A USE OF DEA-DISCRIMINANT ANALYSIS TO MEASURE CORPORATE PERFORMANCE OF JAPANESE MANUFACTURING INDUSTRY: AN INFLUENCE OF R&D EXPENDITURE ON CORPORATE VALUE

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ABSTRACT

This study investigates the influence of R&D expenditure on the corporate value of Japanese manufacturing industry. The methodology for the study is DEA-DA. This research finds that the R&D expenditure is important for the Japanese manufacturing industries to be competitive in a global market. However, the importance of R&D expenditure depends upon the type of industry. Empirical findings identified in this study are useful to other industries (not only manufacturing industry) and other nations (not only Japan).

Keywords: DEA, Discriminant Analysis, Financial Analysis, Japanese Manufacturing Industry.

1. INTRODUCTION

Discriminant Analysis (DA) is a classification method that can predict group membership of a newly sampled observation. In a use of DA, a group of observations whose memberships are already identified are used for the estimation of weights (or parameters) of a discriminant function by some criteria such as the minimization of misclassifications or the maximization of correct classifications. A new sample is classified into one of several groups by DA results.

Recently, [1][2][3] has proposed a new type of nonparametric DA approach that provides a set of weights of a linear discriminant function(s), consequently yielding an evaluation score(s) for the determination of group membership. The new nonparametric DA is referred to as "Data Envelopment Analysis-Discriminant Analysis (DEA-DA)," because it maintains a discriminant capability by incorporating the nonparametric feature of DEA into DA. See [4] for his recent research efforts on DEA.

After reviewing the previous research works, this study needs to mention that they have not sufficiently explored DEA-DA from the practical perspectives of financial evaluation. Hence, this study discusses the practical use of DEA-DA for the financial evaluation, focusing upon a linkage between R&D (Research and Development) expenditure and corporate value measured by Tobin's q. There are a limited number of previous research efforts on the relationship between the two. See, for example, [5][6][7][8]. Consequently, this study creates a new dimension of DEA-DA financial ratio analysis. That is the purpose of this study.

The remaining structure of this article is organized as follows: Section 2 includes a literature review that indicates the position of this research among existing literature on DA.

Section 3 describes the formulation of DEA-DA. Section 4 applies the proposed DEA-DA to examine the corporate performance of Japanese manufacturing industry. The last section (5) documents a concluding comment along with future research agendas.

2. LITERATURE REVIEW

The DA has the following research groups from its methodological developments.

Statistics: A group of research is interested in statistical DA methods. The first contribution may be dating back to [9] and [10]. [See, for instance, [11] which compiled previous contributions concerning statistical DA.] The conventional statistical DA methods usually maintain underlying assumptions on group distributions. For example, two groups come from normal populations with different means, but a same covariance matrix, all of which should be known to us before these applications. Under these assumptions, the statistical DA methods provide a theoretical basis for conducting various statistical inferences and tests. Furthermore, the ordinary least squares regression is usually used to obtain coefficient estimates of a linear discriminant function. Thus, there is a computational simplicity in the statistical DA methods. These are methodological strengths and contributions, indeed. However, it is also true that real data sets do not satisfy such underlying assumptions.

Econometrics: If independent variables are normally distributed, the statistical DA estimator is a true maximum-likelihood estimator and therefore asymptotically more efficient than other DA methods. However, the assumption on normality is not satisfied in many real data sets. To overcome such a shortcoming related to statistical DA, econometricians developed other several DA methods that had a close linkage with the theory of probabilistic choice discussed by psychologists. The most well known research effort in this area was due to [12] who investigated logit and probit models. The two models are solved by maximum-likelihood methods. An important feature of logit and probit analyses is that those models provide the conditional probability of an observation belonging to a certain class, given its independent variables. Both are based on a cumulative probability function and neither requires that independent variables be multivariate normal or that groups have equal covariance matrices, unlike the requirements of statistical DA. Furthermore, these approaches have a close linkage with statistical inferences and various tests.

Mathematical Programming: Mathematical Programming (MP) methods were proposed for solving various DA problems. These methods consist of the third group in this study on DA methodology. The first contribution of this group was due to [13] who documented how to formulate L_1 metric regression by a goal programming model and how to solve the problem by linear programming algorithm. [See [14] for their description on goal programming.] A popularity of MP-based DA among researchers occurred after the research effort of [15][16]. They presented how a DA problem was formulated by goal programming. Based upon the optimization techniques to be used, the third group of DA studies was further classified into (a) linear programming methods (e.g., [17], (b) nonlinear programming methods (e.g., [18], and [19]) and (c) mixed integer programming methods (e.g., [20] and [21]). A comprehensive review on the MP-based DA was found in [22] and [23]. A methodological benefit of the research group is that the MP-based DA methods do not need any assumption on a group distribution. Meanwhile, a shortcoming of the MP-based DA is that statistical inferences and tests are not yet well developed at the level of the statistical and econometric DA approaches.

