ASSESSMENT OF MBA PROGRAMS VIA DATA ENVELOPMENT ANALYSIS

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ABSTRACT

This research presents a technique to assess the relative desirability of AACSB-accredited MBA programs via an Operations Research based tool called Data Envelopment Analysis (DEA). Several attributes of these MBA programs are incorporated into a set of linear programming problems, ultimately determining which programs are most desirable in terms of these attributes. The research finds that of 188 AACSB-accredited MBA programs studied, several possess characteristics that are dominant over others.

INTRODUCTION

When considering MBA programs, several issues usually come to mind: tuition, reputation of the school, and placement issues (i.e., starting salary upon graduation) are some of the more common evaluation criteria. Deciding upon which MBA programs are "best" is usually treated as a subjective issue. *Business Week* and other publications have annual issues dedicated to assessing the "best" MBA programs. These assessments are usually quite subjective, based upon surveys (and interviews) of graduates and companies hiring the graduates. *Barron's* also has an annual issue dedicated to determining the schools which are the "best buys." Again, their models are quite subjective, usually based upon surveys of stakeholders. The fact is, with so many criteria involved, the assessment process is far from trivial.

Data Envelopment Analysis (DEA) is an Operations Research based tool that can assist in this assessment process by jointly considering several appropriate attributes and presenting a single composite score for each MBA program under consideration. This composite score, referred to as *efficiency*, is essentially the objective function of a linear programming model. Doyle and Green (1991) offer a fundamental, yet informative, description of Data Envelopment Analysis. A more detailed description of DEA is offered by Charnes et al. (1994), which concentrates more on the mathematical aspects of DEA.

The intent of this research is twofold. Primarily, it is intended to shed some light on which AACSB-accredited MBA programs are found to be most desirable through the use of DEA—desirable, that is, within the context of a DEA model. The results of this analysis will then be compared with *Business Week's* (October 21, 1996) "Top 25 MBA Programs." Secondly, it is intended to show, in general, how DEA can be used to perform a relatively objective analysis on a subject typically receiving subjective treatment.

This research will show which of the 188 schools analyzed are found to be efficient in terms of Data Envelopment Analysis (referred to as DEA-efficient). Additionally, it will be shown why certain schools not found to be DEA-efficient (referred to as DEA-inefficient) are in fact inefficient, and what can be done to improve their efficiency score.

The following sections of the paper discuss the general methodology of DEA, present the criteria used for the analysis, present the results, and offer conclusions regarding the desirability of the schools as well as describe the benefits of using DEA for such an evaluation.

ASSESSMENT CRITERIA AND DATA

This research examines 191 AACSB-accredited MBA Programs using the following criteria: starting salary upon graduation, difficulty in gaining admission to the school of interest, annual tuition, and average class size. The first two criteria are considered outputs—benefits associated with the school of interest, while the latter two criteria are considered inputs—necessary sacrifices associated with attending the school of interest.

The output of starting salary upon graduation is a straightforward measure—the average salary of graduates as reported by the schools. The level of the school's relative difficulty in gaining admission is measured by two attributes—the average GMAT score of students in the program and the percentage of students denied admission to the program of interest. High levels of starting salary and difficulty in gaining admission indicate a high level of output (benefits) associated with the school of interest.

The annual tuition is also a relatively straightforward measure—the annual tuition required for the school of interest. For state-funded institutions, a weighted-average is used for analysis—the sum of resident tuition multiplied by the percentage of resident students and non-resident tuition multiplied by the percentage of non-resident students.[1] This weighted average can be thought of as the average amount of annual tuition paid per student for the school of interest. The average class size is simply the average size of core (required) classes as reported by the schools. Here, large classes are treated as a cost—a lack of individual interaction between student and faculty. High levels of tuition and large classes represent a high level of input (sacrifices) required to attend the program of interest.

