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# Reputation and Efficiency: A Nonparametric Assessment of America's Top-Rated MBA Programs

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## Abstract

Widely publicized reports of fresh MBAs getting multiple job offers with six-figure annual salaries leave a long-lasting general impression about the high quality of selected business schools. While such spectacular achievement in job placement rightly deserves recognition, one should not lose sight of the resources expended in order to accomplish this result. In this study, we employ a measure of Pareto-Koopmans global efficiency to evaluate the efficiency levels of the MBA programs in Business Week's top-rated list. We compute input- and output-oriented radial and non-radial efficiency measures for comparison. Among three tier groups, the schools from a higher tier group on average are more efficient than those from lower tiers, although variations in efficiency levels do occur within the same tier, which exist over different measures of efficiency.

**Journal of Economic Literature Classification:** I2, D6, N3

**Keywords:** Data Envelopment Analysis, Pareto-Koopmans global efficiency, Reputation

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## 1. Introduction

Since 1988, *Business Week* magazine regularly publishes biennially a list of the top-ranked business schools in the U.S. This ranking reflects survey questionnaire responses from corporate recruiters, on the one hand, and current and recent graduates, on the other. Apart from enhancing the prestige of individual schools, this ranking can significantly influence popular perception about the quality of the MBAs from different schools and, thus, affect their starting salaries. Conceptually, a professional education produces the stock of marketable human capital of the individuals graduating from the program. Although far from perfect, the salary offer received on graduation provides a reasonable index of the market value of the human capital. It is also true, however, that the students enter the program with varying initial stocks of human capital. Pre-MBA earnings provide an index of the human capital acquired prior to entering the program. Thus, the incremental contribution of the program is the differential between the pre- and post-MBA annual earnings.

Reputational ranking of a business school primarily reflects popular perception of its graduates in their post-MBA careers. But one should not neglect the resources expended to accomplish the better achievements in job placement. Harvard MBAs reported average starting base salary of \$90,675 and a total compensation package worth \$163,792 (including other compensation of \$51,917 and a one time signing bonus of \$21,200) for the graduating class of 1998. For the graduates of Marriott School of Business at Brigham Young University (BYU), the corresponding average base salary and total compensation package were \$66,789 and \$99,180, respectively. What is seldom mentioned is that the average pre-MBA salary of Harvard's graduating class was already as high as \$68,000 and a much more modest \$27,684 at BYU. In fact, when accounting for differences in tuition and other expenses, the annuitized value of the gain in earnings for BYU graduates exceeds that for the Harvard graduates. The starting pay package by itself does not accurately reflect the success level of a school. Similarly, most top-rated schools admit only students with high GMAT scores. Thus, their graduates are pre-selected for a successful post-MBA career. In sum, the extent of "value added" is often overstated.

The objective of management education is to produce efficient managers. Efficient management of production requires optimal utilization of resources. Efficiency is inconsistent with either unrealized potential increase in output or avoidable waste of inputs. To what extent do these top rated schools practice what they preach? More specifically, do these schools themselves, when viewed as production units, make efficient use of their resources?

Decision making problems parallel production processes, where desirable outcomes of the decision play the role of outputs while actions or conditions facilitating these outcomes play the role of inputs. The most important achievement of business school widens the difference between the post-MBA and pre-MBA salaries of its graduates. Also, the number of job offers provides another output dimension. Inputs, on the other hand, include faculty and other resources employed as well as the quality of the entering class. Other factors, such as the gender ratio and the proportion of international students, can affect the outputs, and therefore they may enter as inputs in an appropriately specified model.

In this study, we employ Data Envelopment Analysis (DEA) to evaluate the efficiency of *Business Week's* top-rated business schools for the year 1998.[3] Johnes and Johnes (1993) use DEA to measure research efficiency of a number of Economics departments from British

[3] The method of DEA was introduced by Charnes, Cooper, and Rhodes (1978) to non-parametrically measure technical efficiency of production units with reference to a technology exhibiting constant returns to scale. Subsequently, Banker,

universities based on publication and personnel data collected by the Royal Economic Society. Burton and Phimister (1994) apply DEA to evaluate efficiency of a set of "core journals" identified by Diamond (1989). Breu and Raab (1994) analyze the data from the Top-25 National universities and Liberal Arts colleges to measure their efficiency levels using DEA. They find that several of the best-rated universities like Cal Tech (rated $5^{th}$) and Chicago (rated $10^{th}$) operate at less than 90% efficiency. Colbert, Levary and Shaner (1999) determine a more accurate ranking of U.S. MBA programs based on DEA and also compare their efficiency levels with three foreign MBA programs. No study, however, considers a measure of Pareto-Koopmans non-radial efficiency.

Unlike most DEA studies, this paper uses a global (rather than a radial) efficiency measure proposed by Pastor, Ruiz, and Sirvent (1999) to evaluate the MBA programs in the list. Input- and output-oriented radial and non-radial measures are also computed for comparison. Efficiency in the top tier exceeds that in the lower tiers. Several of the schools in the top-25 list, however, emerge as inefficient, while many schools in the lower brackets exhibit high efficiency.[4]

This paper is organized as follows. In section 2, we provide the theoretical background and a brief description of the DEA methodology. Section 3 discusses the implications of the various efficiency measures calculated. Section 4 summarizes the conclusions.

## 2. Non-Radial Measures of Technical Efficiency

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Charnes, and Cooper (1984) generalized the model to accommodate variable returns to scale.

[4] This paper extends and updates unpublished Ray (1998), which evaluates the efficiency of top-40 MBA schools in Business Week's 1994 listing.

Consider the production possibility set:

$$T = \{(x, y): y \text{ can be produced from } x\}, \qquad (1)$$

where $x$ is an $n$-element input bundle and $y$ is an $m$-element output bundle. Unlike parametric models, the non-parametric approach DEA does not specify the production possibility set explicitly. Instead, it only assumes that: (a) all observed input-output bundles are feasible; (b) inputs are freely disposable; (c) outputs are freely disposable; and (d) the production possibility set is convex.

If $(x^0, y^0)$ is a feasible production plan, then $(x^0, y^0) \in T$ implies that $y^0$ can be produced from $x^0$. The Debreu-Farrell input-oriented measure of technical efficiency of the bundle $(x^0, y^0)$ is

$$TE^I(x^0, y^0) = \min \theta : (\theta x^0, y^0) \in T. \qquad (2)$$

Similarly, the corresponding output-oriented measure is

$$TE^O(x^0, y^0) = \tfrac{1}{\varphi^*} \qquad (3)$$

where $\varphi^* = \max \varphi : (x^0, \varphi y^0) \in T$. To evaluate the input-oriented radial technical efficiency of a firm producing output $y^0$ from input $x^0$ under variable returns to scale in any empirical application, one solves the following DEA model due to Banker, Charnes, and Cooper (BCC) using a sample of observed input-output bundles $(x^j, y^j)$ $(j = 1,2,\ldots,N)$:

$$\begin{aligned}
&\min \theta \\
&\text{s.t. } \sum_j \lambda_j y_{rj} \geq y_{r0}; \ (r = 1,2,\ldots,m); \\
&\sum_j \lambda_j x_{ij} \leq \theta \, x_{i0}; \ (i = 1, 2, \ldots, n); \qquad (4) \\
&\sum_j \lambda_j = 1; \qquad \lambda_j \geq 0; \ (j = 1, 2, \ldots, N).
\end{aligned}$$

Similarly, for the output-oriented radial measure, one solves the following problem:

$$\max \phi$$

$$\text{s.t.} \quad \sum_j \lambda_j y_{rj} \geq \phi y_{r0}; \; (r = 1,2,\ldots,m);$$

$$\sum_j \lambda_j x_{ij} \leq x_{i0}; \;\; (I = 1, 2, \ldots, n); \qquad (5)$$

$$\sum_j \lambda_j = 1; \qquad \lambda_j \geq 0; \; (j = 1, 2, \ldots, N).$$

The output-oriented measure is the inverse of the optimal value of the objective function.

