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Competitiveness among Higher Education Institutions: A Two-Stage Cobb-Douglas Model for Efficiency Measurement of Schools of Business

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Abstract

In this paper, we present a methodology for evaluating competing organizations in order to identify best practices among those organizations. We focus attention specifically on competitiveness in the context of a set of business schools for the purpose of identifying those that appear to be most efficient relative to their peers. One of the most widely recognized efficiency measurement methodologies is data envelopment analysis (DEA). DEA literature has witnessed the expansion of the original concept to encompass a wide range of theoretical and applied research areas, with one such area being network DEA, with two-stage DEA in particular. This latter concept and its extensions to multi-stage situations have been particularly influential in such settings as supply chain management. In the conventional two-stage serial model, it is assumed that in each stage efficiency will be defined by the standard ratio of weighted outputs to inputs or inputs to outputs. This depends on whether an input or output orientation is chosen. In terms of the model used, we develop a two-stage approach where at each stage we define efficiency in terms of a Cobb-Douglas function. This serves two important purposes. First, the data in this particular setting appears in the form of percentages or ratings. Therefore, a geometric mean which the Cobb-Douglas function is based on might be deemed as more appropriate than the arithmetic mean concept at the center of the conventional model. Second, unlike some of the previous models that define the aggregate efficiency of the process as the simple product of the scores for the two stages, the Cobb-Douglas structure permits one to define aggregate efficiency as a weighted product of those scores. This permits one to place greater emphasis on one stage versus the other. This allows for a sensitivity analysis on the effect of the "stage weights" on the aggregate score and on the individual scores that make up that aggregate.

Keywords: Data envelopment analysis, competitiveness, Cobb-Douglas, percentage data

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In this paper, we present a methodology for evaluating competing organizations and for identifying best practices among those organizations. While competitiveness is in evidence virtually everywhere, nowhere is it more prevalent than among higher education institutions. Universities and departments within those universities compete annually for the best and brightest students. They must continually re-examine their business models to identify new trends and the ever-changing needs of the incoming student population. Herein, we focus attention specifically on competiveness and what we consider to be the natural extension of competitiveness, namely relative performance measurement and benchmarking. Specifically, we examine these in the context of a set of business schools for the purpose of identifying those schools that appear to be most efficient relative to their peers. At the same time, we identify shortfalls in performance of those institutions that are not performing up to the standard set by the benchmarks. We view efficiency relative to a set of input and output factors.

The terms competitiveness analysis and relative benchmarking are often confused. Competitiveness studies often set out to examine how firms compare with their direct competitors along a set of prescribed dimensions. This leads to ranking those firms' positions relative to their competitors. Competiveness is a subject that is often the focus of studies in business strategy. Organizations are interested in distinguishing themselves from their competition by establishing a reputation as leaders on cost, quality, service, or other dimensions. Thus, many studies of competitiveness look at specific factors or strategies adopted by organizations, with the aim being to examine how or if performance improvement results from the application of such factors or strategies. For example, Kingsley and Malecki (2004) examine the effect of networking among small manufacturers as a policy innovation to promote competitiveness. Their study specifically focuses on networking within 50 small manufacturing firms.

A number of methodologies have been developed for assessing the "health" of an organization relative to its competitors. At least two traditional methodologies, the European Foundation for Quality Management (EFQM) and the Balanced Score Card (BSC) models, have been developed for determining whether an organization meets certain standards (Lamotte & Carter, 2000). Both of these methodologies involve creating a set of standards or targets along various criteria. Once this is done, the firms in question are viewed from the perspective of those standards and what has to be done to meet those standards.

Relative benchmarking and performance measurement, on the other hand, generally refer to identifying those "competitors" that are achieving *best practice.* This would be done by comparing performance among a specific set or *peer group* of organizations. Models that identify best practice comparators can provide an understanding of the processes and skills that create superior performance (Wireman, 2004).

On the other hand, EFQM and BSC models aim more at absolute rather than relative standards. While these tools are very useful in certain settings, it is important to understand that one must be able to establish the levels of various strategic indicators or targets. The organization under study has to achieve these targets in order for it to realize its *long term vision* (Podobnik & Dolinsek, 2008). While competitive analyses have helped companies understand their respective market positions, relative benchmarking can then take over where this opportunity for improvement reaches its limit. By observing the best practices within their relevant peer group, relative benchmarking enables companies to move from a parity business position to a superiority position (Wireman, 2004).

One of the most widely recognized relative efficiency measurement and benchmarking methodologies is data envelopment analysis (DEA). Developed by Charnes, Cooper, and Rhodes (1978) (denoted as CCR), DEA is a model for evaluating the relative efficiencies of a set of comparable and often competing decision-making units (DMUs). In the sections to follow, we develop a modified version of the conventional DEA model. This is then used to analyze a set of business schools.

In the sections to follow, we present a methodology for evaluating the performance of business schools. First, we review the relevant literature on DEA, literature relating to the efficiency evaluation in education, and some of the pertinent literature on competitiveness. Second, the section following this describes an application of the modified DEA model, where the DMUs are business schools. Third, we develop a DEA-based methodology based on the Cobb-Douglas function as presented by the units-invariant multiplicative model of Charnes, Cooper, Seiford, and Stutz (1983). This structure readily lends itself to viewing performance from the perspective of a multiplicative combination of outputs and inputs, rather than an additive one. The resulting DEA frontier becomes piecewise Cobb-Douglas. Fourth and finally, the developed model is applied to a set of data on undergraduate business programs. This is followed by concluding remarks.

Literature Review

In this paper, we focus on a study of competitiveness, benchmarking, and efficiency in higher education. This is viewed from the perspective of a two-stage DEA model. We begin by giving a brief review of some of the pertinent literature in these areas:

Competitiveness

Competitiveness and performance development have been subjects of study for decades. Competiveness is a common concern for many countries, regions within countries, and companies and organizations worldwide. In the book *Competitive Advantage of Nations,* Porter (1998) provided a new point of view based on a competitive strategy framework. He advocates providing the right competitive environment to foster success in performance. In contrast to this, other studies have promoted having adequate market development and institutions. Some of this work provides examples of companies successfully competing in international markets despite having been created in unfavorable environments.

Some of the competitiveness studies have looked at particular tactics such as coaching as a tool for developing personnel in order to enhance the organization's performance (Vidal-Salazar, Ferrón-Vílchez, & Cordón-Pozo, 2012). Kingsley and Malecki (2004) examine networking as a tool for performance enhancement. The articles by Lubitz and Wickramasinghe (2006), Moingeon and Edmondson (1996), Spender (1996), and Wongrassamee, Gardiner, and Simmons (2003) provide further examples. As discussed above, a number of tools have emerged to aid management in undertaking performance improvement. EFQM and BSC methodologies are discussed in several publications including Elliott (1992), Kaplan and Norton (1996), Lascelles and Peacock (1996), Podobnik and Dolinsek (2008).

Regarding competitiveness specifically in education, the literature focuses mainly on the role higher education has played in promoting economic competitiveness. Sum and Jessop (2013) provide a good example of this is their work. The subject of comparative competitiveness addressed in our current paper has not been addressed previously in the same sense.

Data Envelopment Analysis

An important tool for identifying best practice in both competitive and noncompetitive settings is DEA. Arguably, this tool might be seen as a natural extension or augmentation of the EFQM and BSC methodologies. The concept of efficiency is generally linked to the work of Farrell (1957). Twenty years after Farrell's seminal work and building on his ideas, Charnes et al. (1978) (CCR), responding to the need for satisfactory procedures to assess the relative efficiencies of multi-input multi-output production units, introduced this powerful methodology. The original idea behind DEA was to provide a methodology whereby, within a set of comparable *decision-making units* (DMUs), those DMUs exhibiting best practice could be identified and would form an efficient frontier. Furthermore, the methodology enables one to measure the level of inefficiency of nonfrontier units and to identify benchmarks against which such inefficient units can be compared. Given the application presented herein, it is important to note that the very first application of DEA was in the education sector (Charnes, Cooper, & Rhodes, 1981).

It is relevant to point out here that most applications of DEA are in what could be regarded as noncompetitive settings. For example, the branches of a given bank are not in direct competition with each other, strictly speaking. However, efficiency analyses in the branches yield important insights about which of the branches are the benchmarks against which other inefficient branches are compared. The same would be true for a set of comparable hospitals. In the example of business schools discussed below, we argue that the peer units *are* in direct competition.

The CCR model portrays the efficiency of a DMU as a ratio of weighted outputs to weighted inputs, a benefit/cost ratio. This strict segregation of factors or indicators into these two distinct categories is perhaps one of the characteristics that distinguish DEA from tools like the BSC methodology. Unlike BSC, DEA attempts to explain outcomes, outputs, not in absolute terms but rather relative to the resources or circumstances, inputs, which the DMU has at its disposal. The original DEA model, based on a constant returns to scale (CRS) situation, was later extended to allow for variable returns to scale (VRS) (Banker, Charnes, & Cooper, 1984). Both of these radial models see efficiency from the perspective of projection to the frontier by way of either input reduction, an input-oriented model, or output expansion, an output-oriented model. In Charnes, Cooper, Golany, Seiford, & Stutz (1985) these ideas were extended to allow for projections in terms of both input reduction and output expansion, simultaneously. This "additive" model was later adapted to provide for an efficiency score along the lines of the earlier radial measures (Tone, 2001).

