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Evaluating the Technique of Data Envelopment Analysis in Predicting Bankruptcy

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ABSTRACT

Experimental studies across the world show that one of the investors and other activists' expectations in capital market is their ability in predicting the status of activity consistency or the bankruptcy of the companies. To predict bankruptcy, different patterns and techniques are used. Along with the advances in math and computer, the attention of the financial scholars have been directed toward designing and using more exact patterns like data Envelopment analysis (DEA).For this purpose, this study uses DEA technique to predict the bankruptcy likelihood of manufacturing firms, comparing the predictability of this model by 3 methods of Logit, Probit, and Multiple-discriminant analysis. Statistical population of the study included all manufacturing firms accepted in Stock Exchange of Tehran since 2000-2010. The results showed that the accuracy of the designed model under DEA technique is 72 % and the predictability of Logit, Probit, and Multiple-discriminant models has been81, 80, and 70 % respectively. The results also showed the higher predictability and accuracy of Logit model. DEA was proved to be an effective tool for predicting bankruptcy likelihood of manufacturing firms; but, it acted less efficient than Logit and Probit models. No significant difference was observed between DEA and multiple-discriminant analysis in predicting the bankruptcy of the companies.
KEYWORDS: Bankruptcy, DEA, Logit model, Probit model, Multiple-discriminant model.

1. INTRODUCTION

Relevance is a main feature of accounting information in regard with explanatory and predictability attributes. Predictability means that the given information provides the possibility of anticipating the final results of past, present, and future events. Users prefer the information with higher predictability[4].From the other hand, predicting bankruptcy has been a challenging issue for many scientific studies during the last 3 decades[1].Bankruptcy is important in financial studies since its consequences affect the economy of the country, challenging the credibility of financial officials [12].It also impacts the liquidity of capital market and economic development. During bankruptcy, the banks usually reduce financing bankrupt firms, asking for higher interests for compensating extra risks [9]. There are many techniques likeLogit and Probit models, Multiple-discriminant analysis, neural network, fuzzy logic, genetic algorithms, and etc to predict bankruptcy likelihood all of which have some strengths and weaknesses. One of the most effective techniques for this purpose is DEA, used as a non-parametric method for calculating the efficiency of decision-making units. Thus, this study exerted DEA technique to predict the bankruptcy likelihood of manufacturing firms, comparing the predictability of this model with 3 methods of Logit, Probit,and Multiple-discriminant analysis. It also tries to answer the following questions:
1.Does DEA provide a better way for predicting companies' bankruptcy?
2. What are the likely advantages of DEA to other models?

2. Research theories and background

Developing financial markets and competitiveness across the globe, bankrupt firms get off the market. This causes some concerns for capital owners and stockholders. They look for the ways that predict financial crisis and bankruptcies. One way to use investment opportunities and impede resource waste is predicting bankruptcy. For this purpose, first, the companies are informed and warned about bankruptcy to recognize their favorable opportunities from unfavorable ones, investing their resources on proper places[3]. Many firms get bankrupt annually because of facing the following situations:

1. They have to sell their properties with low price.

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2.The conflicts among creditors may delay cashing the assets. Then the probability of physical damage and inventory depreciation increases.

3.A part of company value is spent for lawyers' fee, trial cost, and organizational expenses which are not as important as 1 and 2.