In general, many input bundles exist other than $x^0$, all of which can also produce $y^0$. For the specific output bundle $y^0$, we can define the *input (requirement) set*

$$V(y^0) = \{ x : y^0 \text{ can be produced from } x \}. \qquad (6)$$

For each specific output bundle $y$, there is a specific input set $V(y)$. Thus, the same production possibility set $T$ generates a family of input sets. Every observed input bundle $x^j$ lies in the input set of the corresponding output bundle $y^j$. Further, if $x^0 \in V(y^0)$ and $x^1 \geq x^0$, then $x^1 \in V(y^0)$. Also, if $x^1 \in V(y^0)$ and $y^1 \leq y^0$, then $x^1 \in V(y^1)$. If the production possibility set $T$ is convex, the input sets are also convex.

Many input bundles in the input set of a specific output bundle are inefficient, because one can produce the target output from a smaller input bundle. These are strictly interior points of the input set. By contrast, the isoquant of an output bundle $y^0$ consists only of boundary points of $V(y^0)$. The isoquant of $y^0$ is

$$\overline{V}(y^0) = \{x : x \in V(y^0) \text{ and } \lambda x \notin V(y^0) \text{ if } \lambda < 1\}. \qquad (7)$$

Thus, if $x \in \overline{V}(y^0)$, then it is not possible to reduce all inputs even by the smallest amount and still produce the output level $y^0$. The quantity of at least one input in the $x^0$ bundle must be strictly binding. From the definition of the isoquant, if $x^0 \in \overline{V}(y^0)$, then the input-oriented technical efficiency of $(x^0, y^0)$ equals unity. Indeed, every input-oriented radial projection of an inefficient input-output bundle *(x, y)* lies in the isoquant of the output bundle *y*. The *efficient subset of the isoquant* of any output bundle $y^0$ is defined as

$$V^*(y^0) = \{x : x \in V(y^0) \text{ and } x' \notin V(y^0) \text{ if } x' \le x\}. \qquad (8)$$

Note that if $x^0 \in V^*(y^0)$, then reducing *any* input in the $x^0$ bundle renders the output bundle $y^0$ infeasible. Thus, every input bundle in the efficient subset of the isoquant of an output bundle is technically efficient and no slack exists in any individual input. The non-radial measure, proposed by Färe and Lovell (1978), measures the technical efficiency of a firm relative to a point in the efficient subset of the isoquant.

In an output-oriented analysis of technical efficiency, the objective is to produce the maximum output from a given quantity of inputs. For this, we first define the *(producible) output set* of any given input bundle. For the input bundle $x^0$, the output set

$$P(x^0) = \{ y : (x^0, y) \in T\} \qquad (9)$$

consists of all output bundles that $x^0$ can produce. Because different output sets exist for different input bundles, the production possibility set is equivalently characterized by a family of output sets. If $(x^j, y^j)$ is an actually observed input-output combination, then $y^j \in P(x^j)$. Further, if $y^0 \in P(x^0)$ and if $x^1 \ge x^0$, then $y^0 \in P(x^1)$. Similarly, if $y^0 \in P(x^0)$ and if $y^1 \le y^0$, then $y^1 \in P(x^0)$. Finally, convexity of *T* ensures that each output set *P(x)* is also convex.

The *output isoquant* of any input bundle $x^0$ is defined as

$$\overline{P}(x^0) = \{y : y \in P(x^0) \text{ and } \lambda y \notin P(x^0) \text{ if } \lambda > 1\}. \qquad (10)$$

Thus, if $y^0 \in \overline{P}(x^0)$, then the output-oriented radial technical efficiency of the pair $(x^0, y^0)$ equals unity, because one cannot increase *all* outputs holding the input bundle unchanged. This does not, of course, rule out the possibility that one can increase some individual components of the $y^0$ output bundle. The *efficient subset* of the output isoquant of $x^0$, on the other hand, is

$$P^*(x^0) = \{y : y \in P(x^0) \text{ and } y' \notin P(x^0) \text{ if } y' \geq y^0\}. \qquad (11)$$

Therefore, an output-oriented radial technically efficient projection of $y^0$ produced from $x^0$ onto $P(x^0)$ may include slacks in individual outputs. But no such slacks may exist, if the projection is onto $P^*(x^0)$. The radial measure of output-oriented technical efficiency does not reflect any unutilized potential for increasing individual outputs. Again, as shown below, a non-radial, output-oriented measure does include all potential increases in any component of the output bundle.

The problem of slacks in any optimal solution of a radial DEA model arises because we seek to expand all outputs or contract all inputs by the same proportion. In non-radial models, one allows the individual outputs to increase or the inputs to decrease at different rates. Färe and Lovell (1978) introduced the following output-oriented, non-radial measure of technical efficiency, which they called the Russell measure: [5]

$$RM_y(x^0, y^0) = \frac{1}{\rho_y}, \qquad (12a)$$

where $$\rho_y = \max \tfrac{1}{m} \sum_r \phi_r$$

$$\text{s.t. } \sum_j \lambda_j y_{rj} \geq \phi_r y_{r0}; \; (r = 1,2,\ldots,m);$$

[5] Färe and Lovell allow individual components of the input or output bundle to take zero values. They define the indicator variables $\delta_r$ that take the value 0, if output $r$ is 0, and 1 otherwise. Their objective function is

$$\rho_y = \frac{\sum \phi_r}{\sum \delta_r}.$$

Throughout the present analysis, we assume that all inputs and outputs are strictly positive. The Range Adjusted Measure (RAM) introduced by Cooper, Park, and Pastor (1999) can accommodate zero inputs or outputs unless the relevant input/output is constant across observations.

$$\sum_j \lambda_j x_{ij} \le x_{i0}; \quad (I = 1, 2,..., n); \qquad (12b)$$

$$\sum_j \lambda_j = 1; \phi_r \ge 1; \ (r = 1, 2,...,m); \qquad \lambda_j \ge 0; \ (j = 1, 2,..., N).$$

When output slacks do exist at the optimal solution of a radial DEA model, the non-radial Russell measure falls below the conventional measure obtained from an output-oriented BCC model. That is, because the radial projection is always a feasible point for this problem, $\rho_y \ge \phi^*$. Hence, the non-radial Russell measure of technical efficiency never exceeds the corresponding radial measure.

The analogous input-oriented non-radial measure of technical efficiency is:[6]

$$RM_x(x^0, y^0) = \rho_x, \qquad (13a)$$

where $\rho_x = \min \frac{1}{n} \sum_i \theta_i$

$$\text{s.t.} \quad \sum_j \lambda_j y_{rj} \ge y_{r0}; \ (r = 1,2,...,m);$$

$$\sum_j \lambda_j x_{ij} \le \theta_i x_{i0}; \quad (i = 1, 2,..., n); \qquad (13b)$$

$$\sum_j \lambda_j = 1; \theta_i \le 1; \ (i = 1, 2,..., n); \qquad \lambda_j \ge 0; \ (j = 1, 2,..., N).$$

The optimal solution projects the observed input bundle $x^0$ onto the bundle $x^* = (\theta_1^* x_{10}, \theta_2^* x_{20}, ..., \theta_n^* x_{n0})$ in the efficient subset of the isoquant of the output $y^0$.[7]

[6] See Russell (1985) for a number of limitations of this non-radial measure. Zieschang (1984) proposes a two-step "Russell–extended-Farrell" measure that synthesizes the best features of the conventional radial Debreu-Farrell measure and the non-radial Russell measure. In the input-oriented case, this extended measure emerges by first projecting an observed input bundle $x^0$ radially onto the isoquant of the corresponding output bundle. Once one achieves this proportional scaling (by the factor $\theta$), one projects any input slack present in this bundle $\theta x^0$ further onto the efficient subset of the isoquant by solving the non-radial problem for $RM_x(\theta x^0, y^0)$. When no input slack exists in the radial projection of the observed input bundle, no further adjustment need occur so that the radial and non-radial measures coincide.

[7] In an alternative approach, Torgersen, Forsund, and Kittelsen (1996) adjust the efficient radial projection of the output bundle for slacks in individual outputs to obtain a non-radial projection onto the efficient subset of the output isoquant. Instead of a summary measure of efficiency combining the radial expansion factor with the slacks, they report the potential output quantities individually reflecting the output-specific efficiency levels.

