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BANKRUPTCY PREDICTION MODEL WITH ZETA$_C$ OPTIMAL CUT-OFF SCORE TO CORRECT TYPE I ERRORS*

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This research examines financial ratios that distinguish between bankrupt and non-bankrupt companies and make use of those distinguishing ratios to build a one-year prior to bankruptcy prediction model. This research also calculates how many times the type I error is more costly compared to the type II error. The costs of type I and type II errors (cost of misclassification errors) in conjunction to the calculation of prior probabilities of bankruptcy and non-bankruptcy are used in the calculation of the ZETA$_c$ optimal cut-off score. The bankruptcy prediction result using ZETA$_c$ optimal cut-off score is compared to the bankruptcy prediction result using a cut-off score which does not consider neither cost of classification errors nor prior probabilities as stated by Hair et al. (1998), and for later purposes will be referred to Hair et al. optimum cutting score. Comparison between the prediction results of both cut-off scores is purported to determine the better cut-off score between the two, so that the prediction result is more conservative and minimizes expected costs, which may occur from classification errors.

This is the first research in Indonesia that incorporates type I and II errors and prior probabilities of bankruptcy and non-bankruptcy in the computation of the cut-off score used in performing bankruptcy prediction. Earlier researches gave the same weight between type I and II errors and prior probabilities of bankruptcy and non-bankruptcy, while this research gives a greater weigh on

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type I error than that on type II error and prior probability of non-bankruptcy than that on prior probability of bankruptcy.

This research has successfully attained the following results: (1) type I error is in fact 59,83 times more costly compared to type II error, (2) 22 ratios distinguish between bankrupt and non-bankrupt groups, (3) 2 financial ratios proved to be effective in predicting bankruptcy, (4) prediction using $ZETA_c$ optimal cut-off score predicts more companies filing for bankruptcy within one year compared to prediction using Hair et al. optimum cutting score, (5) Although prediction using Hair et al. optimum cutting score is more accurate, prediction using $ZETA_c$ optimal cut-off score proved to be able to minimize cost incurred from classification errors.

Keywords: bankruptcy prediction; legal bankruptcy; stock based insolvency; type I error; type II error; $ZETA_C$ optimal cut-off score

Introduction

Uncertain condition in Indonesian's economy nowadays put firms in the risk of experiencing financial distress or even bankruptcy. Prediction error towards the continuity of an entity in the future can cause severe loss. There are two types of errors that may occur, namely Type I error and Type II error. Type I error means rejecting a true null hypothesis and Type II error means fail to reject a false null hypothesis. Type I error in hypothesis testing is shown by or the level of significance. This is the probability of rejecting the true null hypothesis. Type II error is shown by b, means the probability of failing to reject a false null hypothesis. If the prediction performed is a prediction about whether a firm is to file for bankruptcy or not in the future, then Type I error can be comprehended as predicting a firm not to file for bankruptcy while in fact the firm does file for bankruptcy. Type II error on the contrary predicts a firm to file for bankruptcy while in fact the firm does not file for bankruptcy. Although both types of prediction errors inflict a certain amount of financial loss, Type I errors inflict a greater financial loss compared to that of Type II errors. Therefore, prediction requires a cut-off score, which classifies a company in to either the bankrupt group or the non-bankrupt group with a minimum cost of classification errors.

Hitherto, there are no theories that affirm definitely what financial ratios must be used in predicting bankruptcy. Ratios used in predicting bankruptcy can vary among different researches. It is merely the subjective consideration of the researcher followed by statistical verification on financial ratios applied.

This research uses the formula of Altman (1977) to calculate the $ZETA_c$ optimal cut-off score. Financial ratios developed by Machfoedz (1994) are used to distinguish between bankrupt and non-bankrupt groups. The distinguishing financial ratios are eventually opted based on statistical testing to build the prediction model. The prediction model in this research is developed in the same way of Avianti (2000) by applying the two-group discriminant analysis.

A cut above or advantage of this research is that it incorporates the Type I and II errors and prior probabilities of bankruptcy and non-bankruptcy in the computation of $ZETA_c$ optimal cut-off score, thus, the prediction result is expected to be able to minimize cost incurred from classification errors compared to the prediction result using the cut-off score as the one stated in Hair et al. (1998), and for later purposes will be referred to Hair et al. optimum cutting score.

Problem Formulation and Research Objective

This research investigates what financial ratios distinguish between bankrupt and non-bankrupt companies and makes use of those distinguishing ratios to build a one-year prior to bankruptcy prediction model. This research also calculates how many times Type I error is more costly compared to Type II error. The costs of Type I and Type II errors (cost of misclassification errors) in conjunction to the calculation of prior probabilities of bankruptcy and non-bankruptcy is used in the calculation of the $ZETA_c$ optimal cut-off score. The bankruptcy prediction result using *ZETAc* optimal cut-off score is then compared to the bankruptcy prediction result using Hair et al. optimum cutting score to determine the better cut-off score to apply in terms of less costly in predicting bankruptcy.

Research Limitations

Some limitations exist in this research, which are:

1. Previous researches, in general, define bankruptcy as legal bankruptcy and this definition is applied as the dependent variable (Beaver 1966/1968; Altman 1968; Ohlson 1980; Zain 1994; etc). However, this research applies the stock based insolvency definition and uses negative equity as its dependent variable (Avianti 2000). In consequence, the term bankruptcy in this research means having a negative equity.
2. The determination of the cost of classification errors is obtained from a sample of two state owned banks (Bank BNI and Bank BRI) and two private banks (Bank Niaga and Bank Danamon) for the year of 1996, 1997, 1999, 2000. Thus, there is a probability that the computation of the cost of classification errors does not provide external validity.
3. No hold out sample is employed in this research; hence, prediction is limited to the original sample. The reason for not employing the hold out sample is because of time con-

sideration and lack of data, which until the point this research was concluded was not available.

Research Benefits

This research is deemed to have the following benefits:

1. This research is expected to become a basis to opt for the cut-off score in conducting bankruptcy prediction.
2. This research is expected to benefit stakeholders of a company in assessing and making short-term decisions regarding the company.
3. This research is expected to become a subject of information and/or consideration for developments in further researches.
4. This research is expected to start and open a discourse of research in Indonesia regarding bankruptcy prediction that incorporates cost of classification errors and prior probabilities of bankruptcy and non-bankruptcy.