The data for this analysis was primarily attained from *Peterson's Guide to MBA Programs* (1997). For some schools, this source did not disclose complete information. In this event, one of two courses of action was taken. The first course of action was for schools appearing on *Business Week's* (October 21, 1996) list of "Top 25 MBA Programs." Here, necessary follow-up was performed to complete the data set for these schools. In several instances, schools appearing on this list were missing information regarding average GMAT scores. To obtain this information, school web pages were searched in addition to consulting the *Princeton Review* (Gilbert, 1997). The second course of action was for the schools that were not on *Business Week's* (October 21, 1996) list of Top 25 MBA programs. Here, follow-up was performed as much as realistically possible so that "gaps" in the data could be filled. Some of these gaps were filled by consulting the MBA Database (Schatz, 1997). There were situations, however, where certain schools had data that could just not be found—despite the efforts previously described. These schools were ultimately excluded from this analysis. The most frequent reason for omitting these schools from the analysis was the fact that there was no disclosure regarding salary upon graduation. The majority of schools omitted from the analysis for this reason were typically smaller programs with a large percentage of part-time students (presumably working full-time), where the placement attributes of the school is perhaps not a major concern. Obtaining complete data for larger programs with a majority of part-time students (presumably working full time) was typically not a problem.

As a result of the specification of the input and output attributes, a data set of 188 AACSB-accredited MBA programs was constructed. It should be noted that the inputs and outputs are in differing units. For example, average GMAT scores are in points, while average starting salary is in US dollars—this complicates the interpretation. To compensate for this, all attributes were standardized and then re-scaled from zero, so that the lowest possible output and input values would be zero.

DATA ENVELOPMENT ANALYSIS METHODOLOGY

DEA is employed to determine the relative efficiency of each of the 188 schools analyzed. This efficiency is a composite ratio of the outputs to the inputs. An efficiency of unity is the highest possible score, and represents a program that is DEA-efficient, while an efficiency of anything less than unity is referred to as DEA-inefficient. Within the context of the analysis, DEA-efficient programs are considered most desirable, and possess a set of attributes that the DEA-inefficient schools do not posses, but strive for.

Consider the output attributes: average starting salary upon graduation, average GMAT scores for students in the program and percentage of students rejected admission for MBA program k, where i=1, 2,...k,...188. These outputs are represented by the variables O_{1k}, O_{2k}, and O_{3k} respectively (s=3 outputs). These outputs have weights of u_{1k}, u_{2k}, and u_{3k}. The inputs of annual tuition and class size are represented by the variables I_{1k} and I_{2k} respectively, with weights of v_{1k} and v_{2k} (r=2 inputs). The general linear programming model used for this Data Envelopment Analysis is as follows:

Max:
$$h_k = \sum_{y=1}^{s}\left(O_{yk}\, u_{yk}\right) + \mu_{yk}\,, \tag{1}$$

for school k

Subject to:
$$\sum_{x=1}^{r}\left(I_{xk}\, v_{xk}\right) + \rho_{xk} = 1\,, \tag{2}$$

for school k

and
$$\left(\sum_{y=1}^{s} O_{yk}\, u_{yk}\right) - \left(\sum_{x=1}^{r} I_{xk}\, v_{xk}\right) + \mu_{xk} \le 0 \tag{3}$$

for all i = 1, 2, ...k....n

μ_{yk}, ρ_{xk} unrestricted, u_{yk}, $v_{xk} \geq 0$

As noted in equation (1), the objective is to maximize the value h_k subject to the constraints given in equations (2) and (3). The h_k value is the relative efficiency of school k. It should be noted that μ_{yk} and ρ_{xk} are slack variables designed to quantify the inefficiency in school k. In basic terms, the DEA model finds the "best value" of each h_k by varying the weights u_{yk} and v_{xk} subject to the "rules" specified in equations (2) and (3). These "rules" in (2) and (3) prohibit any values of h_k from exceeding unity. In short, the above model maximizes the efficiency for each school—showing each school in its best possible light with respect to the rules that efficiency cannot exceed unity.