Regarding these cases, bankruptcy cost is high. It just occurs for the companies which have debt. The companies lacking debt have never been bankrupt. So, financial provision through debts causes increasing bankruptcy likelihood, reducing earnings. As a result, the likelihood of value decrease enhances because of the costs of bankruptcy. Increasing bankruptcy likelihood reduces the current value of the company, enhancing its capital costs [13]. In a research titled" identifying companies' failure: a reevaluation of Logit, Probit, and multiple-discriminant analysis", Lennox (1999) examined the reasons for the bankruptcy of a sample including 949English companies since 1978-1994. Based on Lennox, the most important bankruptcy factors include profitability, financial leverage, cash flows, company size, industrial section, and economic cycles. The results showed higher accuracy of Logit and Probit models, compared with discriminant analysis in predicting companies' failures[5]. Permachandra et al. (2011) compared DEA and Logit regressions to examine the ability of two patterns in evaluating financial disability of the companies. They used 9 financial variables, regarded as the most efficient variables in the past literature. Quantitative data showed the weaker data of DEA in predicting the failures of the companies[10].Using neural network model, Makkian et al. (2008) did a research to predict companies' bankruptcy, comparing it with Logistic and Multiple-discriminant analysis models. They used five financial ratios and their results showed higher accuracy of neural network model compared with two other models[6]. Rostami et al (2010) evaluated financial disability of the accepted companies in stock exchange of Tehran using DEA and logistic models. They concluded that DEA can't be a strong replacement for Logistic model. Also, they demonstrated that Logistic model can significantly yield better results than additional pattern of DEA in evaluating financial disability of the companies.[11]

3. METHODOLOGY

This study used DEA to predict bankruptcy. Its results were compared with the results of Logit, Probit, and Multiple-discriminant analysis models. DEA is a mathematical planning method for evaluating the efficiency of decision-making units with several inputs and outputs. Efficiency measurement has been regarded for its importance in performance evaluation of the companies[7].The reason for more popularity of DEA compared with other methods is the possibility of examining complicated and indefinite relations among several inputs and outputs [2]. DEA is a valuable tool for performance measurement. Against statistical and econometric method, DEA doesn't need a large sample size[10].One advantage of this non-parametric method is the lack of need to estimate function form in analyzing financial ratios and statistical distribution of the ratios[14]. Logit model has wide applications in predicting business failures. By allocating some weights to independent variables, this model predicts the ranking of every sample company. This ranking is used for determining membership likelihood in a definite group. Success or failure likelihood in this model is calculated by the following formula:

$$\boldsymbol{p(z)} = \frac{1}{1 + e^{-z}} = \frac{1}{1 + e^{-(a+b_1x_1+\ \dots\ +b_nx_n)}}$$

Where, X_i (i=1,…,n) shows independent variables, and a and b_i (i=1,…,n) are estimated parameters of the model. *P (z)* likelihood is a number between 0 and1. When *P(z) = 0.5*, bankruptcy or non-bankruptcy chance is equal. The closer this likelihood to0 ,the more bankruptcy likelihood increases. The closer this likelihood to1,the more bankruptcy likelihood decreases.

Probit models are mostly similar to Logit models. But, the former uses cumulative likelihood function which is normal rather than cumulative logistic function. Multiple-discriminant analysis is a multivariable method in which the phenomena are divided into distinct groups with different qualities. This study aimed to recognize the differences among the groups and predict the likelihood of a company's dependency to a specific group. Forsuch predictions, some quantitative independent variables were used. In this method, a company was attributed to a bankrupt or non-bankrupt group according to its achieved score and the maximum similarities. Classification was done based on optimum shortcut point, identified for Multivariable-discriminant analysis model. If the score of a company was lower than shortcut point, it was regarded as a non-bankrupt company.

3.1. Statistical population and sample

Statistical population of the study included all manufacturing companies accepted in Stock Exchange of Tehran since 2000-2010. To measure model fitness, the data of 55 bankrupt and 134non- bankrupt companies were used.

Bankruptcy measure in this study was Act 141 of Business Law in Iran, based on which the firms with minimum accumulated loss, equal with the half of their capital must declare bankruptcy or capital loss. Sample selection of non- bankrupt companies was based on the following conditions:

1. The companies should be manufacturing.
2. Their fiscal year should end in September.
3. Financial information of the companies should be accessible.
4. They should have 10 successive years of activity in Stock Exchange of Tehran since2000- 2010 .

3.2.Variables

To identify the most important financial ratios for selecting main variables of the study, principal component analysis was used. After examining 22financial ratios, 7factors were identified. In analyzing main components, the values over 1were regarded and used as the most significant specific values. To identify those 7 factors, the matrices of components were used. The correlation of each variable was identified with load factor.

