A Multicriteria Discrimination Method for the Prediction of Financial Distress: The Case of Greece*

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Financial distress prediction is an essential issue in finance. Especially in emerging economies, predicting the future financial situation of individual corporate entities is even more significant, bearing in mind the general economic turmoil that can be caused by business failures. The research on developing quantitative financial distress prediction models has been focused on building discriminant models distinguishing healthy firms from financially distressed ones. Following this discrimination approach, this paper explores the applicability of a new non–parametric multicriteria decision aid discrimination method, called M.H.DIS, to predict financial distress using data concerning the case of Greece. A comparison with discriminant and logit analysis is performed using both a basic and a holdout sample. The results show that M.H.DIS can be considered as a new alternative tool for financial distress prediction. Its performance is superior to discriminant analysis and comparable to logit analysis (JEL G33, C61, C44, C25).

Keywords: discrimination, financial distress, mathematical programming, multi-criteria decision aid.

I. Introduction

Financial distress diagnosis and prediction has been a focal point of issue in financial analysis during the past three decades due to its severe

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*A first draft of the M.H.DIS method was presented at the EURO XVI Conference, Innovation and Quality of Life, Brussels, July 12–15, 1998.

(*Multinational Finance Journal*, 1999, vol. 3, no. 2, pp. 71–101)

effects on the operation of a firm, its environment (credit institutions, stockholders, investors, etc.), and even on the whole economy of a country. Bearing also in mind the recent vulnerability of the international banking system and the globalization of the economy, it is apparent that financial distress prediction is now an even more essential process within the financial risk assessment framework. This remark applies to all countries, with different levels of economic development, both the most and the least developed ones. However, although an economically developed country may have the necessary strengths and infrastructure to resist and ultimately overcome the turmoil caused by the distress of an individual corporate entity, emerging economies are considerably much more vulnerable to such a risk. Therefore, special focus should be placed on developing, testing, and implementing early warning systems of financial distress prediction of corporate entities in emerging economies.

Financial distress is a broad concept that comprises several situations in which firms face some form of financial difficulty. The most common terms used to describe these situations are "bankruptcy," "failure," "insolvency," and "default." These terms provide a slightly different definition connected with the specific interest or condition of the firms under examination. Altman (1993) provided a complete description and definition of these terms. Bankruptcy identifies mostly with the legal definition of financial distress. As pointed out by Theodossiou et al. (1996), many financially distressed firms never file for bankruptcy, due to acquisition or privatization, whereas healthy firms often file for bankruptcy to avoid taxes and expensive lawsuits. Altman (1993) defines failure as the situation where "the realized rate of return on invested capital, with allowances for risk consideration, is significantly and continually lower than prevailing rates of similar investments." This is a term of an economic sense and does not indicate the discontinuity of a firm. Insolvency also illustrates a negative performance indicating liquidity problems. Insolvency in a bankruptcy sense indicates negative net worth. Finally, default refers to a situation where a firm violates a condition of an agreement with a creditor and can cause a legal action.

To overcome the differences among these situations, the more general term "financial distress" will be used throughout this article to describe the situation where a firm cannot pay its creditors, preferred stock shareholders, suppliers, etc., or the firm goes bankrupt according to the law. All these situations result in a discontinuity of the firm's operations, unless proper measures are employed.

The advances in quantitative areas, such as statistics, operations research, and artificial intelligence provide financial researchers with several approaches to develop discrimination models for financial distress prediction. Several researchers influenced by the work of Altman (1968) on the application of discriminant analysis, explored ways to develop more reliable financial distress prediction models. Logit analysis, probit analysis, and the linear probability model are the most commonly used techniques as alternatives to discriminant analysis (Ohlson [1980]; Zavgren [1985]; Casey, McGee, and Stinkey [1986]; Peel [1987]; Keasey, McGuinness, and Short [1990]; Skogsvik [1990]). Theodossiou (1991) performed a comparison of these three approaches and concluded that both logit and probit provide similar results that outperform the linear probability model. These approaches have been applied in the Greek context in several studies over the past two decades (Grammaticos and Gloubos [1984]; Gloubos and Grammaticos [1988]; Papoulias and Theodossiou [1992]; Theodossiou and Papoulias [1988]; Theodossiou [1991]; and Vranas [1991, 1992]).

Despite the fact that these approaches have been proposed to overcome discriminant analysis's limitations (Eisenbeis [1977]), they are not free of limitations and problems, such as the difficulty in explaining their parameters, especially in the multi-group case, and the difficulties often encountered in the parameters' estimation procedure (Altman et al. [1981]). Other statistical and econometric methods that have been applied in financial distress prediction include survival analysis (Luoma and Laitinen [1991]), catastrophe theory (Scapens, Ryan, and Flecher [1981]), the recursive partitioning algorithm (Frydman, Altman, and Kao [1985]), and the CUSUM model, a dynamic extension of discriminant analysis that combines discriminant analysis with an optimal stopping rule (Theodossiou [1993]).

Recently the performance of alternative non-parametric approaches has been explored to overcome the aforementioned shortcomings of the statistical and econometric techniques. Among these alternative approaches one can cite mathematical programming (Gupta, Rao, and Bagghi [1990]), expert systems (Messier and Hansen [1988]), artificial neural networks (Altman, Marco, and Varetto [1994]), machine learning and rough sets (Slowinski and Zopounidis [1995]; Dimitras et al. [1999]), and multicriteria decision aid (Zopounidis [1987, 1995];

Zopounidis and Dimitras [1998]).[1]

The main purpose of this paper is to investigate the potential and the applicability of a new discrimination method in financial distress prediction, based on the methodological framework of multicriteria decision aid (MCDA). The M.H.DIS method that is proposed (Multi-Group Hierarchical Discrimination; Zopounidis and Doumpos [2000]) employs a hierarchical discrimination procedure to determine the class into which the firms under consideration belong. The method leads to the development of a set of additive utility functions, which are used to decide upon the classification of each firm into a specific group. The method is compared to discriminant analysis and logit analysis using a sample of Greek industrial firms as in Dimitras et al. (1999).