Theoretical Basis

Ratios are among the most popular and widely used tools of financial analysis (Bernstein and Wild 1998). The result of the calculation of financial ratios obtained from a set of financial statements is able to determine the economic ability of a company (Avianti 2000). Machfoedz (1994) in Avianti (2000) states that financial ratios can be used to predict future events by associating financial ratios with economic phenomena. Prediction is conducted to reduce future uncertainties. Financial ratios can be used to predict future bankruptcy by developing a bankruptcy prediction model. The model developed in this research is purported to represent financial conditions of companies and to predict whether companies will file for bankruptcy or not (Avianti 2000).

Definitions of Bankruptcy

Bankruptcy can be classified into two categories –stock based insolvency and legal bankruptcy (Avianti 2000). Previous researches apply the legal bankruptcy definition as its dependent variable. The term bankrupt in this research as in (Avianti 2000) applies the stock based insolvency definition. A company is said to be bankrupt (stock based insolvency) if it experiences lack of temporary liquidity and continues to have a larger book value of liabilities than assets, thus, the equity becomes negative (including minority interest in the subsidiary's net assets). In such a circumstance, a company is said to be bankrupt from the equity perspective (Ross et al. 1993, and Brigham and Gapensky 1993 in Avianti 2000). The reason why this definition is employed is that data of publicly held companies in Indonesia that are legally bankrupt are very hard to get hold of, if any. The Commerce Court in Indonesia was formed in 1998 and until the point this research was conducted, there were only very few bankruptcy appeals. Consequently, it is very difficult to find data regarding companies having legally bankrupt status.

According to Act Number 4/1994 an institution is stated to be bankrupt by the judgment of court if the debtor retains two or more creditors and does not pay at least one overdue and collectible debt.

Different researchers often define the term bankruptcy differently and due to certain conditions and limitations thus the term bankrupt employed in this research is companies that have negative equities and for that reason other definitions are not cited in this research.

Previous Literature and Hypotheses Development

There have been two types of bankruptcy prediction studies. The first (e.g., Beaver 1966) looks at the relation between individual accounting numbers or ratios and bankruptcy (the univariate approach). The other uses several ratios to predict bankruptcy (the multivariate approach). The univariate approach uses one ratio at a time to predict failure. It is likely that different ratios reflect different aspects of the firm's financial position, so better predictions can be obtained by using combinations of ratios instead of one ratio. For this reason, the multivariate approach quickly supplanted the univariate approach (Watts and Zimmerman 1986).

Several researches were conducted in the bankruptcy prediction domain (companies predicted do not include banking and financial sector companies) as the followings: Beaver (1966; 1968a; 1968b), Altman (1968; 1973), Altman and Lorris (1976), Altman and McGough (1974), Altman et al. (1977), Deakin (1972), Libby (1975), Blum (1974), Edmister (1972), Wilcox (1973), Moyer (1977), Ohlson (1980), Schiedler (1981), Scott (1981), Dambolena and Khoury (1980), Zmijewski (1984), Mensah (1983), Gentry et al. (1987), Barniv and Raveh (1989), Platt and Platt (1990), Zain (1994), and Avianti (2000).

Beaver (1966) used the univariate approach and the main findings of the research was that accounting data in forms of financial ratios have the ability to predict failure for at least five years prior to the failure. Beaver called this approach as a profile analysis.

Altman (1968) used the multivariate discriminant analysis (MDA) to predict bankruptcy. There was a limitation in Altman's model because the prediction accuracy for predictions over than two years prior to bankruptcy became awfully low compared to the prediction of one and two years prior to bankruptcy.

Altman et al. (1977) also developed a bankruptcy prediction model using the MDA. One distinguishing point of this research amongst others is the determination of the cut-off score. Other bankruptcy prediction researches give the same weight between Type I and Type II errors and prior probabilities of bankruptcy and non-bankruptcy. That approach is in contrast with this research that uses the $ZETA_c$ optimal cut-off score, which gives a greater weight on Type I error than Type II error and prior probability of non bankruptcy than prior probability of bankruptcy. One of Altman's essential findings is that Type I error is 35 times more costly than Type II error. Therefore, the cut-off score must weigh Type I error and Type II error differently.

Ohlson (1980) used the logistic regression analysis and developed 3 bankruptcy prediction models; prediction models for one, two, and one or two years prior to bankruptcy. The sampling method used by Ohlson (1980) was proportional with the population. Ohlson (1980) also considered the publication date of financial statements because other researches assumed that financial statements for the year of bankruptcy were published before bankruptcy filings occurred resulting in overstatement of prediction power.

Avianti (2000) built bankruptcy prediction models using 3 different methods. Each method was used to build 3 bankruptcy prediction models-one year, two years, and three years prior to bankruptcy; hence, 9 models were successfully developed. The methods used to build the models were Linier Discriminant Analysis, Linier Discriminant Analysis combined with Principal Component Analysis, and Logistic Regression. Different financial ratios were employed as the predictor variables for each year and each method. Results showed that the linier discriminant model was superior to the other two methods in performing predictions for one and two years prior to bankruptcy. As for the prediction of 3 years prior to bankruptcy, the logistic regression model was superior to the other two models.

Previous researches have proven that financial ratios can be used to build a bankruptcy prediction model. It has been proven that different sets of data will result in different models (Altman 1968; Altman et al. 1977; Ohlson 1980; Avianti 2000). Since financial ratios differ along with different researches that use different data, it is necessary here to determine what financial ratios differ from bankrupt and non-bankrupt companies according to the data used in this research (prediction can only be conducted if any characteristics of the object being predicted do exist, which in this case the objects are bankrupt and non-bankrupt companies. Thus the characteristics that are expected to differ from bankrupt and non-bankrupt companies are financial ratios of both groups). On the basis of the argument above, the following hypothesis is formulated:

H_1: *Financial ratios differ between bankrupt and non-bankrupt companies.*

If financial ratios that distinguish between bankrupt and non-bankrupt companies exist then those financial ratios will be used to develop a one-year prior to bankruptcy prediction model. This step is performed to further understand whether those finan-

Table 1. Percentage of Correctly Classifying of 7 Bankruptcy Prediction Models using the Multivariate Approach

	Type I Cost= Type II Cost			Type I Cost= 2x Type II Cost			Type I Cost= 20x Type II Cost			Type I Cost= 38x Type II Cost		
	NB	**B**	**TS**	**NB**	**B**	**TS**	**NB**	**B**	**TS**	**NB**	**B**	**TS**
Beaver (1966)	99.7	36.1	98.4	99.2	43.1	98.1	91.8	86.1	91.7	91.8	86.1	91.7
Altman (1968)	99.8	6.9	97.9	99.3	33.3	98.0	88.8	84.7	88.8	83.3	93.1	83.5
Blum (1974)	99.8	18.1	98.9	99.4	38.9	98.2	95.9	77.8	95.6	90.6	87.5	90.1
Altman et al. (1977)	99.8	4.2	97.9	98.9	38.9	97.7	91.4	81.9	91.2	84.0	94.4	84.3
Dambolena&Khoury(1980)	99.7	26.4	98.3	98.9	47.2	97.7	95.7	73.6	95.3	83.7	91.6	83.9
Ohlson (1980)	99.8	8.3	98.0	98.8	40.3	97.7	93.5	84.7	95.3	89.6	93.1	89.7
Zmijewski (1983)	99.7	9.7	98,0	99.3	37.5	98.1	95.5	75.0	95.1	86.0	91.2	86.0

