unlikely to satisfy those who are calling for greater accountability.

Clearly graduation rates should be put in some type of context. We have argued in favor using a production frontier for this purpose instead of the more commonly used regression analysis. There are several reasons for this. First, production frontier analysis is more intuitively appealing because it compares institutions to best practice, not average practice. Second, it is less restrictive because it does not impose a functional form on the production surface. Third, it is based on comparisons with institutions in the neighborhood of the institution being rated and not an average based on the entire data set. Fourth, none of its judgments are based on extrapolations outside of the observed data. Fifth, production frontier analysis provides several useful measures, like technical efficiency and input slacks that tell an institution how it differs from its close neighbors that are efficient. Production frontier analysis is not without its difficulties. For example, it is not possible to generate a complete ranking using production frontier analysis. Even using super efficiency scores, there are several institutions tied in the rankings.

Finally, we would like to emphasize that the contribution to university ranking schemes provided by analyses of graduation rate performance is by no means the most important outcome of our frontier approach. Of far greater importance is how frontier analysis helps institutions of higher education understand how they compare to their peers so they can devise methods of catching up to the exemplary performers with comparable inputs. The focus on best practice inherent in production frontier analysis should make it very appealing both for institutions seeking to improve their performance and to those wanting to hold institutions accountable. The time when an inefficient institution could get by using what Burke (2002) calls the "resources and reputation" model is waning. The attractiveness of graduation rates is that they measure an output. If an institution is inefficient in producing this output, it is incumbent on the institution to show that it is producing something else that graduation rates do not measure.

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Appendix

Rank		School	Res.	TE	Input Slacks			
DEA	RES				SAT	Top10	Full	Cost
1	8	Auburn Univ.	0.555	1	0	0	0	0
1	13	Bowling Green State Univ.	0.485	1	0	0	0	0
1	5	Brown Univ.	0.830	1	0	0	0	0
1	51	Florida State Univ.	0.195	1	0	0	0	0
1	4	Fordham Univ.	0.840	1	0	0	0	0
1	1	Harvard Univ.	1.374	1	0	0	0	0
1	10	Howard Univ.	0.500	1	0	0	0	0
1	34	Illinois State Univ.	0.268	1	0	0	0	0
1	84	Indiana State Univ.	0.049	1	0	0	0	0
1	20	Indiana Univ. - Bloomington	0.390	1	0	0	0	0
1	68	Johns Hopkins Univ.	0.109	1	0	0	0	0
1	107	Louisiana State Univ. - Baton Rouge	-0.053	1	0	0	0	0
1	56	Louisiana Tech Univ.	0.170	1	0	0	0	0
1	72	Mississippi State Univ.	0.090	1	0	0	0	0
1	73	New School Univ.	0.086	1	0	0	0	0
1	121	Oklahoma State Univ.	-0.133	1	0	0	0	0
1	15	Pace Univ.	0.433	1	0	0	0	0
1	19	Pennsylvania State Univ.	0.396	1	0	0	0	0
1	2	St. John's Univ.	0.879	1	0	0	0	0
1	33	SUNY - Albany	0.274	1	0	0	0	0
1	16	Syracuse Univ.	0.431	1	0	0	0	0
1	118	Texas A&M Univ. - Commerce	-0.112	1	0	0	0	0
1	76	Univ. of Akron	0.074	1	0	0	0	0
1	35	Univ. of California - Davis	0.266	1	0	0	0	0
1	54	Univ. of California - Irvine	0.181	1	0	0	0	0
1	57	Univ. of Colorado - Denver	0.167	1	0	0	0	0
1	113	Univ. of Georgia	-0.083	1	0	0	0	0
1	40	Univ. of Illinois - Urbana-Champagne	0.243	1	0	0	0	0
1	131	Univ. of Louisville	-0.165	1	0	0	0	0
1	95	Univ. of Missouri - St. Louis	-0.013	1	0	0	0	0
1	14	Univ. of New Hampshire	0.433	1	0	0	0	0
1	6	Univ. of Notre Dame	0.825	1	0	0	0	0
1	55	Univ. of Vermont	0.172	1	0	0	0	0
1	3	Univ. of Virginia	0.843	1	0	0	0	0
1	101	Univ. of Wisconsin - Milwaukee	-0.032	1	0	0	0	0
36	27	Clemson Univ.	0.330	0.999	10	0	0	0
36	58	Univ. of California - Riverside	0.148	0.999	0	0.463	0.065	0
36	87	Univ. of Northern Colorado	0.029	0.999	0	0	0.104	0
39	24	Univ. of Wisconsin - Madison	0.366	0.995	0	0	0.041	0
39	53	Miami Univ. - Oxford	0.182	0.995	17	0	0.129	0
41	39	Tufts Univ.	0.243	0.994	3	0	0.035	0
42	9	Georgetown Univ.	0.520	0.992	0	0	0	705
42	52	Ohio Univ.	0.186	0.992	0	0	0.018	0
44	32	Lehigh Univ.	0.282	0.991	0	0	0.04	2411