No approach focuses on output and input slacks simultaneously, however. Because these are either output-oriented or input-oriented measures, either input slacks or output slacks are ignored. Instead, we consider a non-radial measure that accommodates slacks in both outputs and inputs. An input-output combination $(x^0, y^0)$ is not Pareto-Koopmans efficient if it violates either of the following inefficiency postulates: *(i)* It is possible to increase at least one output in the bundle $y^0$ without reducing any other output and without increasing any input in the bundle $x^0$; or (*ii*) It is possible to reduce at least one input in the bundle $x^0$ without increasing any other input and without reducing any output in the bundle $y^0$.

Clearly, unless $RM_x(x^0, y^0) = RM_y(x^0, y^0) = 1$, at least one of the two inefficiency postulates is violated and $(x^0, y^0)$ is not Pareto-Koopmans efficient. Input-output bundle $(x^0, y^0)$ is Pareto-Koopmans efficient, when both of the following conditions hold:

$$\text{(i) } x^0 \in V^*(y^0) \qquad \text{and} \qquad \text{(ii) } y^0 \in P^*(x^0).$$

Consider the vectors $\theta = (\theta_1, \theta_2, ..., \theta_n)$ and $\phi = (\phi_1, \phi_2, ..., \phi_m)$. A non-radial Pareto-Koopmans measure of technical efficiency of the input-output pair $(x^0, y^0)$ is computed as:

$$\Gamma = \min \frac{\frac{1}{n}\sum_i \theta_i}{\frac{1}{m}\sum_r \phi_r}$$

$$\begin{aligned}
\text{s.t.} \quad & \sum_{j=1}^{N} \lambda_j y_{rj} \geq \phi_r y_{r0}; \qquad (r = 1,2,...,m); \\
& \sum_{j=1}^{N} \lambda_j x_{ij} \leq \theta_i x_{i0}; \qquad (i = 1,2,...,n); \qquad \qquad (14) \\
& \phi_r \geq 1; \ (r = 1,2,...,m); \ \theta_i \leq 1; \ (i = 1,2,...,n); \\
& \sum_{j=1}^{N} \lambda_j = 1; \quad \lambda_j \geq 0; \ (j = 1,2,...,N).
\end{aligned}$$

Note that the efficient input-output projection $(x^*, y^*)$ satisfies

$$x^* = \sum_{j=1}^{N} \lambda_j^* x^j \le x^0 \qquad \text{and} \qquad y^* = \sum_{j=1}^{N} \lambda_j^* y^j \ge y^0 .$$

Thus, $(x^0, y^0)$ is Pareto-Koopmans efficient, if and only if $\phi_r^* = 1$ for each output $r$ and $\theta_i^* = 1$ for each input $i$, implying $\Gamma = 1$. We can visualize the Pareto-Koopmans generalized efficiency measure (GEM) as the product of two factors. The first is the input-oriented component (GEMIN) $\gamma_1 = \frac{1}{n}\sum_i \theta_i$ and the second is an output-oriented component (GEMOUT) $\gamma_2 = \dfrac{1}{\frac{1}{m}\sum_r \phi_r}$. Thus, $\Gamma = \gamma_1 . \gamma_2$.

The objective function in this mathematical programming problem is non-linear. Cooper, Park, and Pastor (1999) note that one can use a linear approximation. In the present context, however, the objective function in (14) linearizes as:

$$\Gamma = f(\theta, \phi) \approx f(\theta^0, \phi^0) + \sum_i (\theta_i - \theta_i^0)\left(\frac{\partial f}{\partial \theta_i}\right)_0 + \sum_r (\phi_r - \phi_r^0)\left(\frac{\partial f}{\partial \phi_r}\right)_0 . \quad (15)$$

Note that $$\frac{\partial f}{\partial \theta_i} = \frac{\frac{1}{n}}{\frac{1}{m}\sum_r \phi_r} \qquad (15a)$$

and $$\frac{\partial f}{\partial \phi_r} = -\frac{\frac{1}{n}\sum \theta_i}{\frac{1}{m}\left(\sum_r \phi_r\right)^2} . \qquad (15b)$$

Thus, using $\theta_i^0 = 1$ for all $i$ and $\phi_r^0 = 1$ for all $r$, at the point of approximation,

$$\Gamma \approx 1 + \frac{1}{n}\sum_i \theta_i - \frac{1}{m}\sum_r \phi_r . \qquad (16)$$

We may, therefore, solve the linear programming problem:

$$\min\ \tfrac{1}{n}\sum_i \theta_i - \tfrac{1}{m}\sum_r \phi_r$$

$$\begin{aligned}
\text{s.t.}\quad & \sum_{j=1}^{N}\lambda_j y_{rj} \ge \phi_r y_{r0}; \qquad (r=1,2,\ldots,m);\\
& \sum_{j=1}^{N}\lambda_j x_{ij} \le \theta_i x_{i0}; \qquad (i=1,2,\ldots,n);\\
& \phi_r \ge 1;\ (r=1,2,\ldots,m);\ \theta_i \le 1;\ (i=1,2,\ldots,n);\\
& \sum_{j=1}^{N}\lambda_j = 1; \lambda_j \ge 0;\ (j=1,2,\ldots,N).
\end{aligned} \tag{17}$$

Once we obtain the optimal $(\theta^*, \phi^*)$ from this problem[8], we use

$$\Gamma^* = \frac{\tfrac{1}{n}\sum_i \theta_i^*}{\tfrac{1}{m}\sum_r \phi_r^*} \tag{18}$$

as a measure of the Pareto-Koopmans efficiency of $(x^0, y^0)$. Note that this LP problem is a special case of the more general optimization problem with the same constraints, but the objective function

$$\min\ \Omega = \sum_i \alpha_i\theta_i - \sum_r \beta_r\phi_r$$

$$\begin{aligned}
\text{s.t.}\quad & \sum_{j=1}^{N}\lambda_j y_{rj} \ge \phi_r y_{r0}; \qquad (r=1,2,\ldots,m);\\
& \sum_{j=1}^{N}\lambda_j x_{ij} \le \theta_i x_{i0}; \qquad (i=1,2,\ldots,n);\\
& \phi_r \ge 1;\ (r=1,2,\ldots,m);\ \theta_i \le 1;\ (i=1,2,\ldots,n);\\
& \sum_{j=1}^{N}\lambda_j = 1; \lambda_j \ge 0;\ (j=1,2,\ldots,N).
\end{aligned} \tag{19}$$

Setting $\alpha_i = \frac{1}{n}$ for all $i$ and $\beta_r = \frac{1}{m}$ for all $r$, we get the Pareto-Koopmans problem. If,

[8] One may choose to use the optimal solution $(\theta^*, \phi^*)$ as the new point of approximation and update (15a-b) to obtain new coefficients for the objective function for the LP problem in (17). The iterative process may be terminated

additionally, we set $\beta_r = 0$ for all *r*, we get the input-oriented Russell measure. Further, when all restrict each $\alpha_i = \alpha,$ we get the usual input-oriented radial DEA problem. Similarly, the restrictions $\alpha_i = 0$ for all *i* lead to the output-oriented Russell problem. Further restricting $\beta_r = \beta$ for all *r*, we get the usual output oriented radial DEA problem.

**3. The Empirical Analysis – Reputation and Efficiency**

In this study, we consider a 2-output, 6-input technology for business schools. The first output GAIN measures the difference between the annuitized pre- and post-MBA earnings flow of a representative graduate of the school, which can be treated as the value added. Management education helps the students acquire and develop various management skills, which make them more valuable to subsequent employers. Therefore, in an efficient market, a graduate with better skills relevant for effective management will be rewarded with a higher salary. Another component of the output bundle is the adjusted placement rate (PLACE). More worthy candidates usually generate multiple job offers. Given that the job placement rate does not reach 100%, however, the average number of offers received by the graduates who actually get any offer is adjusted by the probability that a graduating student has an offer in hand.

