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# DEA as a tool for predicting corporate failure and success: A case of bankruptcy assessment

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ABSTRACT

Using an additive super-efficiency data envelopment analysis (DEA) model, this paper develops a new assessment index based on two frontiers for predicting corporate failure and success. The proposed approach is applied to a random sample of 1001 firms, which is composed of 50 large US bankrupt firms randomly selected from Altman's bankruptcy database and 901 healthy matching firms. This sample represents the largest firms that went bankrupt over the period 1991–2004 and represents a full spectrum of industries. Our findings demonstrate that the DEA model is relatively weak in predicting corporate failures compared to healthy firm predictions, and the assessment index improves this weakness by giving the decision maker various options to achieve different precision levels of bankrupt, non-bankrupt, and total predictions.



## 1. Introduction

The prediction of corporate failures has received widespread attention in accounting and finance disciplines. Mathematical models have been successfully developed in classifying firms as bankrupt or non-bankrupt. The ability of accurate corporate failure assessment is indeed important from the perspective of a firm's stakeholders, creditors, and employees. Warner [1] indicates that the direct costs associated with bankruptcy (such as court costs, lawyer costs, and accountant fees) may be around 5%, and that both direct and indirect costs (such as lost sales, lost profits, higher cost of credit, inability to issue new securities, and lost investment opportunities) may be around 28% [2]. Therefore, it is important to detect potential insolvency at its early stages.

In a comprehensive literature review, Aziz and Dar [3] have identified various techniques used in predicting corporate failure. Their survey illustrates that the literature on corporate bankruptcy assessment is dominated by statistical discriminant analysis and logistic regression. These techniques have their own advantages and disadvantages, and several authors in the past have compared the efficiency of these techniques. Collins and Green [4] show that logistic regression is as good as the discriminant analysis in predicting corporate bankruptcy. More recently, Premachandra et al. [5] have proposed a data envelopment analysis (DEA) model to predict bankruptcy and compare their results with the logistic approach to show that the DEA model could effectively be used in predicting corporate failure. The logistic regression technique computes the probabilities of potential insolvency, and the traditional approach involves using a probability of 0.5 as the cutoff point in classifying bankrupt and non-bankrupt firms. As illustrated in Premachandra et al., the cutoff point of 0.5 may not be appropriate in classifying the firms as bankrupt or non-bankrupt based on the DEA efficiency scores because the DEA efficiency scores may be highly skewed, especially when super-efficiency DEA models are used. Therefore, a proper discriminating or assessment function is essential if DEA is used in classification exercises such as predicting corporate failure.

The purpose of this paper is to propose a new approach based on the additive super-efficiency DEA to eliminate some of the deficiencies of the model proposed by Premachandra et al. [5]. The proposed approach is novel in the sense that, unlike in traditional DEA applications, the proposed approach combines the efficient and inefficient frontiers and defines a discriminant index to classify bankrupt and non-bankrupt firms. The numerical results show that the DEA model in general is weak in predicting bankrupt firms compared to non-bankrupt firms, and the proposed assessment index rectifies this weakness.

The rest of the paper is organized as follows. Section 2 presents a detailed literature review on bankruptcy prediction models. Section 3 deals with the proposed DEA model, and Sections 4 and 5 present data and numerical results. Section 6 concludes the paper.

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## 2. Literature review

The seminal contribution in the literature to address the issue of bankruptcy was written by Altman [6]. Altman [6] was the first to introduce a bankruptcy prediction model using the discriminant analysis technique. He uses a linear combination (referred to as "Z-score") of financial variables to obtain a score for each firm in the sample, which discriminates bankrupt firms from non-bankrupt firms using a cutoff point of 0.5. Altman's model produces adequate results within sample, but its performance out of sample is very poor. Subsequently, Eisenbeis [7] and, more recently, Grice and Ingram [8] use the Altman model for predicting bankruptcy with a more recent data set and find some inadequacies in the discriminant analysis approach. Grice and Ingram [8] re-tested Altman's [6] model on a more recent sample and find that its predictive ability of bankrupt companies fell from 83.5% to 57.8%. Eisenbeis [7] had previously outlined various statistical problems associated with the discriminant analysis approach, but in this study he demonstrates that for matched pair sampling the approach may be adequate. However, in the case of a random sample of firms where the potential failed firms are not around 50%, the predictive ability could seriously be affected.