When attempting to show a school in its best possible light with respect to the DEA model and the other schools being studied, there is a specific occurrence which can produce dubious results. Consider, for example, a school that is difficult in gaining acceptance. In addition, the starting salary of graduates is formidable. Furthermore, the class-sizes are small—students receive a high level of attention from faculty. The only negative is that the annual tuition for this particular school is very high. In short, all attributes associated with this school are favorable with the exception of the tuition. The DEA model defined above, however, would probably show this particular school to be DEA-efficient because the weight associated with tuition, v_{1k}, would be allowed to take on a value of zero, thereby ignoring the fact that tuition for this school is high. This type of situation permits schools to be classified as DEA-efficient when perhaps they should not be.

To prevent this from happening in the analysis, restrictions must be placed on the weights such that they are not permitted to take on negligible (or zero) values. These weight restrictions should reflect the decision-maker's view of the relative importance of the attributes. For this research the following weighting restrictions were applied to the outputs:

The weight of salary was not permitted to be less than, or more than five times that of GMAT score or rejection rate:

$$1 < \frac{u_{1k}}{u_{2k}}, \frac{u_{1k}}{u_{3k}} < 5 \tag{4}$$

This restriction obviously articulates the relative importance placed upon salary, but at the same time, GMAT score and rejection rate are considered as well.

The weight of GMAT score was not allowed to be more than twice that of rejection rate and visa versa:

$$.5 < \frac{u_{2k}}{u_{3k}} < 2 \tag{5}$$

Here, GMAT score and rejection rate are given approximately equal treatment, but some weighting freedom is permitted in attempt to find high levels of efficiency.

The weight of annual tuition was not permitted to be less than, or more than six times that of student to faculty ratio:

$$1 < \frac{v_{1k}}{v_{2k}} < 6 \tag{6}$$

As is the case with the weight restrictions for involving salary, the restriction here treats tuition as the primary input, but considers class size as well.

A DEA model can be analyzed two different ways—an input orientation and an output orientation. An input orientation informs the decision-maker as to how much reduction is needed from the current levels of input for a DEA-inefficient MBA program to become DEA-efficient. An output orientation presents information regarding how much augmentation is needed to the current levels of output for a DEA-inefficient MBA program to become DEA-efficient. DEA-efficient MBA programs, which have an efficiency of unity, require neither input reduction nor output augmentation. Both input and output oriented DEA models are used here to interpret changes necessary for DEA-inefficient programs to become DEA-efficient (Ali, 1995).

RESULTS

General Results

Of the 188 MBA programs analyzed, thirteen were found to be DEA-efficient—they have combinations of inputs and outputs that the remaining 175 MBA programs do not posses. These 13 programs make up what is referred to as the Efficiency Frontier, which is analogous to the Production Possibilities Frontier in Economics. Within the context of the analysis, these programs require neither input reduction nor output augmentation. The x-axis of the Efficiency Frontier is the level of virtual input—the weighted sum of inputs. The virtual input for program k is:

$$(\text{Virtual Input})_k = \sum_{x=1}^{r} I_{xk} v_{xk} \tag{7}$$

The y-axis of the Efficiency Frontier is the level of virtual output—the weighted sum of outputs. The virtual output for program k is:

$$(\text{Virtual Output})_k = \sum_{y=1}^{s} O_{yk} u_{yk} \tag{8}$$

The thirteen MBA programs found to be DEA-efficient were: Nebraska, Indiana University/Purdue University at Fort Wayne (IUPUFW), Texas/Pan Am, McNeese St., San Jose State (SJSU), Oklahoma, Texas, Florida, Harvard, Massachusetts Institute of

Technology (MIT), University California at Berkeley (Berkeley), University of Pennsylvania (Penn), and the University of Chicago (Chicago). In addition to these thirteen programs, five more exhibited virtual inputs and outputs that put them closer to the Efficiency Frontier than the other DEA-inefficient programs. While they were not found to be DEA-efficient, they would require relatively little input reduction or output augmentation to become DEA-efficient. The criteria used for determining whether-or-not a program is DEA "near-efficient" was based on both input reduction and output augmentations being less than 20%. Table 1 details these five programs along with the amounts of input reduction and output augmentation needed to make them DEA-efficient.