Many extensions of these models have been advanced over the years since the appearance of Charnes et al.'s (1978) article, including the Cobb-Douglas model of Charnes et al. (1983). The methodology presented in the current paper is a variant of this work. One of the major directions taken in extending the early work of Charnes et al. (1978) involves settings with multi-stage structures. Färe, Grosskopf, Norris, and Zhang (1994) and Färe and Grosskopf (2000) investigated such structures under the heading "network DEA." This work is very relevant to the application herein which views the education process as consisting of two stages. Much research has been carried out in the interim (Chen, Cook, Kao, & Zhu, 2013; Chen, Cook, Li, & Zhu, 2009; Chen, Cook, & Zhu, 2010; Cook, Liang, & Zhu, 2010; Cook, Zhu, Bi, & Yang, 2010; Cook, Zhu, & Liang, 2011; Kao & Hung, 2008; Liang, Chen, Cook, Du, & Zhu, 2011; Liang, Cook, & Zhu, 2008; Liang, Yang, Cook, & Zhu, 2006). Cook and Liang et al. (2010) provide a comprehensive survey of network DEA.

A number of books and edited journal volumes have been published on DEA theory and its applications. Authors like Cook and Zhu (2005); Cook, Green, and Zhu (2006); Cooper, Seiford, and Tone (2006) have all published texts on DEA theory.

Efficiency Measurement in Education

Within the broad scope of education, frontier efficiency measurement techniques have been applied to many different types of institutions. The articles by Bessent, Bessent, Kennington, and Reagan (1982); Chalos and Cherian (1995); Deller and Rudnicki (1993) apply these measurement techniques to include primary and secondary schools. The article by Athanassopoulos and Shale (1997) applies these techniques to a university. Finally, articles by Beasley (1995), Beasley (1990), Chang, Chung, and Hsu (2012), G. Johnes (1988), G. Johnes (1990), G. Johnes and Johnes (1993), J. Johnes and Johnes (1995), J. Johnes and Yu (2008), Kao and Hung (2008), Madden, Savage, and Kemp (1997), Sinuany-Stern, Mehrez, and Barboy (1994), and Tomkins and Green (1988) apply the measurement techniques to university departments. As is clear from the literature, the DEA approach is the primary frontier technique employed in evaluating the efficiency of education programs (Chalos, 1997; Chang et al., 2012; Charnes et al., 1981; Diamond & Medewitz, 1990; McCarty & Yaisawarng, 1993; Ray, 1991).

Bessent et al. (1982) conducted what is perhaps the best-known and earliest work in the area of education. Employing the well-known Charnes et al. (1978) constant returns-to-scale DEA model, Bessent et al. (1982) examined the productive efficiency of Houston's 241 school districts. The study by Bessent et al. (1982) was one of the first to point out some of the advantages of DEA over techniques used before. These advantages include the incorporation of multiple outputs, the fact that a parametric functional form does not have to be specified for the production function, and the ability to identify reasons why individual schools are inefficient. In addition, Bessent et al. (1982) were the first to use standardized test scores as the measure of educational success; to incorporate issues relating to local, state, and federal funding; and to indicate the quality of teaching inputs with teaching experience, training, and qualifications.

As university administrators seek to improve resource usage, efficiency analysis has become an important concern in managing performance (Avkiran, 1999; Caballero, Galache, Gomez, Molina, & Torrico, 2004; Caroline, Castano, & Cabanda, 2007; Chalos, 1997; Cohn, Rhine, & Santos, 1989; Fandel, 2007; Glass, McKillop, & Hyndman, 1995). Most studies focus on how to allocate educational resource inputs more efficiently to improve output performance. The input indicators are generally units of measurement that represent the factors employed in service delivery. Generally, these inputs include human, financial, and material resources (Martin, 2006). Previous studies often evaluated the performance for the departments of educational institutions using several inputs that include: number of teachers, operating expenses, equipment, and usable floor space. Output indicators measure the yield or activity level of programs and services (Martin, 2006). Based on previous studies, the output indicators of educational departments generally contain research and development (R&D) outputs and teaching outputs (Kao & Hung, 2008; Tyagi, Yadav, & Singh, 2009). R&D outputs include project income as well as the numbers of publications, projects, patents, and awards given to teachers. Teaching outputs used in previous studies have included the numbers of graduates, teaching evaluations, graduate salaries, and employer satisfaction.

In most studies, inputs usually include the number of teaching staff and are sometimes also accompanied by the number of support and administrative staff. In the context of university education, G. Johnes and Johnes, (1993) and J. Johnes and Johnes, (1995) also made a distinction between different types of labor. They also split total the staff into teaching/research staff and research-only staff. These are obvious attempts to capture the differing functions of labor in the educational process. Even within categories of labor, most empirical studies have attempted to incorporate differences in the quality of inputs that may occur across the sample, omission of which would result in misspecification.

Another set of frontier efficiency measurement studies that deserves particular attention is the instances where educational outputs are jointly produced with strictly noneducational outcomes. This is the case with the small number of studies concerned with either universities or academic departments within universities. G. Johnes and Johnes' (1993) and J. Johnes and Johnes' (1995) studies of UK university departments of economics and J. Beasley's (1995) study of UK departments of physics and chemistry are good examples of this line of inquiry. In all three cases, research grants awarded to teaching/research and research-only staff members are the inputs; published works and refereed journal articles are the measured outputs. The G. Johnes and Johnes' (1993) and J. Johnes and Johnes' (1995) approach does differ somewhat in that no allowance is given for actual teaching outputs. Beasley's (1995) study incorporates the number of undergraduates and postgraduates. While the DEA approach used in these studies places no particular weighting on outputs, like the "managerial" choice between teaching and/or research performance, the general finding of these studies is that university departments with higher teaching loads have lower research outcomes. A study by Madden et al. (1997) also examined the efficiency of university departments of economics but no attempt was made to distinguish between teaching/research and research-only staff.

These studies vary enormously in their chosen contexts and overall results. On the other hand, there is broad agreement regarding their conceptualization of the educational process itself. There is also a similarity in the process by which the education process transforms selected inputs into desired outputs.

In a number of respects, the problem setting discussed herein differs from those examined in the literature. First and foremost, this is not a study that focuses strictly on resource usage, like on how all the staff members are utilized, as is the case with the vast majority of previous enquiries. Rather, this is a study focused on students and on the institution's ability to attract and serve students in terms of helping them meet their ultimate goals. The second difference is in the analysis model. In nearly all previous studies, the approach involved conventional applications of the standard CCR model of DEA (Charnes et al., 1978). Here, we instead argue that the process of attracting students, meeting their needs while enrolled, and then viewing the results following graduation is best modeled as a two-stage process. We do point out that one other study done by Chang et al. (2012) viewed efficiency evaluation in a similar way, albeit from a perspective focused on resource-allocation.

Undergraduate Business Programs Viewed as Two-Stage Serial Processes

Each year, business schools around the world compete to attract the best and brightest students. The rapid growth in what universities and colleges can offer students creates tremendous competition between those institutions. Therefore, institutions within the higher education market need to adopt or increase their interests in those features, characteristics, and competitive differentiators used to attract the best applicants.

In a recent study, a set of 41 undergraduate business programs was surveyed to gain an understanding of best practices in terms of admissions criteria and various outcome factors (Avilés-Sacoto, 2012). This study was the backdrop for an MSc thesis at Instituto Tecnológico y de Estudios Superiores Monterrey, Mexico (ITESM). Forty of the business schools are in the USA, while the 41st is the business school Escuela de Negocios, Ciencias Sociales y Humanidades (ENCSH) at ITESM. In the current study, we reduced the scope of the study to 37 schools because the data is incomplete on the remaining four.

Various researchers undertook many previous studies in this area, and there is much debate about what factors are most relevant for the purpose of evaluating efficiency. We have attempted to choose factors that define the quality of the students, which influences the quality of the institution as well. We also focused on factors that reflect the achievements of the students as a result of being at that institution. With this in mind, the following discussion is about the evaluation factors used. We point out that the data for the US schools was taken from the 2011 edition of *Best 373 Colleges* by Franek et al. (2010). The only other institution included in the sample is ENCSH in Mexico, for which the data comes from an internal survey.

Top 25%: This factor is defined as the percentage of students applying to a school who were in the top quartile of their high school classes. Franek et al. (2010), in the *Best 373 Colleges*, points to this factor as an important indicator of how much universities focus their recruitment efforts on academically orientated students. Rinn & Plucker (2004) stated:

> *Conventional wisdom appears to be that, although the intellectual progress of all college students is important, the attitudes and accomplishments of the most talented students help to improve an institution's academic atmosphere and differentiate a university from its peer institutions.* (p. 26)

Reject: Percentage of applicants rejected and are not sent offers of admission. Franek et al. (2010) explain that this rating or its complement, the Admissions rating, is a reflection of a number of factors including test scores and class rank of entering freshmen. As Franek et al. (2010) put it, evidence shows that, "…one of the leading determinants of a good university is the quality of its incoming students" (p. 54). Gansemer-Topf and Schuh (2006) point out that selectivity scores provide information on the general academic qualities needed for admittance. Evidence shows that schools that are more selective through rejecting more applicants may have higher retention and graduation rates.

AcRat: Academic rating of the school. This rating is a measure of how hard students work at the school and how much they get in return for their efforts. Franek et al. (2010) include this rating for putting institutions into the Best Colleges ranking. Academic rating or reputation has been labelled variously as prestige or quality. This value is derived from interconnected factors that lead to competitive advantage and, ultimately, performance superiority (Boyd, Bergh, & Ketchen, 2010).