The literature is rich with studies that have used logistic or probit regression in predicting bankruptcy, for example [5,9,10,11,12]. The traditional approach in using these techniques is to use half of the data sample (estimation sample) for estimating the model and the other half for prediction purposes. These models compute a conditional probability of an observation belonging to a particular category, such as bankrupt or non-bankrupt, and a cutoff point of 0.5 is used to classify the observations. A number of previous studies have shown that the logistic regression approach provides accurate classification within sample (see [13]), but out-of-sample prediction is very poor. Collins and Green [4] show that logistic regression is superior in predicting failed firms compared to the healthy firms. In unrelated literature, Press and Wilson [14] use the technique to predict potential breast cancer and show that the logistic regression approach is superior to the discriminant analysis technique. For a complete review of econometric and operations research methods used to predict financial crisis and mortgage defaults refer to Demyanyk et al. [15].

Among other approaches recently developed that all play an important role in evaluating corporate failures are neural networks [16], CUSUM methodology [17], multidimensional scaling (MDS) techniques [18], the chaos approach [19], and finally DEA [20,21,5]. In addition, Shanmugam and Johnson [22] have proposed a new approach by integrating the DEA and the principal component analysis (PCA) techniques for ranking of decision making units.

Premachandra et al. [5] use an additive DEA model of Charnes et al. [23] to predict bankruptcy. Based on whether the objective function value of the DEA model is positive or not, the firms in the sample were classified as healthy or financially distressed. The authors compare the results from the DEA model with the logistic regression approach and their major findings include (i) the DEA model is superior to the logistic regression approach in predicting financially distressed (bankrupt) firms, whereas (ii) the logistic regression approach is superior to the DEA model in predicting non-bankrupt (healthy) firms. Most bankruptcy prediction models including the DEA are based on financial ratios of an institution. A recent article by Avkiran [24] investigates to what extent the DEA super-efficiency estimates are associated with key financial ratios in order to address inefficiencies that were not obvious in financial ratio analysis.

The purpose of this paper is to propose a new approach based on super-efficient additive DEA model proposed by Du et al. [25] to improve the predictive ability of the Premachandra et al. [5] model.

## 3. Methodology

The methodology used in this paper for bankruptcy prediction is based on DEA. DEA was developed by Charnes et al. [26] to assess the efficiency of decision-making units (DMUs) that have multiple inputs and outputs. Compared to the statistical approaches, DEA has the following unique features that make it an excellent tool for predicting corporate failure.

First, DEA does not require a priori assumptions of the relationship between inputs and outputs. DEA can handle multiple inputs and outputs (or performance measures) in a single mathematical model without the need for the specification of trade-offs among multiple measures related to firm performance. DEA has been demonstrated to be a valuable instrument for performance evaluation and benchmarking (see, for example [27,28]).

Second, DEA examines each DMU uniquely, by generating individual performance (efficiency) scores that are relative to the entire sample under investigation. Mis-specification is a recurring problem in regression analysis, but it is not a concern with DEA models, as DEA creates a best-practice frontier based on peer comparisons within the sample.

Third, recent DEA development can study the frontier shift over a time horizon (for example, the DEA-based Malmquist index by Färe et al. [29]). This allows us to explore the dynamic change of corporate failure or success on a time horizon.

Fourth, DEA does not need a large sample size for bankruptcy evaluation, usually required by such statistical and econometric approaches. The need for such a large sample size is a significant disadvantage to practitioners when investment decisions are made using small samples. DEA can bypass such a difficulty related to a sample size. For example, in the most recent bankruptcy assessment study, Premachandra et al. [5] use the standard additive DEA model established by Charnes et al. [23] to identify a bankruptcy frontier, and the results are compared with the logistic regression technique. They find that DEA outperforms logistic regression in evaluating bankruptcy in an out-of-sample. Thus, DEA is a practical, appealing method for bankruptcy assessment.

In fact, DEA has been proven an excellent tool for identifying best practice or corporate success. The current study proposes to use DEA and integrate the DEA best-practice frontier and bankruptcy frontier to develop a discriminant index for corporate failure and success assessments.

### 3.1. Proposed DEA model

In this section, we introduce our methodology for predicting corporate failure and success based upon DEA. Specifically, the DEA model we based upon is the additive model of Charnes et al. [23]. Suppose we have a set of n DMUs (e.g., firms). Each $DMU_j$ ($j=1, ..., n$) has $m$ inputs and $s$ outputs. The $i$th input and $r$th output of $DMU_j$ ($j=1, ..., n$) are denoted by $x_{ij}$ ($i=1, ..., m$) and $y_{rj}$ ($r=1, ..., s$), respectively. Then, the additive model for a specific $DMU_o$ can be written as

$$\rho_o^* = \max \rho_o = \sum_{i=1}^{m} s_{io}^- + \sum_{r=1}^{s} s_{ro}^+$$

$$\text{s. t.} \quad \sum_{j=1}^{n} \lambda_j x_{ij} + s_{io}^- = x_{io}, \quad i=1,2,\ldots,m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_{ro}^+ = y_{ro}, \quad r=1,2,\ldots,s$$