Note: NB : Non-bankrupt companies
B : Bankrupt companies
TS : Total Sample

Source: Zmijewski (1983, Tabel 5 and Table 6): pp.32-33 in Foster (1986) cial ratios can be used to predict bankruptcy beforehand. As a result the following hypothesis is formulated:

H_2: *Financial ratios can be used to predict bankruptcy beforehand.*

Necessary to stress on are researches of Beaver (1966), Altman (1968), Ohlson (1980) and Avianti (2000). Neither of those considered prior probabilities of bankruptcy and non-bankruptcy nor cost of classification errors (cost occurring from Type I and II errors). According to Zmijewski (1983) in Table 1, if Type I error is given a greater weight than Type II error then the percentage of correctly predicting the bankrupt companies also becomes greater, while the percentage of correctly predicting the non-bankrupt companies becomes smaller. An increase of correctly predicting bankrupt companies means that the amount of companies predicted to be non-bankrupt from those companies supposed to be predicted as bankrupt companies becomes smaller. On the contrary, a decrease of correctly predicting non-bankrupt companies means that the amount of companies predicted to be bankrupt from those companies supposed to be predicted as non-bankrupt becomes greater. Thus, giving a greater weight on Type I error than Type II error will predict more companies as bankrupt companies and less companies as non-bankrupt companies. Accordingly, the following hypothesis is formulated:

H_3: *The percentage of predicting bankrupt companies will become larger by giving a greater weight on Type I error than Type II error compared to the percentage of predicting bankrupt companies of a prediction that gives the same weight on Type I and Type II errors.*

The greater the amount of companies predicted to be bankrupt indicate the lesser the amount of Type I errors. Thus, expected cost of classification errors can be minimized since Type I error is much more costly compared to Type II error. Consequently, a model with a cut-off score that gives a greater weight on Type I error than Type II error is better in terms of more cost effective than a model that gives the same weight on Type I and Type II errors. For this reason the following hypothesis is formulated:

H_4: *Bankruptcy prediction with a cut-off score that incorporates prior probability of bankruptcy and non-bankruptcy and Type I and Type II errors will cut costs occurring from prediction errors.*

Research Methodology, Sample, and Data

Sample of Building the Bankruptcy Prediction Model

The sampling method employed in building the bankruptcy prediction model is the matched pair sampling method based on industrial sectors and size of companies. Industrial sectors are determined based on the categories in the Indonesian Capital Market Directory 2000 and 2001, while the size of companies is determined based on the total asset average in accordance with Bapepam's regulation on Foreign Capital Investment/ Domestic Capital Investment) regarding the criteria of sizes of companies. Averages of total assets used to determine the sizes of companies are obtained from the Indonesian Capital Market Directory 2000 and 2001.

Steps in determining sample are as follows:

1. Determine bankrupt companies in years of 1999 and 2000 and trace their financial statements one year back, which are years of 1998 for bankrupt companies of 1999 and 1999 for bankrupt companies of 2000.
2. Determine non-bankrupt companies that match bankrupt companies determined earlier. Non-bankrupt companies are selected using industrial sectors and sizes as the criteria of matched pairs.

The list of bankrupt and non-bankrupt companies used in building the one-year prior to bankruptcy prediction model is shown in Appendix 2.

Sample Used in Determining Prior Probabilities

Prior probabilities of bankruptcy are calculated using the numbers of bankrupt companies divided by total companies listed on the Jakarta Stock Exchange for years of 1996, 1997, 1999, and 2000, while the calculation of prior probabilities of non-bankruptcy is the numbers of non-bankrupt companies divided by total companies listed on the Jakarta Stock Exchange for years of 1996, 1997, 1999, and 2000.

Sample Used in Calculating Cost of Classification Errors (Type I and Type II errors)

The sample of banks used in computing cost of classification errors are Bank BNI, Bank BRI, Bank Niaga, and Bank Danamon. All data used are data from years 1996, 1997, 1999, and 2000. Assuming that banking characteristics in Indonesia are similar, the two state-owned and two private-owned banks aforementioned are expected to represent the whole banking population.

Data from year 1998 are not included in the determination of the $ZETA_c$ optimal cut-off score (calculation of prior probabilities and cost of classification errors) for the reason that in year 1998 the average credit interest rate and the Central Bank Certificate interest rate boosted very high in comparison with previous and subsequent years because of the economic crisis, thus no new loan at that time was given. The unusual high level of interest rate in year 1998 is deemed to be able to distort the calculation of $ZETA_c$ optimal cut-off score.

Identification and Operational Definition and Variables of Prediction Model

This research uses two types of variables that are dependent variables and independent variables. The dependent variables are categorical (non-metric) that are bankrupt companies and non-bankrupt companies. The independent variables used are metric variables that are financial ratios used by Ou and Penman (1989), Machfoedz (1994), and Avianti (2000). Listed in the Appendix 3 are the financial ratios used.

The Bankruptcy Prediction Model

The bankruptcy prediction model is built by using the two-group discriminant analysis because the dependent variables are non-metric and the independent variables are metric.

H_1 is tested by performing the Wilks Lambda test, which is a test of equality of group means of financial ratios of both groups (bankrupt and non-bankrupt). This test is performed to examine whether distinguishing ratios exist between the two groups. The significance level in this research is 5 percent for the F critical value, which means that financial ratios having significance level under 5 percent are ratios that distinguish between bankrupt groups and non-bankrupt groups. If any financial ratio does have a significance value under 5 percent then a discriminant function can be developed.

Subsequently, the financial ratios that distinguish between bankrupt and non-bankrupt groups are selected to come up with the best variate (linier combination) by applying the stepwise selection algorithm. Financial ratios that constitute the best linier combination are the final financial ratios that are going to be used as independent variables in the discriminant function, which is the bankruptcy prediction model. The prediction using the discriminant function is designed to test H_2.

Description of Hair et al. Optimum Cuting Score

A cutting score is necessary in performing prediction using discriminant analysis. A cutting score is the criterion (score) against which individual's discriminant score is judged to determine into which group the individual should be classified. Those entities whose Z scores are below this score are assigned to one group, while those whose scores are above it are classified in the other group (Hair et al. 1998).