On this basis, the variable with maximum load factor was considered as the most important variable. Independent variables of the study include:

-Return on equity (ROE)
-Debt ratio
-Debt cover ratio
-Collection period
-Inventory turnover
-Debt to equity ratio
-Product to working capital ratio
-Dependent variable was the likelihood of bankruptcy or non- bankruptcy occurrence.

3.3. Offered model of DEA

In evaluating bankruptcy, BCC and CCR patterns can't be used since they don't take negative values; this restricts DEA in predicting bankruptcy because some financial ratios have negative values. In the present study, an additive model was used which had unchangeable transferability, allowing negative values for inputs and outputs.[11] In this model, input reduction and output increase were also concerned.[8] To create the model of data envelopment analysis Suppose we have a set of n DMUs (e.g., firms). Each DMUj j (j=1, ..., n) has m inputs and s outputs. The ith input and rthout put of DMUj (j=1, ..., n) are denoted by xij (i=1, ..., m) and yrj(r =1, ..., s), respectively. Then, the additive model for a specific DMUo can be written as :

ρ_0^*= max $\rho_0 = \sum_{i=1}^{m} s_{i_0}^- + \sum_{r=1}^{s} s_{r_0}^+$

S.t :

$\sum_{j=1}^{n} \lambda_j x_{ij} + s_{i_0}^- = x_{i_0}$ i =، 1، 2 … ، m

$\sum_{j=1}^{n} \lambda_j x_{rj} + s_{r_0}^+ = y_{r_0}$ r =، 2،1 ….، s

$\sum_{j=1}^{n} \lambda_j = 1$

λ_j، $s_{i_0}^-$،$s_{r_0}^+ \geq 0$

j =، 1، 2 … ، ni =، 1، 2 … ، mr = 2، 1، ….، s

Model (1)

Where$s_{i_0}^-$and$s_{r_0}^+$represent input and output slacks for DMUounder evaluation.A DMUo is efficient or on the DEA frontier if and only if $s_{i_0}^{-*} = s_{r_0}^{+*} = 0$isat optimality. The additive DEA model (1) determines inefficiency in each input and each output in a single model. the model presented above (1) does not yield an efficiency score in-between [0,1]. We, therefore, develop the following index as the efficiency score based upon model (1).

Let$\{\rho_0^*$; λ_j^* ، j =، 1، 2 … ، n ، $s_{i_0}^{-*}$، i =، 1، 2 … ، m ،$s_{r_0}^{+*}$، r = 2، 1،…، s }

be an optimal solution to model (1). Then we can define

$$\sigma_0^* = \frac{1-(1/m)\sum_{i=1}^{m} s_{i_0}^{-*}/x_{i_0}}{1+(1/s)\sum_{r=1}^{s} s_{r_0}^{+*}/y_{r_0}}$$

as the additive efficiency score for DMUo. It can be verified that σ_0^*falls between zero and one, and is unit-invariant and monotonedecreasing in input/output slacks. DMUo is called additive efficient if and only ifσ_0^*=1, indicating that all optimal slacks are zero. In order to discriminate the performance of efficient DMUs, we can employ the related super-efficiency model.to obtain the super-efficiency of an efficient DMUo under model (1), we cannot simply modify additive model (1) by removing DMUo from the reference set. If we do that, the resulting model may not have a feasible solution. Therefore, for an additive efficient DMUo under model (1), weneed to adopt the following proposed super-efficiency model.

$\beta_0^* = \min\beta_0 = \frac{1}{m+s}\ \left(\sum_{i=1}^{m}\frac{t_{i_0}^-}{x_{i_0}} + \sum_{r=1}^{s}\frac{t_{r_0}^+}{y_{r_0}}\right)$

s.t :

$x_{i_0} + t_{i_0}^- \geq \sum_{\substack{j=1\\ j\neq 0}}^{n} \lambda_j x_{ij}$ i =، 1، 2 …، m

$y_{r_0} - t_{r_0}^+ \geq \sum_{\substack{j=1\\ j\neq 0}}^{n} \lambda_j x_{rj}$ r = 2، 1،…، s

