PressAcademia

Journal of Business, Economics and Finance

Year: 2015 Volume: 4 Issue: 3

THE COMPARISION OF THE FINANCIAL FAILURE WITH ARTIFICIAL NEURAL NETWORK AND LOGIT MODELS[1]

DOI:10.17261/Pressacademia.2015313060

Ebru Caglayan Akay [1], Tugba Gokdemir [2]

[1] Marmara University, Email: ecaglayan@marmara.edu.tr

[2] Uludağ University, Email: tugbagokdemir@uludag.edu.tr

Keywords

Financial failure,
Logit Model,
Neural Networks

JEL Classification

G17

ABSTRACT

The purpose of this study is to predict of the financial failure of the companies traded at the Istanbul Stock Exchange, determine the financial rates affecting the financial failure and build a model by which companies having a financial failure risk could be detected. For this purpose, experiment set data and financial failure model have been estimated by using artificial neural network and logit models. The performances of artificial neural network and logit models have been compared by the analysis of the control set data and validity of these models. The 2008-2013 data of the manufacturing industry companies traded at Istanbul Stock Exchange have been used and, distinctly from the similar studies in the literature, along with the model in which all failure criteria exist, three different models, where the criteria of making loss in two or more consecutive years and debt surpassing active are handled, have been built and the effects of the criteria on financial failure have been compared. At the end of the study, in the determination of the financial failure, the fact that debt surpassing active is much more effective than making loss in 2 or more consecutive years has been supported with both artificial neural network and logit model results. In financial failure studies, some findings about the fact that debt surpassing active is a more important indicator have been obtained. Furthermore, the fact that the most important rates affecting financial failure are liquidity and financial structure rates has been determined with the models built.

1. INTRODUCTION

The technological advancement in the twenty first century plays an important role in changing field of operation, position and capital structure of the companies. While the companies following the time and advancing technology obtain a chance of international competition, the ones not following this advancement go or are in the verge of bankruptcy. A number of crises have been experienced both in our country and the world.

[1] Compiled from a postgraduate thesis.

These crises cause the financial structure of companies disrupt and have adverse effects both for the companies and economy of the World. For this reason, recently, interest in the approaches which could predict the financial failure have been increased. Considering the studies carried out, it may be concluded that interest in the analysis where qualitative preference models and artificial neural network are used have particularly increased. Numerous definition about the company failure have been made and quite a number of indicators about the failure have been suggested. Companies experiencing problems and financial problems faced by all the companies may be defined as failures. The four criteria used in the literature extensively are the point in question. These are bankruptcy; company's failing to fulfill its obligations, company's failure to pay its debts and financial failure, respectively. Though these terms may substitute each other from time to time, there are differences between their real use (Altman, 2006). From the financial failure criteria

- *Bankruptcy*
- *Losing half of the capital*
- *Making loss for 2 or more consecutive years*
- *Loan default*
- *Debts surpassing the active*

have been extensively used in the analysis. In the studies carried out, while financial failure is modeled, dependent variable is formed according to these criteria and financial rates are used as an independent variable. In this study, different from the previous studies, models with three different dependent variables (model in which is debts surpassing active criterion is taken as the first dependent variable, two or more consecutive years of loss is taken as second dependent criterion and taking all failure criteria into account extensively used in the literature is taken as the third dependent criterion) have been built and the artificial neural network (back propagation, multi layered artificial neural network) and the success of classification of the logit model have been compared. Of the companies traded at the Istanbul Stock Exchange, 142 companies whose 2008-2013 balance sheet and statement of income reached have been included in the analysis. In three different models, some estimations about the success and failure of the companies have been made and which analysis is more useful to use has been determined according to the results obtained via training set, test (confirmation +set) set and artificial neural network analysis. Analysis have been carried out by classifying the artificial neural network into two groups as experiment/training and control/test sets by its nature. Computer programs Stata 12 and Matlab softwares have been used for logit models and artificial neural network, respectively. In the second part succeeding the introduction part of the study literature review, and in the third and fourth parts methodology and data and variables have been included, respectively. In last part, results obtained from the logit and artificial neural network have been discussed.