According to Hair et al. (1998), the optimal cutting score will differ depending on whether the sizes of the groups are equal or unequal. Since this research applies the matched pair sampling method by which the number of members in each group are equal thus the formula to compute the cutting score or the Hair et al. optimum cutting score is as follow:

$$Z_{CE} = \frac{Z_A + Z_B}{2}$$

where,

Z_{CE} = critical cutting score value for equal group sizes

Z_A = centroid for group A (bankrupt)

Z_B = centroid for group B (non-bankrupt)

Centroid's of each group (Z_A and Z_B) is computed by calculating the average of the *Z* discriminant scores of each group.

Description of ZETA$_c$ *Optimal Cut-Off Score*

ZETAc optimal cutoff score is obtained from the following formula:

$$ZETA_c = \ln \frac{q_1 C_i}{q_2 C_{ii}}$$

where,

q_1 = prior probability of bankruptcy

q_2 = prior probability of non-bankruptcy

C_i = cost of Type I error

C_{ii} = cost of Type II error

Prior probability of bankruptcy (q_1) is computed by dividing the number of bankrupt companies with the total companies listed on JSX for each year. Prior probability of non-bankruptcy (q_2) is computed by dividing the number of non-bankrupt companies with the total companies for each year. Both prior probabilities of bankruptcy and non-bankruptcy are computed for years of 1996, 1997, 1999, and 2000.

Type I error is analogous to that of an accepted loan that defaults and the Type II error to a rejected loan that would have resulted in a successful payoff. Thus, Type I and Type II errors (C_i and C_{ii}) are computed by the following formulas:

$$C_i = 1 - \left(\frac{\text{Amount of loan loses recovered}}{\text{Gross loan loses (charged-off}} \right)$$

Type II (C_{ii}) is computed by the following formula:

$$C_{ii} = r - i$$

r = effective interest rate on the loan, which is computed as follow:

$$r = \left(\frac{LR}{TL} \text{ x ILR} \right) + \left(\frac{LF}{TL} \text{ x ILF} \right)$$

CR = loans given in Rupiah

CF = loans given in Foreign currencies (after converted into Rupiah)

ICR = average interest rate of loans given in Rupiah and Foreign currencies)

TC = total credit distributed (total loans given in Rupiah and Foreign currencies)

i = effective opportunity cost for the bank (one year average of the 30 days Central Bank Certificate interest rate for years 1996, 1997, 1999, and 2000).

The *ZETA$_c$* optimal cut-off score gives a greater weight on Type I error than Type II error and prior probabilities of non-bankruptcy than prior probability of bankruptcy. Type I error is given a greater weight compared to Type II error because Type I error is more costly than Type II error. Prior probability of non-bankruptcy is also given a greater weight than prior probability of bankruptcy since the probability of a company to file for bankruptcy is much more smaller than the probability of a company to not file for bankruptcy.

In the formula above, q_1 is multiplied by C_i to incorporate the cost of Type I error with the probability of bankruptcy to understand the probability of Type I error to occur. Furthermore, q_2 is also multiplied by C_{ii} to incorporate the cost of Type II error with the probability of non-bankruptcy to understand the probability of Type II error to occur. In view of that, $ZETA_c$ optimal cut-off score is a cut-off score used in bankruptcy prediction based on the consideration of probabilities of occurrences of Type I and II errors.

Comparison of the one-year prior to bankruptcy prediction results between predictions using Hair et al. optimum cutting score and predictions using $ZETA_c$ optimal cut-off score is designed to test H_3.

The prediction results between predictions using Hair et al. optimum cutting score and predictions using $ZETA_c$ optimal cut-off score will be different. The differences of the prediction results are difference in the occurrences of Type I and Type II errors by each prediction using different cut-off scores. Therefore, H_4 can be tested.

Research Findings

Described below are the research findings that are organized in a systematically order. The findings are described based on the steps first conducted in the research.

Test of Equality of Group Means of Financial Ratios of Both Groups (Bankrupt and Non-bankrupt)

Result of the test of equality of group means using Wilks Lambda showed that 22 financial ratios among the 47 financial ratios tested have significance levels under 5 percent as shown in Table 2.

Based on the test result below, H_1 that indicated that distinguishing ratios exist between bankrupt and non-bankrupt groups is supported.

Stepwise Selection Algorithm

The stepwise selection algorithm is performed in order to obtain the best variate (linier combination) from the 22 distinguishing financial ratios above, which will be used in the linier discriminant function. Results of the stepwise selection algorithm showed that only two financial ratios, i.e. net worth to total assets (X_{36}) and net worth to total liabilities (X_{47}); are best to be used as independent variables in the discriminant function.

Discriminant Function Built

The Canonical Discriminant Function Coefficient obtained for the one-year prior to bankruptcy prediction can be seen in Table 3.

The one-year prior to bankruptcy prediction model built is as follows:

Table 2. **Significantly Different Financial Ratios between Bankrupt and Non-bankrupt Groups**

Variables	Wilks' Lambda	F	Sig.
Cash to current liabilities (X_1)	0.846	9.801	0.003
Quick assets to current liabilities (X_3)	0.845	9.883	0.003
Current assets to current liabilities (X_4)	0.798	13.695	0.001
Current assets to total liabilities (X_5)	0.809	12.775	0.001
Earnings before taxes to sales (X_9)	0.924	4.445	0.04
Gross profit to sales (X_{10})	0.927	4.258	0.044
Net income to sales (X_{12})	0.924	4.445	0.04
Current assets to total assets (X_{19})	0.909	5.434	0.024
Working capital to total assets (X_{23})	0.748	18.213	0
Total liabilities to current assets (X_{24})	0.765	16.59	0
Operating income to total liabilities (X_{25})	0.868	8.205	0.006
Current liabilities to total assets (X_{26})	0.759	17.18	0
Working capital to total assets (X_{29})	0.748	18.213	0
Quick assets to total assets (X_{31})	0.886	6.944	0.011
Net worth to total assets (X_{36})	0.494	55.346	0
Total liabilities to total assets (X_{38})	0.498	54.401	0
Net income to fixed assets (X_{40})	0.904	5.754	0.02
Earnings before income taxes to total assets (X_{42})	0.761	17.005	0
Net income to total assets (X_{43})	0.719	21.082	0
Sales to current liabilities (X_{44})	0.884	7.069	0.01
Net income to total liabilities (X_{45})	0.819	11.926	0.001
Net worth to total liabilities (X_{47})	0.785	14.758	0