$\sum_{\substack{j=1\\ j\neq 0}}^{n} \lambda_j = 1 \lambda_j$، $t_{i_0}^-$،$t_{r_0}^+ \geq 0$

j =، 1، 2 … ،n ،$j \neq 0$ ،i =، 1، 2 … ، m ،r = ،1،2…، s

Model (2)

It can be seen that after DMUo is removed from the reference set of model (1), we need to modify the constraints and the objective function of model (1). The constraints should be modified because we need to increase the inputs and decrease the outputs for DMUo to reach the frontier constructed by the remaining DMUs. We change the objective from maximization to minimization, so that the resulting model is bounded. We divide each slack by its corresponding input/output in the objective tomake the resulting model unit invariant.

Let$\{\beta_0^*$; λ_j^* ،j =، 1، 2 … ، n ، j≠ 0،$t_{i_0}^{-*}$، i =، 1، 2 … ، m ،$t_{r_0}^{+*}$، r = ، 2،1 ….، s }

be an optimal solution to model (2). Then we can define

$\delta_0^* = \frac{(1/m)\sum_{i=1}^{m}(x_{i_0} + t_{i_0}^{-*})/x_{i_0}}{(1/s)\sum_{r=1}^{s}(y_{r_0} + t_{r_0}^{+*})/y_{r_0}} \geq 1$

as the additive super-efficiency score for an efficient DMUo. Denote the DEA score (from models (1) and (2) for identifying the failure frontier as θ_1 and the corresponding score for identifying the success frontier asθ_2.Namely$\theta_1$is associated with the bankruptcy frontier model, and$\theta_2$is associated with the non-bankruptcy frontier model. We then define our prediction or assessment index as

$\lambda\theta_1 - (1-\lambda)\,\theta_2$Model (3)

where$\lambda$is a user-specified weight reflecting the relative emphasison the two frontiers. Note that negativeθ_2 is used in (3), as one isa bankrupt frontier and the other is a success frontier. For θ_1 andθ_2 .we used normalized values, as the skewness of the distributions of the original values of θ_1 and θ_2 is substantially different.Specifically, when a DMU is inefficient, $\theta_1$represents theefficiency score

$\sigma_0^* = \frac{1-(1/m)\sum_{i=1}^{m} s_{i_0}^{-*}/x_{i_0}}{1+(1/s)\sum_{r=1}^{s} s_{r_0}^{+*}/y_{r_0}}$

based on model (1). When a DMU is efficient under model (1),then θ_1 represents the superefficiency score

$\delta_0^* = \frac{(1/m)\sum_{i=1}^{m}(x_{i_0} + t_{i_0}^{-*})/x_{i_0}}{(1/s)\sum_{r=1}^{s}(y_{r_0} + t_{r_0}^{+*})/y_{r_0}} \geq 1$

based upon model (2). $\theta_2$is obtained in the same manner. Thedifference between $\theta_1$and θ_2 lies in the fact that different sets ofinputs and outputs are related toθ_1 andθ_2.[10]

4. RESULTS

4.1. Examining firms' efficiency based on research variables

In bankruptcy assessment, the smaller values in the financial ratios, which could possibly cause financial distress, are considered to be input variables, and the larger values in those ratios, which could cause financial distress, are classified as output variables and the corresponding efficiency score is denotedby θ_1.the efficiency score of thenon-bankruptcy frontier DEA model beθ_2.

In contrast, if we swap the inputs and outputs, namely, the larger values in those financial ratios are classified as inputs and smaller values are classified as outputs,we identify the non-bankruptcy frontier for the firm.

4.2. Examining firms' efficiency based on bankruptcy frontier

Input and output variables for getting efficiency based on bankruptcy frontier are shown in Table1. Using DEAP software, the efficiency of all bankrupt and non- bankruptfirms was calculated based on bankruptcy frontier. Fig.1 shows companies' efficiency based on bankruptcy frontier.