This article uses a more recent sample of firms than other Greek financial distress articles. Furthermore, the development of the financial distress prediction models is not based solely on statistical analysis regarding the significance of the financial ratios used; there has also been a collaboration with an experienced expert credit analyst of a leading Greek commercial bank. This enables the development of financial distress prediction models that are not exclusively based on the statistical properties of the sample used, but furthermore, they consider the decision-making policy of actual financial/credit analysts. This is a significant issue, bearing in mind that the ultimate users of financial distress prediction models are financial/credit analysts. In that regard, any financial distress prediction model that is developed must be consistent with the procedures and the policy used by financial/credit analysts, whose judgment on the significance of financial ratios cannot be substituted by statistical measures.

The rest of the article is organized as follows. Section II outlines the basic characteristics, features, mathematical formulation, and operation of the M.H.DIS method. Section III discusses the data used in the application along with some preliminary findings. Section IV presents the results obtained from the application of the M.H.DIS method, while in section V these results are compared to discriminant and logit analysis. Finally, section VI concludes the article, summarizes the main

1. For a comprehensive review of the existing methodologies in financial distress prediction, one may refer to the recent works of Keasey and Watson (1991), Dimitras, Zanakis, and Zopounidis (1996), and Altman and Saunders (1998).

findings of this research, and proposes some future research directions.

II. The Multi-Group Hierarchical Discrimination Method

A. Problem Formulation

Let $A=(a_1, a_2, ..., a_N)$ be a set of N firms described (evaluated) along a set of m attributes $X=(x_1, x_2, ..., x_m)$. The objective is to classify the firms into q *ordered* classes $C_1 \succ C_2 \ldots \succ C_q$ (C_1 is preferred to C_2, C_2 is preferred to C_3, etc.). In financial distressed prediction, usually two classes of firms are considered, i.e., the healthy ones and the distressed ones. The healthy firms constitute class C_1 (in the subsequent discussion this class is denoted as H-healthy), while financially distressed firms constitute class C_2 (in the subsequent discussion this class is denoted as D-distressed). Since healthy firms are in a better position than the distressed ones, class H is considered to be better than class D (class H is preferred to D; i.e. $H \succ D$). The subsequent presentation of the M.H.DIS method will focus on this two-group case. Details on the use of the method in addressing multi-group discrimination problems can be found in Zopounidis and Doumpos (2000).

In discriminating among the two classes of firms, it is assumed that the decision maker's preferences are monotonic functions on the attributes' scale. This assumption implies that as the evaluation of a firm on an attribute x_i, that is negatively related to financial distress, increases, the decision regarding the classification of this firm into the class of healthy firms is more favorable to a decision regarding its classification into the class of financially distressed firms. For example, as the profitability of a firm increases, an analyst will be more favorable in classifying the firm as healthy, rather than classifying it as financially distressed. A similar implication is also made for all attributes x_i that are positively related to financial distress.

The decision regarding the classification of the firms is based on the development of two additive utility functions, characterizing the healthy and the financially distressed firms, respectively. The form of these utility functions is the following:[2]

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2. These expressions are equivalent to $U^H(X)=\sum_{i=1}^{m} u_i^H(x_i)$ and $U^D(X)=\sum_{i=1}^{m} u_i^D(x_i)$ if $u_i^H(x_i)$ and $u_i^D(x_i)$ are not normalized in the interval [0,1].

$$U^H(X) = \sum_{i=1}^{m} h_i u_i^H(x_i) \text{ and } U^D(X) = \sum_{i=1}^{m} d_i u_i^D(x_i),$$

where, $u_i^H(x_i)$ and $u_i^D(x_i)$ are marginal (partial) utility functions of the attribute vector related to the healthy and distressed outcome normalized between 0 and 1, and $U^H(X)$ and $U^D(X)$ are global utilities (similar to the discriminant scores) expressed as weighted average of marginal utilities, X= (x_1, x, …, x_m), and the weights h_i and d_i sum-up to 1, i.e. $\sum h_i = 1$ and $\sum d_i = 1$. If the global utility of a firm according to the utility function $U^H(X)$ is higher than the global utility estimated according to the utility function $U^D(X)$, then the firm is considered to be healthy. Otherwise, if the global utility of a firm according to the utility function $U^D(X)$ is higher than the global utility estimated according to the utility function $U^H(X)$, then the firm is considered to be financially distressed. After model development is completed, the decision maker can investigate possible modifications of this classification rule that provide better predictions.

The estimation of the additive utility functions in M.H.DIS is accomplished through mathematical programming techniques. More specifically, two linear programs and one mixed-integer program are solved to estimate optimally the two additive utility functions $U^H(X)$ and $U^D(X)$, both in terms of the total number of misclassifications and the "clarity" of the obtained classification. Details on the estimation procedure are presented in the Appendix.

III. Data and Preliminary Findings

A. Sample selection

The data used in this article are composed of the basic and the holdout sample as in Dimitras et al. (1999). The basic sample, consisting of 80 Greek industrial firms, is used to develop a financial distress prediction model, while the holdout sample, consisting of 38 firms, is used to evaluate the predictability of the model developed.

The sampling procedure employed for the construction of the basic sample is the following. Initially, using the reports of the Greek

TABLE 1. List of Financial Ratios

Notation	Financial ratio
NI/*GP*	Net Income / Gross Profit
GP/*TA*	Gross Profit / Total Assets
NI/*TA*	Net Income / Total Assets
CA/*CL*	Current Assets / Current Liabilities
QA/*CL*	Quick Assets / Current Liabilities
TD/*TA*	Total Debt / Total Assets
NW/*NFA*	Net Worth / Net Fixed Assets
CL/*TA*	Current Liabilities / Total Assets

statistical organization ICAP, the financial statements of 40 firms that faced financial distress during the period 1986-1990 were collected. Among these 40 firms, 6 faced financial distress in 1986, 10 in 1987, 9 in 1988, 11 in 1989, and 4 in 1990. For each of the financially distressed firms, financial data are collected for up to 5 years prior to financial distress. For instance, for the firms that faced financial distress in 1986, the collected financial data span the period 1981-1985. Consequently, the basic sample actually spans the period 1981-1989. To facilitate the presentation and discussion of the results, each year prior to financial distress will be denoted as year –1, year –2, year –3, year –4 and year –5. Year –1 refers to the first year prior to financial distress (e.g., for the firms that faced financial distress in 1986, year –1 refers to 1985); year –2 refers to the second year prior to financial distress (e.g., for the firms that faced financial distress in 1986, year –2 refers to 1984), etc. The financially distressed firms operate 13 different industrial sectors including food firms, textile firms, chemical firms, transport, wear and footwear industries, metallurgical industries, etc. The financially distressed firms are matched with 40 healthy firms of approximately the same size (i.e., similar total assets and number of employees) from the same business sectors.