Position of this research: It is clear that this study belongs to the third research group of DA. The previous DA studies in this research group have been looking for the development of new DA models and these related computational issues. DEA-DA was developed under such a research direction. Unfortunately, the previous research efforts on DEA-DA have not yet clearly discussed how to use it for real DA applications. Hence, this study describes DEA-DA from a practical perspective of evaluating financial performance and corporate value of firms.

3. DEA-DISCRIMINANT ANALYSIS

DEA-DA has two stages for computation. The first stage identifies an existence of an overlap between two groups of observations. Then, the first stage classifies observations not belonging to the overlap. The second stage classifies the observations in the overlap.

Stage 1: To discuss the first stage, we consider the following formulation:

$$\min \left\{ s \left| \begin{array}{l} \sum_{f=1}^{h} \lambda_f z_{fj} - d + s \geq 0,\ j \in G_1,\ \sum_{f=1}^{h} \lambda_f z_{fj} - d - s \leq -\varepsilon,\ j \in G_2, \\ \sum_{f=1}^{h} |\lambda_f| = 1,\ \lambda_f, d \,\&\, s : \text{URS}. \end{array} \right. \right\} \quad (1)$$

The objective function of (1) minimizes an unknown variable (*s*) that indicates the size of an overlap between G_1 and G_2. The overlap is surrounded by d-s (as a lower bound of G_1) and d+s (as an upper bound of G_2). The discriminant score for group classification is expressed by a scalar value "d". Both d and s are unrestricted (URS). A very small number (ε) is incorporated into (1) in order to separate the two groups clearly. When an observation exists on an estimated discriminant function, we have a difficulty in its classification. The small number is included in (1) for such classification convenience. All the factors (z_{fj}) of the j-th observation are connected by a discriminant function ($\sum_{f=1}^{h} \lambda_f z_{fj}$). The subscript (f) stands for the f-th financial factor. Furthermore, these weights are restricted in such a manner that the sum of absolute values of λ_f (for all f = 1, .., h) is unity. Consequently, (1) estimates each weight by a percentile expression, so that we can examine which weight is important or not in terms of group classification. The weight restriction is known as "normalization."

Sign of the unknown variable (s): The first stage identifies the existence of an overlap by $s^* \geq 0$ on optimality of (1). An opposite case ($s^* < 0$) indicates no overlap.

Model (1) has the following reformulation because we cannot solve (1) directly.

$$\min \left\{ s \left| \begin{array}{l} \sum_{f=1}^{h} \left(\lambda_f^+ - \lambda_f^-\right) z_{fj} - d + s \geq 0,\ j \in G_1, \\ \sum_{f=1}^{h} \left(\lambda_f^+ - \lambda_f^-\right) z_{fj} - d - s \leq -\varepsilon,\ j \in G_2, \\ \sum_{f=1}^{h} \left(\lambda_f^+ + \lambda_f^-\right) = 1, \\ \zeta_f^+ \geq \lambda_f^+ \geq \varepsilon \zeta_f^+ \ (\text{for all } f), \\ \zeta_f^- \geq \lambda_f^- \geq \varepsilon \zeta_f^- \ (\text{for all } f), \\ \zeta_f^+ + \zeta_f^- \leq 1 \ (\text{for all } f), \\ \lambda_f^+ + \lambda_f^- \geq \varepsilon \ (\text{for all } f), \\ d \,\&\, s : \text{URS}, \\ \zeta_f^+ \,\&\, \zeta_f^- : \text{binary, and all other} \\ \qquad \text{variables} \geq 0. \end{array} \right. \right\} \quad (2)$$

At the end of the first stage, we need to separate all observations into subsets. To explain the classification, let $\lambda_f^* \left(= \lambda_f^{+*} - \lambda_f^{-*}\right)$, d^* and s^* be an optimal solution of (2). Then, the original data set (G) is classified into the following subsets $G = G_1 \cup G_2 = C_1 \cup D_1 \cup C_2 \cup D_2$

where $C_1 = \left\{ j \in G_1 \middle| \sum_{f=1}^{h} \lambda_f^* z_{fj} > d^* + s^* \right\}$, $C_2 = \left\{ j \in G_2 \middle| \sum_{f=1}^{h} \lambda_f^* z_{fj} < d^* - s^* \right\}$, $D_1 = G_1 - C_1$ and $D_2 = G_2 - C_2$. Based upon the result, we determine that observations in C_1 belong to G_1 and those of C_2 belong to G_2 because those observations locate clearly above or below an overlap identified from (2). The two subsets ($D_1 \cup D_2$) consist of the overlap whose observations are not yet classified in the first stage.