Table 3. **Canonical Discriminant Function Coefficient**

	Function
	1
X36	10.086
X47	-.824
(Constant)	-2.060

Unstandardized coefficients

$$\boxed{Z = -2.060 + 10.086X_{36} - 0.824X_{47}}$$

where,

Z = discriminant index (classification score)

X_{36} = net worth to total assets

X_{47} = net worth to total liabilities

Computation of Hair et al. Optimum Cutting Score

In Appendix 1 the *Z* score for each company has been computed, thus the centroids or the average of *Z* scores for each group can be computed as follows:

Centroid for bankrupt group = -1.247

Centroid for non-bankrupt group = 1.175

Hair et al. optimum cutting score $= \dfrac{-1.247 + 1.175}{2}$

Computation of ZETA$_c$ *Optimal Cut-Off Score*

Table 4 shows the computation of prior probability of bankruptcy (q_1) and prior probability of non-bankruptcy (q_2). Table 4 shows that prior probability of non-bankruptcy is much greater compared to prior probability of bankruptcy. There is a 5.0943 percent of probability of bankruptcy to happen, while the probability of a company to not file for bankruptcy is 94.9058 percent.

Table 5 shows the Type I and Type II errors in metric forms happening in year 1996, 1997, 1999, and 2000 in Bank Niaga, Bank Danamon, Bank BNI, and Bank BRI. From Table 5, how costly Type I error is compared to Type II error can be computed by dividing the average value of C_i with the average value of C_{ii}, hence the result is 59.83 (0.891/0.015).

Table 4. **Computation of Prior Probability of Bankruptcy (q_1) and Non-Bankruptcy (q_2)**

Year	Bankrupt Companies	Non-Bankrupt Companies	Total Companies	q_1	q_2
1996	1	210	211	0.00474	0.99526
1997	15	212	227	0.06608	0.93392
1999	9	225	234	0.03846	0.96154
2000	24	230	254	0.09449	0.90551
Average of q_1 and q_2				0.050943	0.949058

Table 5. **Type I and Type II errors in metric forms of each bank in years of 1996, 1997, 1999, and 2000**

Name of Banks	Year	C_i	C_{ii}
Bank Niaga	1996	0.941	0.012
Bank Danamon	1996	1.000	0.029
Bank BNI	1996	0.749	-0.003
Bank BRI	1996	0.618	0.056
Bank Niaga	1997	0.838	0.045
Bank Danamon	1997	1.000	0.081
Bank BNI	1997	0.748	-0.002
Bank BRI	1997	0.738	0.045
Bank Niaga	1999	0.999	-0.084
Bank Danamon	1999	0.954	-0.050
Bank BNI	1999	0.994	-0.007
Bank BRI	1999	0.983	0.016
Bank Niaga	2000	0.997	-0.015
Bank Danamon	2000	0.985	0.014
Bank BNI	2000	0.979	0.036
Bank BRI	2000	0.738	0.065
Average of C_i dan C_{ii}		**0.891**	**0.015**

Accordingly, the cost incurred by the occurrence of Type I error is 59.83 times more than the cost incurred by the occurrence of Type II error. The considerable cost that must be incurred if prediction errors occur, moreover if Type I error occurs is the reason for the determination of a new cut-off score ($ZETA_c$ optimal cut-off score). Therefore, the $ZETA_c$ optimal cut-off score, where the calculation will be elaborated below, is more tight in predicting meaning that more companies will be predicted as bankrupt while less companies will be predicted as non-bankrupt compared to the prediction result that utilizes Hair et al. optimum cutting score. In other words, prediction using $ZETA_c$ optimal cut-off score is more conservative and more cost effective compared to prediction using Hair et al. optimum cutting score.

Description of the calculation of q_1C_i and q_2C_{ii} for each bank and each year of 1996, 1997, 1999, and 2000 is shown in Table 6.

Based on Table 7, averages of q_1C_i and q_2C_{ii} for years 1996, 1997, 1999, and 2000 respectively are 0.046 and 0.014. Accordingly, $ZETA_c$ optimal cut-off score can be computed as:

$$\boxed{\ln \left[\frac{0.046}{0.014}\right] = 1.19}$$

Table 6. **Calculations of q_1C_i and q_2C_{ii} for Each Bank in Years of 1996, 1997, 1999, and 2000**

Name of Banks	Year	C_i	C_{ii}	q_1	q_2	q_1C_i	q_2C_{ii}
Bank Niaga	1996	0.941	0.012	0.005	0.995	0.004	0.012
Bank Danamon	1996	1.000	0.029	0.005	0.995	0.005	0.029
Bank BNI	1996	0.749	-0.003	0.005	0.995	0.004	-0.003
Bank BRI	1996	0.618	0.056	0.005	0.995	0.003	0.056
	Average of q_1C_i dan q_2C_{ii} for year 1996					***0.004***	***0.023***
Bank Niaga	1997	0.838	0.045	0.066	0.934	0.055	0.042
Bank Danamon	1997	1.000	0.081	0.066	0.934	0.066	0.076
Bank BNI	1997	0.748	-0.002	0.066	0.934	0.049	-0.002
Bank BRI	1997	0.738	0.045	0.066	0.934	0.049	0.042
	Average of q_1C_i dan q_2C_{ii} for year 1997						***0.055***
0.039							
Bank Niaga	1999	0.999	-0.084	0.038	0.962	0.038	-0.081
Bank Danamon	1999	0.954	-0.050	0.038	0.962	0.037	-0.048
Bank BNI	1999	0.994	-0.007	0.038	0.962	0.038	-0.007
Bank BRI	1999	0.983	0.016	0.038	0.962	0.038	0.016
	Average of q_1C_i dan q_2C_{ii} for year 1999						***0.038***
-0.030							
Bank Niaga	2000	0.997	-0.015	0.094	0.906	0.094	-0.013
Bank Danamon	2000	0.985	0.014	0.094	0.906	0.093	0.013
Bank BNI	2000	0.979	0.036	0.094	0.906	0.092	0.032
Bank BRI	2000	0.738	0.065	0.094	0.906	0.070	0.059
	Average of q_1C_i dan q_2C_{ii} for year 2000					***0.087***	***0.023***

Table 7. **Averages of q_1C_i and q_2C_{ii} for Years 1996, 1997, 1999, and 2000**

Year	q_1C_i	q_2C_{ii}
1996	0.004	0.023
1997	0.055	0.039
1999	0.038	-0.030
2000	0.087	0.023
Average	**0.046**	**0.014**

Prediction Results Using both Hair et al. Optimum Cutting Score and ZETA$_c$ *Optimal Cut-Off Score*

The one year prior to the bankruptcy prediction using either Hair et al. optimum cutting score or *ZETA$_c$* optimal cut-off score was performed by means of the “if function”. Bankrupt companies were given a 0 (zero) code while non-bankrupt companies were given a 1 (one) code. For predictions using Hair et al. optimum cutting score, the "if function" made was if the *Z* discriminant score of a company is smaller than –0.036 then that company will be categorized in the bankrupt group (code 0) and if incorrect will be categorized in the non-bankrupt group (code 1). As for the prediction using $ZETA_c$ optimal cut-off score the "if function" made was if the *Z* discriminant score of a company is smaller than 1.198 then that company will be categorized in the bankrupt group (code 0) and if incorrect will be categorized in the non-bankrupt group (code 1).