The six inputs include: (i) the faculty-student ratio (FSRATIO), (ii) the average GMAT score of the incoming class (GMAT), (iii) the degree of selectivity in the admission process measured by the proportion of applications rejected (REJECT), (iv) the percentage of male students in the class (MALE), (v) the percentage of U.S. students in the class (US), and (vi) the expenditure per student (BUDGET). Faculty-student ratio measures an important school input.

when the optimal values of $(\theta,\ \phi)$ change by less than some small value in two successive iterations.

An increase in the FSRATIO should contribute positively to the output bundle. The student's background is measured in two alternative ways. One possible measure is the proportion of applicants accepted for admission by a school. The more selective the school is, the higher is its rejection rate and the better is the quality of its graduating students. Self-selection, however, may occur in the applicant pools across schools, where better applicants target only the more reputed schools (like Harvard or Stanford). In that case, the second quartile of the pool of applicants for one school may include better applicants than the top quartile for another. Hence, a rejection rate of 80% for both schools does not imply the same quality of the students admitted. An alternative measures selectivity by the average GMAT scores of the in-coming class across schools. In this study, we include both measures of student quality as inputs.

The two demographic variables, MALE and US, reflect characteristics of the students that may affect their salaries without affecting their managerial ability. Due to family constraints, a female MBA exhibits less mobility than the male graduates in her class, implying that her starting salary is lower, on average. Also, a gender bias may exist against female graduates in the market. For both reasons, a school with a higher proportion of female students may find that the expected salary increase (pre- vs. post-MBA) is lower. Similar logic applies for a school with a higher proportion of international students. Often, due to visa problems, MBAs who are not U.S. residents accept jobs that pay lower than average. On the other hand, outstanding MBAs who are foreign nationals may return to their own countries. As a result, the average salaries of those who accept employment in the U.S. probably are lower. By including the inputs MALE and US, we control for these two "qualitative dimensions" of the student input. Finally, BUDGET measures resources spent per student. The data for the individual schools used in this study were downloaded from the *Business Week* website. The appendix provides details of construction of the various input and output variables.

Table 1 reports the input-output data for the individual schools used in this study and the group-wise average values. The schools are listed according to their ranking in the *Business Week* list. They are grouped into 3 categories – tier-1 consists of the top-25 schools, tier-2 includes the next 25 schools, and tier-3 includes 11 schools from the next lower category. On average, the schools from a higher category achieve higher salary gain and a better placement record than schools from a lower category. At the individual school level, Carnegie Mellon University shows the highest gain ($43,376), closely followed by New York University ($43,354). At the other end, University of Florida shows a modest gain of $21,636. In terms of placement, Purdue University with 4.1 job offers per graduate proves most successful, while SUNY Buffalo and Thunderbird with only 1.5 offers per graduate show the poorest performance. Examining school resources, the top-25 schools possess a substantially lower faculty-student ratio than the schools in the other categories while the tier-2 schools have a substantially lower expenditure per pupil compared to the other two categories. Georgia Tech with an expenditure level of $173,054 towers over all others. Tulane, University of Georgia, Harvard, and University of Pennsylvania also spend in excess of $100,000 per student. University of Tennessee, Knoxville spends a mere $3,400 per student. South Carolina spending of $9,400 per pupil was the second lowest. Schools in higher categories are, as expected, more selective with both higher average GMAT scores and higher rejection rates. Stanford accepts only 7% of the applicants and enrolls a class with an average GMAT score of 722. At the other extreme, Clark Atlanta (ranked 54$^{th}$) with a rejection rate near 30% possesses an average GMAT score of 430. The proportion of US students does not move much (between 71.6% and 73.6%), on average, across all three categories. Compared to the other categories, tier-3 schools possess a higher proportion of female students (33.8%).

Table 2 reports the group-wise and individual average levels of the global efficiency measure (GEM), along with its various components. The average levels of Pareto-Koopmans global efficiency measure equal 90.7% for tier-1, 85.6% for tier-2, and 74.1% for tier-3 schools. Because the overall score, GEM, is the product of the two components, GEMIN and GEMOUT, we also examine them separately. The input-oriented factor, GEMIN, reflects the inefficiency associated with possible reduction in inputs, while the output-oriented factor, GEMOUT, shows the inefficiency due to unrealized potential increase in outputs. For the top-25 schools, both input- and output-efficiency levels (GEMIN and GEMOUT) equal about 95%. Tier-2 schools show a lower level of output efficiency than input efficiency. The difference is more pronounced for the tier-3 schools. Of the 25 schools in tier-1, 10 are inefficient. Two schools (Texas-Austin and Indiana) operate at efficiency as low as 66%, six others (including Dartmouth, Virginia, UCLA, and UC Berkeley) operate at efficiency below 80% while three others (including 6$^{th}$ ranked Columbia, and 9$^{th}$ ranked Stanford) operate below 90% efficiency. In all cases, the output efficiency component falls below the input efficiency component. Among the tier-2 schools, 12 operate at less than 100% Pareto-Koopmans efficiency. Arizona (53%), Georgia (46%), and Penn State (51%) exhibit the least efficiency not only within this group, but also in the whole sample. Among the tier-3 schools, only 2 (Boston and Clark Atlanta) of the 11 are efficient. The columns $\phi_1$ and $\phi_2$ show the potential increase in the two outputs, if the school attains its Pareto-Koopmans efficient projection. For example, the optimal value of $\phi_1$ for Dartmouth is 1.24. This implies that the average salary gain achieved by its graduates could reach nearly $37,075 (instead of the actual $29,899). The input contraction factors $\theta_1$ through $\theta_5$ do not show any significant potential for input reduction. For the per student expenditure, the optimal value of $\theta_6$ is below 0.50 for Indiana (0.31), Georgia (0.21), Penn State (0.41), Georgia Tech (0.27), and Tulane (0.37).

Table 3 shows the individual and group-wise average values of the radial and non-radial input- and output-oriented efficiency measures along with the GEM and its input- and output-oriented components. Note that the GEMIN (GEMOUT) measure often exceed the corresponding RUSSIN (RUSSOUT) measure. This occurs because the input-oriented (output-oriented) Russell measure ignores slacks in the outputs (inputs) in the optimization. The average output-oriented measures of efficiency (RUSSOUT, GEMOUT, BCC) compare favorably within each category. But the input-oriented BCC radial measure exceeds the non-radial Russell measure (especially for the tier-3 schools) by large amounts. This clearly reflects the presence of very high levels of slack in a particular input (BUDGET) in a number of schools in this category. While the BCC radial measure ignores this slack, the input-oriented Russell measure captures the slack. At the individual level, schools operate at respectable levels of efficiency, in general, when only radial input- or output-oriented BCC measures are considered. But even by the output-oriented BCC radial measure several schools (Arizona (0.67), Georgia (0.66), Texas A&M (0.66), UC-Davis (0.66) and Washington-Seattle (0.63)) operate at particularly low levels of efficiency.

## 4. Conclusion

In this paper, we formulate a DEA model to obtain Pareto-Koopmans measures of technical efficiency for the top-61 business schools from the 1998 ranking of *Business Week.* We categorize the schools into 3 groups -- the top 25 schools, the schools ranked from 26$^{th}$ to 50$^{th}$

place, and the following 11 schools. Several top-rated schools exhibit technical inefficiency, since it is possible to increase their "outputs" while reducing some of their "inputs" at the same time. On the other hand, many lower-rated schools exhibit high efficiency. Our results show that reputational rankings are principally based on the outcomes measured by salary gains and placement rates without relating these outcomes to the inputs used. A school with less spectacular salary gains can exhibit more efficient production when both inputs and outputs are taken into consideration. That is, many of the schools in the "runner up" list are fully efficient while several from the "top-25" list are not. Further, a radial measure of efficiency -- whether input- or output- oriented -- generally presents an unduly favorable picture of the performance of a school when any kind of technical inefficiency exists.

Finally, a note of caution is in order. The present study looks at the MBA programs purely from the standpoint of technical efficiency in resource utilization. Numerous other factors significantly influence the image of a business school. A more efficient program need not match an applicant’s best choice. Personal cost-benefit ratios may dominate the input-output ratio embodied in these technical efficiency measures. Also, our study looks only at the starting salaries of business school graduates and fails to take account of how their incomes grow over time once they are employed.