45	11	College of William and Mary	0.494	0.989	0	0	0.036	0
46	21	Yale Univ.	0.387	0.987	0	0.047	0	19196
47	12	Northwestern Univ.	0.489	0.985	0	0.052	0	4553
48	17	Pepperdine Univ.	0.412	0.984	0	0.218	0	4664
49	31	Univ. of Michigan - Ann Arbor	0.291	0.981	0	0	0.073	0
50	25	Seton Hall Univ.	0.356	0.980	0	0	0	2823
50	46	Virginia Tech	0.222	0.980	0	0	0.006	0
52	41	Dartmouth Univ.	0.239	0.979	0	0	0	16089
53	7	Univ. of Missouri - Kansas City	0.578	0.976	0	0.089	0	1192
53	30	Univ. of Delaware	0.313	0.976	0	0	0.088	492
55	23	Stanford Univ.	0.371	0.975	0	0.069	0	2133
56	22	Michigan State Univ.	0.376	0.973	0	0	0	0
56	43	DePaul Univ.	0.227	0.973	4	0	0	0
58	29	Duquesne Univ.	0.319	0.972	0	0.224	0	0
59	82	Colorado State Univ.	0.057	0.970	51	0	0	0
60	28	Columbia Univ.	0.320	0.969	0	0.081	0	3159
61	143	Wake Forest Univ.	-0.237	0.968	0	0	0.031	16484
62	70	Univ. of California - Los Angeles	0.098	0.967	0	0.142	0	0
63	59	Univ. of Pennsylvania	0.134	0.964	0	0.109	0	11255
64	26	Univ. of Connecticut	0.342	0.963	0	0	0	0
65	36	Marquette Univ.	0.257	0.961	0	0	0.05	0
65	65	Duke Univ.	0.121	0.961	0	0.048	0	9686
67	127	Univ. of Houston	-0.152	0.960	0	0.049	0.012	0
68	71	Univ. of North Carolina - Chapel Hill	0.097	0.958	0	0.022	0	25
68	96	Univ. of California - Santa Barbara	-0.016	0.958	0	0.283	0	0
70	120	Washington Univ. in St. Louis	-0.130	0.954	0	0.06	0	24288
71	18	Univ. of Denver	0.410	0.952	0	0.019	0	0
71	135	Univ. of Chicago	-0.170	0.952	0	0.035	0	12593
73	145	Massachusetts Inst. of Technology	-0.245	0.948	0	0.101	0	5192
74	60	SUNY - Binghamton	0.134	0.945	0	0	0.007	0
75	112	Univ. of California - San Diego	-0.081	0.944	0	0.149	0	0
76	42	West Virginia Univ.	0.232	0.942	0	0.034	0.011	0
76	115	Rensselaer Polytechnic Institute	-0.098	0.942	0	0	0.061	0
78	45	Univ. of South Carolina - Columbia	0.223	0.940	0	0.113	0	0
78	119	Univ. of Central Florida	-0.113	0.940	28	0	0	0
80	63	Univ. of the Pacific	0.127	0.935	0	0.035	0.008	0
80	77	Texas A&M Univ. - College Station	0.069	0.935	0	0	0	0
82	141	Rice Univ.	-0.232	0.934	0	0.101	0	13462
82	147	Brandeis Univ.	-0.265	0.934	0	0.01	0	414
82	153	Vanderbilt Univ.	-0.284	0.934	0	0	0.013	0
85	90	Univ. of Southern California	0.018	0.933	0	0.017	0	0
86	105	North Dakota State Univ.	-0.047	0.931	0	0	0.102	0
87	74	Univ. of Massachusetts - Amherst	0.083	0.929	0	0	0	0
88	75	Univ. of San Francisco	0.083	0.925	0	0	0	0
89	104	Univ. of New Mexico	-0.041	0.924	0	0.008	0	0
90	149	Emory Univ.	-0.271	0.923	0	0.171	0	12594
91	50	Univ. of South Dakota	0.198	0.917	0	0	0	0
92	47	Purdue Univ. - West Lafayette	0.205	0.916	0	0.027	0	0
93	126	Univ. of California - Berkeley	-0.148	0.915	0	0.205	0	0
94	81	Univ. of Iowa	0.059	0.914	0	0	0	0