4.3. Efficiency extent of the companies based on non- bankruptcy frontier

Input and output variables for getting efficiency based on non-bankruptcy frontier are shown in Table2. Fig. 2shows companies' efficiency based on non-bankruptcy frontier.

4.4. DEA model

To examine DEA model, the fitness of Logit regression model was examined based on research variables, using the following equation:

$$P(v_{it} = 1) = \frac{e^{Z_{it}}}{1 + e^{Z_{it}}}$$

$$Z_{it} = \theta_0 + \theta_1 dea1_{it} + \theta_2 dea2_{it} + \varepsilon$$

Where,

$\boldsymbol{v_{it}}$: Bankrupcy of ith company in year t

(Bankruptcy is identified by 1 and non- bankruptcy is identified by0)

$\boldsymbol{dea\_1_{it}}$: Efficiency extent of the companies based on bankruptcy frontier of ith company in year t

$\boldsymbol{dea\_2_{it}}$: Efficiency extent of the companies based on non-bankruptcy frontier ofith company in year t

ε : Regression residues for *i*th company in year t

According to likelihood value in significance test (p=0.064) shown in Table 3 and 4 it can be concluded that the model is not statistically significant and due to its resulted determination coefficient it just identifies 4% of distribution. Table 5 shows logistic regression coefficients and gives the following formula:

$$Z_{it} = -0.224 - 2.638 dea1_{it} + 3.555 dea2_{it} + \varepsilon$$

Estimation accuracy of the model was72%. It was 98.5% for non-bankrupt companies and 7.3% for bankrupt companies, shown in Table 6 .

4.5. logit model

Logit regression model fitness was tested based on the following equation:

$$P(v_{it} = 1) = \frac{e^{Z_{it}}}{1 + e^{Z_{it}}}$$

$$Z_{it} = \theta_0 + \sum_{j=1}^{8} \theta_j xj_{it} + \varepsilon$$

According to likelihood value in significance test (P=0.000) shown in Table 7 and8, it can be concluded that the model is statistically significant and due to its resulted determination coefficient it identifies 27% of distribution. Table 9 shows logistic regression coefficients and gives the following formula:

$$Z_{it} = 487.667 - 0.024X_1 + 0.003X_2 + 0.0004X_3 + 0.001X_4 + 0.220X_5 - 0.228X_6 - 0.005X_7 + \varepsilon$$

Estimation accuracy was 81%.For non-bankrupt companies, it was 99% and it was 36% for bankrupt companies shown in Table10.

4.6. Probit model

Probit regression model was measured based on the following equation:

$$P(v_{it} = 1) = NP(\theta_0 + \sum_{j=1}^{8} \theta_j xj_{it} + \varepsilon)$$

According to likelihood value in significance test (P=0.000) shown in Table 11, it can be concluded that the model is statistically significant. Table 12 shows probit regression coefficients and gives the following formula:

$$P(v_{it} = 1) = NP(135 - 0.0102X_1 + 0.0019X_2 + 0.0001X_3 + 0.0005X_4 + 0.0915X_5 - 0.0742X_6 - 0.0024X_7 + \varepsilon$$

Estimation accuracy was 80%. For non-bankrupt companies, it was 99% and 33% for bankrupt companies, shown in Table13.

4.7. Multiple-discriminant model

Multiple-discriminant model was examined based on the following equation:

$$v_{it} = b_0 + \sum_{j=1}^{8} b_j xj_{it}$$

Regarding the likelihood value in significance test (P=0.243)and comparing it with significance level, it can be said that the model is statistically insignificant, as shown in Table 14 and15.

Table 16 shows non-standardized coefficient Focal functionsand gives the following formula:

$$v_{it} = -55.07 - 0.001X_1 + 0.001X_2 + 0.003X_3 + 0.001X_4 + 0.121X_5 - 0.011X_6 - 0.015X_7$$

Estimation accuracy in the sample is shown in Table17. Estimation accuracy was 70%. It was 84% for non-bankrupt companies and 36% for bankrupt companies.