In Table 8 and 9, prediction results using Hair et al. optimum cutting score and $ZETA_c$ optimal cut-off score are shown respectively (see Appendix 1 for details of prediction results). Table 8 elucidates that 28 bankrupt companies from the overall of 29 bankrupt companies were correctly classified and 24 non-bankrupt companies from the overall of 29 non-bankrupt companies were correctly classified. Thus, the canonical linier discriminant model using Hair et al. optimum cutting score predicted bankrupt companies as many as 33 companies and non-bankrupt companies as many as 25 companies. It also can be concluded that 1 Type I error and 5 Type II errors occurred from the prediction.

Table 8. **Prediction Results with Hair et al. Optimum Cutting Score**

	Classifications	**Predicted Group Membership**		
		Bankrupt	**Non-bankrupt**	**Total**
Count	Bankrupt	28	1	29
	Non-bankrupt	5	24	29
%	Bankrupt	96.5	3.5	100,0
	Non-bankrupt	17.2	82.8	100,0

Table 9. **Prediction results with $ZETA_c$ Optimal Cut-Off Score**

	Classifications	**Predicted Group Membership**		
		Bankrupt	**Non-bankrupt**	**Total**
Count	Bankrupt	29	0	29
	Non-bankrupt	14	15	29
%	Bankrupt	100.0	0.0	100.0
	Non-bankrupt	48.3	51.7	100.0

Table 9 elucidates that 29 bankrupt companies from the overall of 29 bankrupt companies were correctly classified and 15 non-bankrupt companies from the overall of 29 non-bankrupt companies were correctly classified. Thus, the canonical linier discriminant model using $ZETA_c$ optimal cut-off score predicted bankrupt companies as many as 43 companies and non-bankrupt companies as many as 15 companies. It also can be concluded that no Type I error and 14 Type II errors occurred from the prediction.

It is understood from the predictions in Tables 8 and Table 9 that predictions using Hair et al. optimum cutting score is more accurate than predictions using $ZETA_c$ optimal cut-off score. However, predictions using Hair et al. optimum cutting score will imperil more because by putting the same weight between Type I error and Type II error will result in the same opportunity towards the occurrence of Type I error and Type II error. Although more misclassifications were made in predictions using $ZETA_c$ optimal cut-off score, it is more safe or conservative because the chance of a certain company to be predicted as bankrupt becomes greater (from 33 companies predicted as non-bankrupt using Hair et al. optimum cutting to 43 companies predicted as bankrupt using $ZETA_c$ optimal cut-off score) and the chance of a certain company to be predicted as non-bankrupt becomes smaller (from 25 companies predicted as non-bankrupt using Hair et al. optimum cutting to 15 companies predicted as bankrupt using $ZETA_c$ optimal cutoff score).

Therefore, H_2 which stated that financial ratios could be used to predict bankruptcy before hand is supported based on both prediction results using Hair et al. optimum cutting score (28 bankrupt companies from the overall of 29 bankrupt companies were correctly predicted and 24 non-bankrupt companies from the overall of 29 non-bankrupt companies were also correctly predicted) and $ZETA_c$ optimal cut-off score (all bankrupt companies were correctly predicted and 15 non-bankrupt companies from the overall of 29 non-bankrupt companies were also correctly predicted)

H_3 stated that the percentage of predicting bankrupt companies will become larger by giving a greater weight on Type I than Type II errors compared to the percentage of predicting bankrupt companies of a prediction that gives the same weight on Type I and Type II errors. Predictions using Hair et al. optimum cutting score that puts the same weight between Type I errors and Type II errors predict bankrupt companies as many as 33 companies, while predictions using $ZETA_c$ optimal cut-off score that puts a greater weight on Type I errors as much of 59.83 times more costly than Type II errors predict bankrupt companies as many as 44 companies. Consequently, H_3 is also supported.

H_4 stated that predictions using $ZETA_c$ optimal cut-off score would cut expected costs incurred from prediction errors. The cost cut, even though the prediction results were not as accurate as prediction results using Hair et al. optimum cutting score can be seen from the success of $ZETA_c$ optimal cut-off score in deleting 1 Type I error that occurred in the prediction using Hair et al. optimum cutting score. Since Type I error is 59,83 times more costly compared to Type II error, $ZETA_c$ optimal cut-off score that successfully deleted the Type I error even though only as many as 1 Type I error compared to Hair et al. optimum cutting score is better to use in predicting bankruptcy in terms of more cost effective. Although predictions using $ZETA_c$ optimal cut-off score result in more Type II errors compared to predictions using Hair et al. optimum cutting score (from 5 Type II errors using Hair et al. optimum cutting score to 14 Type II errors using $ZETA_c$ optimal cut-off score), predictions using $ZETA_c$ optimal cut-off score is still more cost effective than predictions using Hair et al. optimum cutting score.

The cost cut incurred in use of $ZETA_c$ optimal cut-off score compared to the use of Hair et al. optimum cutting score can be seen as follows:

***ZETAc* Optimal Cut-Off Score**	**Hair et al. Optimum Cutting Score**
Type I error = 0	Type I error = 1
Type II errors = 14	Type II errors = 5

Type I error = 59.83 Type II error
Cost cut = 59.83 Type II error – 9 Type II errors
= 50.83 Type II errors

Based on the calculation above, the use of $ZETA_c$ optimal cut-off score in comparison with the use of Hair et al. optimum cutting score will cut costs as much as 50.83 times of the cost of Type II error. For this reason, predictions of one-year prior to bankruptcy using $ZETA_c$ optimal cut-off score will cut expected costs that may occur from predictions errors and is more conservative in performing predictions. Thus, H_4 has been supported.

Conclusions

In this research, four hypotheses have been developed and tested. The conclusions are as follows:

1. Financial ratios do in fact differ between bankrupt and non-bankrupt companies. The Wilks Lambda statistical test proved that 22 ratios differ significantly in the level of significance of 5 percent between bankrupt and non-bankrupt companies.
2. Two financial ratios from the overall of 22 financial ratios that distinguish bankrupt and non-bankrupt companies can be used as variables

of predictions in the one-year prior to bankruptcy prediction model. The two financial ratios belong to the Leverage and Equity group, which are the net worth to total assets ratio (X_{36}), and the net worth to total liabilities ratio (X_{47}).