94	99	Univ. of Florida	-0.030	0.914	0	0.129	0	0
96	78	Univ. of Washington	0.062	0.913	0	0.001	0	0
97	80	George Washington Univ.	0.059	0.909	0	0.097	0	0
98	151	Worcester Polytechnic Institute	-0.282	0.908	0	0.017	0	2462
98	186	California Institute of Technology	-0.905	0.908	0	0.211	0	21722
100	83	Univ. of Oregon	0.054	0.905	0	0	0	0
101	44	Western Michigan Univ.	0.223	0.902	0	0.005	0	0
101	86	Iowa State Univ.	0.039	0.902	0	0	0	0
103	69	Northern Illinois Univ.	0.105	0.899	0	0	0	0
103	88	American Univ.	0.025	0.899	0	0.037	0	0
105	116	Univ. of Texas - Austin	-0.108	0.898	0	0.039	0	0
106	48	Univ. of Alabama	0.203	0.896	0	0.077	0	0
107	166	New York Univ.	-0.388	0.893	0	0.187	0	2550
108	64	Loyola Univ. Chicago	0.121	0.889	0	0.051	0	1430
108	109	Kent State Univ.	-0.062	0.889	0	0	0.032	0
110	181	Univ. of Rochester	-0.568	0.888	0	0.088	0	6140
111	38	St. Louis Univ.	0.245	0.887	0	0.044	0	0
112	117	Univ. of San Diego	-0.109	0.886	0	0.166	0	0
113	183	Carnegie Mellon Univ.	-0.654	0.884	0	0.165	0	4520
114	124	Baylor Univ.	-0.144	0.882	0	0.017	0	0
115	100	Clark Univ.	-0.031	0.881	0	0.079	0	410
115	144	Univ. of Montana	-0.238	0.881	0	0	0.124	0
117	138	Univ. of Texas - Dallas	-0.203	0.880	17	0	0	0
118	123	Univ. of Maryland - College Park	-0.144	0.878	0	0.053	0	0
119	62	Univ. of Maine - Orono	0.127	0.876	0	0.018	0	0
119	171	Tulane Univ.	-0.428	0.876	0	0.15	0	26
121	125	Hofstra Univ.	-0.144	0.873	0	0	0	4265
122	66	Univ. of Toledo	0.112	0.872	0	0	0	0
123	91	Univ. of Nebraska - Lincoln	0.016	0.871	0	0.038	0	0
124	140	Univ. of Southern Mississippi	-0.227	0.870	0	0.186	0.041	0
124	173	Case Western Reserve Univ.	-0.454	0.870	33	0.292	0	0
126	98	Univ. of Pittsburgh	-0.024	0.865	0	0	0	0
127	178	Boston Univ.	-0.493	0.865	0	0.177	0	4242
128	177	Clarkson Univ.	-0.490	0.864	0	0.006	0	4291
129	103	Catholic Univ. of America	-0.037	0.861	0	0.117	0	0
130	165	Brigham-Young Univ. - Provo	-0.371	0.859	0	0.155	0	0
131	61	Univ. of North Carolina - Greensboro	0.131	0.858	0	0	0	0
132	97	Washington State Univ.	-0.019	0.856	0	0.216	0.004	0
133	146	Univ. of Maryland - Baltimore County	-0.257	0.855	0	0	0	0
134	85	Oregon State Univ.	0.043	0.854	0	0.054	0	0
135	94	Northeastern Univ.	-0.013	0.848	0	0	0	1318
136	160	Univ. of Miami	-0.322	0.846	0	0.219	0	1146
137	155	Stevens Institute of Technology	-0.296	0.844	15	0.238	0	0
138	67	Univ. of Rhode Island	0.112	0.842	0	0.031	0	0
139	169	Univ. of Missouri - Columbia	-0.401	0.841	0	0.021	0	0
140	110	Ohio State Univ. - Columbus	-0.067	0.837	0	0.079	0	0
140	176	Illinois Institute of Technology	-0.487	0.837	76	0.281	0	0
142	158	Texas Christian Univ.	-0.305	0.836	0	0.125	0	0
143	37	Andrews Univ.	0.253	0.828	0	0	0	2370
144	106	Univ. of Tennessee - Knoxville	-0.047	0.825	0	0.054	0	0