Table.18 shows the Ratio test for comparing the models of efficiency and Multiple-discriminant regression. The results show that the accuracy of Multiple-discriminant regression is not higher. Also, Z test results don't confirm a significant difference between Multiple-discriminant regression and DEA.

Conclusion

This study aimed to predict bankruptcy likelihood of the firms using DEA. Exerting key financial ratios and DEA, efficiency score of the companies based on bankruptcy extent or the lack of it was calculated. Then, the predictability of DEA model and Logit, Probit, and Multiple-discriminant models for bankruptcy was compared. The results of testing 4models showed that DEA is an effective tool for predicting firms' bankruptcy, but not as efficient as Logitand Probit models. No significant difference was found between the predictability of firms' bankruptcy by two models of DEA and Multiple- discriminate models. Multiple–discriminant model was as accurate as Logit model in identifying bankrupt companies. Comparing the results of 4 models, the accuracy and predictability of Logit regression was higher than other 3 models. Probit model had accuracy close to Logit model; but, its function was lower and less efficient than Logit model. DEA and Multiple–discriminant model had similar predictability but their predictability was at lower rate, compared with Logit and Probit models.

Suggestions for further studies

Based on the findings of the study the following suggestions can be represented:

-Comparing Logit and Probit models with techniques of artificial- Intelligence like supportive vector machine, genetic algorithm, and fuzzy logic in bankruptcy prediction

-Using other DEA variations like BCC and CCR and examining if they yield the same results of this study.

-Upgrading this research using future data of fiscal years of stock companies, entering other qualitative variables like inflation for bankruptcy prediction.

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Appendix

Table1.Input and output variables for getting efficiency based on bankruptcy frontier

output	Return On Equity
Input	Debt to equity ratio
Input	Debt ratio
Output	Product to working capital ratio
Output	Debt cover ratio
Input	Collection period
Output	Inventory turnover

Fig1. Efficiency extent of the companies based on bankruptcy frontier

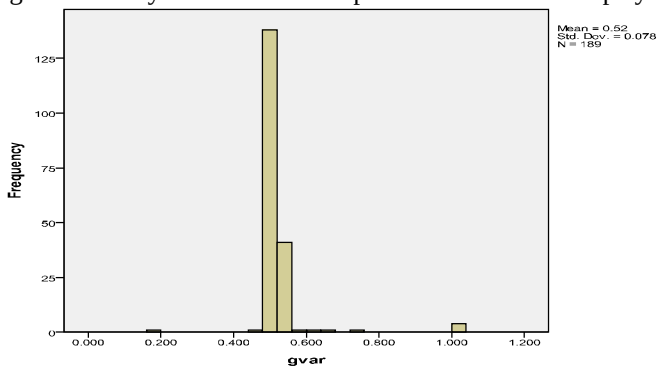

Table2. Input and output variables for getting efficiency based on non-bankruptcy frontier

inputs	Return On Equity
output	Debt to equity ratio
output	Debt ratio
inputs	Product of working capital ratio
inputs	Debt coverage ratio
output	Collection period
inputs	Inventory turnover

Fig2. Efficiency extent of firms based on non- bankruptcy frontier

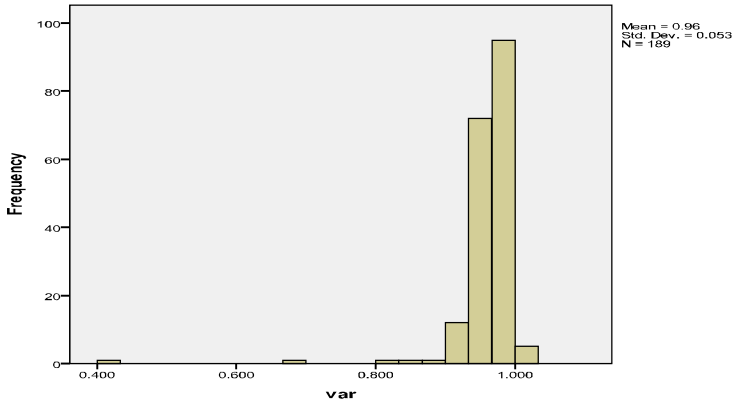

Table3.Regression statistics

Coefficient ofdetermination Nagelkerke	Coefficient ofdetermination Cox & Snell	-2 Log likelihood
0.041	0.029	222.440