2. LITERATURE REVIEW

In the recent years, interest of various researchers and pragmatists in financial failure have gradually increased and different company failure estimation models, based on several prediction methods, have been built. It can be concluded that in the analysis of the company failure, econometric models such as failure discriminant analysis (e.g. Beaver, 1966; Altman, 1968; Gentry, et al,1987; Aly, et al., 1992; Sori and Jalil, 2009; Wong and Ng, 2010) logit and probit (Ohlson, 1980; Altman, et al.,1994; Aziz and Lawson, 1989; Court and Rodloff, 1990; Foreman, 2003; Laitizen, et al., 1996; Abdullah, 2008; Doğanay, et al., 2006; Lin and Mc Clean 2001) have been preferred. It is known that logit model particularly in comparison with the conventional prediction models, such as discriminant analysis and multiple regression analysis, is one the most preferred models in company success *(Tucker, 1996).* In their studies Court and Rodloff (1990) compared Multiple Discriminant Analysis and Logit Model and suggested that logit model gave more successful results than discriminant analysis. In the recent years, advancement in the information technology has enabled artificial neural networks, an artificial intelligence technology to be used. These advancements has made artificial neural network be a tool suitable for use in estimating financial failure and some studies in which financial failure is estimated have begun to take place in the literature (e.g. Shah and Murtaza, 2000; Moshiri and Norman, 2000; Koleyni, 2009; Wallace, 2008; Huang, et al., 2007; Tae, et al., 2004; Rodriquez, 1999; Aktaş, et al., 2003; Tyree and Long, 1997; Thawornwong and Enke, 2004; Roh , 2007; Kodogiannis ve Lolis, 2002; Akkaya, et al., 2011)

Some studies in the literature have taken discriminant analysis, logit models and artificial neural network, which are extensively used in the prediction of financial failure, together and compared their performances. For example; in their studies Latizen, et al (1996) have compared Multiple Discriminant, Logit and Artificial Neural Network and have confirmed that artificial neural network give better results comparing with the other statistical methods. In their studies, Altman et al (1994) have compared Artificial Neural Network, Linear Discriminant and Logit Analysis and at the end of their study have observed that statistical analysis models have given better results compared to artificial neural networks.

3. METHODOLOGY

In the study, it is aimed to determine the most suitable method by comparing performances of the binary logit model and artificial neural network in the estimation of the financial failures of the companies operating at the manufacturing sector. Logit model is the one where dependent variable is categorical (intermittent, discontinuous) and independent variable may be continuous and categorical or double sided (Czepiel, 2009). In logit model, obtaining "odds ratio" is of a crucial importance. Odds ratio is closely related with probability rate. An event has an odds ratio as it has probability. Probability is used to express that most people are able to see the probability of an event happening it is known that probability value changes between 0 and 1; from this point "0" probability shows that the event will not happen whereas "1" shows that it will happen. Yet, there are different ways to define the probability of an event happening and odds ratio is one of them. Should a probability of an event happening be "p", its probability not happening is

"1-p". The odds ratio of an event, in other words the ratio of an event happening and not happening is defined as "0" *(Allison, 2012)*.

$$O = \frac{p}{1-p}$$

p = probability of an event happening

1-p= probability of an event not happening

$$p = \frac{O}{1+O}$$

Logit model may be expressed as

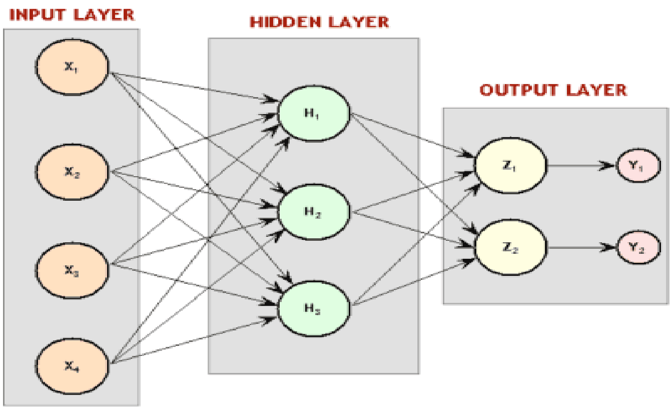
$$\log\left[\frac{pi}{1-pi}\right] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k$$