Stage 2: In a case when two groups have an overlap, we need to reclassify all the observations in the overlap ($D_1 \cup D_2$), because the group membership of these observations is still unknown and needs to be determined. Mathematically, the second stage has the following formulation:

$$\min \left\{ \sum_{j \in D_1} y_j + \sum_{j \in D_2} y_j \middle| \begin{array}{l} \sum_{f=1}^{h} \left(\lambda_f^+ - \lambda_f^-\right) z_{fj} - c + M y_j \geq 0,\ j \in D_1, \\ \sum_{f=1}^{h} \left(\lambda_f^+ - \lambda_f^-\right) z_{fj} - c - M y_j \leq -\varepsilon,\ j \in D_2, \\ \sum_{f=1}^{h} \left(\lambda_f^+ + \lambda_f^-\right) = 1, \\ \zeta_f^+ \geq \lambda_f^+ \geq \varepsilon \zeta_f^+ \ (\text{for all } f), \\ \zeta_f^- \geq \lambda_f^- \geq \varepsilon \zeta_f^- \ (\text{for all } f), \\ \zeta_f^+ + \zeta_f^- \leq 1 \ (\text{for all } f),\ \sum_{f=1}^{h} \left(\zeta_f^+ + \zeta_f^-\right) = h, \\ c : \text{URS}, \zeta_f^+, \zeta_f^- \ \& \ y_j : \text{binary}, \\ \text{and all other variables} \geq 0. \end{array} \right\} \quad (3)$$

Here, the binary variable (y_j) counts the number of observations classified incorrectly. The objective function minimizes the number of misclassifications. We need to prescribe a large number (M) in (3). A discriminant score (c) is newly incorporated into (3) as an unknown unrestricted variable. The new score for the second stage substitutes for the previous discriminant score (d) in (2) for the first stage.

Non-Zero Condition (*NZC*): A possibility, to which we need to pay attention, is a simultaneous occurrence of $\lambda_f^+ = 0$ and $\lambda_f^- = 0$ in (3). The occurrence of zeros in the paired variables does not imply a mathematical problem as the computational result of (3). However, to control the number of positive estimates of λ_f^+ and λ_f^-, we may add the following Non-Zero Condition (NZC) in (3):

$$\textit{NZC:} \sum_{f=1}^{h} \left(\zeta_f^+ + \zeta_f^-\right) = p. \quad (4)$$

Here, p-pairs avoid a simultaneous occurrence of $\lambda_f^+ = 0$ and $\lambda_f^- = 0$.

After obtaining an optimal solution on λ_f^* and c* from (3), the second stage classifies observations in the overlap as follows: if $\sum_{f=1}^{h} \lambda_f^* z_{fj} \geq c^*$, then the j-th observation belongs to G_1 or if $\sum_{f=1}^{h} \lambda_f^* z_{fj} \leq c^* - \varepsilon$, then it belongs to G_2. Thus, all the observations in G are classified in either G_1 or G_2.

4. AN APPLICATION TO JAPANESE MANUFACTURING INDUSTRY

Japanese manufacturing industries are often classified into "Industry of the 20th Century" and "Industry of the 21st Century". This study empirically compares between influences of R&D expenditure on the financial performance of the two Japanese manufacturing industries. In this study, the industry of the 20th century includes (a) nonferrous industry, (b) general machinery industry and (c) transportation machinery & apparatuses industry. Meanwhile, the industry of the 21st century includes (a) electrical machinery & apparatuses industry and (b) precision machinery & apparatuses industry.

The research has the following two business assertions:

Business Assertion 1: The R&D expenditure enhances the corporate values of Japanese manufacturing firms.

Business Assertion 2: The influence of the R&D expenditure depends upon the type of Japanese manufacturing industry.

To investigate the above assertions, this study sampled the financial factors of 357 manufacturing firms from 2004 to 2007 in accordance with the Japanese accounting period. The total sample size is 1071 (= 3 annual periods x 357 firms). Hereafter, this study refers to the industry of the 20th century as Type I and the industry of the 21st century as Type II. Type I includes 219 firms so that the total sample number of Type I is 657 (= 3 annual periods x 219 firms). Type II includes 138 firms so that the total sample number of Type II is 414 (= 3 annual periods x 138 firms).

The criterion to separate the two groups is Tobin's q, or so-called "simple q", which corresponds to (the market value of common equity – the book value of common equity + the total assets) / the total assets at the end of each fiscal period. See [24] and [25]. G1 consists of firms with high q and G2 consists of firms with low q.