Enroll: Percentage of invited students who enrolled after being sent acceptance letters. This rating reflects of the quality of the institution because students want to be there. It also reflects well on the capability of the admissions office to close deals.

Scholar: Percentage of students who have earned or hold scholarships. On the one hand, Franek et al. (2010) sees this as being on par with factors that put institutions into the Top 25%. This is because it is a clear reflection of the quality of incoming students.

Intern: Percentage of enrolled students who obtained overseas internships while in the program. Higher education institutions have implemented various initiatives to promote the skills, knowledge, and intercultural understanding for creating international agreements. Doyle et al. (2010) see international internships as making students more competitive, giving them the opportunity to develop a wider perspective on the world, and often allowing them to develop foreign language skills. In addition, internships give students a wider set of skills to allow them to compete in the job market. In this sense, the employment prospects for students can only be enhanced by internships.

Jobs: Percentage of students who obtained employment in their chosen fields within six months of graduation. Boyd et al. (2010) argue that prospective students will seek to be admitted to the most prominent programs in order to maximize future income. In short, Alumni are satisfied with their educations when they are prepared for employment and when the costs of their educations give them greater returns on their investments (Delaney, 2008; Lauer, 2002).

The relationships among these variables are complex, and it is not at all obvious what an appropriate production function might look like in this context. Viewing this setting as one to which a relative efficiency model could be applied, clearly a conventional DEA model might be appropriate. This can be done if one accepts the argument that university and student quality measures like Top 25%, Reject, and Acrat impact outcomes such as Enrol, Scholar, Intern, and Jobs. In other words, one can look at this from the perspective of cause and effect. However, one can clearly make the case as well, as backed up by Franek et al. (2010) and others, that the final goal of most graduates is Jobs. Thus, performance in the program such as being enrolled in the program, scholarships earned, and internships served have an important influence on success in the job market. This would seem to speak to the argument that a more appropriate model structure is one that views the student experience as consisting of two stages: namely accomplishments while in the program such as getting enrolled, receiving internships, and earning scholarships, and the earned accomplishment at the end of the program which is success in the job market.

Given this argument, we therefore take the position that efficiency can be modeled as a two stage process, as displayed schematically in Figure 1:

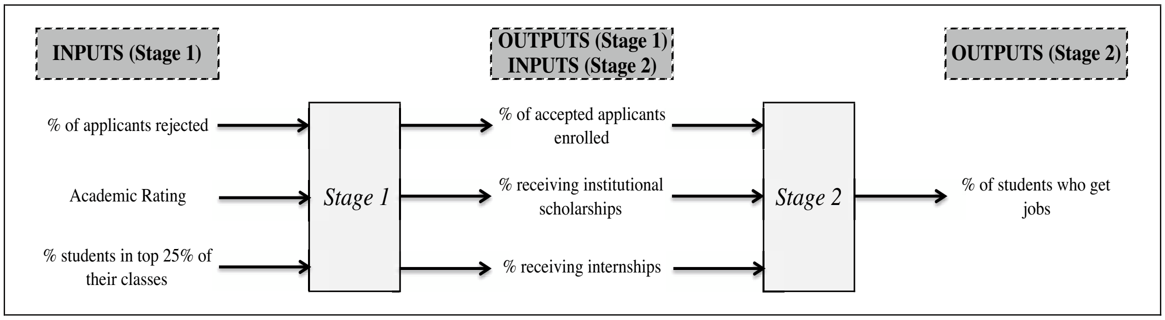

Figure 1. Two-stage serial process.

Stage 1 can be looked upon as the process of attracting applicants to programs and realizing the resulting outcomes once applicants are enrolled. The inputs to this stage are intended to reflect the combined quality of the institution and the students who apply there. The factors Reject and AcRat are measures of institutional reputation and quality. Top 25% is an indication of the quality of students applying. Outputs here are taken as those factors that reflect the combined accomplishments of the institution and the enrolled students. Specifically, Enroll measures the success of the institution in converting applicants to enrolled students. Scholar and Intern are important indicators of both institutional and student achievements while the student is in the program.

Stage 2 captures the accomplishments of students and institutions following graduation. The inputs to this stage are the outputs from Stage 1. From the students' perspective, Jobs are the major output from this stage.

In the following section, we investigate the modeling of efficiency for the two-stage processes as presented in Figure 1. We first examine the conventional serial process where the efficiency measures for each stage are represented by the Charnes et al. (1978) radial projection model. This utilizes the added combinations of outputs and inputs. This is followed by a multiplicative methodology following the Cobb-Douglas method. This method directly extends the conventional version in permitting the imposition of weights on the stage-specific measures.

Modeling Efficiency in Two-Stage Processes

The Conventional Two-Stage Serial Process

One area of DEA research is network DEA, particularly two-stage DEA. This latter research area, including its extensions to multi-stage situations, has been particularly influential in such settings as supply chain management (Liang et al., 2006). Cook and Liang et al. (2010) provide a survey of network models.

One of the common two-stage structures investigated in the literature on DEA is the serial process wherein the outputs from the first stage become the inputs to the second stage. Some variants of this permit outputs from Stage 1 to leave the system and inputs to the second stage to enter the system at that point; other two stage systems are *closed* in that nothing enters or leaves the system between the stages. It is this latter closed system where nothing enters or leaves that is analyzed in this study. The usual objective, if one regards the two stage process as the DMU, is to view that process as one where inputs enter the DMU at Stage 1 and outputs exit from Stage 2. Various methods have been suggested for evaluating the sub-efficiencies of each of the two stages and for then combining these to get the overall DMU efficiency. The importance to the organization of having a measure of overall efficiency, as well as sub-efficiencies, is to allow it to detect where it is and is not competitive.

In the conventional two-stage serial model, it is assumed that in each stage efficiency will be defined by the standard CCR ratio of weighted outputs to weighted inputs or weighted inputs to weighted outputs, depending on whether an input or output orientation is chosen. In the current paper, the DEA efficiency measurement relating to performance is applied to a set of 37 undergraduate business programs. In terms of the model used, we develop a two-stage approach where at each stage we define efficiency in terms of a Cobb-Douglas function. This serves two important purposes. First, the data in this particular setting appear in the form of percentages or ratings. Therefore, a geometric mean, on which the Cobb-Douglas function is based, might be deemed as more appropriate than the arithmetic mean concept at the center of the CCR model. Second, the model of Kao and Hwang (2008) defines the aggregate efficiency of the process as the simple product of the scores for the two stages. In contrast, the Cobb-Douglas structure permits one to define aggregate efficiency as a *weighted* product of those scores. This permits one to place greater or lesser emphasis on one stage versus the other. This allows for a sensitivity analysis on the effect of the "stage weights" on the aggregate score and on the individual scores that make up that aggregate.

As background for the development of our model for the process pictured in Figure 1, we briefly review the methodology for one of the most common structures for two-stage serial processes. For simplicity of presentation, ignoring the application-specific variables for the moment, we assume there are $n(j=1,\ldots,n)$ DMUs to be evaluated. For DMU *j,* let $\{x_{ij}\}_{i=1}^{I}$ denote the inputs to Stage 1, $\{y_{rj}\}_{r=1}^{R}$ the outputs from Stage 2, and $\{z_{dj}\}_{d=1}^{D}$ the intermediate variables that serve simultaneously as outputs from the first stage and inputs to the second stage. Their corresponding multipliers are denoted by ν_i, u_r, η_d, respectively.

To evaluate the overall efficiency of business schools, we use an input-oriented model. Furthermore, we decided to use the VRS model of Banker et al. (1984), (denoted as BCC) as opposed to the original Charnes et al. (1978) CRS model. This is because the data appears in the form of ratios and percentages. It is important to point out that in the case of an output-oriented rather than an input-oriented model, the VRS methodology ensures that projections to the frontier do not exceed values of the variables experienced by the frontier units; specifically, percentages and ratings will not exceed 100% under VRS. This is not guaranteed under CRS.

In this setting, one can represent the input-oriented VRS efficiency for Stage 1 as the solution to the radial projection model:

$$\hat{e}_o^1 = \max\left[\sum_d \eta_d z_{do} - u^1\right] / \sum_i \nu_i x_{io},$$

Subject to:

$$\left[\sum_d \eta_d z_{dj} - u^1\right] / \sum_i \nu_i x_{ij} \le 1, \quad \forall j; \tag{1}$$

ν_j, $\eta_d \geq 0$, u^1 unrestricted in sign.

The stage 2 model is given by:

$$\hat{e}_o^2 = \max\left[\sum_r u_r y_{ro} - u^2\right] / \sum_d \eta_d z_{do},$$

Subject to:

$$\left[\sum_r u_r y_{rj} - u^2\right] / \sum_d \eta_d z_{dj} \le 1, \quad \forall j; \tag{2}$$

u_j, $\eta_d \geq 0$, u^2 unrestricted in sign.

We note that in the conventional CCR and BCC models, multiple inputs and multiple outputs are replaced by a single virtual input and output, respectively. This is through using additive or arithmetic combinations of the variables.