Insert Table 1 About Here

Interpretation of the input reduction and output augmentation values is straightforward. Consider, for example, Lamar University. For this program to become DEA-efficient, a linear combination of the inputs of tuition and class size would have to be reduced 3.31% below their current levels. This program could also become DEA-efficient by having a linear combination of the outputs of average starting salary upon graduation, average GMAT score and percentage of students rejected for admission increased to 1.38% above their current levels.

Figure 1 provides some perspective regarding the efficiency frontier.

Insert Figure 1 About Here

Figure 1 shows where the DEA-efficient and near-efficient schools exist with respect to the Efficiency Frontier. A distinctive characteristic of the Efficiency Frontier is its convex shape (Banker, et al., 1984 and Charnes, et al., 1978). The DEA-efficient programs are actually on the frontier (noted above the line), while the near-efficient programs are just "southeast" of the frontier (noted below the line).

The frontier provides some interesting information. The "northeast" end of the frontier includes schools like Harvard, MIT, Penn, and Stanford—programs frequently regarded as formidable. These schools are relatively expensive, but their benefits can be sizable (salaries, etc). At the "southwest" end of the frontier are schools like IUPUFW, Texas/Pan-American and McNeese St. These schools typically do not provide the same magnitude of benefits (salaries, etc.) as the schools at the other end of the frontier, but the benefits offered do offset the sacrifices necessary to attend (i.e., tuition). Regardless of what end of the frontier these schools reside, they share the common attribute of having their input requirements offset by their outputs. It is interesting to note that several schools on or near the frontier are state-funded programs which have generally favorable reputations. These schools would be especially attractive to prospective in-state students who could avoid paying the more expensive out-of-state tuition—this analysis used a weighted average for tuition (as previously described) as the input tuition attribute.

Sensitivity Analysis

Both inputs and outputs used for this DEA model can be considered stochastic—they will vary slightly over time. For example, tuition for some schools will change at different rates than at other schools. To address the stochastic nature of the inputs and outputs involved here, a sensitivity analysis was performed to determine which of the DEA-efficient programs were the most robust—least sensitive to unfavorable changes in their levels of inputs and outputs. In this context, an unfavorable change means a decrease of x percent in all outputs of a DEA-efficient program and a simultaneous increase of x percent in all inputs of a DEA-efficient program. Additionally, all DEA-inefficient programs have their outputs increased by x percent and their inputs decreased by x percent. In short, this change basically means that DEA-efficient programs are forced to appear less desirable and DEA-inefficient programs are forced to appear more desirable (Thompson et al, 1994, Thrall, 1996). After this change of x percent is made for all schools, the model is re-run and the set of DEA-efficient programs are interpreted. If an MBA program initially found to be DEA-efficient continues to exist in the efficient set of programs after a change has been made, the program can be considered robust—insensitive to unfavorable changes. For this research, four different levels of change were explored: 2.5%, 5%, 7.5% and 10%.

In addition to performing a sensitivity analysis with respect to the input and output values for each school as previously described, another sensitivity analysis was performed to examine the robustness of the thirteen schools originally found to be DEA-efficient when weighting constraints were made more restrictive. Consider the weighting restrictions as presented in equations (4), (5) and (6). To make these weighting constraints more restrictive, an adjustment factor (AF—which is a percentage) was chosen to "tighten" the range to which the ratios were permitted to take. Generically this can be expressed as follows:

$$\text{Lower Bound} * (1 + \text{AF}) < \text{Ratio} < \frac{\text{Upper Bound}}{(1 + \text{AF})} \tag{7}$$

This "tightening" of the multiplier bounds essentially reduces the amount of freedom that the DEA model weights have when attempting the maximize the efficiency of the school of interest (refer to equations [1] through [3]).[2]

MBA programs originally found to be DEA-efficient that also show DEA-efficiency when the weighting constraints were made more restrictive can be thought of as robust, or insensitive to weighting restrictions. For this research, three adjustment factors were used: 5%, 10% and 15%.