**APPENDIX – Inputs and Outputs in DEA**

Output 1: **GAIN** = average post MBA salary + annuity value of first year compensation
- average pre MBA salary
- 2 years times annuity value of tuition and fee including room & board

where (1) annuity value of first year compensation includes average signing bonus and average other compensation; interest rate is equal to 5% for the next 25 years

(2) 2 years *annuity value of tuition and fee includes room & board (that is, Annual Out-of-State Tuition*probability(out-of-state)+ Annual In-State Tuition*[1-Probbability(out of state)]+Room & Board) and also making annuity values by using 5% interest rate for the next 25 years

Output 2: **PLACE** = job offers by graduation
=Average Job Offers per student * the percentage of graduates with job offers

Input 1: **FSRATIO** = faculty- student ratio
= (resident faculty+0.5 visiting faculty) / (full time student + 0.5 part time student)

Input 2: **GMAT** = average GMAT score

Input 3: **REJECT** = 100 – selectivity (applicants accepted), unit: percentage

Input 4: **MALE** = 100 – female enrollment percentage, unit: percentage

Input 5: **US** = 100 – international enrollment percentage, unit:percentage

Input 6: **BUDGET** = 1998/99 school budget / enrollment
Where enrollment = full time student + 0.5 * part time student

## References:

Banker, R.D., A. Charnes, and W.W. Cooper (1984) "Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis", *Management Science*, pp 1078-1092.

Breu, T.M. and R.L. Raab (1994) "Efficiency and Perceived Quality of the Nation's "Top 25" National Universities and national Liberal Arts Colleges: An Application of Data Envelopment Analysis to Higher Education", *Socio-Economic Planning Sciences*, vol 28, pp 33-45.

Burton, M.P. and E. Phimister (1995) "Core Journals: A Reappraisal of the Diamond List", *The Economic Journal*, vol 105, pp 361-373.

Charnes, A., W.W. Cooper, and E. Rhodes (1978) "Measuring the Efficiency of Decision Making Units", *European Journal of Operational Research*, vol 2, pp 429-444.

Colbert, A., R.A. Levary, and M.C. Shaner (2000) “Determining the Relative Efficiency of MBA Programs using DEA”, *European Journal of Operational Research*, vol 125, pp 656-669.

Cooper, W.W., Park, K.S. and Pastor, J.T. (1999) “RAM: A range adjusted measure of efficiency for use with additive models, and relations to other models and measures in DEA”, *Journal of Productivity Analysis*, vol 11, pp 5-42.

Diamond, A.M. (1989) "The Core Journals in Economics", *Current Contents*, vol 21, pp 4-11.

Färe, R. and C.A.K. Lovell (1978) "Measuring the Technical Efficiency of Production", *Journal of Economic Theory*; vol 19, pp 150-162.

Johnes, G. and J. Johnes (1993) "Measuring the Research Performance of U.K. Economics Departments: An Application of Data Envelopment Analysis", *Oxford Economic Papers*, vol 45, pp 332-347.

Pastor, J.T., J.L. Ruiz, and I. Sirvent (1997) "An Enhanced DEA Russell Graph Efficiency Measure", *European Journal of Operational Research*, vol 115, pp 596-607.

Ray, S. C. (1998), “Pareto-Koopmans Measure of Efficiency in Management Education: How Well managed are America’s Top-40 Business Schools?”, Presented at the 2000 North American Productivity Workshop.

Russell, R. R. (1985) "Measures of Technical Efficiency", *Journal of Economic Theory*, vol 35, pp 109-126.

Torgersen, A.M., F. Forsund, and S. C. Kittelsen (1996) "Slack-adjusted Efficiency Measurement and Ranking of Effcient Units", *Journal of Productivity Analysis,* vol 7, pp 379-398.

Varian, H. (1984) "The Nonparametric Approach to Production Analysis", *Econometrica*, vol 54, pp 579-594.

Zieschang (1984). “An Extended Farrell Efficiency Measure”, *Journal of Economic Theory,* 33, 387-396.

Table 1: The Business Schools Data and Summary Statistics

| | | | output 1 | output 2 | input 1 | input 2 | input 3 | input 4 | input 5 | input 6 |
|---|---|---|---|---|---|---|---|---|---|---|
| **no** | **Tier** | **school name** | **Gain** | **PLACE** | **FSRATIO** | **GMAT** | **REJECT** | **MALE** | **US** | **BUDGET** |
| Group Average | | top 25 average | 34897 | 3.017 | 0.141 | 666.60 | 78.920 | 70.440 | 71.600 | 58971 |
| | | next 25 average | 30126 | 2.463 | 0.211 | 629.16 | 61.800 | 69.800 | 72.200 | 39782 |
| | | tier-3 average | 28548 | 2.374 | 0.214 | 606.91 | 57.455 | 66.182 | 73.636 | 62320 |
| 1 | top 25 | Pennsylvania (Wharton) | 32262 | 3.1 | 0.04146 | 685 | 87 | 71 | 69 | 109184 |
| 2 | top 25 | Northwestern (Kellogg) | 35172 | 3.3 | 0.09054 | 695 | 86 | 68 | 76 | 70270 |
| 3 | top 25 | Chicago | 33904 | 3.3 | 0.07003 | 690 | 76 | 78 | 77 | 49148 |
| 4 | top 25 | Michigan | 39531 | 3.4 | 0.11582 | 672 | 78 | 72 | 74 | 70648 |
| 5 | top 25 | Harvard | 27616 | 3.7 | 0.12912 | 689 | 87 | 70 | 74 | 111049 |
| 6 | top 25 | Columbia | 34198 | 2.8 | 0.11799 | 680 | 88 | 64 | 72 | 62305 |
| 7 | top 25 | Duke (Fuqua) | 41123 | 3.1 | 0.13595 | 664 | 83 | 67 | 75 | 66322 |
| 8 | top 25 | Cornell (Johnson) | 36783 | 3.1 | 0.09012 | 647 | 72 | 74 | 68 | 48527 |
| 9 | top 25 | Stanford | 30179 | 3.4 | 0.11812 | 722 | 93 | 71 | 71 | 67114 |
| 10 | top 25 | Dartmouth (Tuck) | 29889 | 2.6 | 0.10590 | 671 | 88 | 71 | 76 | 66756 |
| 11 | top 25 | UVA (Darden) | 40022 | 2.6 | 0.14227 | 685 | 85 | 70 | 79 | 72784 |
| 12 | top 25 | UCLA (Anderson) | 30477 | 2.6 | 0.09945 | 690 | 86 | 72 | 76 | 49451 |
| 13 | top 25 | NYU (Stern) | 43354 | 2.5 | 0.13480 | 675 | 82 | 62 | 66 | 57697 |
| 14 | top 25 | Carnegie Mellon | 43376 | 3.5 | 0.16184 | 654 | 70 | 76 | 61 | 59675 |
| 15 | top 25 | MIT (Sloan) | 41206 | 3.5 | 0.13418 | 690 | 87 | 73 | 63 | 79096 |
| 16 | top 25 | UC Berkeley | 34906 | 2.2 | 0.15212 | 674 | 89 | 62 | 66 | 44015 |
| 17 | top 25 | Washington University (Olin) | 34739 | 3.0 | 0.16635 | 624 | 67 | 74 | 69 | 67486 |
| 18 | top 25 | Texas at Austin | 30365 | 2.9 | 0.25491 | 661 | 77 | 75 | 78 | 49214 |
| 19 | top 25 | UNC (Kenan-Flagler) | 33762 | 2.8 | 0.16173 | 642 | 76 | 73 | 79 | 21142 |
| 20 | top 25 | Yale | 42775 | 2.8 | 0.12269 | 682 | 75 | 68 | 70 | 56970 |
| 21 | top 25 | Indiana (Kelley) | 33149 | 2.7 | 0.25865 | 635 | 60 | 72 | 81 | 84201 |
| 22 | top 25 | Maryland (Smith) | 31288 | 3.2 | 0.14627 | 653 | 79 | 64 | 61 | 24332 |
| 23 | top 25 | Wisconsin -- Madison | 22273 | 2.7 | 0.17188 | 613 | 53 | 69 | 68 | 19792 |
| 24 | top 25 | Purdue (Krannert) | 35638 | 4.1 | 0.21011 | 623 | 75 | 74 | 64 | 27378 |
| 25 | top 25 | USC (Marshall) | 34445 | 2.6 | 0.18248 | 650 | 74 | 71 | 77 | 39708 |
| 26 | next 25 | Arizona (Eller) | 24863 | 2.4 | 0.30597 | 637 | 78 | 64 | 82 | 59701 |
| 27 | next 25 | Arizona State | 28795 | 2.6 | 0.09845 | 628 | 58 | 70 | 81 | 16850 |
| 28 | next 25 | Babson (Olin) | 28527 | 2.2 | 0.13092 | 634 | 58 | 65 | 69 | 12830 |
| 29 | next 25 | BYU (Marriott) | 41294 | 2.4 | 0.25641 | 639 | 58 | 78 | 82 | 28187 |
| 30 | next 25 | Emory (Goizueta) | 31862 | 2.4 | 0.13721 | 640 | 64 | 67 | 75 | 62791 |
| 31 | next 25 | Georgetown | 36750 | 2.6 | 0.16145 | 637 | 65 | 65 | 67 | 30470 |
| 32 | next 25 | Georgia (Terry) | 28516 | 2.2 | 0.54777 | 640 | 75 | 80 | 80 | 129299 |
| 33 | next 25 | Illinois at Urbana-Champaign | 26196 | 2.6 | 0.26680 | 612 | 55 | 70 | 56 | 20520 |
| 34 | next 25 | Iowa | 32793 | 2.5 | 0.25089 | 613 | 73 | 75 | 65 | 30975 |
| 35 | next 25 | Michigan State (Broad) | 33154 | 3.7 | 0.45082 | 628 | 74 | 72 | 62 | 62295 |
| 36 | next 25 | Notre Dame | 28668 | 2.7 | 0.32321 | 613 | 43 | 72 | 75 | 71786 |
| 37 | next 25 | Ohio State (Fisher) | 28632 | 2.5 | 0.24595 | 642 | 73 | 71 | 76 | 19922 |
| 38 | next 25 | Penn State (Smeal) | 29896 | 2.1 | 0.40467 | 618 | 75 | 74 | 77 | 66926 |
| | | | **output 1** | **output 2** | **input 1** | **input 2** | **input 3** | **input 4** | **input 5** | **input 6** |