Here, pi value, y=1 is probability of happening. Left side of the equality may be expressed as "logit" or "log- odds ratio" *(Allison, 2012).* In the logit model parameter estimation may be made with the smallest squares and most similarity methods. [2]

Artificial neural networks are the computer systems having been built for the solution to the complicated problems which cannot be solved by the advancement of the new technological devices and formed with the inspiration from the biological neural networks *(Kohonen, 2000).* Artificial neural networks are analyzed in three main parts which are input, intermediary and output layers. These layers come together to form artificial neural networks. Artificial neural network model may be seen in **Figure 1**.

[2] *For further information:* Aldrich, John Herbert. And Nelson, Forrest (1984) **"Linear Probability, Logit, and Probit Models"** Sage University Papers Series. Quantitative Applications İn The Social Sciences. Allison,P (2012) **"Logistic Regression Regression Models: Theory And Implementation Using"** Sas®: Theory And Application, Second Edition . Hosmer, Dw., Lemeshow, S., and Sturdıvant, Rodney X. (2013). **"Applied Logistic Regression"**, Third Edition .John Willey & Sons, 307, New York-Usa. Cramer, J. S. (2003) **"Logit Models From Economıcs and Other Fıelds"** University Of Amsterdam and Tinbergen Institute. Pampel, Fred C. (2000) **"Logıstıc Regressıon: A Prıme"** University Of Colorado.

Figure 1: Artificial Neural Network Model[3]



In the analysis, from the artificial neural network types, feed network type has been used because of its ability and success in the classification in the financial estimation and dependent variable estimation *(Thawornwong, 2004).* In a feed forward network, transaction components are generally delaminated. In this type of network, information flow is directly sent to output layer from the input layer and this information flow is carried out one way *(Haykin, 2009)*.[4]

4. DATA AND VARIABLES

In the study, of the companies traded at the Istanbul Stock Exchange, data of the 142 companies whose 2008-2013 balance sheet and statement have been used and while financial failure is examined, distinctly from the other studies, three different models have been estimated for the artificial neural networks and logit analysis of the three different dependent variables. The definition of the variables used in the estimations have been summarized below.

---

[3]*Reference: https://dctekkilic.wordpress.com/2015/03/23*

[4] *For further information:* Kohonen, T. (2000) **"Self Organizing Network"** 3rd.New York Spring Series İn İnformation Sciences. Wallace Martin P. (2008) **"Neural Networks And Theır Applıcatıon To Fınance**", Business Intelligence Journal ,67-76 ,Freeman ,J.A. , Skapura ,D.M.,(1992) "**Neural Network Algorithm Applications And Programing Techniques"** (1-40)Addisson-Wesley Publishing Company. Hagan , M.T., Demuth. H.B. Behale, M.H., and Jesus, O. (2010) **"Neural Network Design"**2.Nd. Edition, S.2-6. Haykin ,Simon (2009) **"Neural Networks And Learning Machines"** Third Edition ,Mc Master University,Hamilton,Onterio,Kanada,1-76 .Patterson ,David W. (1996) **"Artificial Neural Networks Theory And Applications"**, İnstute Of Systems Science National University Singapure , 1-90. Graupe,Daniel (2007) **"Prıncıples Of Artıfıcıal Neural Networks"** 2nd Edition Advanced