The holdout sample is compiled in a similar fashion; it includes 19 firms from 9 different industrial sectors that faced financial distress during the period 1991-1993. The financial data of these firms are collected for up to three years prior to financial distress, thus the holdout sample spans the period 1988-1992. The financially distressed firms in the holdout sample are matched by size with 19 healthy firms for the same three-year period.

Table 1 presents the financial variables (ratios) used in this article.

The selection of these ratios is based on the availability of financial data, their relevance to financial distress prediction as reported in the international financial literature, as well as on the experience of an expert credit manager of a leading Greek commercial bank.

ICAP reports gross profit as the difference between sales and their cost. Net income is measured before taxes. Net fixed assets are adjusted to fixed assets after subtracting depreciation. Net worth is considered as the sum of stockholder's equity and reserve capital, while total debt is the sum of long-term debt and current liabilities (long-term debt includes provisions for future expenses). Current assets are reported as the sum of inventories, accounts payable, securities, and cash. Quick assets are considered as the sum of the latter three (accounts payable, securities, and cash). Finally, the figures reported by ICAP on total assets are the sum of net worth and total debt, or equivalently, the sum of net fixed assets and current assets.

B. Preliminary findings

Among the financial ratios considered, net income/gross profit, gross profit/total assets, and net income/total assets are related to the profitability of the firms. High values of these ratios correspond to profitable firms. Thus, all of these ratios are negatively related to the probability of financial distress. The expert credit analyst with whom there has been collaboration has suggested the ratio net income/gross profit as a profit margin measure of firms. Note that this ratio actually combines the ratios of gross profit margin (gross profit/sales) and net profit margin (net income/sales). The financial ratios gross profit/total assets and net income/total assets have already been used in previous studies on financial distress prediction both in Greece and internationally (Frydman, Altman, and Kao [1985]; Gloubos and Grammaticos [1988]; Messier and Hansen [1988]; Theodossiou [1991]; Vranas [1992]; Gupta, Rao, and Bagghi [1990]). The financial ratios current assets/current liabilities and quick assets/current liabilities involve the liquidity of the firms and are commonly used to predict financial distress (Altman, Hadelman, and Narayanan [1977]; Gloubos and Grammaticos [1984]; Zavgren [1985]; Keasey, McGuinness, and Short [1990]; Theodossiou [1991]; Theodossiou et al. [1996]). Firms having enough liquid assets (current assets) are in better liquidity position and are more capable in meeting their short-term obligations to their creditors. Thus, these two ratios are negatively related to the probability of financial distress. Finally, the last three ratios (total debt/total assets, net worth/net fixed assets, current liabilities/total assets) are related to the solvency (financial leverage) of the firms. The ratios total debt/total assets and current liabilities/total assets have been used in the past in several studies on financial distress prediction (Ohlson [1980]; Zavgren [1985]; Gloubos and Grammaticos [1988]; Platt and Platt [1990]; Theodossiou [1991]; Theodossiou et al. [1996]). High values on these ratios indicate severe indebtedness, in which case the firms have to generate more income to meet their obligations and repay their debt. Consequently both ratios are positively related to the probability of financial distress. The ratio net worth/net fixed assets, a working capital ratio, has been suggested by the expert credit analyst to examine the way that the firms finance their investments in fixed assets. Firms that manage to finance their investments in fixed assets through net worth will need less additional credit, thus retaining their debt burden under control. Thus, this ratio is negatively related to the probability of financial distress.

Of course the different industry sectors included both in the basic and the holdout sample are expected to have different financial characteristics, thus presenting differences in the financial ratios that are employed. Some researchers have examined the industry effects on financial distress prediction models by adjusting the financial ratios to industry averages. However, the findings are controversial. Platt and Platt (1990) concluded that an adjusted financial distress prediction model performs better than an unadjusted one, while Theodossiou (1987) did not find any essential difference or improvement. Furthermore, Theodossiou et al. (1996) argue that adjusted industry or time models implicitly assume that failure rates for businesses are homogenous across industries and time, an assumption which is hardly the case. On this basis, no adjustment to the industry sector is being made on the financial ratios.

Table 2 presents the results of a *t*-test regarding the differences in the means of financial ratios for the healthy and the financially distressed firms. The test is performed only on the basic sample (5 years). The results indicate that the differences in the means of most ratios between the two groups of firms are statistically significant at the 1% level. The financial ratio net income/gross profit (*NI*/*GP*) is consistently insignificant at the 1% level throughout the five years. With regard to this ratio it should be noted that its high mean value for the financially distressed firms in year –2 as well as the negative mean

TABLE 2. Test for the Differences in the Means of Financial Ratios for Each Group of Firms in the Basic Sample

Financial Ratios		Year –1	Year –2	Year –3	Year –4	Year –5
	Healthy	.3261	.3189	.2061	.2080	–.0454
NI/*GP*	Distressed	–1.7478	.6656	–5.5369	–4.0253	–.9718
	t-value	(2.18)*	(–.57)***	(1.87)**	(1.72)**	(1.25)***
	Healthy	.3088	.3015	.2999	.2810	.3131
GP/*TA*	Distressed	.1630	.1935	.1792	.1961	.2192
	t-value	(3.33)	(2.59)*	(2.74)	(1.89)**	(1.38)***
	Healthy	.1067	.1024	.0773	.0867	.0894
NI/*TA*	Distressed	–.1399	–.0824	–.0833	–.0432	–.0265
	t-value	(5.98)	(5.27)	(4.45)	(5.24)	(4.27)
	Healthy	1.7519	1.7479	1.6687	1.6220	1.5701
CA/*CL*	Distressed	.9025	.9713	.9512	1.0297	1.0754
	t-value	(5.46)	(5.36)	(5.21)	(4.28)	(3.22)
	Healthy	1.0289	.9452	.9460	.8837	.8728
QA/*CL*	Distressed	.5758	.6095	.5612	.6049	.5896
	t-value	(4.31)	(3.80)	(4.68)	(3.35)	(3.25)
	Healthy	.5840	.5937	.5955	.6041	.6006
TD/*TA*	Distressed	1.0196	.9374	.9126	.8076	.7617
	t-value	(–5.78)	(–5.05)	(–4.28)	(–4.12)	(–3.63)
	Healthy	2.6271	2.5764	2.6688	2.9144	2.4635
NW/*NFA*	Distressed	–.3330	1.2411	.5842	.7641	.8760
	t-value	(3.84)	(1.14)***	(3.07)	(2.99)	(3.00)
	Healthy	.4965	.4949	.4971	.5100	.5094
CL/*TA*	Distressed	.8521	.7774	.7595	.6696	.6126
	t-value	(–4.22)	(–3.61)	(–3.15)	(–2.68)	(–1.94)**

