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# Evaluating Predictive power of Data Envelopment Analysis Technique Compared with Logit and Probit Models in Predicting Corporate Bankruptcy

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## ABSTRACT

*Simultaneous with extensive environmental changes and the rapid development of technology which has increasingly accelerated economy, competitiveness economical enterprises have restricted earning profit and make probable closing of bankrupt firms. Thus it seems necessary to find a model that can predict financial crisis and bankruptcy of companies. Nowadays occurrence of significant progress in other sciences, such as computer and math attract the attention of the financial scholars 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 and also compare its predictability with* 2 *methods : Logit and Probit models. Study sample includes all manufacturing firms listed in Stock Exchange of Tehran from* 2000-2010*. The results showed that the accuracy of the designed model under DEA technique is %*72 *and the predictability of Logit and Probit models has been*81*, and %*80 *respectively. The results also showed 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.*

**Keywords:** *Bankruptcy, Data Envelopment Analysis ,Logit model, Probit 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(Khajavi،2010)From the other hand, predicting bankruptcy has been a challenging issue for many scientific studies during the last 3 decades(.Ching – Ching, 2010)Bankruptcy is important in financial studies since its consequences affect the economy of the country, challenging the credibility of financial officials(Tonatiuh Pena,2009)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. (Nikbakht,2010)

There are many techniques like Logit 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. Using data envelopment analysis models in addition to determining the relative efficacy also determines weaknesses of organization in different index and provides them with utility rates which specify organization policy into preferment of the efficiency and productivity.(Cooper,2010).

## 2- LITERATURE REVIEW

Bankruptcy always has diverted wide range of individuals, organizations and the general part of the community. It is very difficult to provide an accurate definition for interest groups bankruptcy. But it can be claimed that it will be influenced bankruptcy phenomena more than others, Management, investors, creditors, competitors, and legal institutions. Investors with predict bankruptcy, not only to prevent the risk of burning their capital, but its use as a tool to reduce the risk of your portfolio (Etemadi,2007 ). Hence, They are the ways that could estimate the company's financial bankruptcy, because in case of bankruptcy, stock price of companies sharply decreases(Rasoulzadeh,2000).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. (Weston,2003)

Bankruptcy prediction models is one of the techniques and tools to predict the future state of the company's in that likelihood of bankruptcy estimate with compositions a group of financial ratio. Bankruptcy prediction models can be classified in three groups, statistical modeling, artificial intelligence, and theoretical. Statistical models themselves are divided into two groups, univariate and multivariate. Multivariate statistical model is composed of Multiple discriminant analysis models, linear probability, logit, probit,the total cumulative and Partial adjustment processes.

Artificial neural networks, genetic algorithms, recursive Afraz, rough sets, support vector machines, Sion-based reasoning and fuzzy logic, are composed artificial intelligence techniques and theoretical models is also including criterion analysis of sheet / entropy theory, Bankruptcy theory of gambling, Cash management theory and theories of credit risk.(Firouziyan et al,2010)

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.( Premachandra,2011)

Xu et al.(2009) In order to predicting financial bankruptcy were used efficiency score as predictive variables.they using data from the Shanghai Stock Exchange companies.corporate failures were predicted by using DEA. Results showed that efficiency scores are an effective predictor variable.(Xu et al,2009)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(.Rostami,2010)Mousavi et al (2008) did a research titled "Financial distress prediction using data envelopment analysis".They were used in this study The Efficiency scores as predictive variables in order to predict the occurrence of financial distress.For this purpose first designed a model using this variable and to better evaluate the results, were designed as a comparison Pattern based on multiple discriminant analysis model.the results showed that pattern designed for companies using DEA based on Efficiency scores the ability to predict the occurrence of distress finance in the manufacturing companies accepted in Tehran Stock Exchange for within two years before it occurrence.( Mousavi et al, 2008)Thus, this study exerted DEA technique to predict the bankruptcy probability of manufacturing firms and compare the predictability of this model with 2 methods of Logit and Probit.

