# Measuring Relative Efficiency and Effectiveness

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## INTRODUCTION

The performance of an organization is a function of its efficiency and effectiveness. *Efficiency* is the degree to which inputs are used to produce outputs. *Effectiveness* is the degree to which organizational goals are met.

Efficiency provides a starting point for our discussion, as it continues to be an active area of research. Efficiency is defined as the ratio of total output to total input. However, in the real world, outputs and inputs are rarely measured in the same units. Therefore, one cannot characterize efficiency by simply dividing the sum of outputs by the sum of inputs. One way to address this problem is to assign weights to each output and input. Weights can be determined using a variety of approaches including cost-accounting information and subject matter expertise. By assigning fixed weights, whether equal or based on relative importance, an efficient frontier is created a priori. In other words, the efficient frontier and all isoquants (contour lines) are not determined by the data, but rather by subjective opinion.

Data Envelopment Analysis (DEA) provides an alternative to these fixed weight approaches and is data-driven. DEA is an established nonparametric approach for estimating the relative efficiency of peer entities called decision making units (DMUs). In practice, DMUs can represent a wide variety of entities including countries, economic sectors, business units, organizations, institutions, projects, processes, products, and policies. In all cases, DMUs may use multiple inputs to produce multiple outputs. DEA has been applied in many sectors including Energy, Education, Healthcare, and Finance. See Galterio et al. (2009) and Paradi et al. (2011) for examples.

Effectiveness differs from efficiency in that it focuses solely on outputs. Simply stated, effectiveness is the degree to which results are achieved. Fortunately, DEA can also be used to measure the relative effectiveness of DMUs by simply using a vector of 1s in place of all inputs (Chang et al., 1995; Tsai & Huang, 2011). The frontier DEA determines from this modified data set is the effectiveness (possibility) frontier.

Finally, once measures of efficiency and effectiveness are computed, they can be used together to characterize total performance. In fact, some researchers have explicitly defined total performance as a function of both measures. See Eriksson et al. (2007), Fugate et al. (2011), and Tucker and Hargreaves (2008) for examples. However, this raises important questions. For instance, what is the appropriate mathematical model to combine these measures? Although each case is unique, we provide guidelines for measuring the total performance of mutually exclusive alternatives as well as portfolios. We also discuss a method for measuring total organizational performance over time.

The objective of this chapter is to provide an overview of DEA, making it more accessible for

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researchers and practitioners. We address several obstacles in understanding and using DEA that might otherwise limit its potential as a performance measurement tool.

## BACKGROUND

The first DEA model was developed by Charnes, Cooper, and Rhodes (1978), known as the CCR model, and used the ratio of weighted outputs to weighted inputs to measure the relative efficiency of DMUs, where the weights were determined via a constrained optimization model. Banker, Charnes, and Cooper's (1984) BCC model extended the CCR model by introducing a convexity constraint which allowed for variable returns to scale. This allowed the separate measurement of technical and scale efficiencies. The CCR and BCC models are considered radial models because they measure radial distances between DMUs and the efficient frontier; a frontier comprised of a set of DMUs not dominated by any other DMU. Stemming from these early works, several models have since been developed to address specific questions in a variety of operational settings.

From the observed output and input data, DEA models determine and project a production possibility set of DMUs. For each DMU, DEA models solve a linear programming model to produce a relative efficiency score and a target point that lies on the efficient frontier. This target point represents the best projection of the DMU and serves as a benchmark for comparison. This target point can be viewed in two ways: as a DMU that uses an identical amount of input to produce more output, or as a DMU that uses less input to produce the same output. DEA models calculate a relative efficiency score ranging from 0 to 100%, where a score of 100% indicates that the DMU is on the efficient frontier. Any score below 100% represents the proximity of the DMU to the frontier, determined using the radial distance from the origin.

As mentioned previously, the factor weights in DEA models are determined via optimization rather than by individual preference. The result is that two DMUs may be scored as 100% efficient, even though they have very different performance profiles. For example, DMU A could excel at converting certain inputs into output, while DMU B is best at converting other inputs into the same output. The result is that DEA compares each DMU under the most favorable of conditions to the remaining DMUs using those same conditions.

Early DEA studies focused on measuring the efficiency of hospitals, schools, and maintenance wings but have since expanded to include new types of entities like policies and projects. This allows DEA to be used in policy and project selection problems faced by many organizations. Throughout the 1980s and 1990s, most studies utilized the CCR and BCC models with only minor enhancements. However, in the past decade DEA research has been extremely active, producing several new models. For example, Dimitris et al. (2012) showed how virtual inputs and outputs can be used to capture nonlinearities in value functions. Adler and Yazhemsky (2010) used principal component analysis (PCA) and DEA to achieve increasing levels of discrimination in scores. Thanassoulisa et al. (2012) proposed using unobserved DMUs as an alternative to weight restrictions, a common method used to represent value judgments. Du et al. (2010) considered extensions of non-radial super-efficiency to additive models. Kao and Lin (2011) showed how qualitative factors can be incorporated into DEA models. Similarly, Harrison et al. (2012) explored alternative ways to model non-discretionary variables.

In addition to the theoretical research that has been conducted, discipline specific adaptations of DEA have also occurred. For example, Picazo-Tadeo et al. (2011) created eco-efficiency models based on DEA and found that eco-efficiency is closely related to technical inefficiency; the main focus of many DEA models. Blomberg et al. (2012) developed DEA models to measure energy efficiency and to study the impacts of energy

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