3. Predictions using Hair et al. optimum cutting score correctly predicted 28 bankrupt companies from the overall of 29 bankrupt companies and 24 non-bankrupt companies from the overall of 29 non-bankrupt companies. As predictions using $ZETA_c$ optimal cut-off score correctly predicted all bankrupt companies and 15 non-bankrupt companies from the overall of 29 non-bankrupt companies. Thus, this study documents that financial ratios can be used to predict bankruptcy beforehand.
4. Predictions using $ZETA_c$ optimal cut-off score that puts a greater weight on Type I error as much as 59.83 times more costly than Type II error and a greater weight on prior probability of non-bankruptcy (94.9058%) than prior probability of bankruptcy (5.0943%) predicted bankrupt companies as many as 43 companies from the overall sample of 58 companies and predicted 15 non-bankrupt companies from the overall sample of 58 companies. The predictions using Hair et al. optimum cutting score predicted bankrupt companies as many as 33 companies from the overall sample of 58 companies and predicted 25 non-bankrupt companies from the overall sample of 58 companies.

   From the one-year prior to bankruptcy prediction results, it can be concluded that the use of $ZETA_c$ optimal cut-off score although not as accurate as predictions using Hair et al. optimum cutting score is still better to use in terms of more conservative. In view of that a chance of a certain company to be predicted as bankrupt becomes greater and as non-bankrupt becomes smaller. In other words, the probability of occurrences of Type I errors are minimized.
5. The use of $ZETA_c$ optimal cut-off score in comparison with the use of Hair et al. optimum cutting score will cut costs as much as 50.83 times of the cost of Type II error. For this reason, predictions of one-year prior to bankruptcy using $ZETA_c$ optimal cut-off score is more safe, cost effective, and conservative, in performing predictions.

Recomendations

1. Up to now, independent variables used to distinguish between bankrupt and non-bankrupt companies and then for performing bankruptcy predictions are merely from financial statement data published by companies. There is a great possibility that market data such as stock price, market capitalization of a company, macro-economic condition, etc can be used to predict bankruptcy beforehand. Further research is expected to incorporate market data in building bankruptcy prediction models.

2. The sample of bankrupt and non-bankrupt companies in building the one-year prior to bankruptcy prediction model is limited to companies listed on JSX in years of 1999 and 2000. Further research is expected to use wider range of pooled data so that the model built better represents the real condition of the population.
3. The sample of banks in the computation of *ZETA$_c$* optimal cut-off score only uses two state-owned banks and two private owned banks. It is expected that a specific research is conducted to investigate the cost occurring from Type I errors and Type II errors so that the computation of *ZETA$_c$* optimal cut-off score becomes more accurate as conducted by Altman (1977) in his exceptional research, "*Lending error costs for commercial banks: Some conceptual and empirical issues, Journal of Commercial Bank Lending*, October".
4. This research did not use a hold out sample because of time consideration and lack of data. Further research is expected to use a hold out sample (a different set of data than the data used in building the bankruptcy prediction model) in order to validate the model and cut-off score built with the intention that the results of the research also becomes more valid.

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APPENDIX

Appendix 1

Code	(Constant)	10.086 X36	-0.824 X47	Z	Hair et al. Optimum Cutting	$ZETA_c$ Optimal Cut-Off Score
0	-2,060	0,097	0,108	-1,167	0	0
0	-2,060	0,036	0,037	-1,726	0	0
0	-2,060	0,128	0,147	-0,891	0	0
0	-2,060	0,083	0,090	-1,301	0	0
0	-2,060	0,002	0,002	-2,045	0	0
0	-2,060	0,144	0,168	-0,750	0	0
0	-2,060	0,249	0,332	0,180	1	0
0	-2,060	0,144	0,168	-0,751	0	0
0	-2,060	0,175	0,212	-0,471	0	0
0	-2,060	0,015	0,015	-1,922	0	0
0	-2,060	0,102	0,114	-1,121	0	0
0	-2,060	0,173	0,209	-0,489	0	0
0	-2,060	0,086	0,094	-1,270	0	0
0	-2,060	0,100	0,111	-1,146	0	0
0	-2,060	0,065	0,069	-1,462	0	0
0	-2,060	0,036	0,037	-1,728	0	0
0	-2,060	0,009	0,009	-1,977	0	0
0	-2,060	0,065	0,069	-1,464	0	0
0	-2,060	0,042	0,043	-1,676	0	0
0	-2,060	0,086	0,094	-1,273	0	0
0	-2,060	0,007	0,008	-1,991	0	0
0	-2,060	0,095	0,104	-1,193	0	0
0	-2,060	0,134	0,154	-0,839	0	0
0	-2,060	0,087	0,095	-1,260	0	0
0	-2,060	0,085	0,093	-1,278	0	0
0	-2,060	0,001	0,001	-2,051	0	0
0	-2,060	0,092	0,101	-1,218	0	0
0	-2,060	0,154	0,181	-0,661	0	0
0	-2,060	0,091	0,098	-1,218	0	0
1	-2,060	0,731	2,718	3,074	1	1
1	-2,060	0,385	0,626	1,308	1	1
1	-2,060	0,163	0,195	-0,572	0	0
1	-2,060	0,304	0,437	0,645	1	0
1	-2,060	0,297	0,422	0,585	1	0
1	-2,060	0,522	1,092	2,305	1	1
1	-2,060	0,802	4,043	2,694	1	1

Continued from Appendix 1

Code	(Constant)	10.086 X36	-0.824 X47	Z	Hair et al. Optimum Cutting	ZETA$_c$ Optimal Cut-Off Score
1	-2,060	0,849	5,636	1,862	1	1
1	-2,060	0,477	0,911	1,998	1	1
1	-2,060	0,058	0,061	-1,527	0	0
1	-2,060	0,690	2,223	3,065	1	1
1	-2,060	0,305	0,438	0,653	1	0
1	-2,060	0,533	1,141	2,375	1	1
1	-2,060	0,241	0,317	0,108	1	0
1	-2,060	0,596	1,477	2,737	1	1
1	-2,060	0,229	0,298	0,008	1	0
1	-2,060	0,253	0,339	0,214	1	0
1	-2,060	0,836	5,084	2,179	1	1
1	-2,060	0,880	7,320	0,782	1	0
1	-2,060	0,186	0,217	-0,365	0	0
1	-2,060	0,135	0,156	-0,826	0	0
1	-2,060	0,641	1,782	2,932	1	1
1	-2,060	0,371	0,590	1,197	1	1
1	-2,060	0,267	0,364	0,332	1	0
1	-2,060	0,505	1,020	2,193	1	1
1	-2,060	0,502	1,007	2,171	1	1
1	-2,060	0,355	0,552	1,071	1	0
1	-2,060	0,145	0,170	-0,734	0	0
1	-2,060	0,424	0,735	1,608	1	1