Note: Parentheses include the *t*-values for testing the null hypothesis that the means of the financial ratios in the two groups of firms are equal.* Statistically insignificant at the 1% level . **Statistically insignificant at the 5% level.***Statistically insignificant at the 10% level.

value for the healthy firms in year –5 are both due to the existence of outlier cases. The ratio gross profit/total assets (*GP*/*TA*) is statistically insignificant in years –2, –4 and –5 (at the 1% level). Theodossiou (1991) has also found this ratio to be insignificant in one of the years that he considered in his study. Other ratios that are occasionally insignificant include net worth/net fixed assets (*NW*/*NFA*) and current liabilities/total assets (*CL*/*TA*). According to these results, it is decided not to include in the further analysis the ratio net income/gross profit which is found insignificant throughout the considered period.

Except for the statistical significance of the financial ratios, another issue that is of major importance in developing financial distress prediction models through statistical and econometric techniques, is the multicollinearity among the financial ratios. The correlation analysis results presented in table 3 indicate that the majority of the considered financial ratios is significantly correlated at the 5% level, except for ratio net worth/net fixed assets, whose correlation with all the other ratios is limited. The existing correlation poses multicollinearity problems on the application of discriminant and logit analysis, leading to unstable and difficult-to-explain parameter estimates. The higher correlations are evident between the quick and the current ratio, as well as between the ratios total debts/total assets and current liabilities/total assets. Between these two pairs of ratios, it is decided to retain in the further analysis the quick ratio and the ratio total debts/total assets. The quick ratio is not affected by the inventories' turnover and consequently it provides a more reliable measure of the liquidity of the firms compared to the current ratio. The ratio of total debts/total assets constitutes a global measure of the firms' debt burden considering both long-term debts and current liabilities. Thus, it is preferred over the ratio current liabilities/total assets.

The subsequent subsections present in detail the results of the M.H.DIS method, discriminant analysis, and logit analysis in financial distress prediction using the two samples of firms described above.

IV. Results Obtained Through the M.H.DIS Method

The data of the basic sample regarding the first year prior to financial distress are used to develop the financial distress prediction models. In the case of the M.H.DIS method two additive utility functions are developed, since there are only two groups of firms (healthy and financially distressed). The procedure leading to the development of these utility functions proceeds in the following way. Initially LP1 is solved to determine an initial pair of utility functions to explore whether it is possible to classify correctly all firms in year –1 of the basic sample used for model development. According to the developed utility functions, two firms are misclassified, one healthy classified as distressed and one distressed classified as healthy. This solution is optimal in terms of the total classification error function *EC'*(cf. Appendix). Then, beginning from the solution of LP1, MIP is solved to examine whether it is possible to find an alternative pair of utility

TABLE 3. Correlation Analysis

	NI/GP	*GP/TA*	*NI/TA*	*CA/CL*	*QA/CL*	*TD/TA*	*NW/NFA*	*CL/TA*
NI/GP	1	.0714	.2242*	.0957*	.0856	–.2300*	.0205	–.2315*
GP/TA		1	.4204*	.1531*	.1959*	–.1565*	–.0328	–.0290
NI/TA			1	.3780*	.3545*	–.6265*	.0423	.5208
CA/CL				1	.8329*	–.5954*	.0217	–.6109
QA/CL					1	–.4865*	–.0859	–.5058*
TD/TA						1	–.0253	.8806*
NW/NFA							1	.0090
CL/TA								1

Note: *Statistically significant at the 5% level.

TABLE 4. Financial Ratios' Weights Estimated Through the M.H.DIS Method

	LP-MIP		LP2	
	U^H	U^D	U^H	U^D
GP/TA	28.58%	52.92%	30.78%	7.83%
NI/TA	.91%	11.15%	11.47%	70.59%
QA/CL	47.39%	34.35%	.79%	.79%
TD/TA	.79%	.79%	56.13%	14.67%
NW/NFA	22.33%	.79%	.83%	6.13%

functions that will classify correctly either of the two firms misclassified by LP1. In this application, the solution of MIP concluded that this is not possible. Thus, the utility functions developed by LP1 and the classification of the firms remain unchanged. Finally, beginning with the solution of MIP, LP2 is employed to find a pair of utility functions, that do not change the obtained classification, but maximizes the minimum difference *d* between healthy and distressed firms (cf. Appendix). This leads to a new pair of utility functions, which differ from the ones initially developed through LP1. Table 4 presents the weights of the financial ratios in the utility functions obtained through LP1, MIP and LP2.

The utility function U^H characterizes the healthy firms, while the utility function U^D characterizes the financially distressed firms. This pair of utility functions used for financial distress prediction purposes is the one developed by the LP2. Formally, these functions are the following:

$$U^H(X) = .3078u^H(GP/TA) + .1147u^H(NI/TA)$$

$$+ .0079u^H(QA/CL) + .5613u^H(TD/TA) + .0083u^H(NW/NFA),$$

$$U^D(X) = .0783u^D(GP/TA) + .7059u^D(NI/TA)$$

$$+ .0079u^D(QA/CL) + .1467u^D(TD/TA) + .0613u^H(NW/NFA).$$

The differences in the weights of the financial ratios in the two utility functions can be explained as follows. Consider, for example, the ratio gross profit/total assets (*GP*/*TA*). Its weight in the utility function U^H is 30.78%, while its weight in the utility function U^D is only 7.83%. This significant difference indicates that, while higher values of gross profit/total assets are a significant characteristic of healthy firms, low values do not necessarily indicate financial distress. Actually, the ratios that characterize the distressed firms are the profitability ratio of net income/total assets (*NI*/*TA*) and, to a smaller extent, the solvency ratio of total debts/total assets (*TD*/*TA*). The latter ratio is a significant factor in describing/identifying the healthy firms, followed by gross profit/total assets (*GP*/*TA*) and net income/total assets (*NI*/*TA*). These results indicate that profitability and solvency are the two main distinguishing characteristics of healthy and financially distressed firms, at least for the case of Greece. Figure 1 presents the marginal utility functions of the five financial ratios in the two additive utility functions.