| no | Tier | school name | Gain | PLACE | FSRATIO | GMAT | REJECT | MALE | US | BUDGET |
|---|---|---|---|---|---|---|---|---|---|---|
| 39 | next 25 | Pittsburgh (Katz) | 22119 | 2.0 | 0.13897 | 641 | 51 | 69 | 59 | 28971 |
| 40 | next 25 | Rice (Jones) | 30290 | 3.0 | 0.15260 | 632 | 52 | 71 | 83 | 39994 |
| 41 | next 25 | Rochester (Simon) | 36797 | 2.4 | 0.09692 | 652 | 67 | 76 | 52 | 39374 |
| 42 | next 25 | SMU (Cox) | 30029 | 2.4 | 0.14783 | 636 | 68 | 68 | 78 | 36348 |
| 43 | next 25 | South Carolina (Darla Moore) | 30730 | 1.8 | 0.18470 | 604 | 40 | 67 | 75 | 9400 |
| 44 | next 25 | Tennessee -- Knoxville | 27237 | 3.1 | 0.27778 | 615 | 68 | 70 | 88 | 3611 |
| 45 | next 25 | Texas A&M | 24347 | 2.0 | 0.15676 | 619 | 67 | 60 | 72 | 54054 |
| 46 | next 25 | Thunderbird | 28026 | 1.5 | 0.07606 | 601 | 32 | 63 | 53 | 42989 |
| 47 | next 25 | UC Irvine | 30147 | 3.3 | 0.11680 | 650 | 73 | 73 | 71 | 31986 |
| 48 | next 25 | Vanderbilt (Owen) | 33859 | 2.6 | 0.11458 | 635 | 58 | 71 | 73 | 45650 |
| 49 | next 25 | Wake Forest (Babcock) | 27938 | 2.2 | 0.08198 | 633 | 55 | 76 | 81 | 28175 |
| 50 | next 25 | William & Mary | 31689 | 2.5 | 0.15842 | 630 | 65 | 58 | 73 | 21452 |
| 51 | tier-3 | Boston College | 24185 | 2.0 | 0.13966 | 622 | 55 | 68 | 76 | 14414 |
| 52 | tier-3 | Boston University | 30980 | 2.1 | 0.12876 | 608 | 63 | 66 | 59 | 25271 |
| 53 | tier-3 | Case Western (Weatherhead) | 26607 | 2.5 | 0.12446 | 614 | 60 | 64 | 62 | 39839 |
| 54 | tier-3 | Clark Atlanta | 37634 | 2.6 | 0.24151 | 430 | 30 | 40 | 90 | 22642 |
| 55 | tier-3 | Florida (Warrington) | 21634 | 2.5 | 0.24457 | 610 | 58 | 72 | 85 | 73772 |
| 56 | tier-3 | Georgia Tech (DuPree) | 28289 | 2.9 | 0.29000 | 632 | 55 | 72 | 69 | 173054 |
| 57 | tier-3 | Minnesota (Carlson) | 32939 | 3.2 | 0.18908 | 620 | 54 | 68 | 80 | 54276 |
| 58 | tier-3 | SUNY Buffalo | 26170 | 1.5 | 0.15509 | 598 | 59 | 68 | 68 | 23595 |
| 59 | tier-3 | Tulane (Freeman) | 34169 | 2.4 | 0.38564 | 632 | 58 | 73 | 58 | 127660 |
| 60 | tier-3 | UC Davis | 24223 | 2.3 | 0.25746 | 663 | 72 | 61 | 90 | 38701 |
| 61 | tier-3 | Washington -- Seattle | 27200 | 2.2 | 0.19733 | 647 | 68 | 76 | 73 | 92295 |