## 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. (Masihabadi,2009). 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.(Cooper,2010) DEA is a valuable tool for performance measurement. Against statistical and econometric method, DEA doesn't need a large sample size (Premachandra,2011).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 .(Weston,1992) With the progress and development of this method, DEA is currently an active area of research in the measurement of efficiency and it has been significantly welcomed by many researchers.Overall DEA method widespread acceptance and the rapid growth of its application in empirical studies imply its abilities and advantages (Emami meybodi,1999).

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

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membership likelihood in a definite group. Success or failure likelihood in this model is calculated by the following formula:

$$\boldsymbol{p(z)} = \frac{1}{1+\mathrm{e}^{-\mathrm{z}}} = \frac{1}{1+\mathrm{e}^{-(\mathrm{a}+\mathrm{b}_1\mathrm{x}_1+\ldots\ +\mathrm{b}_\mathrm{n}x_n)}}$$

Where, $X_{\mathrm{i}}$ (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 and 1.

When *P(z) = 0.5*, bankruptcy or non-bankruptcy chance is equal. The closer this likelihood to 0 , the more bankruptcy likelihood increases. The closer this likelihood to 1, the more bankruptcy likelihood decreases.

Probit model is used when the dependent variable was qualitative and to be able to provide only the values zero and one (As bankruptcy and non-bankruptcy). Probit models are mostly similar to Logit models. But, the former uses cumulative likelihood function which is normal rather than cumulative logistic function.

$$\mathrm{P}\ (X_{\mathrm{i}}\ ,\ \hat{a}\ ) = F\ (a + \hat{a}\ X_{\mathrm{i}}\ )$$

$$F\ (a + \hat{a}\ X_{\mathrm{i}}\ ) = \int_{-\infty}^{\hat{a}+\hat{a}x_i} \frac{1}{(2\pi)^{\frac{1}{2}}}\ e^{\frac{-x^2}{2}} dz$$

***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 134 non- 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 22 financial ratios, 7 factors were identified. In analyzing main components, the values over 1 were 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. (Rostami,2011) In this model, input reduction and output increase were also concerned.(Mehrgan,2008) 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 rth output 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 :

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

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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 = 1،2 ، ….، s

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

$\lambda_j$، $s_{i_0}^{-}$ ، $s_{r_0}^{+}$ $\geq 0$

j = 1، 2 ، … ، n i = 1، 2 ، … ، m r = 1، 2، ….، s

**Model** (1)

Where $s_{i_0}^{-}$ and $s_{r_0}^{+}$ represent input and output slacks for DMUo under evaluation. A DMUo is efficient or on the DEA frontier if and only if $s_{i_0}^{-*} = s_{r_0}^{+*} = 0$ is at 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 { $\rho_0^*$ ; $\lambda_j^*$ ، j = 1، 2 ، … ، n ، $s_{i_0}^{-*}$ ، i = 1، 2 ، … ، m ، $s_{r_0}^{+*}$ ، r = 1، 2، … ، 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 $\sigma_0^*$ falls between zero and one, and is unit-invariant and monotone decreasing in input/output slacks. DMUo is called additive efficient if and only if $\sigma_0^*=1$, 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), we need 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 :

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

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

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

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 to make the resulting model unit invariant.

Let { $\beta_0^*$ ; $\lambda_j^*$ ، j = 1، 2 ، … ، n ، j≠ 0 ، $t_{i_0}^{-*}$ ، i = 1، 2 ، … ، m ، $t_{r_0}^{+*}$ ، r = 1 ،2 ، ….، 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 $\theta_1$ and the corresponding score for identifying the success frontier as$\theta_2$.

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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:

$$\lambda\theta_1 - (1 - \lambda)\theta_2 \qquad \textbf{Model } (3)$$

where $\lambda$ is a user-specified weight reflecting the relative emphasis on the two frontiers. Note that negative $\theta_2$ is used in (3), as one is a bankrupt frontier and the other is a success frontier. For $\theta_1$ and $\theta_2$ .we used normalized values, as the skewness of the distributions of the original values of $\theta_1$ and $\theta_2$ is substantially different. Specifically, when a DMU is inefficient, $\theta_1$ represents the efficiency 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 $\theta_1$ 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. The difference between $\theta_1$ and $\theta_2$ lies in the fact that different sets of inputs and outputs are related to $\theta_1$ and $\theta_2$. (Premachandra,2011)

## 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 denoted by $\theta_1$ . the efficiency score of the non-bankruptcy frontier DEA model be $\theta_2$.