The classification of the firms as healthy and financially distressed for both the basic and the holdout sample, according to the financial distress prediction model developed through the M.H.DIS method, are illustrated in table 5. After the development of the two aforementioned additive utility functions, there has been a further investigation regarding the classification rule that provided the best results on the basis of the basic sample. Using a procedure similar to the one used to determine the optimal cut-off point in discriminant analysis, it was found that the best classification rule was to classify a firm as healthy if $U^H - U^D > .121$, otherwise classify the firm as distressed.

In the results presented in table 5, the total classification error is computed as the average of the type I and type II error. Of course, the total cost of misclassification is a function of the a priori probabilities and costs of misclassification. The cost associated with the type I error (classification of a financially distressed firm as healthy) is usually higher than the cost associated with the type II error (classification of a healthy firm as financially distressed). However, the a priori probability that a firm belongs to the financially distressed group is considerably lower than the probability that a firm belongs to the healthy group. In this regard, the assumption that both types of error contribute equally to the total misclassification cost is not an unreasonable one (for more details on the manipulation of the probabilities and the costs associated with the type I and II errors, see Theodossiou et al. [1996] and Bardos [1998]).

The obtained results are indicative of the efficiency of the M.H.DIS method. The classification error of the developed model does not exceed 22.5%, even five years prior to financial distress in the basic

Place Figure Gross Profits/Total Assets

Place Figure Net Income/Total Assets

Place Figure Quick Assets/Total Liability

FIGURE 1.—Marginal Utility Functions in the Financial Distress Prediction Model Developed Through the M.H.DIS Method.

Place Figure Total Debt/Total Assets

Place Figure Net Worth/Net Fixed Assets

FIGURE 1.— (Continued)

sample. In the holdout sample, the classification error ranges between 28.95% and 42.11%. The increase in the classification error in the holdout sample is not surprising, since it consists of different firms, and furthermore it involves a different time period.

As far as the two individual error types are concerned, it is apparent that in the results of the M.H.DIS method, the type I error is higher than the type II error, except for years –1 and –2 in the holdout sample. This indicates that the developed financial distress prediction model characterizes better the healthy firms than the financially distressed ones. This is not surprising, bearing in mind the fact that the process that leads to financial distress is a dynamic one. In the beginning of this

TABLE 5. Classification Results Obtained Through the M.H.DIS Method

	Basic Sample					Hold-out Sample		
	Year –1	Year –2	Year –3	Year –4	Year –5	Year –1	Year –2	Year –3
Type I error	2.50%	20.00%	20.00%	25.00%	25.00%	21.05%	36.84%	47.37%
Type II error	2.50%	2.50%	12.50%	17.50%	20.00%	36.84%	42.11%	36.84%
Total error	2.50%	11.25%	16.25%	21.25%	22.50%	28.95%	39.47%	42.11%

process, the financial characteristics of financially distressed firms are often similar to the financial characteristics of healthy firms (Theodossiou [1993]). As the financial distress process evolves, the financial position of distressed firms deteriorates gradually, and consequently their characteristics become more distinguishable as opposed to the healthy firms. On the contrary, healthy firms generally have a stable, good financial performance throughout a specific time period. Thus, it is generally easier to identify the healthy firms from the financially distressed ones.

Comparison with Discriminant Analysis and Logit Analysis

Discriminant analysis (*DA*) can be considered as the first approach to take into account multiple factors (variables) in discriminating among different groups of objects. *DA* is a multivariate statistical technique that leads to the development of a linear discriminant function maximizing the ratio of among-group to within-group variability, assuming that the variables follow a multivariate normal distribution and that the dispersion matrices of the groups are equal. Clearly, both of these assumptions pose a significant problem on the application of *DA* in real-world situations, since they are difficult to meet. The selection of *DA* for comparison purposes in this case study was decided upon the popularity of the method among financial researchers in addressing financial classification problems, such as financial distress prediction.

Logit analysis (*LA*) is an alternative parametric approach to *DA* that has been widely used in financial distress prediction to overcome *DA*'s limitations (multivariate normality and equality in dispersion matrices among groups). *LA* provides the probability of occurrence of an outcome described by a dichotomous (or polytomous) dependent variable using coefficients of the independent variables. The developed *LA* model has the form of the cumulative logistic probability function $F(\alpha+\beta X_i)=\dfrac{1}{1+e^{-(\alpha+\beta X_i)}}$. In this article, $F(\alpha+\beta X_i)$ is defined as the probability for a firm i to be healthy, given the vector of independent variables X_i. Based on this probability, a firm is classified as healthy or financially distressed, using a "cutoff" probability. Maximum likelihood estimation procedures are employed to determine the parameters α and β. The consideration of *LA* in this comparative study complements the obtained results, since its advantages make it more appealing in

TABLE 6. Financial Distress Prediction Models Developed Through DA and LA

	DA	*LA*
GP/TA	.4462	–4.7252
	(1.97)	(–1.23)
NI/TA	.6586	57.9741
	(2.29)*	(2.78)*
QA/CL	.2102	–3.0594
	(1.91)	(–1.12)
TD/TA	–.1419	–14.5585
	(–.74)	(–2.34)*
NW/NFA	.0159	.1886
	(1.10)	(.41)
Constant term	–.1673	13.7814
	(–.76)	(2.08)*

Note: Parentheses include *t*–values. * Significant at the 5% level

financial distress prediction than *DA*.

Both *DA* and *LA* are applied following the same methodology that is used for the development of the financial distress prediction model through the M.H.DIS method. More specifically, the first year prior to financial distress for the basic sample is used for model development purposes. Since the aim of the application of *DA* and *LA* is to compare them with the M.H.DIS method, it is decided not to use a stepwise procedure for selecting the financial ratios that will be included in the developed financial distress prediction models. Instead, all of the considered financial ratios are incorporated in the developed models so that the comparison between *DA*, *LA*, and the M.H.DIS method is performed on the same basis.

Table 6 presents the financial distress prediction models developed through *DA* and *LA* (constant terms and coefficients of financial ratios).