0 = bankrupt
1 = non-bankrupt

Appendix 2. *Sample of Bankrupt and Non-bankrupt Companies*

No.	Bankrupt Companies	Non-bankrupt Companies
1	PT Citatah Industri Marmer Tbk	PT Aneka Tambang Tbk
2	PT Prasidha Aneka Niaga Tbk	PT Multi Bintang Indonesia Tbk
3	PT Texmaco Jaya Tbk	PT Teijin Indonesia Fiber Corporation (TIFICO) Tbk
4	PT Polysindo Eka Perkasa Tbk	PT Budi Acid Jaya Tbk
5	PT Panca Wiratama Sakti Tbk	PT Pudjiadi Prestige Limited Tbk
6	PT PP Perkebunan London Sumatra Indonesia Tbk	PT Astra Argo Lestari Tbk
7	PT Alter Abadi Tbk	PT Timah Tbk
8	PT Davomas Abadi Tbk	PT Sari Husada Tbk
9	PT SMART Corporation Tbk	PT Mayora Indah Tbk
10	PT Argo Pantes Tbk	PT Panasia Indosyntec Tbk
11	PT Primarindo Asia Infrastucture Tbk	PT Sepatu Bata Tbk
12	PT Surya Dumai Industri Tbk	PT Sumalindo Lestari Jaya Tbk
13	PT Surabaya Agung Industri Pulp Tbk	PT Suparma Tbk
14	PT Toba Pulp Lestari (PT Indirayon Utama) Tbk	PT Fajar Surya Wiwesa Tbk
15	PT Tri Polyta Indonesia Tbk	PT Lautan Luas Tbk
16	PT Argha Karya Prima Industry Tbk	PT Wahana Jaya Perkasa (PT UGAHARI) Tbk
17	PT Mulia Industrindo Tbk	PT Surya Toto Indonesia Tbk
18	PT Texmaco Perkasa Engineering Tbk	PT Komatsu Indonesia Tbk
19	PT GT Kabel Indonesia (Kabelmetal Indonesia) Tbk	PT Sumi Indokabel (IKI Indah Kabel Indonesia) Tbk
20	PT Gajah Tunggal Tbk	PT Astra International Tbk
21	PT Indomobil Sukses International Tbk	PT Astra Otoparts Tbk
22	PT GT Petrochem Industries Tbk	PT United Tractor Tbk
23	PT Ciputra Development Tbk	PT Bukit Sentul Tbk
24	PT Dharmala Intiland Tbk	PT Duta Pertiwi Tbk
25	PT Jakarta Setiabudi Property Tbk	PT Jakarta International Hotel & Development Tbk
26	PT Kawasan Industry Jababeka Tbk	PT Jaya Real Property Tbk
27	PT Lippo Land Development Tbk	PT Bakrieland Development (Elang Realty) Tbk
28	PT Modernland Realty Tbk	PT Surya Semesta Internusa Tbk
29	PT Suryamas Duta Makmur Tbk	PT Summarecon Agung Tbk

Appendix 3. *Financial Ratios Used to Build the One-Year Prior to Bankruptcy Prediction Model*

No.	Financial Ratios	Abbreviation
	Short Term Liquidity (I)	
1.	Cash to current liabilities (X_1)	CCL
2.	Cash flow to current liabilities (X_2)	CFCL
3.	Quick assets to current liabilities (X_3)	QACL
4.	Current assets to current liabilities (X_4)	CACL
	Long Term Solvency (II)	
5.	Current assets to total liabilities (X_5)	CATL
6.	Net worth and long term debt to fixed assets (X_6)	NWLTDFA
7.	Net worth to fixed assets (X_7)	NWFA
	Profitability (III)	
8.	Operating income to Earnings before taxes (X_8)	OINEBT
9.	Earnings before taxes to sales (X_9)	EBTS
10.	Gross profit to sales (X_{10})	GPS
11.	Operating income to sales (X_{11})	OIS
12.	Net income to sales (X_{12})	NIS
	Productivity (IV)	
13.	Inventory to working capital (X_{13})	IvWC
14.	Cost of goods sold to inventory (X_{14})	COGSIv
15.	Sales to quick assets (X_{15})	SQA
16.	Sales to cash (X_{16})	SC
17.	Sales to accounts receivables (X_{17})	SAR
18.	Cash flow to total assets (X_{18})	CFTA
19.	Current assets to total assets (X_{19})	CATA
20.	Quick assets to inventory (X_{20})	QAIv
21.	Inventory to sales (X_{21})	IvS
22.	Sales to total assets (X_{22})	STA
23.	Working capital to total assets (X_{23})	WCTA
	Indebt ness (V)	
24.	Total liabilities to current assets (X_{24})	TLCA
25.	Operating income to total liabilities (X_{25})	OITL
26.	Current liabilities to total assets (X_{26})	CLTA

Continued from Appendix 3

No.	Financial Ratios	Abbreviation
	Investment Intensiveness (VI)	
27.	Cash flow to total liabilities (X_{27})	CFTL
28.	Sales to fixed assets (X_{28})	SFA
29.	Working capital to total assets (X_{29})	WCTA
30.	Current assets to sales (X_{30})	CAS
31.	Quick assets to total assets (X_{31})	QATA
32.	Net worth to sales (X_{32})	NWS
33.	Working capital to sales (X_{33})	WCS
34.	Inventory to total assets (X_{34})	IvTA
35.	Cash flow to sales (X_{35})	CFS
	Leverage (VII)	
36.	Net worth to total assets (X_{36})	NWTA
37.	Current liabilities to inventory (X_{37})	CLIv
38.	Total liabilities to total assets (X_{38})	TLTA
	Return on Investment (VIII)	
39.	Earnings before taxes to net worth (X_{39})	EBTNW
40.	Net income to fixed assets (X_{40})	NIFA
41.	Net income to net worth (X_{41})	NINW
42.	Earnings before taxes to total assets (X_{42})	EBTTA
43.	Net income to total assets (X_{43})	NITA
	Equity (IX)	
44.	Sales to current liabilities (X_{44})	SCL
45.	Net income to total liabilities (X_{45})	NITL
46.	Current liabilities to net worth (X_{46})	CLNW
47.	Net worth to total liabilities (X_{47})	NWTL