The literature suggests a number of approaches for deriving an overall score for the two stages combined and from these deriving scores for the individual stages. Two of the methodologies are those based on game theoretic principles, namely the cooperative and noncooperative game models (Cook & Liang et al., 2010). The noncooperative or noncentralized approach views the two stages as players in a game and adopts a leader-follower methodology. The cooperative game or centralized methodology, the approach adopted in this study, derives the best aggregate efficiency score for the two stages combined. Then, one sets out to derive scores for the two stages separately, which are such that when put together yield the overall score.

One of the original models for the two stage process was put forward by Kao and Hwang (2008) and is a form of the cooperative or centralized approach. In their model, the overall efficiency is calculated using $e_o = e_o^1 \cdot e_o^2$. Specifically, their model, designed for CRS settings only, is given by:

$$\hat{e}_o = \max\left[\sum_d \eta_d z_{do} / \sum_i \nu_i x_{io}\right] x \left[\sum_r u_r y_{ro} / \sum_d \eta_d z_{do}\right] = \sum_r u_r y_{ro} / \sum_i \nu_i x_{io},$$

Subject to:

$$\sum_d \eta_d z_{dj} / \sum_i \nu_i x_{ij} / \leq 1, \quad \forall j; \tag{3}$$

$$\sum_r u_r y_{rj} / \sum_d \eta_d z_{dj} / \leq 1, \quad \forall j;$$

$$\nu_j, \eta_d, u_r \geq 0.$$

It is noted that the two sets of constraints in Equation 3 are required to ensure that any multipliers chosen are feasible for each stage of the process. Specifically, the two ratios for each DMU are restricted to be at or below unity. We further note that normally one would impose the additional set of constraints:

$$\sum_r u_r y_{rj} / \sum_i v_i x_{ij} \leq 1, \quad \forall j.$$

However, these are redundant in the presence of the other restrictions.

To accommodate VRS settings, as is needed in the application addressed herein, Chen et al. (2009) proposed an additive approach for combining the two stages, as opposed to the multiplicative formulation suggested by Kao and Hwang (2008). Under the Chen et al. (2009) approach, the objective function of Equation 3 for the VRS setting, is replaced by:

$$\hat{e}_o = \max \left\{ w_1 \cdot \left[\left[\sum_d \eta_d z_{do} - u^1 \right] / \sum_i \nu_i x_{io} \right] + w_2 \cdot \left[\left[\sum_r u_r y_{ro} - u^2 \right] / \sum_d \eta_d z_{do} \right] \right\}. \tag{4}$$

In this function, w_1, w_2 are weights the user can specify.

We now turn to what might be viewed as a more appropriate methodology than those above, in the case that data appear as percentages.

A Cobb-Douglas Model for Two-Stage Processes

Suppose DMU_o is under evaluation. Then, with inputs x_{ij} and outputs y_{rj}, the units-invariant multiplicative model of Charnes et al. (1983), for an input orientation, is given by:

$$e_o^* = \max \frac{e^{\xi} \prod_r y_{ro}^{\mu_r}}{e^{\delta} \prod_i x_{io}^{v_i}},$$

Subject to:

$$\frac{e^{\xi} \prod_r y_{ro}^{\mu_r}}{e^{\delta} \prod_i x_{ij}^{v_i}} \leq 1, \quad \forall j; \tag{5}$$

$$\delta, \xi \geq 0, \mu_r, v_i \geq 1.$$

In this case, multiple outputs and inputs are replaced by a single virtual output and virtual input by way of a weighted geometric rather than arithmetic aggregation as in Equation 1. We point out that the notation *e* in e^{ξ}, for example, is the natural number whose normal logarithm is unity. Now, taking the previous logarithms, Equation 5 can be transformed to the linear form:

$$\log \hat{e}_o^* = \max \xi + \sum_r \mu_r \hat{y}_{ro} - \delta - \sum_i v_i \hat{x}_{io},$$

Subject to:

$$\xi + \sum_r \mu_r \hat{y}_{rj} - \delta - \sum_i v_i \hat{x}_{ij} \leq 0, \quad \forall j; \tag{6}$$

$$\xi, \delta \geq 0, v_i, \mu_r \geq 1.$$

We point out that in Equation 5 the term $\frac{e^{\xi}\prod_r y_{rj}^{\mu_r}}{e^{\delta}\prod_k x_{ij}^{\nu_i}}$ could be replaced by $\frac{e^{\beta}\prod_r y_{rj}^{r}}{\prod_k x_{ij}^{\nu_i}}$ where $\beta$is unrestricted in sign. Hence, in Equation 6 the expression $\xi - \delta$ can be negative or positive and can therefore be replaced by β. For purposes of the development below, we retain the two nonnegative variables ξ and δ.

The notation $\hat{x}, \hat{y}$ in Equation 6 denotes the logarithm of the original data. It can be observed that in the solution of this linear programming problem, either ξ, δ, or both will equal 0, meaning that the projected point on the Cobb-Douglas frontier will experience increasing, decreasing, or constant turns to scale.

Using Equation 5 as a backdrop, we propose the following two-stage Equation 7 for describing overall efficiency of the DMU.

Comparing this formulation to the Kao & Hwang (2008) model, we note that Equation 7 provides for a more general structure, allowing for differential weights p_1, p_2 on the Stage 1 and Stage 2 efficiency ratios, respectively. It is assumed that these satisfy the condition $p_1 + p_2 = 1$.

$$e^*_{o_{agg}} = \max \left[\frac{e^{\xi}\prod_r z_{do}^{\eta_d}}{e^{\gamma}\prod_i x_{io}^{\nu_i}}\right]^{p_1} x \left[\frac{e^{\gamma}\prod_r z_{ro}^{\mu_d}}{e^{\delta}\prod_i z_{do}^{\eta_d}}\right]^{p_2},$$

Subject to:

$$\left[\frac{e^{\xi}\prod_r z_{dj}^{\eta_d}}{e^{\gamma}\prod_i x_{ij}^{\nu_i}}\right] \leq 1, \quad \forall j; \tag{7}$$

$$\left[\frac{e^{\gamma}\prod_r y_{rj}^{\mu_d}}{e^{\xi}\prod_d z_{dj}^{\eta_d}}\right] \leq 1, \quad \forall j;$$

$$\xi, \gamma, \delta \geq 0, v_i, \eta_d, \mu_r \geq 1.$$

Applying the logarithmic transformation to Equation 7, which is analogous to that used to convert Equation 5 to the linear form in Equation 6, that Equation 7 is equivalent to the linear programming problem:

$$\log \hat{e}_{o_{agg}} = \max p_1 \left[\xi + \sum_d \eta_d \hat{z}_{do} - \gamma - \sum_i v_i \hat{x}_{io}\right] + p_2 \left[\delta + \sum_r \mu_r \hat{y}_{ro} - \xi - \sum_d \eta_d \hat{z}_{do}\right],$$

Subject to:

$$\xi + \sum_d \eta_d \hat{z}_{dj} - \gamma - \sum_i v_i \hat{x}_{ij} \leq 0, \quad \forall j; \tag{8}$$

$$\delta + \sum_r \mu_r \hat{z}_{rj} - \xi - \sum_d \eta_d \hat{z}_{dj} \leq 0, \quad \forall j;$$

$$\xi, \gamma, \delta \geq 0, v_i, \eta_d, \mu_r \geq 1.$$

As mentioned earlier, the notation $\hat{x}, \hat{z}, \hat{y}$ denotes logarithms of the original data x, z, y.

Equation 8 yields a measure of log efficiency of the overall two-stage DMU. Letting $\hat{\xi}, \hat{\gamma}, \hat{\delta}, \hat{\nu}_i, \hat{\eta}_d, \hat{\mu}_r$ denote the optimal solution in Equation 8, the simplified efficiency measure is then taken from Equation 7:

$$\hat{e}_{o_{agg}} = \left[\frac{e^{\hat{\xi}}\prod_d z_{do}^{\hat{\eta}_d}}{e^{\hat{\gamma}}\prod_i x_{io}^{\hat{\nu}_i}}\right]^{p_1} x \left[\frac{e^{\hat{\delta}}\prod_r y_{ro}^{\hat{\mu}_r}}{e^{\xi}\prod_d z_{do}^{\hat{\eta}_d}}\right]^{p_2}. \tag{9}$$

Given an optimal log linear efficiency score arising out of Equation 8, which yields the Cobb-Douglas score $\hat{e}_{o\,agg}$ from Equation 9, one needs to derive efficiency scores for the individual stages such that these are consistent with this aggregate score. One approach is to adopt a leader-follower methodology similar to that discussed in Cook and Liang et al. (2010) for linear representations of two-stage systems. As a specific example, if Stage 1 is chosen as being the highest priority stage or the leader and stage 2 is chosen as the follower, Equation 10 below can be used to get an efficiency measure for that stage. In this model, we maximize the efficiency score of the first stage for DMU_o subject to the usual requirement that the corresponding first and second stage scores for every other DMU do not exceed unity constraints 10b and 10c. At the same time, any multipliers used must be such that the aggregate score is not compromising 10d.

$$\hat{e}_o^1 = \left[\frac{e^{\xi}\prod_d z_{do}^{\eta_d}}{e^{\gamma}\prod_i x_{io}^{v_i}}\right], \tag{10a}$$