In all prediction models, financial ratios with positive signs are negatively related to financial distress and financial ratios with negative signs are positively related to financial distress. In the developed *DA* model, all ratios have the expected sign. On the contrary, in the *LA* model, the ratios gross profit/total assets (*GP*/*TA*) and quick assets/current liabilities (*QA*/*CL*) have a reverse sign from the one that should be expected.To apply both models in predicting financial distress in years –2 to –5 of the basic sample and in the three years of the holdout sample, a cutoff point/probability must be determined that

TABLE 7. Error Rates for the DA and LA Models in the Basic Sample

Cut-off	Type I Error					Type II Error					Total Error				
point	Year –1	Year –2	Year –3	Year –4	Year –5	Year –1	Year –2	Year –3	Year –4	Year –5	Year –1	Year –2	Year –3	Year –4	Year –5
A. *DA*															
–.009	17.5	27.5	30	27.5	32.5	12.5	12.5	22.5	17.5	22.5	15	20	26.25	22.5	27.5
–.007	17.5	27.5	27.5	27.5	30	12.5	12.5	22.5	17.5	22.5	15	20	25	22.5	26.25
–.005	17.5	25	25	27.5	30	12.5	12.5	22.5	17.5	22.5	15	18.75	23.75	22.5	26.25
–.003	17.5	22.5	25	27.5	27.5	12.5	17.5	22.5	20	22.5	15	20	23.75	23.75	25
–.001	17.5	22.5	25	25	27.5	12.5	17.5	22.5	20	25	15	20	23.75	22.5	26.25
B. *LA*															
Cut-off prob.															
.76	2.5	12.5	17.5	20	35	15	5	17.5	20	17.5	8.75	8.75	17.5	20	26.25
.77	2.5	10	17.5	20	32.5	15	7.5	20	20	17.5	8.75	8.75	18.75	20	25
.78	2.5	10	17.5	17.5	32.5	15	7.5	20	20	17.5	8.75	8.75	18.75	18.75	25
.79	2.5	10	17.5	17.5	30	15	10	22.5	22.5	20	8.75	10	20	20	25
.80	2.5	10	17.5	17.5	30	15	10	22.5	22.5	20	8.75	10	20	20	25

TABLE 8. Error Rates for the DA and LA Models in the Holdout Sample

	Type I Error			Type II Error			Total Error		
Cut-off point	Year –1	Year –2	Year –3	Year –1	Year –2	Year –3	Year –1	Year –2	Year –3
A. *DA*									
–.009	31.58	47.37	57.89	42.11	36.84	26.32	36.84	42.11	42.11
–.007	31.58	47.37	57.89	42.11	36.84	26.32	36.84	42.11	42.11
–.005	31.58	42.11	57.89	42.11	36.84	26.32	36.84	39.47	42.11
–.003	31.58	42.11	57.89	47.37	36.84	26.32	39.47	39.47	42.11
–.001	31.58	42.11	57.89	47.37	36.84	26.32	39.47	39.47	42.11
B. *LA*									
Cut-off prob.									
.76	21.05	42.11	63.16	36.84	36.84	26.32	28.95	39.47	44.74
.77	21.05	42.11	63.16	36.84	36.84	26.32	28.95	39.47	44.74
.78	21.05	42.11	63.16	36.84	36.84	26.32	28.95	39.47	44.74
.79	21.05	42.11	57.89	36.84	36.84	31.58	28.95	39.47	44.74
.8	21.05	42.11	57.89	36.84	36.84	31.58	28.95	39.47	44.74

minimizes the total cost of misclassification. As has been discussed in the application of the M.H.DIS method, the total cost of misclassification is considered as the average of the type I and type II errors. Tables 7 and 8 present the estimates for error rates of the financial distress prediction models developed through *DA* and *LA* for different values of the cut-off point (*DA*) and the cut-off probability (*LA*).[3]

Regarding the basic sample, the best performance (in terms of the total error) of the developed *DA* model is obtained when the cutoff point is set equal to –.005 (cf. table 7). However, the performance of the *DA* model (for the basic sample) is inferior to the results of the M.H.DIS method. Concerning the *LA* model, the best performance is obtained when the cutoff probability is set equal to .78. The results of this model are comparable to the ones of M.H.DIS. In particular, the *LA* model provides lower total classification error than M.H.DIS in years –2 and –4, while M.H.DIS is superior in the rest of the years (–1, –3 and –5).

In the holdout sample (table 8), M.H.DIS and *LA* outperform *DA* in year –1. In year –2 all methods provide the same total classification error, while in year –3 M.H.DIS and *DA* provide the best results.

In terms of the type I and type II error, *DA* is always inferior compared to M.H.DIS, expect for years –2 and –3 in the holdout sample (type II error). In the basic sample, the *LA* model generally provides lower type I error rates and higher type II error rates than M.H.DIS. However, in the holdout sample its type I error is significantly high, especially in years –2 and –3, while the type II decreases to lower levels than M.H.DIS.

V. Concluding Remarks and Future Perspectives

The primary objective of this article was to investigate the applicability and the performance of the M.H.DIS multicriteria decision aid method in financial distress prediction as opposed to well-known methods, namely discriminant and logit analysis. The application that was presented has indicated that this new non-parametric approach can be successfully applied in one of the most complex problems in corporate finance, which is of major academic and practical interest particularly

3. The cutoff point and cutoff probability are determined using the basic sample, since this is the sample used for model development.

in the context of an emerging economy. The comparison with discriminant and logit analysis pronounces the remark that this new approach constitutes a competitive alternative to existing parametric financial distress prediction techniques.

Furthermore, it should be noted that, since M.H.DIS is a non–parametric classification method, it does not make any assumptions on the distributions of the variables that are used to predict financial distress. This feature enables the incorporation of qualitative variables into the analysis of financial distress. In this way, improved financial distress prediction models can be developed, bearing in mind the fact that the poor performance on some financial ratios is actually the symptom of financial distress rather than its cause. In most cases, financial distress is caused by inappropriate management, lack of organization, inability to meet the challenges of the competitive business environment, changes in the trend of the business sector within which firms operate, etc. Such significant factors have a direct impact on the probability of financial distress, but they are non-quantifiable, while their distributional properties (they do not follow a normal distribution) make them inappropriate for common *DA* models. On the other hand, *LA* models are not based on distributional assumptions. In order to incorporate such qualitative variables into these models, one should quantify the qualitative scale used for their measurement. However, such a transformation of a qualitative scale into a quantitative one changes the nature of qualitative variables and the ways that are perceived by the financial/credit analyst who is the ultimate user of financial distress prediction models. On the contrary, the utility-based approach that is employed in the M.H.DIS method enables the analyst to retain the qualitative scale in the analysis, thus taking full advantage of the information that qualitative variables entail.