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- bankrupt firms was calculated based on bankruptcy frontier. Fig.1 shows companies' 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 |

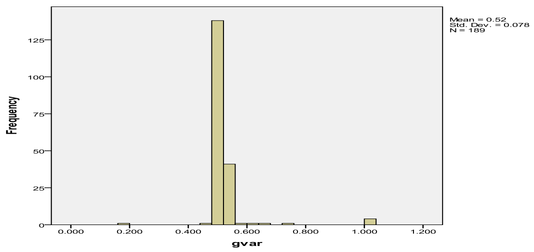


**Table**1.Input and output variables for getting efficiency based on bankruptcy frontier

**Fig**1. Efficiency extent of the companies 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. 2 shows companies' 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 |

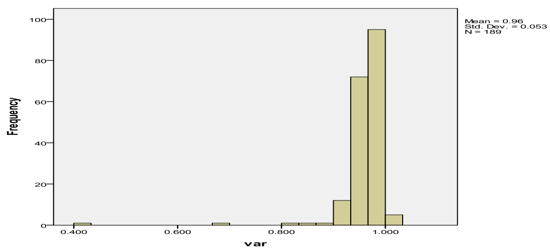


**Fig**2. Efficiency extent of firms based on non- bankruptcy frontier

**Table**2. Input and output variables for getting efficiency based on non-bankruptcy frontier

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***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,

$\boldsymbol{v}_{\mathbf{it}}$: Bankrupcy of ith company in year t

(Bankruptcy is identified by 1 and non- bankruptcy is identified by 0)

$\boldsymbol{dea\_1}_{\mathbf{it}}$: Efficiency extent of the companies based on bankruptcy frontier of ith company in year t

$\boldsymbol{dea\_2}_{\mathbf{it}}$: Efficiency extent of the companies based on non-bankruptcy frontier of $ith$ company in year t

$\boldsymbol{\varepsilon}$ **:** Regression residues for *i* th company in year t

**Table**3.Regression statistics

| Coefficient of determination Nagelkerke | Coefficient of determination Cox & Snell | -2 Log likelihood |
|---|---|---|
| 0.041 | 0.029 | 222.440 |

**Table**4. Significant regression test

| Sig. | df | Chi-square |
|---|---|---|
| 0.064 | 2 | 5.513 |

**Table**5. Logistic regression coefficients

| | Sig. | df | Wald Statistic | Standard deviation | Coefficient |
|---|---|---|---|---|---|
| Dea 1 | 0.601 | 1 | 0.274 | 5.040 | −2.638 |
| Dea 2 | 0.239 | 1 | 1.387 | 3.018 | 3.555 |
| Constant | 0.970 | 1 | 0.001 | 5.976 | −0.224 |

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:

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

**Table**6.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 |

Estimation accuracy of the model was %72. It was %98.5 for non-bankrupt companies and % 7.3 for bankrupt companies, shown in Table 6 .

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### *4.5. logit model*

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

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

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

**Table**7. Regression statistics

| Coefficient of determination Nagelkerke | Coefficient of determination Cox & Snell | -2 Log likelihood |
|---|---|---|
| 0.273 | 0.191 | 187.898 |

**Table**8. Significant regression test

| Sig. | df | Chi-square |
|---|---|---|
| 0.000 | 7 | 40.055 |

**Table**9. 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 |

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:

$$Z_{it} = 487.667 - 0.024X_1 + 0.003X_2 + 0.0004\mathrm{X}_3 + 0.001\mathrm{X}_4 + 0.220\mathrm{X}_5 - 0.228\mathrm{X}_6 - 0.005\mathrm{X}_7 + \varepsilon$$

**Table**10. 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 |

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

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***4.6. Probit model***

Probit regression model was measured based on the following equation:

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

**Table**11. Significant regression test

| Sig. | df | Chi-square |
|---|---|---|
| 0.000 | 7 | 34.984 |

**Table**12. Probit regression 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 |

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:

$$P(v_{it} = 1) = NP(135 - 0.0102X_1 + 0.0019X_2 + 0.0001\mathrm{X}_3 + 0.0005\mathrm{X}_4 + 0.0915\mathrm{X}_5 - 0.0742\mathrm{X}_6 - 0.0024\mathrm{X}_7 + \varepsilon$$

**Table**13.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 |

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

**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 and Probit models for bankruptcy was compared. The results of testing 3 models showed that DEA is an effective tool for predicting firms' bankruptcy, but not as efficient as Logit and Probit models and the DEA has a weak performance in identifying the companies bankrupt than non-bankrupt companies. Comparing the results of 3 models, the accuracy and predictability of Logit regression was higher than other 2 models. Probit model had accuracy close to Logit model; but, its function was lower and less efficient than Logit model.

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**REFERENCES**


1. Ching – Ching, Y. Der Jang, Ch. Ming Fu, H. (2010-March). A hybrid approach of DEA ، rough set and support vector machines for business failure prediction. *Expert System with Application*, 37(2), pp.1535-1541.
2. Cooper, W et al (2010). DEA, models and applications, Translated by Mirhasani, A. Amirkabir University Press, pp. 1-3.
3. Emami Meibodi,A.(1999). Principles of measuring Efficiency and Productivity. *Studies and business research Institution Press*, pp.47.
4. Etemadi,H. and Dehkordi,H.(2007). A review of bankruptcy prediction models, *Accountant monthly*, 5, 39.
5. Firouzian,M.,Javid,D. and Najmodini,N.(2010). Application of genetic algorithms in the bankruptcy prediction and compared with Altman Z model Companies listed on the Tehran Stock Exchange. *Review of Accounting and Auditing in Iran*,65 , pp.100.
6. Khajavi, S. and Ebrahimi, E. (2010). *Middle accounting*. *Tehran, Termeh* (3rd ed.). pp-22.
7. Masihabadi, A. Vahedian, M. (2009). Companies' efficiency based on DEA and debt payment in due time. *Accounting Researches*, winter. No.4. pp-7
8. Mehrgan, M.(2008-Spring and Summer). *Quantitative models (DEA) in evaluating companies' performance* (2nd ed.). Management Faculty Publication, Tehran, pp-103.
9. Mousavi,M. and Tabarestani,M.(2008-Summer). Financial distress prediction using DEA. .*Accounting and Audit Research in Iran*, 2, pp-1.
10. Nikbakht, M. and Sharifi,M.(2010- Spring and Summer).Predicting financial bankruptcy of the companies in Stock Exchange of Tehran,using neural network. *Industrial management*, 2(4), pp. 164.
11. Premachandra, I.M. and Yao Chen, J. (2011). DEA as a tool for predicting corporate failure and success: A case of bankruptcy assessment, *Omega*, 39, pp. 620–626
12. Rasoulzadeh,M.(2000). Application Altman model at status determination bankruptcy companies. *Tadbir monthly*, No.120, PP-62
13. Rostami,M., Fallah,M. and Eskandari,F.(2011). Evaluating financial disability of the accepted companies in Stock Exchange of Tehran;A comparative study of DEA and Logit models. *Management Researches of Iran*. 15(3), fall. pp-135.
14. Tonatiuh Pena,C.Serafin Martinez,J.Bolanle,A. (2009). Learning Techniques Bankruptcy Prediction: A Comparison of Some Statistical Models. *Banco de Mexico Working Paper*. PP.1-33
15. Weston, J. Copeland, F. Thomas, E. (1992). Managerial finance, Dryden Press (9th ed.).
16. Weston, B.(2003) .Financial management. Translated by Abdeh, H, Pishbord, PP-21
17. Xu X. Wang Y. (2009). Financial failure prediction using efficiency as a predictor. *Expert System with Application*, 36, pp.366-377.