Table 2: Pareto-Koopmans Measure of Efficiency and its Components

| no | tier | school name | $\phi_1$ | $\phi_2$ | $\theta_1$ | $\theta_2$ | $\theta_3$ | $\theta_4$ | $\theta_5$ | $\theta_6$ | GEMIN | GEMOUT | GEM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Group Average | | Top 25 average | 1.048 | 1.090 | 0.987 | 0.970 | 0.943 | 0.993 | 0.969 | 0.887 | 0.958 | 0.943 | 0.907 |
| | | next 25 average | 1.108 | 1.190 | 0.919 | 0.974 | 0.978 | 0.982 | 0.970 | 0.869 | 0.949 | 0.893 | 0.856 |
| | | tier-3 average | 1.301 | 1.240 | 0.857 | 0.964 | 0.980 | 0.960 | 0.954 | 0.730 | 0.908 | 0.812 | 0.741 |
| 1 | top 25 | Pennsylvania (Wharton) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 2 | top 25 | Northwestern (Kellogg) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 3 | top 25 | Chicago | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 4 | top 25 | Michigan | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 5 | top 25 | Harvard | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 6 | top 25 | Columbia | 1.03 | 1.00 | 1.00 | 0.87 | 0.68 | 1.00 | 1.00 | 0.83 | 0.90 | 0.98 | 0.88 |
| 7 | top 25 | Duke (Fuqua) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 8 | top 25 | Cornell (Johnson) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 9 | top 25 | Stanford | 1.19 | 1.00 | 1.00 | 0.92 | 0.84 | 1.00 | 1.00 | 0.80 | 0.93 | 0.91 | 0.85 |
| 10 | top 25 | Dartmouth (Tuck) | 1.24 | 1.18 | 1.00 | 0.94 | 0.77 | 1.00 | 0.92 | 0.70 | 0.89 | 0.83 | 0.73 |
| 11 | top 25 | UVA (Darden) | 1.00 | 1.23 | 1.00 | 0.91 | 0.77 | 1.00 | 0.86 | 0.69 | 0.87 | 0.90 | 0.78 |
| 12 | top 25 | UCLA (Anderson) | 1.21 | 1.18 | 1.00 | 0.92 | 0.81 | 1.00 | 0.91 | 0.95 | 0.93 | 0.84 | 0.78 |
| 13 | top 25 | NYU (Stern) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 14 | top 25 | Carnegie Mellon | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 15 | top 25 | MIT (Sloan) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 16 | top 25 | UC Berkeley | 1.00 | 1.37 | 1.00 | 0.93 | 0.81 | 1.00 | 1.00 | 0.74 | 0.92 | 0.84 | 0.77 |
| 17 | top 25 | Washington University (Olin) | 1.21 | 1.12 | 1.00 | 1.00 | 0.97 | 0.96 | 0.95 | 0.80 | 0.95 | 0.86 | 0.81 |
| 18 | top 25 | Texas at Austin | 1.17 | 1.41 | 0.82 | 0.94 | 0.97 | 0.99 | 0.82 | 0.56 | 0.85 | 0.77 | 0.66 |
| 19 | top 25 | UNC (Kenan-Flagler) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 20 | top 25 | Yale | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 21 | top 25 | Indiana (Kelley) | 1.10 | 1.33 | 0.85 | 0.88 | 1.00 | 0.87 | 0.90 | 0.31 | 0.80 | 0.82 | 0.66 |
| 22 | top 25 | Maryland (Smith) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 23 | top 25 | Wisconsin -- Madison | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 24 | top 25 | Purdue (Krannert) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 25 | top 25 | USC (Marshall) | 1.05 | 1.43 | 1.00 | 0.94 | 0.95 | 1.00 | 0.87 | 0.81 | 0.93 | 0.81 | 0.75 |
| 26 | next 25 | Arizona (Eller) | 1.46 | 1.52 | 0.72 | 0.89 | 0.79 | 1.00 | 0.87 | 0.44 | 0.78 | 0.67 | 0.53 |
| 27 | next 25 | Arizona State | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 28 | next 25 | Babson (Olin) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 29 | next 25 | BYU (Marriott) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 30 | next 25 | Emory (Goizueta) | 1.20 | 1.28 | 1.00 | 0.94 | 0.98 | 1.00 | 0.95 | 0.72 | 0.93 | 0.81 | 0.75 |
| 31 | next 25 | Georgetown | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 32 | next 25 | Georgia (Terry) | 1.25 | 1.86 | 0.38 | 0.97 | 1.00 | 0.93 | 0.80 | 0.21 | 0.72 | 0.64 | 0.46 |
| 33 | next 25 | Illinois at Urbana-Champaign | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 34 | next 25 | Iowa | 1.08 | 1.58 | 0.83 | 1.00 | 0.98 | 0.96 | 1.00 | 0.89 | 0.94 | 0.75 | 0.71 |
| 35 | next 25 | Michigan State (Broad) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 36 | next 25 | Notre Dame | 1.32 | 1.00 | 0.59 | 0.86 | 1.00 | 0.76 | 1.00 | 0.52 | 0.79 | 0.86 | 0.68 |
| 37 | next 25 | Ohio State (Fisher) | 1.16 | 1.49 | 0.94 | 0.95 | 0.97 | 1.00 | 0.96 | 1.00 | 0.97 | 0.76 | 0.73 |
| 38 | next 25 | Penn State (Smeal) | 1.19 | 1.93 | 0.52 | 1.00 | 0.98 | 0.99 | 0.84 | 0.41 | 0.79 | 0.64 | 0.51 |
| no | tier | school name | $\phi_1$ | $\phi_2$ | $\theta_1$ | $\theta_2$ | $\theta_3$ | $\theta_4$ | $\theta_5$ | $\theta_6$ | GEMIN | GEMOUT | GEM |
| 39 | next 25 | Pittsburgh (Katz) | 1.34 | 1.12 | 1.00 | 0.97 | 1.00 | 0.97 | 1.00 | 1.00 | 0.99 | 0.81 | 0.81 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 40 | next 25 | Rice (Jones) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 41 | next 25 | Rochester (Simon) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 42 | next 25 | SMU (Cox) | 1.19 | 1.37 | 1.00 | 0.96 | 1.00 | 1.00 | 0.89 | 1.00 | 0.97 | 0.78 | 0.76 |
| 43 | next 25 | South Carolina (Darla Moore) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 44 | next 25 | Tennessee -- Knoxville | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 45 | next 25 | Texas A&M | 1.44 | 1.49 | 1.00 | 0.94 | 0.93 | 1.00 | 1.00 | 0.59 | 0.91 | 0.68 | 0.62 |
| 46 | next 25 | Thunderbird | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 47 | next 25 | UC Irvine | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 48 | next 25 | Vanderbilt (Owen) | 1.05 | 1.06 | 1.00 | 0.95 | 1.00 | 0.93 | 0.95 | 0.94 | 0.96 | 0.95 | 0.91 |
| 49 | next 25 | Wake Forest (Babcock) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 50 | next 25 | William & Mary | 1.00 | 1.02 | 1.00 | 0.92 | 0.82 | 1.00 | 1.00 | 1.00 | 0.96 | 0.99 | 0.94 |
| 51 | tier-3 | Boston College | 1.22 | 1.21 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.82 | 0.82 |
| 52 | tier-3 | Boston University | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 53 | tier-3 | Case Western (Weatherhead) | 1.23 | 1.03 | 1.00 | 1.00 | 0.98 | 1.00 | 1.00 | 0.86 | 0.97 | 0.89 | 0.86 |
| 54 | tier-3 | Clark Atlanta | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 55 | tier-3 | Florida (Warrington) | 1.93 | 1.29 | 0.76 | 0.96 | 1.00 | 0.91 | 0.82 | 0.66 | 0.85 | 0.62 | 0.53 |
| 56 | tier-3 | Georgia Tech (DuPree) | 1.43 | 1.06 | 0.62 | 0.92 | 1.00 | 0.89 | 1.00 | 0.27 | 0.78 | 0.80 | 0.63 |
| 57 | tier-3 | Minnesota (Carlson) | 1.08 | 1.00 | 1.00 | 0.90 | 1.00 | 0.89 | 0.99 | 0.57 | 0.89 | 0.96 | 0.86 |
| 58 | tier-3 | SUNY Buffalo | 1.27 | 1.76 | 1.00 | 1.00 | 1.00 | 0.92 | 1.00 | 1.00 | 0.99 | 0.66 | 0.65 |
| 59 | tier-3 | Tulane (Freeman) | 1.07 | 1.18 | 0.35 | 1.00 | 1.00 | 0.98 | 1.00 | 0.37 | 0.78 | 0.89 | 0.70 |
| 60 | tier-3 | UC Davis | 1.50 | 1.53 | 0.86 | 0.83 | 0.80 | 1.00 | 0.82 | 0.66 | 0.83 | 0.66 | 0.55 |
| 61 | tier-3 | Washington -- Seattle | 1.58 | 1.57 | 0.84 | 0.99 | 1.00 | 0.98 | 0.86 | 0.63 | 0.88 | 0.63 | 0.56 |