145	79	Univ. of Idaho	0.062	0.819	0	0.035	0	0
145	179	Univ. of California - Santa Cruz	-0.535	0.819	0	0.679	0	110
147	130	Wichita State Univ.	-0.162	0.818	0	0	0	256
147	133	North Carolina State Univ. - Raleigh	-0.167	0.818	0	0.018	0	0
149	92	Univ. of Wyoming	-0.006	0.816	0	0.095	0	0
150	49	Temple Univ.	0.200	0.809	0	0.031	0	2687
150	93	Northern Arizona Univ.	-0.012	0.809	0	0.077	0	0
152	111	Univ. of Kansas	-0.079	0.807	0	0.071	0	0
153	134	Univ. of Mississippi	-0.169	0.804	0	0.165	0.003	0
154	142	Univ. of Kentucky	-0.235	0.801	0	0.055	0	0
155	89	Univ. of Utah	0.025	0.799	0	0.044	0	0
156	136	Univ. of Oklahoma	-0.181	0.794	0	0.119	0	0
157	154	SUNY - Buffalo	-0.291	0.792	0	0.035	0	700
158	162	Univ. of Alabama - Huntsville	-0.326	0.791	0	0.228	0	0
159	108	Old Dominion Univ.	-0.059	0.790	0	0.052	0	0
160	150	Drexel Univ.	-0.277	0.789	0	0.019	0	0
161	161	Montana State Univ.	-0.325	0.788	0	0.018	0.107	0
162	122	Nova Southeastern Univ.	-0.133	0.779	0	0.118	0	0
163	129	Texas Tech Univ.	-0.161	0.774	0	0.048	0	0
164	132	Florida Institute of Technology	-0.167	0.765	0	0.09	0	0
165	182	Michigan Technological Univ.	-0.577	0.762	0	0.126	0	0
166	114	Ball State Univ.	-0.085	0.759	0	0	0	144
166	159	SUNY - Stony Brook	-0.307	0.759	0	0.064	0	369
168	102	Virginia Commonwealth Univ.	-0.037	0.758	0	0	0	356
169	152	Univ. of Arizona	-0.284	0.755	0	0.139	0	0
170	139	Middle Tennessee State Univ.	-0.217	0.744	0	0	0.039	0
171	137	Univ. of South Florida	-0.184	0.736	0	0.102	0	100
171	148	Univ. of North Texas	-0.269	0.736	0	0.044	0	0
173	163	Univ. of Hawaii - Manoa	-0.366	0.726	0	0.137	0	74
174	157	Arizona State Univ.	-0.303	0.719	0	0.117	0	0
175	156	Southern Illinois Univ. - Carbondale	-0.302	0.712	0	0	0	663
176	164	Univ. of North Dakota	-0.371	0.706	0	0.061	0	1175
177	187	Univ. of Missouri - Rolla	-1.126	0.702	0	0.209	0	0
178	175	Univ. of Arkansas - Fayetteville	-0.475	0.701	0	0.122	0.011	0
179	172	Univ. of Minnesota - Twin Cities	-0.441	0.700	0	0.077	0	0
180	170	Indiana Univ. of Pennsylvania	-0.412	0.693	0	0.062	0	633
181	128	Wright State Univ.	-0.157	0.681	0	0	0	844
182	185	Univ. of Tulsa	-0.860	0.679	0	0.199	0	1094
183	184	Polytechnic Univ.	-0.675	0.676	0	0.152	0	1952
184	168	New Jersey Institute of Technology	-0.398	0.667	0	0.084	0	0
185	167	Univ. of Texas - Arlington	-0.392	0.660	0	0.068	0	0
186	180	Univ. of Illinois - Chicago	-0.545	0.647	0	0.096	0	1256
187	174	Univ. of Alabama - Birmingham	-0.469	0.564	0	0.048	0	1015