Subject to:

$$\hat{e}_o^1 = \left[\frac{e^{\xi}\prod_d z_{do}^{\eta_d}}{e^{\gamma}\prod_i x_{ij}^{v_i}}\right] \leq 1, \quad \forall j; \tag{10b}$$

$$\hat{e}_o^1 = \left[\frac{e^{\delta}\prod_r y_{rj}^{\mu_r}}{e^{\gamma}\prod_k z_{dj}^{\eta_d}}\right] \leq 1, \quad \forall j; \tag{10c}$$

$$\left[\frac{e^{\xi}\prod_d z_{do}^{\eta_d}}{e^{\gamma}\prod_i x_{io}^{v_i}}\right]^{p_1} x \left[\frac{e^{\delta}\prod_r y_{ro}^{\mu_r}}{e^{\xi}\prod_d z_{do}^{\eta_d}}\right]^{p_2} = \hat{e}_{oagg}; \tag{10d}$$

$$\xi, \gamma, \delta \geq 0, v_i, \eta_d, \mu_r \geq 1. \tag{10e}$$

In linear form, Equation 10 becomes:

$$\log \hat{e}_o^1 = \max \xi + \sum_d \eta_d \hat{z}_{do} - \gamma - \sum_i v_i \hat{x}_{io},$$

Subject to:

$$\xi + \sum_d \eta_d \hat{z}_{dj} - \gamma - \sum_i v_i \hat{x}_{ij} \leq 0, \quad \forall j; \tag{11}$$

$$\delta + \sum_r \mu_r \hat{y}_{rj} - \xi - \sum_d \eta_d \hat{z}_{dj} \leq 0, \quad \forall j;$$

$$p_1\left[\xi + \sum_d \eta_d \hat{z}_{do} - \gamma - \sum_i v_i \hat{x}_{io}\right] p_2 \left[\delta + \sum_r \mu_r \hat{y}_{ro} - \xi - \sum_d \eta_d \hat{z}_{do}\right] = \log \hat{e}_{oagg};$$

$$\xi, \gamma, \delta \geq 0, v_i, \eta_d, \mu_r \geq 1.$$

Let $\tilde{\xi}, \tilde{\gamma}, \tilde{\delta}, \tilde{\nu}_i, \tilde{\eta}_d, \tilde{\mu}_r$ denote the optimal solution to Equation 11. Then, the efficiency score for the Sage 1 portion of DMU_o is given by $\hat{e}_o^1 = \left[\frac{e^{\tilde{\xi}}\prod_d z_{do}^{\tilde{\eta}_d}}{e^{\tilde{\gamma}}\prod_i x_{io}^{\tilde{\nu}_i}}\right]$. It then follows that the Stage 2 score is given by $\hat{e}_o^2 = \{\hat{e}_{o\,agg} / [\hat{e}_o^1]^{p_1}\}^{1/p_2}$. Similar derivations apply in the case that Stage 2 is chosen as the leader, with Stage 1 being the follower.

Restricted Projection to the Frontier

It is useful to look at the dual envelopment version of Equation 8, which is Equation 12. It is noted that in this conventional additive model, the sum of slacks in the envelopment problem arises from the imposition of lower bounds of unity, as opposed to zero, on the multipliers ν_i, η_d, μ_r in the primal multiplier problem in Equation 8. The result is a projection to the frontier in a direction that accounts for those dimensions for which the lower bound of unity was imposed. Clearly, if a different lower bound was imposed, like ε, the same projection would result. Furthermore, if one relaxes these lower bound constraints and executes such nonzero lower bounds on only a *subset* of the primal multipliers, projection to the frontier will only be in those directions. This represents an important feature of the model as a tool for competitive evaluation of a set of DMU in that any given DMU can decide which dimensions or factors are the ones on which it wishes to compete. Users of the model can then evaluate where it stands on those factors.

$$\begin{aligned}
&\min -\left[\sum_r s_r^1 + \sum_i s_i^2 + \sum_d s_d^3\right];\\
&\sum_j \lambda_j^1 - \sum_j \lambda_j^2 \geq p_1 - p_2;\\
&\sum_j \lambda_j^1 \hat{z}_{dj} - \sum_j \lambda_j^2 \hat{z}_{dj} - s_d^3 \geq (p_1 - p_2)\hat{z}_{do}, \quad \forall d;\\
&-\sum_j \lambda_j^1 \geq p_1;\\
&\sum_j \lambda_j^2 \geq p_2;\\
&-\sum_j \lambda_j^1 \hat{x}_{ij} - s_i^2 \geq -p_1 \hat{x}_{io}, \quad \forall i;\\
&\sum_j \lambda_j^2 \hat{y}_{rj} - s_r^1 \geq -p_2 \hat{y}_{ro}, \quad \forall r;\\
&\lambda_j^1, \lambda_j^2, s_r^1, s_i^2, s_d^3 \geq 0, \forall j, i, d, r.
\end{aligned} \tag{12}$$

In the section to follow, we apply this model to data pertaining to the performance of 37 business schools.

Efficiency Analysis of Business Schools

Table 1 provides the list of universities included in our sample. This is followed by Table 2 which displays the data on 37 business schools relative to the variables discussed in Section 2. Table 3 presents the same data as in Table 2 but in natural logarithmic form.

The first analysis of efficiency is presented in Table 4. Here, Column 2 presents the log efficiency of each of the business programs arrived at by solving the log-additive Equation 8. A reminder that the dual form of this model takes the form of the envelopment model shown as Equation 12. Hence, the log efficiency score can be viewed in terms of the sum of all input and output slacks along all dimensions. Column 3 presents the same results but as the actual efficiencies, the antilog of the values in Column 2. It is noted that in this first analysis we have set $p_1 = p_2 = 0.50$, giving equal importance to performance in each of the two stages. In this analysis, two schools, #37 and #24, are DEA efficient, showing scores of 100% in Column 3. These are the only DMUs on the Cobb-Douglas frontier. All other schools are inefficient.

To arrive at efficiency scores for the two stages in each DMU, one of the two stages was chosen as the leader and the appropriate log efficiency model was solved. In the case of Stage 1 being the leader, this would follow Equation 11. The resulting efficiency score in the case of choosing Stage 1 as the leader is then given by $\hat{e}_o^1 = \left[\dfrac{e^{\tilde{\xi}} \prod_d z_{do}^{\tilde{\eta}_d}}{e^{\tilde{\gamma}} \prod_i x_{io}^{\tilde{\nu}_i}}\right]$. With this rating in place, the corresponding Stage 2 follower efficiency score is then given by $\hat{e}_o^2 = \{\hat{e}_{o\,agg} / [\hat{e}_o^1]^{p_1}\}^{1/p_2}$. Note that with Stage 2 as the leader, Equation 11 would be modified by replacing the objective function with $\log \hat{e}_o^2 = \max \delta + \sum_r \mu_r \hat{y}_{ro} - \xi - \sum_d \eta_d \hat{z}_{do}$. Given that there is a choice of leader, two sets of analyses were now conducted; first setting Stage 1 as the leader and deriving the Stage 1 and Stage 2 ratings and then repeating this with Stage 2 as the leader. In this particular application, the values for the Stage 1 and Stage 2 scores turned out to be invariant to the choice of leader. This phenomenon may be the result of a unique optimal solution arising from Equation 8 for any given DMU. Columns 4 and 5 show the Stage 1 log efficiencies and actual efficiencies, respectively; Columns 6 and 7 display the corresponding Stage 2 scores. It is noted that only two DMUs for #37 and #24 are efficient in both stages, meaning that in the aggregate these two DMUs are efficient as well.

To examine the sensitivity of efficiency scores of DMUs to the choice of weights p_1, p_2 applied to the two stages, two additional analyses were carried out, namely using $p_1 = 0.25, p_2 = 0.75$. The results of these analyses are shown in Table 5. The results of $p_1 = 0.10, p_2 = 0.90$, appears in Table 6. No particular trend emerges from these three scenarios other than the observation that significantly different scores can arise, depending on the choice of these weights. What this means is that in any given situation a clear understanding of the importance to be attached to the two stages should be made before embarking on an analysis of efficiency.

From a competitive standpoint, perhaps the choice of weights p_1, p_2 is secondary to choosing which input and output factors to focus attention on. Specifically, one might criticize the Cobb-Douglas methodology for its characterization of efficiency in terms of all slacks (Equation12). Efficiency scores as represented in Table 4, for example, presume that projections to the frontier along all dimensions are allowable. However, projections that call for an increase in a factor such as the percentage of students obtaining jobs are definitely relevant and of interest to the organization; a slack implying a reduction in the percentage of students in the top quartile is not relevant. This feature of the additive model is clearly undesirable. As discussed above, the structure has the advantage of permitting one to select those factors on which the organization wishes to compete and then defines efficiency in terms of only those factors. With this concept in mind, two additional analyses were carried out. Table 7 shows the results when efficiency is defined only in terms of Jobs. That is, a lower bound of unity was applied only to the multiplier for Jobs, while all other lower bounds were set to zero, meaning that the objective function in Function 12 would be restricted to $\min -[s_1^1]$. A second analysis was then carried out focusing on both Jobs and Internships, specifically using a restricted objective function $\min -[s_1^1 + s_3^3]$. Table 7 displays the efficiency scores in this case, while Table 8 shows the actual slacks for both Jobs and Internships. Table 9 provides useful information to the school in terms of its competitive position on these two key factors.

Conclusions

This paper provides a methodology for evaluating the relative performance of a set of competing entities, with specific reference to a set of business schools. We view the DMU, the school, from the perspective of its efficiency in attracting top students. Subsequently, the success of the school is measured in the number of students earning scholarships, internships, and, later on, employment. We view the process as involving two stages: the first stage relates to the admission process in attracting student applications; the second stage describes the success of students in the job market following graduation, relative to such factors as their abilities to acquire scholarships and internships while still in their program.