Table 3: Radial and Non-radial Measures of Technical Efficiency

| | | | | input-oriented measures | | | | output-oriented measures | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| no | tier | school name | GEM | CCR | BCC | RUSSIN | GEMIN | CCR | BCC | RUSSOUT | GEMOUT |
| Group Average | | top 25 average | 0.907 | 0.934 | 0.968 | 0.928 | 0.958 | 0.933 | 0.945 | 0.933 | 0.943 |
| | | next 25 average | 0.856 | 0.890 | 0.962 | 0.901 | 0.949 | 0.890 | 0.911 | 0.891 | 0.893 |
| | | tier-3 average | 0.741 | 0.823 | 0.946 | 0.843 | 0.908 | 0.823 | 0.849 | 0.811 | 0.812 |
| 1 | top 25 | Pennsylvania (Wharton) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 2 | top 25 | Northwestern (Kellogg) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 3 | top 25 | Chicago | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 4 | top 25 | Michigan | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 5 | top 25 | Harvard | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 6 | top 25 | Columbia | 0.88 | 0.92 | 0.97 | 0.89 | 0.90 | 0.92 | 0.93 | 0.92 | 0.98 |
| 7 | top 25 | Duke (Fuqua) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 8 | top 25 | Cornell (Johnson) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 9 | top 25 | Stanford | 0.85 | 0.96 | 0.97 | 0.91 | 0.93 | 0.96 | 0.96 | 0.88 | 0.91 |
| 10 | top 25 | Dartmouth (Tuck) | 0.73 | 0.79 | 0.91 | 0.81 | 0.89 | 0.79 | 0.79 | 0.79 | 0.83 |
| 11 | top 25 | UVA (Darden) | 0.78 | 0.91 | 0.92 | 0.84 | 0.87 | 0.91 | 0.93 | 0.86 | 0.90 |
| 12 | top 25 | UCLA (Anderson) | 0.78 | 0.83 | 0.93 | 0.84 | 0.93 | 0.83 | 0.83 | 0.83 | 0.84 |
| 13 | top 25 | NYU (Stern) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 14 | top 25 | Carnegie Mellon | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 15 | top 25 | MIT (Sloan) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 16 | top 25 | UC Berkeley | 0.77 | 0.88 | 0.96 | 0.84 | 0.92 | 0.88 | 0.88 | 0.83 | 0.84 |
| 17 | top 25 | Washington University (Olin) | 0.81 | 0.86 | 0.95 | 0.85 | 0.95 | 0.85 | 0.86 | 0.86 | 0.86 |
| 18 | top 25 | Texas at Austin | 0.66 | 0.72 | 0.86 | 0.73 | 0.85 | 0.71 | 0.77 | 0.76 | 0.77 |
| 19 | top 25 | UNC (Kenan-Flagler) | 1.00 | 0.99 | 1.00 | 1.00 | 1.00 | 0.99 | 1.00 | 1.00 | 1.00 |
| 20 | top 25 | Yale | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 21 | top 25 | Indiana (Kelley) | 0.66 | 0.76 | 0.86 | 0.70 | 0.80 | 0.76 | 0.81 | 0.81 | 0.82 |
| 22 | top 25 | Maryland (Smith) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 23 | top 25 | Wisconsin -- Madison | 1.00 | 0.90 | 1.00 | 1.00 | 1.00 | 0.90 | 1.00 | 1.00 | 1.00 |
| 24 | top 25 | Purdue (Krannert) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 25 | top 25 | USC (Marshall) | 0.75 | 0.82 | 0.87 | 0.80 | 0.93 | 0.82 | 0.86 | 0.79 | 0.81 |
| 26 | next 25 | Arizona (Eller) | 0.53 | 0.64 | 0.85 | 0.66 | 0.78 | 0.64 | 0.67 | 0.67 | 0.67 |
| 27 | next 25 | Arizona State | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 28 | next 25 | Babson (Olin) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 29 | next 25 | BYU (Marriott) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 30 | next 25 | Emory (Goizueta) | 0.75 | 0.81 | 0.90 | 0.82 | 0.93 | 0.81 | 0.81 | 0.80 | 0.81 |
| 31 | next 25 | Georgetown | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 32 | next 25 | Georgia (Terry) | 0.46 | 0.62 | 0.84 | 0.55 | 0.72 | 0.62 | 0.66 | 0.64 | 0.64 |
| 33 | next 25 | Illinois at Urbana-Champaign | 1.00 | 0.89 | 1.00 | 1.00 | 1.00 | 0.89 | 1.00 | 1.00 | 1.00 |
| 34 | next 25 | Iowa | 0.71 | 0.89 | 0.95 | 0.84 | 0.94 | 0.88 | 0.88 | 0.75 | 0.75 |
| 35 | next 25 | Michigan State (Broad) | 1.00 | 0.95 | 1.00 | 1.00 | 1.00 | 0.95 | 1.00 | 1.00 | 1.00 |
| 36 | next 25 | Notre Dame | 0.68 | 0.92 | 0.98 | 0.76 | 0.79 | 0.92 | 0.96 | 0.86 | 0.86 |
| 37 | next 25 | Ohio State (Fisher) | 0.73 | 0.81 | 0.90 | 0.83 | 0.97 | 0.81 | 0.83 | 0.76 | 0.76 |
| 38 | next 25 | Penn State (Smeal) | 0.51 | 0.67 | 0.87 | 0.63 | 0.79 | 0.67 | 0.70 | 0.64 | 0.64 |
| | | | | input-oriented measures | | | | output-oriented measures | | | |

| no | tier | school name | GEM | CCR | BCC | RUSSIN | GEMIN | CCR | BCC | RUSSOUT | GEMOUT |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 39 | next 25 | Pittsburgh (Katz) | 0.81 | 0.73 | 0.98 | 0.95 | 0.99 | 0.73 | 0.86 | 0.81 | 0.81 |
| 40 | next 25 | Rice (Jones) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 41 | next 25 | Rochester (Simon) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 42 | next 25 | SMU (Cox) | 0.76 | 0.79 | 0.90 | 0.83 | 0.97 | 0.79 | 0.81 | 0.78 | 0.78 |
| 43 | next 25 | South Carolina (Darla Moore) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 44 | next 25 | Tennessee -- Knoxville | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 45 | next 25 | Texas A&M | 0.62 | 0.65 | 0.92 | 0.79 | 0.91 | 0.65 | 0.66 | 0.65 | 0.68 |
| 46 | next 25 | Thunderbird | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 47 | next 25 | UC Irvine | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 48 | next 25 | Vanderbilt (Owen) | 0.91 | 0.94 | 0.95 | 0.93 | 0.96 | 0.94 | 0.95 | 0.94 | 0.95 |
| 49 | next 25 | Wake Forest (Babcock) | 1.00 | 0.97 | 1.00 | 1.00 | 1.00 | 0.97 | 1.00 | 1.00 | 1.00 |
| 50 | next 25 | William & Mary | 0.94 | 0.97 | 1.00 | 0.95 | 0.96 | 0.97 | 0.99 | 0.99 | 0.99 |
| 51 | tier-3 | Boston College | 0.82 | 0.82 | 0.99 | 0.96 | 1.00 | 0.82 | 0.83 | 0.82 | 0.82 |
| 52 | tier-3 | Boston University | 1.00 | 0.96 | 1.00 | 1.00 | 1.00 | 0.96 | 1.00 | 1.00 | 1.00 |
| 53 | tier-3 | Case Western (Weatherhead) | 0.86 | 0.83 | 0.99 | 0.95 | 0.97 | 0.83 | 0.94 | 0.88 | 0.89 |
| 54 | tier-3 | Clark Atlanta | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 55 | tier-3 | Florida (Warrington) | 0.53 | 0.68 | 0.86 | 0.69 | 0.85 | 0.68 | 0.71 | 0.62 | 0.62 |
| 56 | tier-3 | Georgia Tech (DuPree) | 0.63 | 0.88 | 0.94 | 0.73 | 0.78 | 0.88 | 0.91 | 0.80 | 0.80 |
| 57 | tier-3 | Minnesota (Carlson) | 0.86 | 0.98 | 0.98 | 0.89 | 0.89 | 0.98 | 0.98 | 0.96 | 0.96 |
| 58 | tier-3 | SUNY Buffalo | 0.65 | 0.77 | 0.97 | 0.91 | 0.99 | 0.77 | 0.77 | 0.66 | 0.66 |
| 59 | tier-3 | Tulane (Freeman) | 0.70 | 0.89 | 0.98 | 0.73 | 0.78 | 0.89 | 0.90 | 0.89 | 0.89 |
| 60 | tier-3 | UC Davis | 0.55 | 0.64 | 0.83 | 0.71 | 0.83 | 0.64 | 0.66 | 0.66 | 0.66 |
| 61 | tier-3 | Washington -- Seattle | 0.56 | 0.60 | 0.87 | 0.69 | 0.88 | 0.60 | 0.63 | 0.63 | 0.63 |