Endnotes

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[1] The first chapter of Joseph C. Burke (2002) provides a good summary of this movement.

[2] See Melodie E. Christal (1998).

[3] Alexander W. Astin (1993) called for care in interpreting graduation rates, and Astin (1997) used data on student characteristics to predict graduation performance and argued that institutions should compare their own graduation rates with the forecasts for their student bodies.

[4] See http:///www2.edtrust.org/edtrust/collegeresults (accessed January 19, 2005)

[5] The adjusted R^2 for this regression is .8, and the coefficient for X is statistically significant at the 1% level.

[6] When E. Thanassoulis (1993) compares regression analysis with production frontier estimation, his first advantage for the production frontier estimation is its freedom from the requirement of a functional form.

[7] One could criticize this linear example as being two simple. A curve with a declining slope might provide a better fit to the data. Yet observations such as firm 1 would still be possible. As our results will demonstrate, there will be points on the extremes that will be technically efficient but below the regression line.

[8] Although the measure of technical efficiency for firm seven will be quite high, there may be a substantial amount of input slack. This is possible at the edge of a frontier if one (or more) input can be reduced without decreasing output. We discuss input slack more thoroughly later in the paper.

[9] See Färe, Grosskopf, and Lovell (1994) for a full discussion of the costs and benefits of non-parametric techniques.

[10] The first code for solving the linear programming problem to identify an efficient unit isoquant in the CRS case dates to Boles (1966). The method became more widely known following the work by Charnes, Cooper and Rhodes (1978). Banker, Charnes, and Cooper (1984) extended the CRS model to account for the possibility of variable returns to scale (VRS).

[11] In this paper we are concerned with technical efficiency only. Our inputs have no clear price measure so we cannot determine if there exists any allocative inefficiency. On the other hand, Ferrier and Lovell (1990) argue that input slacks are a measure of allocative inefficiency.

[12] Our use of the 25th percentile for SAT scores follows William D. Mangold, Luann Bean and Douglas Adams, 2003.

[13] The technique we use for computing cost per full-time undergraduate is available from the authors on request.

[14] See Robert S. Pindyck and Daniel L Rubinfeld (1991), pages 260-262 for a discussion of this type of estimation.

[15] How we measure two of them differs. US News uses the mean SAT of the entering class. As mentioned earlier, we use the 25th percentile. More importantly, our measure of spending more accurately represents the undergraduate program since we include capital costs and exclude expenditures on graduate programs.

[16] Suppose on average that public universities grade more leniently or offer a less rigorous curriculum than private universities. In this case public institutions could

systematically achieve higher than predicted graduation rates, but the difference would not reflect a positive quality difference in favor of public institutions.

[17] In this study we use the multi-stage DEAP Version 2.1 developed by Tim Coelli (1992) to create our approximation of the production frontier for college graduation rates.

[18] With four inputs and one output, each institution not on the efficient frontier can have a maximum of five peers that determine for it the local efficient surface.

[19] The full output of the DEA analysis is available from the authors on request. The full output includes a listing of each school's peers, the peer weights, a measure of scale efficiency, and all input slacks.

[20] Faculty in science departments, for instance, tend to earn more than the university average and the capital needs of most science departments exceeds that of humanities and social science departments.

[21] Many studies of university performance use inputs (like research spending, or classroom hours) as proxies for output. We have focused instead on graduation rates as a clear output, recognizing that this single measure does not capture the full scope of a university's function.