Of course the possible application fields of the M.H.DIS method are not restricted to financial distress prediction. The method can also be applied to several other fields of financial management, including credit risk assessment, portfolio selection, company acquisitions, credit card evaluation, evaluation of bank branches efficiency, venture capital investments, country risk, etc. The application of the method to study these financial problems, along with the comparison with multivariate statistical and econometric techniques, with other MCDA methods, and other classification techniques from the fields of mathematical programming, neural networks, machine learning, etc., would lead to a more comprehensive examination of the performance of the M.H.DIS method.

Appendix:

Mathematical programming formulations for the estimation of the utility functions in the M.H.DIS method

The mathematical programming formulations used in M.H.DIS to estimate optimally the utility functions for the classification of the firms as healthy or financially distressed include two linear programs and a mixed-integer one. The objective of the estimation procedure is twofold: to identify a pair of utility functions that minimizes the overall misclassification cost and maximizes the "clarity" of the classification. The latter objective is similar to the among-groups variance maximization in discriminant analysis. These two objectives are addressed through a lexicographic approach. First, the minimization of the overall misclassification cost is pursued and, then the maximization of the "clarity" of the classification is sought.

The outcome of this procedure is a pair of additive utility functions U^H and U^D that accommodates these two objectives. The former characterizes the healthy firms, while the latter characterizes the distressed ones. Both utility functions are normalized between 0 and 1, while the marginal utilities of the financial ratios x_i are monotone functions on the financial ratios' scale as follows: If x_i is positively related to financial distress, then $u_i^H(x_i)$ is a decreasing function and $u_i^D(x_i)$ is an increasing function. Otherwise, if x_i is negatively related to financial distress, then $u_i^H(x_i)$ is an increasing function and $u_i^D(x_i)$ is a decreasing function. These properties (normalization and monotonicity) are incorporated as constraints to all mathematical programming formulations presented below.

Pursuing the first objective on the development of the two utility functions (i.e., minimization of the overall misclassification cost) requires the minimization of the following function:

$$EC = w_H \times (\text{Type II error}) + w_D \times (\text{Type I error}) = w_H \left(\frac{1}{N_H} \sum_{i=1}^{N_H} I_{i,H} \right) + w_D \left(\frac{1}{N_D} \sum_{i=1}^{N_D} I_{i,D} \right), \tag{A1}$$

where, N_H and N_D are the number of healthy and distressed firms in the model development sample, while $I_{i,H}$ and $I_{i,D}$ are integers representing the classification status of each firm (0 indicates correct classification, whereas 1 indicates misclassification). The weighting parameters w_H and w_D should be defined on the basis of the cost of misclassifications and the a-priori probabilities of default: $w_H = \pi_H C_H$, $w_D = \pi_D C_D$, such that $w_H + w_D = 1$ and $w_H \geq 0$, $w_D \geq 0$, where π_H and π_D are the a-priori probabilities associated with the healthy and distress groups and C_H and C_D are the misclassification costs associated with the type II and type I, error respectively. The definition of w_H and w_D depends upon the decision maker. Generally, the cost of misclassifying a distressed firm is higher than the cost of misclassifying a healthy one (i.e., $C_D > C_H$). However, the a-priori probability that a firm is distressed is smaller than the a-priori probability that a firm is healthy (i.e., $\pi_H < \pi_D$). Therefore, setting $w_H = w_D = .5$ is a reasonable choice.

The development of a pair of utility functions that minimize the overall misclassification cost (1) (let $EC_{\min}$ denote the minimum overall misclassification cost) requires the use of mixed-integer programming techniques. However, solving mixed-integer programming formulations in cases where there are many integer variables is a computationally intensive procedure. Even in cases of samples consisting of 50 firms (i.e., 50 integer variables) the development of the optimal classification rule could be a highly time-consuming process if there is a significant degree of group overlapping. To address this issue, M.H.DIS initially employs an alternative error function EC' that approximates the overall classification cost:

$$EC' = w_H\left(\frac{1}{N_H}\sum_{i=1}^{N_H} e_{i,H}\right) + w_D\left(\frac{1}{N_D}\sum_{i=1}^{N_D} e_{i,D}\right). \tag{A2}$$

The terms in the parentheses in (2) are surrogates of the type II and type I errors. In this error function EC', the classification error for a healthy firm i is denoted as $e_{i,H}$, whereas the classification error for a distressed firm i is denoted as $e_{i,D}$. Both these classification errors are positive real numbers representing the magnitude of the violation of the classification rules employed during model development:

$$\begin{aligned} e_{i,H} &= \begin{cases} U^D(X_i) - U^H(X_i), \text{ if } U^H(X_i) < U^D(X_i) \\ 0, \text{ otherwise} \end{cases}, \\ e_{i,D} &= \begin{cases} U^H(X_i) - U^D(X_i), \text{ if } U^D(X_i) < U^H(X_i) \\ 0, \text{ otherwise} \end{cases}. \end{aligned} \tag{A3}$$

The minimization of the function EC' is performed through the solution of the following mathematical programming problem:

*LP*1*: Minimization of the overall classification error*

$$\text{Min } EC' = w_H\left(\frac{1}{N_H}\sum_{i=1}^{N_H} e_{i,H}\right) + w_D\left(\frac{1}{N_D}\sum_{i=1}^{N_D} e_{i,D}\right).$$

Subject to:

$$U^H(X_i) - U^D(X_i) + e_{i,H} \geq s, i = 1,2,\ldots,N_H, \tag{A4}$$

$$U^D(X_i) - U^H(X_i) + e_{i,D} \geq s, i = 1,2,\ldots,N_D, \tag{A5}$$

$$e_{i,H} \geq 0, e_{i,D} \geq 0.$$

LP1 is a simple linear programming problem that can be easily solved even for large data sets. In constraints (4)-(5) s is a small positive constant used to ensure the strict inequalities presented in definition (3) of the error variables $e_{i,H}$ and $e_{i,D}$.