This study uses six financial factors for the proposed financial analysis. First, R&D I (R&D Intensity): R&D expenditure divided by total revenue (%). Second, NITR (Ratio of net income to total revenue): net income divided by total revenue (%). Third, LISE (Ratio of liability with interest to shareholder's equity): total liability with interest divided by shareholder's equity (%). Fourth, Gror1 (Growth rate of total revenue on 1 year): (total revenue in this period – total revenue in the previous period) / total revenue in this period (%). Fifth, Exec (Ratio of executive shareholdings to total shares): executive shareholdings divided by total shares (%). Sixth, DPR (Dividend payout ratio): total dividend divided by revenue before tax (%).

Table 1 summarizes resulting parameter estimates of DEA-DA and logit regression. This study uses the logit regression as a methodological alternative of the proposed DEA-DA. The bottom of Table 1 indicates the classification rate (i.e., the number of observations classified correctly divided by the number of total observations). As summarized in Table 1, DEA-DA outperforms the logit regression in terms of the classification rates. For example, DEA-DA has 76.52% and 78.37% as the classification rates for Type I and Type II, respectively. Meanwhile, the logit regression has 69.82% and 69.71% for the two cases. This study does not deny the importance of the logit regression. Rather, this study wants to convey a message that an empirical study needs to consider the existence of a methodological bias. Hence, we use the results from the two methods as our empirical evidences.

Table 1: Results of DEA-DA and Logit estimation

Industries		Type I Industry			Type II Industry		
Models		DEA-DA		Logit	DEA-DA		Logit
		1st Stage	2nd Stage		1st Stage	2nd Stage	
		Weights / Parameters					
Variables	Discriminant Score / Constant	-0.035	-0.056	-0.028	-0.185	-0.013	0.262
	R&D I	0.107	0.207	1.070*** (0.268)	0.091	0.102	0.932*** (0.229)
	NITR	0.022	0.408	0.690*** (0.172)	0.161	0.256	1.338*** (0.329)
	LISE	-0.129	0.205	0.186 (0.046)	0.038	0.000	0.245 (0.060)
	Gror1	-0.036	0.027	0.378*** (0.094)	0.555	0.347	1.571 (0.386)
	Exec	-0.038	-0.154	-0.108 (-0.027)	-0.070	0.000	-0.256 (-0.063)
	DPR	-0.667	-0.000	-1.676* (-0.419)	-0.086	0.295	-0.268 (-0.066)
Classification Rate	High q Firms	81.10%		65.24%	69.23%		66.35%
	Low q Firms	71.95%		74.39%	87.50%		73.08%
	Total Firms	76.52%		69.82%	78.37%		69.71%

Note: the number within ( ) indicates a marginal effect of each parameter measured by logit regression. For example, the marginal effect (0.229) of R&D I indicates that if the R&D Intensity increases in one unit, the probability of an observation classified into G1 (group with high q) increases in 22.9 percentage point.

This study finds the following results from Table 1: First, R&D I and NITR have same signs between DEA-DA and logit regression in the two industries. Exec and DPR have same signs between the two methods in Type I. LISE and Gror1 have same signs between the two methods in Type II. Second, DEA-DA has high weights on NITR, R&D I, LISE and Exec in Type I. The logit regression identifies a statistical significance on NIOR and R&D I among those variables. Third, DEA-DA has high weights on Gror1, DPR, NITR and R&D I in Type II. The logit regression identifies a statistical significance on NIOR and R&D I among them.

Business Implications: The three empirical findings have the business implication that NITR and R&D I have a positive influence on the corporate value (measured by Tobin's q) of Type I (Industry of the 20th Century) and Type II (Industry of the 21st Century). Thus, this study confirms the first business assertion that the R&D expenditure is important for the two Japanese manufacturing industries. Furthermore, the importance of R&D expenditure in Type I is larger than that of Type II. Thus, this study confirms the second business assertion. In addition, it is important to note that the high level of growth and dividend enhances the corporate value of the Type II industry.

5. CONCLUSION AND FUTURE EXTENSIONS

This study investigated the influence of R&D expenditure on the corporate value of Japanese manufacturing industry. DEA-DA was used as the methodology for the study. This research finds that the R&D expenditure is important for the Japanese manufacturing industries to be competitive in a global market. However, the positive influence of R&D expenditure on corporate value is larger in Type I than that of Type II because Type I is a technologically matured industry and Type II is an industry in which technology innovations have been constantly occurring. As a result, the R&D expenditure is directly associated with the performance enhancement of the Type I industry compared to the case with the Type II industry. In this sense, the Type II is a high risk and high return industry.

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