Rather than selecting the conventional DEA model as commonly applied in such studies, we proceeded with a Cobb-Douglas methodology. This approach is somewhat more amenable to the percentage data involved. Unlike earlier two-stage models expressed in multiplicative form, like in Kao and Hwang (2008) which attaches equal weights to the two stages, our methodology permits variable, user-specified weights on the stage-scores. Furthermore, one of the useful and appealing features of our approach is its ability to focus on user-specified competitive drivers. We illustrate this with two analyses, one with Jobs only as the driver and another where both Jobs and Internships are the focus.

In the usual multi-stage models, the principal focus is on the outputs from the final stage. The model used herein, permits one to select those outputs from whichever stages they choose and consider projection to the frontier specifically along those dimensions. This is rather like designating certain inputs or outputs as discretionary versus nondiscretionary.

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Appendix

Table 1
List of Universities (37 DMUs)

DMU	Universities
1	University of Notre Dame (Mendoza)
2	University of Virginia (McIntire)
3	Massachusetts Institute of Technology (Sloan)
4	University of Pennsylvania (Wharton)
5	Cornell University
6	Emory University (Goizueta)
7	University of Michigan (Ross)
8	Boston College (Carroll)
9	University of Texas (McCombs)
10	New York University (Stern)
11	University of North Carolina (Kenan-Flagler)
12	University of Richmond (Robins)
13	Miami University (Farmer)
14	Babson College
15	Wake Forest University
16	Indiana University (Kelley)
17	Villanova University
18	Bentley University
19	Carnegie Mellon University (Tepper)
20	College of William and Mary (Mason)
21	University of Illinois
22	Pennsylvania State University (Smeal)
23	Southern Methodist University (Cox)
24	University of Washington (Foster)
25	Rensselaer Polytechnic Institute (Lally)
26	Boston University
27	Case Western Reserve University (Weatherhead)
28	Santa Clara University (Leavey)
29	DePaul University
30	University of Wisconsin
31	Michigan State University (Broad)
32	Texas A&M University (Mays)
33	Syracuse University (Whitman)
34	Fordham University
35	University of Georgia (Terry)
36	Georgia Institute of Technology
37	ITESM

Table 2
Data for Schools of Business

	Stage 1						Stage 2			
	Inputs			Outputs			Inputs			Outputs
	x1	x2	x3	z1	z2	I	z1	z2	I	J
DMU	% students in top 25% of their class	% of applicants rejected	Academic rating	% of accepted applicants enrolled	% receiving institutional scholarships	% receiving internships	% of accepted applicants enrolled	% receiving institutional scholarships	% receiving internships	% students who get jobs
1	0.950	0.730	0.900	0.990	0.370	0.790	0.990	0.370	0.790	0.950
2	0.970	0.680	0.930	0.960	0.200	0.863	0.960	0.200	0.863	0.780
3	1.000	0.890	0.970	0.650	0.580	0.909	0.650	0.580	0.909	0.940
4	1.000	0.830	0.910	0.750	0.430	0.852	0.750	0.430	0.852	0.930
5	0.980	0.810	0.920	0.800	0.420	0.853	0.800	0.420	0.853	0.930
6	0.980	0.700	0.920	0.990	0.370	0.862	0.990	0.370	0.862	0.840
7	0.990	0.500	0.830	0.820	0.380	0.897	0.820	0.380	0.897	0.810
8	0.950	0.700	0.890	0.280	0.300	0.841	0.280	0.300	0.841	0.830
9	0.950	0.560	0.740	0.640	0.190	0.842	0.640	0.190	0.842	1.000
10	0.920	0.620	0.810	0.360	0.530	0.923	0.360	0.530	0.923	0.930
11	0.960	0.680	0.830	1.000	0.480	0.773	1.000	0.480	0.773	0.970
12	0.870	0.610	0.940	0.260	0.610	0.777	0.260	0.610	0.777	1.000
13	0.740	0.210	0.770	0.200	0.650	0.708	0.200	0.650	0.708	0.710
14	0.870	0.600	0.850	0.280	0.460	0.851	0.280	0.460	0.851	0.640
15	0.910	0.620	0.890	0.900	0.420	0.788	0.900	0.420	0.788	0.930
16	0.710	0.270	0.760	0.460	0.600	0.738	0.460	0.600	0.738	0.900
17	0.880	0.540	0.880	0.300	0.500	0.890	0.300	0.500	0.890	0.820
18	0.790	0.570	0.800	0.330	0.600	0.862	0.330	0.600	0.862	0.900
19	0.930	0.640	0.990	0.210	0.500	0.970	0.210	0.500	0.970	0.850
20	0.980	0.660	0.940	0.950	0.310	0.617	0.950	0.310	0.617	0.970
21	0.890	0.290	0.720	0.450	0.310	0.749	0.450	0.310	0.749	0.720
22	0.860	0.480	0.770	0.450	0.260	0.737	0.450	0.260	0.737	0.950
23	0.730	0.470	0.760	0.520	0.790	0.749	0.520	0.790	0.749	0.800
24	0.130	0.420	0.750	0.740	0.150	0.636	0.740	0.150	0.636	0.550
25	0.900	0.570	0.840	0.250	0.900	0.564	0.250	0.900	0.564	0.620
26	0.910	0.580	0.720	0.350	0.420	0.821	0.350	0.420	0.821	0.760
27	0.870	0.300	0.810	0.100	0.500	0.735	0.100	0.500	0.735	0.900
28	0.760	0.410	0.830	0.230	0.680	0.688	0.230	0.680	0.688	0.820
29	0.290	0.260	0.750	0.330	0.630	0.629	0.330	0.630	0.629	0.660
30	0.910	0.430	0.770	0.990	0.460	0.683	0.990	0.460	0.683	0.630
31	0.700	0.270	0.710	0.990	0.260	0.678	0.990	0.260	0.678	0.920
32	0.890	0.330	0.710	0.530	0.380	0.581	0.530	0.380	0.581	0.740
33	0.730	0.400	0.800	0.380	0.590	0.870	0.380	0.590	0.870	0.680
34	0.730	0.510	0.840	0.190	0.700	0.876	0.190	0.700	0.876	0.800
35	0.890	0.460	0.720	0.990	0.710	0.532	0.990	0.710	0.532	0.750
36	0.950	0.410	0.720	0.610	0.220	0.612	0.610	0.220	0.612	0.780
37	0.350	0.180	0.843	0.680	0.230	0.471	0.680	0.230	0.471	0.690

Table 3
Log Data for Schools of Business

	Stage 1						Stage 2			
	Inputs			Outputs			Inputs			Outputs
	x1	x2	x3	z1	z2	I	z1	z2	I	J
DMU	% students in top 25% of their class	% of applicants rejected	Academic rating	% of accepted applicants enrolled	% receiving institutional scholarships	% receiving internships	% of accepted applicants enrolled	% receiving institutional scholarships	% receiving internships	% students who get jobs
1	-0.051	-0.315	-0.105	-0.010	-0.994	-0.236	-0.010	-0.994	-0.236	-0.051
2	-0.030	-0.386	-0.073	-0.041	-1.609	-0.147	-0.041	-1.609	-0.147	-0.248
3	0.000	-0.117	-0.030	-0.431	-0.545	-0.095	-0.431	-0.545	-0.095	-0.062
4	0.000	-0.186	-0.094	-0.288	-0.844	-0.160	-0.288	-0.844	-0.160	-0.073
5	-0.020	-0.211	-0.083	-0.223	-0.868	-0.159	-0.223	-0.868	-0.159	-0.073
6	-0.020	-0.357	-0.083	-0.010	-0.994	-0.149	-0.010	-0.994	-0.149	-0.174
7	-0.010	-0.693	-0.186	-0.198	-0.968	-0.109	-0.198	-0.968	-0.109	-0.211
8	-0.051	-0.357	-0.117	-1.273	-1.204	-0.173	-1.273	-1.204	-0.173	-0.186
9	-0.051	-0.580	-0.301	-0.446	-1.661	-0.172	-0.446	-1.661	-0.172	0.000
10	-0.083	-0.478	-0.211	-1.022	-0.635	-0.080	-1.022	-0.635	-0.080	-0.073
11	-0.041	-0.386	-0.186	0.000	-0.734	-0.257	0.000	-0.734	-0.257	-0.030
12	-0.139	-0.494	-0.062	-1.347	-0.494	-0.252	-1.347	-0.494	-0.252	0.000
13	-0.301	-1.561	-0.261	-1.609	-0.431	-0.345	-1.609	-0.431	-0.345	-0.342
14	-0.139	-0.511	-0.163	-1.273	-0.777	-0.161	-1.273	-0.777	-0.161	-0.446
15	-0.094	-0.478	-0.117	-0.105	-0.868	-0.238	-0.105	-0.868	-0.238	-0.073
16	-0.342	-1.309	-0.274	-0.777	-0.511	-0.304	-0.777	-0.511	-0.304	-0.105
17	-0.128	-0.616	-0.128	-1.204	-0.693	-0.117	-1.204	-0.693	-0.117	-0.198
18	-0.236	-0.562	-0.223	-1.109	-0.511	-0.149	-1.109	-0.511	-0.149	-0.105
19	-0.073	-0.446	-0.010	-1.561	-0.693	-0.030	-1.561	-0.693	-0.030	-0.163
20	-0.020	-0.416	-0.062	-0.051	-1.171	-0.483	-0.051	-1.171	-0.483	-0.030
21	-0.117	-1.238	-0.329	-0.799	-1.171	-0.289	-0.799	-1.171	-0.289	-0.329
22	-0.151	-0.734	-0.261	-0.799	-1.347	-0.305	-0.799	-1.347	-0.305	-0.051
23	-0.315	-0.755	-0.274	-0.654	-0.236	-0.289	-0.654	-0.236	-0.289	-0.223
24	-2.040	-0.868	-0.288	-0.301	-1.897	-0.453	-0.301	-1.897	-0.453	-0.598
25	-0.105	-0.562	-0.174	-1.386	-0.105	-0.573	-1.386	-0.105	-0.573	-0.478
26	-0.094	-0.545	-0.329	-1.050	-0.868	-0.197	-1.050	-0.868	-0.197	-0.274
27	-0.139	-1.204	-0.211	-2.303	-0.693	-0.308	-2.303	-0.693	-0.308	-0.105
28	-0.274	-0.892	-0.186	-1.470	-0.386	-0.374	-1.470	-0.386	-0.374	-0.198
29	-1.238	-1.347	-0.288	-1.109	-0.462	-0.464	-1.109	-0.462	-0.464	-0.416
30	-0.094	-0.844	-0.261	-0.010	-0.777	-0.381	-0.010	-0.777	-0.381	-0.462
31	-0.357	-1.309	-0.342	-0.010	-1.347	-0.389	-0.010	-1.347	-0.389	-0.083
32	-0.117	-1.109	-0.342	-0.635	-0.968	-0.543	-0.635	-0.968	-0.543	-0.301
33	-0.315	-0.916	-0.223	-0.968	-0.528	-0.139	-0.968	-0.528	-0.139	-0.386
34	-0.315	-0.673	-0.174	-1.661	-0.357	-0.132	-1.661	-0.357	-0.132	-0.223
35	-0.117	-0.777	-0.329	-0.010	-0.342	-0.631	-0.010	-0.342	-0.631	-0.288
36	-0.051	-0.892	-0.329	-0.494	-1.514	-0.491	-0.494	-1.514	-0.491	-0.248
37	-1.050	-1.715	-0.171	-0.386	-1.470	-0.753	-0.386	-1.470	-0.753	-0.371