Dependent Variable: For the first model, while dependent variable is formed according to the debts surpassing active, data set consists of 130 companies. It has been found that the number of successful companies is 65 and unsuccessful companies are 77. In order to equalize the number of successful-unsuccessful companies 12 unsuccessful companies have been left out of observation. In the second model, dependent variable is the situation of making loss for 2 or more consecutive years and 116 companies constitutes the data set. It has been detected that the number of the successful companies is 84 and unsuccessful companies is 58. So as to equalize the number of successful and unsuccessful companies, financial ratio of the 36 successful companies have been taken into account and they have been left out of the sample. In the third model, dependent variable is the model where all failure criteria have been taken into account and 106 companies constitute the data set. While the number of the successful companies is 53, the number of unsuccessful companies has been obtained to be 89. To equalize the number of successful and unsuccessful companies financial ratio of the 36 unsuccessful companies have been taken into account and they have been left out of the observation. In order to group the companies in the data set, of the values "0" has been given to financially unsuccessful, "1" to financially successful companies and dependent variables have been formed for three models[5].

Independent Variables : In all the models in the study, liquidity ratios, financial structure ratios, profitability ratios and operation ratios have been taken as independent variables. In our models, it has been found out that liquidity ratios and financial structure ratios have meaningful effects on determining the financial failure statistically. In the analysis, 30 financial rates in Appendix 1 have taken place in models as independent variable.

5. RESULTS

In order to analyze the financial failure, three different dependent variables have been formed and for each dependent variable both logit models and artificial neural networks have been estimated. In MODEL 1, the criterion of debts surpassing active has been analyzed. In this model, of the 30 independent variables only Liquidity Rate (acid test rate), Short Term Foreign Fund (STFF)/Total Funds and STTF /Total Foreign Funds financial rates have been observed to be statistically significant. The observation number for experiment/training set is 90 and for control/test set is 40. While training set consists of 45 successful, 45 unsuccessful companies, test set includes 20 successful and 20 unsuccessful companies.

The criterion of making loss for 2 or more consecutive years has been analyzed in MODEL 2. Discretely from the first model, in this model of the 30 independent variables, Long Term Foreign Funds (LTFF)/Total Funds and Operating Profit Margin Ratios have been found statistically significant. In the model, observation number for experiment/training

[5] In the study it was aimed to build different models for all failure criteria, yet as the number of independent variables is not enough, models could not be built. The reason why these three models were chosen is the number of successful and unsuccessful companies was high.

set is 80; control/test set is 36. While training set consists of 40 successful and 40 unsuccessful companies test set contains 18 successful and 18 unsuccessful companies. In MODEL 3, all the failure criteria have been taken into consideration. In this model, of 30 independent variables, LTFF/Total Funds and LTFF/ Total Foreign Funds financial ratios have been analyzed to be statistically significant. The number of observation in the model is 76 for experiment/training set and 30 for control/test set. While training set consists of 38 successful and 38 unsuccessful companies, test set includes 15 successful and 15 unsuccessful companies.

In Appendix 2, Logit Model Results and Classification Success Values of Experiment/Training Set of the three models and in Appendix 3 Logit Model Results and Classification Success Values of Control/Test set are situated in. In Appendix 4, the results of artificial neural networks for three models[6] have been summarized. In the estimation of the artificial neural networks, back prop as learning algorithm, multi layered perception as the type of the network have been used. In the analysis, since the single layered perception are limited to solve the nonlinear problems, multi layered perception have been suggested and back prop learning rule, known as a learning rule of this network, has been used. In Appendix 2, once the meaningfulness of the three models has been analyzed, all models have been observed to be at 99% confidence level. It can be concluded that Logit Model estimated for MODEL 1 has correctly classified successful companies by 93.33% and unsuccessful companies by 95.56% on the experiment/training set. Logit Model has been able to classify 42 of 45 successful companies (93.33%) and 43 of the 45 unsuccessful companies (95.56 %) correctly. Of the 45 successful and 45 unsuccessful companies, 3 (6.67 %) and 2 (4.44 %) companies have been misgraded as unsuccessful and successful companies, respectively. Total classification power of the model is 94.44%. According to these results, it can be concluded that the classification power of the unsuccessful companies of the logit model on experiment/training set for the first model is higher than its classification power of the successful companies.