The results of the two sensitivity analyses are shown in Table 2.

Insert Table 2 About Here

The table is straightforward. The first column is the name of the school initially found to be DEA-efficient. Columns 2-5 show the results from the first sensitivity analysis while columns 6-8 show the results from the second sensitivity analysis. An "X" indicates that a school of interest remains in the efficiency set despite the applicable change.

The first sensitivity analysis shows that most schools remain robust up through a 5% unfavorable change in output and input values (Florida, Oklahoma and Texas leave the efficiency set with a 2.5% change and SJSU and Texas/Pan Am leave the set with a 5% change). A 7.5% change results in only three schools remaining in the efficiency set (Harvard, IUPUFW and McNeese St.), while only IUPUFW remains in the efficiency set when subjected to a 10% unfavorable change in terms of outputs and inputs.

The second sensitivity analysis shows that the set of DEA-efficient schools remains completely intact when subjected to a 5% tightening of the multiplier bounds. When the multiplier bounds are tightened 10%, only Texas/Pan Am leaves the efficiency set, and only Penn leaves the efficiency set when the multiplier bounds are tightened 15%.

It is appropriate to note that when a program initially found to be DEA-efficient leaves the efficiency set due to a restriction imposed by sensitivity analysis, it will not return to the efficiency set provided the restrictions continue to become more “binding.” This reasoning applies to both sensitivity analyses performed here. For example, once SJSU leaves the efficiency set when the unfavorable change is 5% (SA-1), it will not return to the efficiency set when the unfavorable change is 7.5% or 10%.

DEA Results Compared to *Business Week*

Table 3 shows the efficiency measures of the *Business Week* “Top 25 MBA Programs” in terms of input reduction and output augmentation:

Insert Table 3 About Here

From inspection of Table 2, it is clear that while there is some agreement between the *Business Week* assessments and this research, there are also some conflicting results. Of the 25 programs cited by *Business Week*, this research classifies seven of them as DEA-efficient or near-efficient. In two instances a classification or “high inputs” was made if the required output augmentation was discovered to be less than 20%. The remaining sixteen MBA programs classified as DEA-inefficient receive that classification due to the fact that they are both input-excessive and output-deficient—they need large amounts of input reduction and/or output augmentation to improve their DEA-efficiency status.

SUMMARY

This research has presented a technique known as Data Envelopment Analysis to assess the desirability of several AACSB-accredited MBA programs. An attractive feature of this tool is that it can be used to make assessments of several alternatives (in this case MBA programs) when there are several attributes to be considered (in this case salary, tuition, etc.). The technique uses concepts of Linear Programming to optimize an objective function subject to a set of rules, or constraints. For this research, the objective function optimized was the efficiency score for each MBA program, and the constraints were various restrictions on the virtual inputs and outputs in addition to weighting restrictions. The DEA model finds a solution that maximizes the efficiency for each school subject to all relevant constraints, essentially showing each school in its best possible light while subjected to the constraints.

Specifically, 188 programs were evaluated and thirteen were found to be DEA-efficient, while five others were found to be near-efficient. Of these seventeen schools generally found to be most desirable, some are perhaps not surprising (i.e., Harvard, MIT), while others are perhaps surprising (i.e., McNeese State, Texas/Pan-American). Regardless of the reputations possessed by these eighteen schools, they share a common characteristic with regard to this research—the benefits reaped from attending and graduating from these programs generally justify the sacrifices necessary to attend them. The results also show some similarities and differences with an assessment of programs made by *Business Week*. Sensitivity analyses were also performed examining the robustness of the schools found to be DEA-efficient. The first analysis shows that most schools in the original DEA-efficiency set remain insensitive to unfavorable changes in outputs and inputs through a 5% level of change. Very few schools in the original efficiency set are robust to unfavorable changes beyond 5%. The second sensitivity analysis shows that most all schools remain insensitive to the “tightening” of the weighting restrictions through 15%.