Solving LP1 yields an initial pair of utility functions that minimizes the total classification error function EC' (let $EC'_{\min}$ denote the minimum total classification error obtained after solving LP1). If these utility functions classify correctly all firms, then all the error variables $e_{i,H}$ and $e_{i,D}$ will be zero. Therefore, in such a case $EC'_{\min}$ = $EC_{\min}$ = 0. However, this is not always the case. Often, it is not possible to classify correctly all firms in order to achieve a zero overall cost of misclassification (i.e., $EC'_{\min} \neq 0 \Leftrightarrow EC_{\min} \neq 0$). In such cases, bearing in mind the fact that EC' is an approximation of EC, it becomes apparent that the utility functions corresponding to $EC'_{\min}$ will not necessarily yield the minimum overall misclassification cost $EC_{\min}$. For example, consider that in a sample consisting of four firms (two healthy and two distressed), the utility functions obtained after solving LP1 lead to two misclassified firms i (healthy) and j (distressed) with the following classification errors: $e_{i,H}$=.2 and $e_{j,D}$=.1. In this case $EC'_{\min}$ =.075 and EC=.5 (assuming w_H=w_D=.5). However, an alternative solution that classifies j correctly (i.e., $e_{j,D}$=0) but assigns a misclassification error to firm i equal to .5 is clearly preferred. In this case EC'=.125>$EC'_{\min}$, but $EC_{\min}$=.25<EC. Thus, through this simple example it becomes apparent that it could be possible to find an alternative pair of utility functions than the one developed through LP1 that yields a classification error $EC' \geq EC'_{\min}$, but provides a lower overall misclassification cost. In M.H.DIS this possibility is explored through the solution of MIP.

MIP: Minimization of the overall mis-classification cost

$$\text{Min } EC = w_H\left(\frac{1}{N_H}\sum_{i=1}^{N_H^{mis}} I_{i,H}\right) + w_D\left(\frac{1}{N_D}\sum_{i=1}^{N_D^{mis}} I_{i,D}\right).$$

Subject to:

$$\left.\begin{array}{l} U^H(X_i) - U^D(X_i) \geq s, i = 1,2,\ldots,N_H^{cor} \\ U^D(X_i) - U^H(X_i) \geq s, i = 1,2,\ldots,N_D^{cor} \end{array}\right\}, \tag{A6}$$

$$\left.\begin{array}{l} U^H(X_i) - U^D(X_i) + I_{i,H} \geq s, i = 1,2,\ldots,N_H^{mis} \\ U^D(X_i) - U^H(X_i) + I_{i,D} \geq s, i = 1,2,\ldots,N_D^{mis} \end{array}\right\}, \tag{A7}$$

$I_{i,H}$, $I_{i,D}$ integers.

Starting with the initial utility functions developed through LP1, MIP explores the possibility of modifying these utility functions so that the overall misclassification cost is minimized. This minimization is performed without changing the correct classifications obtained by LP1 (i.e., all firms correctly classified by the initial pair of utility functions are retained as correct classifications; cf. constraints (6)). The overall misclassification cost considered in the objective of MIP, is a function of the number of misclassifications. The integer error variables $I_{i,H}$ and $I_{i,D}$ are used as indicators of the correct classification of the firms. Note that these error variables are not associated to all firms, but only to the ones misclassified by LP1 (constraints (7)). The number of healthy firms misclassified by LP1 is denoted as N_H^{mis}, whereas denotes the number of distressed firms misclassified by LP1. Similarly, N_H^{cor} and N_D^{cor} denote the number of healthy and distressed firms, respectively, classified correctly by LP1. All of these correct classifications are retained (constraints (6)). Since, in most cases, the number of firms misclassified by LP1 (N_H^{mis} + N_D^{mis}) is a small part of the whole sample, the number of integer variables in MIP is small, thus facilitating its easy solution.

The pair of utility functions developed after solving initially LP1 and then MIP is optimal in terms of the overall misclassification cost. However, the ultimate purpose of the utility functions developed through M.H.DIS is to be used for financial distress prediction. Of course, it is difficult to ensure high predictability during model development. However, utility functions that clearly distinguish healthy from financial distressed firms are expected to have higher predictability than utility functions that yield the same overall misclassification cost but achieve a "marginal" discrimination during model development. Traditional discriminant analysis addresses this issue through the maximization of the among-groups variance. In M.H.DIS, the measure employed to assess the distance between the two groups of firms according to the developed discrimination model (utility functions) is the minimum difference *d* between the global utilities of the correctly classified firms identified after solving MIP (d>0).

$d = \min\{d_1, d_2\}$ where,

$$d_1 = \min_{i=1,2,\ldots,N_H^{cor'}} \{U^H(X_i) - U^D(X_i)\},$$

and,

$$d_2 = \min_{i=1,2,\ldots,N_D^{cor'}} \{U^D(X_i) - U^H(X_i)\}.$$

($N_H^{cor'}$ and $N_D^{cor'}$ denote the number of healthy and distressed firms, respectively, classified correctly by MIP).

The maximization of *d* is achieved through the solution of the following linear programming formulation (LP2).

LP2: Maximization of the minimum distance

Max *d*

Subject to:

$$\left.\begin{array}{l} U^H(X_i) - U^D(X_i) - d \geq s, i = 1,2,\ldots,N_H^{cor'} \\ U^D(X_i) - U^H(X_i) - d \geq s, i = 1,2,\ldots,N_D^{cor'} \end{array}\right\}, \tag{A8}$$

$$\left.\begin{array}{l} U^H(X_i) - U^D(X_i) \leq 0, i = 1,2,\ldots,N_H^{mis'} \\ U^D(X_i) - U^H(X_i) \leq 0, i = 1,2,\ldots,N_D^{mis'} \end{array}\right\}, \tag{A9}$$

$$d \geq 0.$$

LP2 begins with the utility functions obtained after solving MIP. $N_H^{mis'}$ and $N_D^{mis'}$ denote the number of healthy and distressed firms, respectively, misclassified by MIP. LP2 seeks to modify the utility functions developed through MIP in order to maximize the distance measure *d*. All firms misclassified by the utility functions developed through MIP are retained as misclassified. Thus, the utility functions developed through LP2 do not affect the overall misclassification cost, since all correct classifications and misclassifications resulted after solving MIP are retained [constraints (8) and (9), respectively].

The pair of utility functions obtained after solving LP2 is the one used for financial distress prediction purposes.

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