In the logit model estimated for MODEL 2, the rate of classifying the successful companies correctly is 77.50%, whereas the rate of discriminating the unsuccessful companies correctly is 75%. Logit model has managed to classify the 31 of the 40 successful companies (77.50%) and 30 of the 40 unsuccessful companies (75%) correctly. 9 of the 40 successful companies (6.67 %) and 10 of the 40 unsuccessful companies (4.44%) have been misgraded as unsuccessful and successful companies, respectively. The total classification ratio of the model is 76.25 %, Contrary to the first model, the classification power of the unsuccessful companies of the second model of the logit model has been found to be lower than its power of classifying successful companies

[6] In the determination ıf the suitable artificial neural network, trial and error method have been use extensively. In this context, various combinations of the parameters such as the number of hidden layers, the number of knots in the hidden layers, learning rate, momentum term, activation function have been tried and the one with the best performance both on experiment/training and control/test set has been obtained.

In the logit model estimated for MODEL 3, the correct classification of the successful and unsuccessful companies has been observed to be equal with 84.21 %. Logit model model has managed to classify 32 of the 38 successful companies (15.79%) and 32 of the 38 unsuccessful companies correctly. 6 of the 38 companies and 6 of the unsuccessful companies have been misgraded as unsuccessful and successful companies, respectively. Total classification ratio of the model is equal and it is 84.21 %.

When three models in Appendix 2 compared, it can be concluded that the highest classification success in the training set of the logit analysis belongs to the first model. When the other two models are analyzed, it may be seen that the 3. Model is more successful comparing to the second model. Both the third and the second model have managed to classify the successful companies better than unsuccessful companies.

According to Appendix 3, when the general meaningfulness of all three models are checked, all models are at the 99% level of confidence on control/test data. When validity analysis of the models are checked;

For MODEL 1, on control/test set data, the ratio of classifying successful companies correctly is 95% 1st Logit model has classified 18 of 20 successful companies and 19 of 20 unsuccessful companies correctly. 2 of the 20 successful (10.00%) and 1 of the 20 unsuccessful companies (5.00%) have been misgraded as unsuccessful and successful companies respectively. As in the experiment set, in the first model of the logit model, the power of classifying unsuccessful companies has been observed to be higher than the power of classifying successful companies. The total classification ratio of the model is 92.50%.

In MODEL 2 control/test set data, companies the power of classifying both successful and unsuccessful correctly is equal and this value is 77.78%. Model has classified 14 of the 18 successful (77.78%) and 18 unsuccessful companies (77.78%) correctly. 4 of the 18 unsuccessful companies (22.22%) and 4 of the 18 successful companies (22.22%) have been misgraded as successful and unsuccessful companies, respectively. The total classification rate is same and is at 77.78% .The classification power of the second model has been found to be lower comparing to the first model. In other words, validity analysis results have shown that debts surpassing active criterion is more effective than making loss criterion.

For MODEL 3, as a result of the validity analysis, the power of classifying successful and unsuccessful companies correctly is equal and this rate is at 93.33%. Model has classified 14 of the 15 successful companies (93.33%) and 14 of the 15 unsuccessful companies (93.33%) correctly. Of 15 unsuccessful companies, 1 of them (6.67%) has been classified as successful and of 15 successful companies 1 (6.67%) has been misgraded as unsuccessful. For the third model, on control/test set, as on the experiment/training set, the percentages of the successful and unsuccessful companies are seemed to be equal. In logit analysis, in the experiment/training set and control/test set of Model 3, the classification ratios of the successful and unsuccessful companies are observed to be equal.

In Appendix 3, when three models are compared, the third model has been observed to give better results in the control/test set of logit analysis. When the other two models are compared, first model has been observed to be more successful comparing to the second model. When the logit analysis results are checked, the least successful results are at the second model both for experiment/training and control/test set. According to this result, in the determination of the financial failure, criterion of making loss has been observed to be unsuccessful.