Table 4
Efficiency Scores (p_1 = 0.50 and p_2 = 0.50)

1	2	3	4	5	6	7
DMU	Log e_{oagg}	e^ Log e_{oagg}	Log e_{o1}	e^ Log e_{o1}	Log e_{o2}	e^ Log e_{o2}
1	-1.236	0.291	-0.891	0.410	-1.580	0.206
2	-1.730	0.177	-1.464	0.231	-1.996	0.136
3	-1.467	0.231	-0.606	0.546	-2.329	0.097
4	-1.471	0.230	-0.897	0.408	-2.045	0.129
5	-1.454	0.234	-0.817	0.442	-2.091	0.124
6	-1.687	0.185	-0.541	0.582	-2.834	0.059
7	-1.511	0.221	-0.457	0.633	-2.564	0.077
8	-1.671	0.188	-2.052	0.129	-1.291	0.275
9	-0.363	0.696	-0.725	0.484	0.000	1.000
10	-1.225	0.294	-0.598	0.550	-1.851	0.157
11	-1.028	0.358	-0.570	0.566	-1.486	0.226
12	-0.786	0.456	-1.572	0.208	0.000	1.000
13	-0.537	0.584	0.000	1.000	-1.074	0.342
14	-1.667	0.189	-1.584	0.205	-1.750	0.174
15	-1.267	0.282	-0.653	0.521	-1.880	0.153
16	-0.863	0.422	0.000	1.000	-1.725	0.178
17	-1.513	0.220	-1.231	0.292	-1.796	0.166
18	-1.316	0.268	-0.596	0.551	-2.036	0.131
19	-1.637	0.195	-1.233	0.291	-2.042	0.130
20	-1.086	0.338	-2.107	0.122	-0.064	0.938
21	-0.935	0.392	-1.009	0.365	-0.862	0.423
22	-0.898	0.408	-1.645	0.193	-0.151	0.860
23	-1.290	0.275	-0.296	0.744	-2.283	0.102
24	0.000	1.000	0.000	1.000	0.000	1.000
25	-1.668	0.189	-2.296	0.101	-1.040	0.353
26	-1.279	0.278	-1.166	0.312	-1.391	0.249
27	-1.049	0.350	-2.098	0.123	0.000	1.000
28	-1.273	0.280	-1.522	0.218	-1.025	0.359
29	-0.622	0.537	0.000	1.000	-1.243	0.289
30	-1.481	0.227	-0.629	0.533	-2.334	0.097
31	-0.280	0.756	0.000	1.000	-0.560	0.571
32	-0.775	0.461	-0.552	0.576	-0.998	0.369
33	-1.316	0.268	-0.318	0.728	-2.314	0.099
34	-1.380	0.251	-1.110	0.329	-1.651	0.192
35	-1.158	0.314	0.000	1.000	-2.316	0.099
36	-1.114	0.328	-1.956	0.141	-0.271	0.763
37	0.000	1.000	0.000	1.000	0.000	1.000

Table 5
Efficiency Scores (p_1 = 0.25 and p_2 = 0.75)

1	2	3	4	5	6	7
DMU	Log e_{oagg}	e^ Log e_{oagg}	Log e_{o1}	e^ Log e_{o1}	Log e_{o2}	e^ Log e_{o2}
1	-1.397	0.247	-0.920	0.399	-1.557	0.211
2	-1.393	0.248	-3.237	0.039	-0.779	0.459
3	-1.798	0.166	-1.762	0.172	-1.810	0.164
4	-1.732	0.177	-1.849	0.157	-1.693	0.184
5	-1.745	0.175	-1.774	0.170	-1.735	0.176
6	-1.959	0.141	-2.036	0.131	-1.934	0.145
7	-1.831	0.160	-1.704	0.182	-1.874	0.154
8	-1.104	0.332	-3.669	0.026	-0.249	0.779
9	-0.181	0.834	-0.725	0.484	0.000	1.000
10	-1.387	0.250	-1.803	0.165	-1.248	0.287
11	-1.253	0.286	-0.583	0.558	-1.476	0.229
12	-0.393	0.675	-1.572	0.208	0.000	1.000
13	-0.806	0.447	0.000	1.000	-1.074	0.342
14	-1.634	0.195	-2.237	0.107	-1.434	0.238
15	-1.569	0.208	-0.674	0.510	-1.867	0.155
16	-1.294	0.274	0.000	1.000	-1.725	0.178
17	-1.532	0.216	-1.980	0.138	-1.383	0.251
18	-1.548	0.213	-1.585	0.205	-1.536	0.215
19	-2.320	0.098	-6.052	0.002	-1.077	0.341
20	-0.547	0.579	-2.187	0.112	0.000	1.000
21	-0.890	0.411	-1.117	0.327	-0.814	0.443
22	-0.500	0.607	-1.703	0.182	-0.099	0.906
23	-1.787	0.168	-0.296	0.744	-2.283	0.102
24	0.000	1.000	0.000	1.000	0.000	1.000
25	-1.354	0.258	-2.296	0.101	-1.040	0.353
26	-1.335	0.263	-1.166	0.312	-1.391	0.249
27	-0.525	0.592	-2.098	0.123	0.000	1.000
28	-1.149	0.317	-1.522	0.218	-1.025	0.359
29	-0.932	0.394	0.000	1.000	-1.243	0.289
30	-1.908	0.148	-0.629	0.533	-2.334	0.097
31	-0.420	0.657	0.000	1.000	-0.560	0.571
32	-0.875	0.417	-0.606	0.546	-0.965	0.381
33	-1.717	0.180	-1.019	0.361	-1.949	0.142
34	-1.410	0.244	-1.826	0.161	-1.272	0.280
35	-1.517	0.219	-0.654	0.520	-1.804	0.165
36	-0.659	0.518	-2.455	0.086	-0.060	0.942
37	0.000	1.000	0.000	1.000	0.000	1.000

Table 6
Efficiency Scores (p_1 = 0.10 and p_2 = 0.90)