Table4. Significant regression test

Sig.	df	Chi-square
0.064	2	5.513

Table5. Logistic regression coefficients

	Sig.	df	WaldStatistic	Standard deviation	Coefficient
Dea1	0.601	1	0.274	5.040	-2.638
Dea2	0.239	1	1.387	3.018	3.555
Constant	0.970	1	0.001	5.976	-0.224

Table6.To accurately estimate of bankruptcy

		Estimation of bankruptcy		Percentage of accuracy
		0	1	
Observed Bankruptcy	0	132	2	98.5
	1	51	4	7.3
Percent				72.0

Table7. Regression statistics

Coefficient ofdetermination Nagelkerke	Coefficient ofdetermination Cox & Snell	-2 Log likelihood
0.273	0.191	187.898

Table8. Significant regression test

Sig.	df	Chi-square
0.000	7	40.055

Table9. Logistic regression coefficients

	Sig.	df	Wald Statistic	Standard deviation	Coefficient
ROE	0.000	1.000	14.264	0.006	-0.024
Inventory turnover	0.09	1.000	2.821	0.002	0.003
Collection period	0.761	1.000	0.092	0.001	0.0004
Product of working capital ratio	0.927	1.000	0.008	0.007	0.001
Debt ratio	0.005	1.000	7.983	0.078	0.220
Debt to equity ratio	0.004	1.000	8.214	0.080	-0.228
Debt coverage ratio	0.691	1.000	0.158	0.012	-0.005
Constant	0.054	1.000	3.723	252.742	487.667

Table10.To accurately estimate of bankruptcy

		Estimation of bankruptcy		Percentage of accuracy
		0	1	
Observed Bankruptcy	0	133	1	99.3
	1	35	20	36.4
Percent				81.0

Table11. Significant regression test

Sig.	df	Chi-square
0.000	7	34.984

Table12.Probitregression coefficients

	Sig.	df	Wald Statistic	Standard deviation	Coefficient
Intercept	0.279	1	1.171	124.7689	-135.00
ROE	0.000	1	13.910	0.0027	0.0102
Inventory turnover	0.059	1	3.557	0.0010	-0.0019
Collection period	0.924	1	0.009	0.0007	-0.0001
Product of working capital ratio	0.892	1	0.018	0.0040	-0.0005
Debt ratio	0.012	1	6.343	0.0363	-0.0915
Debt to equity ratio	0.009	1	6.856	0.0283	0.0742
Debt coverage ratio	0.724	1	0.124	0.0069	0.0024

Table13.To accurately estimate of bankruptcy

		Estimation of bankruptcy		Percentage of accuracy
		0	1	
Observed Bankruptcy	0	133	1	99
	1	37	18	33
Percent				80.0

Table14. Table eigenvalue function

Canonical Correlation	Cumulative %	% of Variance	Eigenvalue
0.220	100.0	100.0	0.051[a]

Table15. Table meaningful test

Sig.	df	Chi-square	Wilks' Lambda
0.243	7	9.130	0.951

Table16. Tablenon-standardized coefficient Focal functions

	Function
	1
ROE	-0.001
Inventory turnover	0.001
Collection period	0.003
Product to working capital ratio	0.001
Debt ratio	0.121
Debt to equity ratio	-0.011
Debt cover ratio	-0.015
(Constant)	-55.071

Table17.To accurately estimate of bankruptcy

		Estimation of bankruptcy		Percentage of accuracy
		0	1	
Observed Bankruptcy	0	112	22	83.6
	1	35	20	36.4
Percent				69.8

Table 18.Ratio test for comparing the models of efficiency and Multiple-discriminant regression.

	Accuracy	p- value	Z test
Multiple discriminant analysis	69.8%	0.325	0.453
Data envelopment analysis	72.0%		