In the analysis of artificial neural networks, training of the networks has been done on experiment/training set data one year before the failure. After trained, the network having the optimum performance has been recorded on the computer programme used. Afterwards, the financial rates of the companies until a year before the failure have been presented to network and outputs have been obtained. Network outputs obtained have been grouped with “0, 50” based on cut score. As a result of this, companies whose cut score is over “0, 50” have been classified as “successful” and the ones with below “0, 50” have been classified as “unsuccessful”. In order to search to what extent artificial neural network trained by using the experiment/training are valid apart from the data, validity analysis has been made as in the logit model.

When Appendix 4 is analyzed, it can be seen that MODEL 1 has managed to group the unsuccessful and successful companies son experiment/training set with a correct classification rate of 86.67% and 68.89 %, respectively. The model has discriminated 31 out of 45 successful (68.89%) and 39 out of 45 unsuccessful (86.67 %) companies correctly. 14 of the 45 successful (31.11%) and 6 of the 45 unsuccessful companies have been misgraded as unsuccessful and successful companies respectively. Total classification rate is 77.78%. In the 1st model the success of the logit analysis in training set is higher than artificial neural network analysis. In the control set, on the other hand, the correct classification rate of successful companies is 90.00 % and unsuccessful companies are 95.00%. Model 20 has discriminated 18 out of 20 (90.00%) successful companies and 19 out of 20 unsuccessful (95.00 %) companies correctly. 2 of the 20 successful (10.00%) and 1 of the 20 unsuccessful companies (5.00%) have been misgraded as unsuccessful and successful respectively. The results of both logit analysis and artificial neural network validity analysis are same and their total classification rates have been determined as 92.50%. The power of classifying unsuccessful companies on both experiment/training and control/test set is seen to be higher than the power of discriminating successful companies.

MODEL 2 has discriminated successful companies by 75.00% and unsuccessful companies by 70.00% correctly. 2nd model managed to classify 30 out of 40 successful companies (75.00%) and 28 out of 40 unsuccessful companies (70.00%) correctly. 10 of 40 successful (25.00%) and 12 of 40 unsuccessful companies (30.00%) have been misgraded as unsuccessful and successful, respectively. Total classification rate is 72.50%. For the second model, the power of discriminating unsuccessful companies on experiment/training set has been observed to be higher than the power of classifying successful companies. The same result has been obtained for the logit model as well. When the control/test set of the second model is analysed, the rate of discriminating successful companies is 94.44% and unsuccessful companies is 95.00%. The model, has managed to correctly classify the 17 out of 18 companies (94.44%) and 16 out out of 18 unsuccessful companies (88.89%). 2 of the 18 unsuccessful (11.11%) and one of the 18 successful companies (5.56%) set have been misgraded as successful and unsuccessful, respectively. In the 2nd model test set, artificial neural networks have shown a higher success of classification than the logit analysis.

For MODEL 3, the power of classifying the unsuccessful companies on experiment/training set 92.10% has been observed to be lower than the power of discriminating successful companies 97.37%. Model 3 has correctly classified the 31 out of 38 successful (68.89%) and 35 out of 38 unsuccessful companies (95.00%). 1 of the 38 successful (2.63%) and 3 of the 38 unsuccessful companies (7.90%) have been misgraded as unsuccessful and successful, respectively. The total classification power of the model is at 94.74%. The power of classifying successful and unsuccessful companies and total classification success rate of the third model on control/test data are same and this rate is at 100.00%. The model has discriminated the companies flawlessly. All of the 15 successful and unsuccessful companies have been classified correctly.

When Appendix 4 is analyzed, the 3rd model is seemed to have given better results in the training/test set of the three models. When the other two models are analyzed, 1st model has been observed to give better results than the 2nd model. In all three models the reason why the the results of artificial neural network is higher is that the network has been trained.

According to artificial neural network results, the least successful results for both experiment/training set and control/test have been recorded by the 2nd model, the least successful model. With this result, the fact that making loss criterion is not by itself enough to determine the financial failure has been proved by artificial neural networks as well.