1	2	3	4	5	6	7
DMU	Log e_{oagg}	e^ Log e_{oagg}	Log e_{o1}	e^ Log e_{o1}	Log e_{o2}	e^ Log e_{o2}
1	-1.493	0.225	-0.920	0.399	-1.557	0.211
2	-1.024	0.359	-3.237	0.039	-0.779	0.459
3	-1.805	0.164	-1.762	0.172	-1.810	0.164
4	-1.709	0.181	-1.849	0.157	-1.693	0.184
5	-1.739	0.176	-1.774	0.170	-1.735	0.176
6	-1.944	0.143	-2.036	0.131	-1.934	0.145
7	-1.857	0.156	-1.704	0.182	-1.874	0.154
8	-0.591	0.554	-3.669	0.026	-0.249	0.779
9	-0.073	0.930	-0.725	0.484	0.000	1.000
10	-1.304	0.272	-1.803	0.165	-1.248	0.287
11	-1.387	0.250	-0.583	0.558	-1.476	0.229
12	-0.157	0.855	-1.572	0.208	0.000	1.000
13	-0.967	0.380	0.000	1.000	-1.074	0.342
14	-1.473	0.229	-2.535	0.079	-1.354	0.258
15	-1.732	0.177	-1.361	0.257	-1.774	0.170
16	-1.553	0.212	0.000	1.000	-1.725	0.178
17	-1.443	0.236	-1.980	0.138	-1.383	0.251
18	-1.541	0.214	-1.585	0.205	-1.536	0.215
19	-1.228	0.293	-2.594	0.075	-1.077	0.341
20	-0.219	0.804	-2.187	0.112	0.000	1.000
21	-0.844	0.430	-1.117	0.327	-0.814	0.443
22	-0.214	0.808	-2.136	0.118	0.000	1.000
23	-2.085	0.124	-0.296	0.744	-2.283	0.102
24	0.000	1.000	0.000	1.000	0.000	1.000
25	-1.145	0.318	-2.511	0.081	-0.993	0.371
26	-1.262	0.283	-1.884	0.152	-1.192	0.304
27	-0.210	0.811	-2.098	0.123	0.000	1.000
28	-1.074	0.342	-1.522	0.218	-1.025	0.359
29	-1.119	0.327	0.000	1.000	-1.243	0.289
30	-2.163	0.115	-0.629	0.533	-2.334	0.097
31	-0.504	0.604	0.000	1.000	-0.560	0.571
32	-0.879	0.415	-1.174	0.309	-0.846	0.429
33	-1.856	0.156	-1.019	0.361	-1.949	0.142
34	-1.327	0.265	-1.826	0.161	-1.272	0.280
35	-1.689	0.185	-0.654	0.520	-1.804	0.165
36	-0.299	0.741	-2.455	0.086	-0.060	0.942
37	0.000	1.000	0.000	1.000	0.000	1.000

Table 7
Efficiency Scores (p_1 = 0.25 & p_2 = 0.75) Lower bound = 1 on Jobs Multiplier

1	2	3	4	5	6	7
DMU	Log e_{oagg}	e^ Log e_{oagg}	Log e_{o1}	e^ Log e_{o1}	Log e_{o2}	e^ Log e_{o2}
1	-0.038	0.962	0.000	1.000	-0.051	0.950
2	-0.186	0.830	0.000	1.000	-0.248	0.780
3	-0.046	0.955	0.000	1.000	-0.062	0.940
4	-0.054	0.947	0.000	1.000	-0.073	0.930
5	-0.054	0.947	0.000	1.000	-0.073	0.930
6	-0.131	0.877	0.000	1.000	-0.174	0.840
7	-0.158	0.854	0.000	1.000	-0.211	0.810
8	-0.140	0.870	0.000	1.000	-0.186	0.830
9	0.000	1.000	0.000	1.000	0.000	1.000
10	-0.054	0.947	0.000	1.000	-0.073	0.930
11	-0.023	0.977	0.000	1.000	-0.030	0.970
12	0.000	1.000	0.000	1.000	0.000	1.000
13	-0.202	0.817	0.000	1.000	-0.270	0.764
14	-0.335	0.716	0.000	1.000	-0.446	0.640
15	-0.054	0.947	0.000	1.000	-0.073	0.930
16	-0.074	0.928	-0.001	0.999	-0.099	0.906
17	-0.149	0.862	0.000	1.000	-0.198	0.820
18	-0.079	0.924	0.000	1.000	-0.105	0.900
19	-0.122	0.885	0.000	1.000	-0.163	0.850
20	-0.013	0.987	-0.052	0.949	0.000	1.000
21	-0.234	0.791	-0.025	0.975	-0.304	0.738
22	-0.033	0.968	-0.042	0.959	-0.030	0.971
23	-0.167	0.846	-0.014	0.986	-0.218	0.804
24	0.000	1.000	0.000	1.000	0.000	1.000
25	-0.301	0.740	-0.640	0.527	-0.188	0.829
26	-0.206	0.814	0.000	1.000	-0.274	0.760
27	-0.036	0.965	-0.142	0.867	0.000	1.000
28	-0.137	0.872	-0.189	0.827	-0.120	0.887
29	-0.210	0.811	0.000	1.000	-0.280	0.756
30	-0.340	0.712	-0.024	0.976	-0.446	0.640
31	-0.038	0.963	0.000	1.000	-0.050	0.951
32	-0.162	0.850	-0.247	0.781	-0.134	0.875
33	-0.289	0.749	0.000	1.000	-0.386	0.680
34	-0.167	0.846	0.000	1.000	-0.223	0.800
35	-0.160	0.852	-0.347	0.707	-0.097	0.907
36	-0.110	0.896	-0.298	0.742	-0.048	0.953
37	0.000	1.000	0.000	1.000	0.000	1.000

Table 8

Efficiency Scores (p_1 = 0.25 & p_2 = 0.75) Lower bound = 1 on Jobs & Internships Multiplier

1	2	3	4	5	6	7
DMU	Log e_{oagg}	e^ Log e_{oagg}	Log e_{o1}	e^ Log e_{o1}	Log e_{o2}	e^ Log e_{o2}
1	-0.229	0.795	-0.099	0.906	-0.273	0.761
2	-0.405	0.667	-0.155	0.856	-0.488	0.614
3	-0.286	0.752	-0.013	0.988	-0.377	0.686
4	-0.269	0.764	-0.061	0.940	-0.339	0.713
5	-0.273	0.761	-0.051	0.950	-0.347	0.707
6	-0.366	0.693	-0.017	0.983	-0.483	0.617
7	-0.404	0.668	0.000	1.000	-0.538	0.584
8	-0.284	0.753	-0.226	0.798	-0.304	0.738
9	-0.014	0.986	-0.056	0.946	0.000	1.000
10	-0.262	0.770	-0.035	0.966	-0.337	0.714
11	-0.203	0.816	-0.116	0.890	-0.232	0.793
12	-0.043	0.958	-0.172	0.842	0.000	1.000
13	-0.207	0.813	0.000	1.000	-0.277	0.758
14	-0.489	0.613	-0.149	0.861	-0.602	0.548
15	-0.237	0.789	-0.104	0.901	-0.281	0.755
16	-0.130	0.878	0.000	1.000	-0.173	0.841
17	-0.330	0.719	-0.099	0.906	-0.406	0.666
18	-0.240	0.787	-0.082	0.921	-0.292	0.747
19	-0.328	0.720	-0.062	0.940	-0.417	0.659
20	-0.088	0.916	-0.352	0.703	0.000	1.000
21	-0.300	0.741	-0.015	0.985	-0.395	0.674
22	-0.103	0.902	-0.252	0.777	-0.053	0.948
23	-0.267	0.766	-0.109	0.897	-0.320	0.726
24	0.000	1.000	0.000	1.000	0.000	1.000
25	-0.301	0.740	-0.640	0.527	-0.188	0.829
26	-0.314	0.730	0.000	1.000	-0.419	0.658
27	-0.054	0.947	-0.218	0.804	0.000	1.000
28	-0.166	0.847	-0.304	0.738	-0.119	0.887
29	-0.210	0.811	0.000	1.000	-0.280	0.756
30	-0.442	0.643	-0.153	0.858	-0.538	0.584
31	-0.048	0.953	0.000	1.000	-0.064	0.938
32	-0.162	0.850	-0.247	0.781	-0.134	0.875
33	-0.448	0.639	-0.133	0.876	-0.597	0.550
34	-0.307	0.736	-0.133	0.876	-0.365	0.695
35	-0.160	0.852	-0.347	0.707	-0.097	0.907
36	-0.142	0.867	-0.364	0.695	-0.069	0.934
37	0.000	1.000	0.000	1.000	0.000	1.000

Table 9
Inefficiencies in Jobs and Internships

1	2	3	4	5
DMU	Log e_{oagg}	e^ Log e_{oagg}	Internships Inefficiency	Job Inefficiency
1	-0.229	0.795	0.214	0.015
2	-0.405	0.667	0.341	0.064
3	-0.286	0.752	0.269	0.016
4	-0.269	0.764	0.243	0.026
5	-0.273	0.761	0.245	0.027
6	-0.366	0.693	0.259	0.107
7	-0.404	0.668	0.272	0.131
8	-0.284	0.753	0.247	0.036
9	-0.014	0.986	0.014	0.000
10	-0.262	0.770	0.248	0.013
11	-0.203	0.816	0.203	0.000
12	-0.043	0.958	0.043	0.000
13	-0.207	0.813	0.012	0.195
14	-0.489	0.613	0.198	0.290
15	-0.237	0.789	0.207	0.029
16	-0.130	0.878	0.085	0.044
17	-0.330	0.719	0.224	0.105
18	-0.240	0.787	0.203	0.036
19	-0.328	0.720	0.255	0.072
20	-0.088	0.916	0.088	0.000
21	-0.300	0.741	0.188	0.111
22	-0.103	0.902	0.103	0.000
23	-0.267	0.766	0.134	0.132
24	0.000	1.000	0.000	0.000
25	-0.301	0.740	0.000	0.300
26	-0.314	0.730	0.156	0.158
27	-0.054	0.947	0.036	0.017
28	-0.166	0.847	0.069	0.095
29	-0.210	0.811	0.000	0.209
30	-0.442	0.643	0.118	0.323
31	-0.048	0.953	0.048	0.000
32	-0.162	0.850	0.000	0.162
33	-0.448	0.639	0.204	0.243
34	-0.307	0.736	0.190	0.116
35	-0.160	0.852	0.000	0.159
36	-0.142	0.867	0.142	0.000
37	0.000	1.000	0.000	0.000