CONCLUSIONS

When considering this analysis as a whole, one must also give consideration to the variables selected as outputs and inputs. When salary, rate of rejection and average

GMAT scores were selected as outputs and average tuition and average class size were selected as inputs, they were selected in an attempt to show the most important attributes pertinent to the problem at hand. Other possible inputs and outputs were not considered for this study. Consider, for example, part-time MBA programs. Here, students are presumably working full-time which means it will probably take them longer to complete the program. In this instance, these part-time students incur an opportunity cost of lost benefits due to their being in the program longer than their full-time counterparts. At the same time, however, these part-time students (many of whom *are* presumably working full time) are earning income while simultaneously working on their MBA, which could be considered as an alleviating measure to some of this opportunity cost.

Another issue to consider is that of financial aid. The information sources used for this research typically report a statistic of the percentage of students receiving financial aid, but do not report an average amount of financial aid received per student—which for this study, is considered more informative. Because of this, the financial aid issue is not incorporated as a variable here and the basic assumption made pertaining to tuition is that whatever financial aid is awarded by the schools is proportional to their tuition level.

One of the primary motivations for performing this research was to provide some objective treatment of assessing MBA programs since this topic typically receives only subjective treatment. This subjective treatment has typically involved surveying students and alumni, in addition to employers of the program's graduates. Here, the exploration of the desirable programs is made via a mathematical model, where selection of attributes (and their weighting) is the only subjective component. In addition to the somewhat objective nature of this analysis, one of its advantages is that not only can DEA inform the decision-makers of the most DEA-efficient MBA programs, but it can also inform them of the ones that are not efficient and the necessary measures to make them efficient. This information could be useful to prospective students who are considering MBA programs, in addition to faculty and administrators of MBA programs exploring means of self-study and improvement.

While this technique has value in its objective approach to assessment of MBA programs, it should not be viewed as a vehicle that always results in an optimum decision—finding the "best" school. Information needed to find the "best" school comes from many sources, some of which are not quantitative. Rather than using DEA as an unconditional tool to determine the very best schools, it should be thought of as a device to assist in finding schools which are generally favorable due to the fact that the benefits associated with these schools justify the sacrifices necessary to attend them.

Endnotes

1. The tuition figure used is tuition and fees for a single academic year, based upon 24 semester hours or 36 quarter hours.
2. It is appropriate to note that "widening" of the multiplier bounds was also performed and the set of DEA-efficient programs remained intact, which shouldn't be surprising considering that "narrower," more restrictive multiplier bounds resulted in the same DEA-efficiency set.

References

Ali, I. (1995). ***IDEAS v.5.1***, Amherst, MA: 1 Consulting.

Banker, R.D., Charnes, A. and Cooper, W.W. (1984). "Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis," **Management Science**, 30(9), 1078-1092.

Byrne, J., Leonhardt, D., Bongiorno, L.and Jesperson, F. (1996, October 21). "The Top Business Schools," **Business Week**, 110-122.

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

Charnes, A., Cooper, W.W., Lewin, A. and Seiford, L. (1994). ***Data Envelopment Analysis: Theory, Methodology and Applications***. Boston, MA: Kluwer Academic Publishers.

Doyle, J.R. and Green, R.H. (1991). "Comparing Products Using Data Envelopment Analysis," **Omega**. 19(6), 631-638.

Gilbert, N. (1997). ***The Princeton Review: The Best MBA Programs.*** New York, NY: Random House.

Peterson's Guide to MBA Programs. (1997). Princeton, NJ: Peterson's.