For the validity analysis of the models, in the first model, the artificial neural networks and logit analysis are same while in the second model classifying power of artificial neural network has been found to be superior. On the training set data, on the other hand, artificial neural networks are more successful than logit model, only in the third model. In the 1st and 2nd model logit analysis have given better results is training set data. When dependent variables of the three models are analyzed, the most superior model has been found out to be the model 1, while the most superior one for the artificial neural networks is the 3rd model. According to the results of the study, it has been found out that debts surpassing active criterion has given results close to the third model built with combination of the all failure criteria and even has more successful classifying power than the third model in logit models.

6. CONCLUSION

In this study, some models have been built on the sample consisting of 142 companies traded at the Istanbul Stock Exchange and in order to estimate financial failure a year in avance the logit model, one of the conventional methods, and artificial neural networks have been compared. In the first model, it has been observed that in both logit and artificial neural networks, the classification rate of unsuccessful companies in both training set and test have been higher. This result has shown that debts are more effective on the determination of the unsuccessful. When the second model is analyzed, the success of classifying successful companies are higher in the logit and artificial neural networks for both training and test set. In this model, artificial neural network has given better results than logit analysis. The total classification success rate of the 2nd model has been lower than both of the models. In the third model, on the other hand, for logit and artificial neural network, successful companies in training and test set have shown more successful classification results than the unsuccessful companies. In this model, artificial neural networks have given better results than logit analysis as well. The classification power rate of the third model is higher than the other two models. The results obtained have shown that it is a more important criterion for companies to take all failure criteria into account. When two models are compared, it has been proved that debts were a more important criterion than making loss. When the dependent variables of the three models are analyzed, it has been found out that the most superior model in the logit analysis has been the 1st model, while the one in the artificial neural network has been the 3rd model.

In all three models built with the logit analysis, the rates obtained by long term and short term foreign funds have been found meaningful. As a result, it may be concluded that the most important rates in the analysis of the financial failure are liquidity and financial structure rates and these rates make importance differences in the successful and unsuccessful company groups. The findings obtained show that total debt is of a crucial importance on company failure. In the validity analysis of the models, in the model estimated according to debt surpassing active criterion, the classification power rate of artificial neural network and logit analysis have been found to be equal and in the other two models the classification power rate of artificial neural networks has been greater. On the training set data, on the other hand, only artificial neural network where all criteria dealt with has been more successful than the logit model. In the criteria of debt surpassing active and making loss for two or more consecutive years, logit analysis has given more successful results in the training set. At the end of the study, the criteria of debts surpassing active and making loss for 2 or more consecutive years have been compared with each other in the estimation of the financial failure and debt surpassing active has been found to be a stronger indicator of the failure.

REFERENCES

- Abdullah, N.A. (2008), "Predicting Corporate Failure of Malaysia's Listed Companies: Comparing Multiple Discriminant Analysis Logistic Regression and Hazard Model", *International Research Journal of Finance and Economics*, Issue: 15, 201-218

- Aktaş, Ramazan. Doğanay, Mete and Yıldız, Birol (2003), "Mali Başarısızlığın Öngörülmesi: İstatistiksel Yöntemler ve Yapay Sinir Ağı Karşılaştırması", *Ankara Üniversitesi SBF Dergisi*, 58-4

- Akkaya, Göktuğ Cenk. Demireli, Erhan and Yakut, Ümit Hüseyin(2009), "İşletmelerde Finansal Başarısızlık Tahminlemesi Yapay Sinir Ağları Modeli ile İMKB Üzerine Bir Uygulama", *Eskişehir Osmangazi Üniversitesi Sosyal Bilimler Dergisi,* 10(2) 187

- Aldrich, John Herbert. ve Nelson, Forrest (1984), "Linear Probability, Logit, And Probit Models", *Sage University Papers Series. Quantitative Applications İn The Social Sciences ,*

- Allison, P (2012), "Logistic Regression Regression Models: Theory And Implementation Using", Sas®*: Theory And Application, Second Edition*

- Altman, Edward I. (1968), "Financial Ratios, Discriminant Analysis And Prediction Of Corporate Bankruptcy", *The Journal Of Finance*, 23 (4): 589-590.