Thompson, R.G., Langemeier, L.N., Lee, C. Lee, E. and Thrall, R.M. (1990). "The Role of Multiplier Bounds in Efficiency Analysis with Application to Kansas Farming," **Journal of Econometrics**, 46, 93-108.

Thompson, R.G., Dharmapala, P.S. and Thrall, R.M. (1994). "Sensitivity Analysis of Efficiency Measures with Applications in Kansas Farming and Illinois Coal Mining." ***Data Envelopment Analysis: Theory, Methodology and Applications.*** Boston, MA: Kluwer Academic Publishers, 393-422.

Thrall, R.M. (1996). "Duality, Classification and Slacks in DEA." **Annals of Operations Research**. 66, 109-137.

Schatz, M. (1997). ***The MBA Database***, Unicorn Research Corporation.

Solorzano, L. (1996), ***Barron's Best Buys in College Education***, Fourth Edition.

Wong, Y.B. and Beasley, J.E. (1990). "Restricting Weight Flexibility in Data Envelopment Analysis," **Journal of the Operational Research Society**, 41(9), 829-835.

Table 1
Near Efficient MBA Programs

School	Input Reduction	Output Augmentation
Lamar University	3.31%	1.38%
Northern Illinois University	17.68%	9.21%
Stanford University	15.79%	4.89%
University of California at Irvine	13.43%	7.73%
University of Massachusetts at Lowell	16.09%	8.62%

Table 2
Results of Sensitivity Analyses

DEA Efficient School	2.5% (SA-1)	5.0% (SA-1)	7.5% (SA-1)	10.0% (SA-1)	5% (SA-2)	10% (SA-2)	15% (SA-2)
Nebraska	X	X			X	X	X
IUPUFW	X	X	X	X	X	X	X
Texas/Pan Am	X				X		
McNeese St	X	X	X		X	X	X
SJSU	X				X	X	X
Oklahoma					X	X	X
Texas					X	X	X
Florida					X	X	X
Harvard	X	X	X		X	X	X
MIT	X	X			X	X	X
UC/Berkeley	X	X			X	X	X
Penn	X	X			X	X	
Chicago	X	X			X	X	X

Table 3
***Business Week* "Top 25 MBA Programs"—DEA Results**

Rank	School	Input Reduction	Output Augmentation	Comment
1	Pennsylvania	N/A	N/A	DEA Efficient
2	Michigan	54.4%	36.12%	DEA-Inefficient
3	Northwestern	46.24%	19.43%	High Inputs
4	Harvard	N/A	N/A	DEA Efficient
5	Virginia	46.01%	25.97%	DEA-Inefficient
6	Columbia	60.21%	32.93%	DEA-Inefficient
7	Stanford	15.79%	4.89%	Near Efficient
8	Chicago	N/A	N/A	DEA Efficient
9	MIT	N/A	N/A	DEA Efficient
10	Dartmouth	51.73%	20.72%	DEA-Inefficient
11	Duke	58.06%	32.89%	DEA-Inefficient
12	UCLA	33.58%	17.16%	High Inputs
13	California	N/A	N/A	DEA Efficient
14	NYU	55.34%	32.99%	DEA-Inefficient
15	Indiana	35.05%	26.09%	DEA-Inefficient
16	Washington Univ.	73.59%	71.89%	DEA-Inefficient
17	Carnegie-Mellon	64.01%	45.46%	DEA-Inefficient
18	Cornell	57.93%	40.91%	DEA-Inefficient
19	North Carolina	52.75%	24.05%	DEA-Inefficient
20	Texas	N/A	N/A	DEA Efficient
21	Rochester	61.33%	51.11%	DEA-Inefficient
22	Yale	58.03%	33.36%	DEA-Inefficient
23	SMU	75.36%	73.31%	DEA-Inefficient
24	Vanderbilt	62.62%	54.79%	DEA-Inefficient
25	American (Thunderbird)	76.19%	88.22%	DEA-Inefficient

Figure 1
Efficiency Frontier with Near-Efficient Programs