- Altman,E. Marco G and Varetto,F. (1994), "Corporate Distress Diagnosis: Comparisons Using Linear Discriminant Analysis And Neural Networks", *Journal Of Banking & Finance*, 18,Pp. 505–529

- Chung,Kim-Choy. Tan, Shin and Holdsworth, David K. (2008), "Insolvency Prediction Model Using Multivariate Discriminant Analysis And Artificial Neural Network For The Finance Industry İn New Zealand", *International Journal Of Business And Management,* 3 (1): 19-29.

- Cramer,J. S. (2003)," Logit Models From Economıcs And Other Fıelds", *University Of Amsterdam And Tinbergen Institute*

- Court, P.W. and Radloff, S.E. (1990), "A Comparison Of Multivariate Dicriminant And Logistic Analysis İn The Prediction Of Corporate Failure İn South Africa", *De*

Ratione, 4(2):11-15.Dobson Aj (1990). An İntroduction To Generalized Linear Models. Chapman And Hall

- Czepiel ,Scott A. (2009), " Maximum Likelihood Estimation Of Logistic Significant Factors Associated With Substance Abuse İn School-Aged Children", *Georgia State University,Mathematics Theses Department Of Mathematics And Statistics ,* 4-1

- Foreman, D. R (2003), "A Logistic Analysis Of Bankruptcy Within The Us Local Telecommunications İndustry", *Journal Of Economics And Bussiness*. 55, 135-166

- Graupe, Daniel (2007), "Prıncıples Of Artıfıcıal Neural Networks", *2nd Edition Advanced Series On Circuits And Systems – Vol. 6. University Of Lllinois, Chicago, Usa New Jwrsey . London Sıngapore .Beıjıng . Shan*

- Haykin, Simon (2009), "Neural Networks And Learning Machines", *Third Edition Mc Master University,Hamilton,Onterio,Kanada*,1-76

- Hosmer, Dw., Lemeshow, S., and Sturdıvant, Rodney X. (2013), "Applied Logistic Regression", *Third Edition .John Willey & Sons, New York-Usa,* 307

- Huang, W, Laı, K. K., Nakamorı, Y., Wang, S., Yu, L., (2007), "Neural Networks In Finance And Economics Forecasting", *International Journal Of Information Technology & Decision Making, Vol*. 6, No. 1113–140 *International Educational And Professional Publisher)*Thousand Oaks London New Delhi University Of Colorado, Bould

- Kodogıannıs, V. Lolıs, A., (2002), "Forecasting Financial Time Series Using Neural Network And Fuzzy System-Based Techniques*", Neural Comput & Applic*, 11:90–102

- Kohonen,T. (2000) , "Self Organizing Network", *3rd.New York Spring Series İn İnformation Sciences.*

- Moshırı, Saeed. Cameron, Norman. (2000), "Neural Network Versus Econometric Models İn Forecasting Inflation", *Journal of Forecasting J. Forecast*. 19, 201,217

- Ohlson J. A. (1980), "Financial Ratios And The Probabilistic Prediction Of Bankruptcy*", Journal Of Accounting Research*, 18-1 1, 109-131

- Rodrıguez, Agustin Alonso (1999), "Forecasting Economic Magnitudes With Neural Network Models", *Real Colegio Universitario Escorial-Maria Cristina--Spain. An Earlier Version Of This Study Was İncorrectly Printed İn The May 1999 İssue Of Iaer*

- Roh, T. H., (2007), "Forecasting The Volatility Of Stock Price Index*", Expert Systems With Applications* 33, 916–922.

- Patterson, David W. (1996), "Artificial Neural Networks Theory And Applications", *İnstute Of Systems Science National University Singapure* , 1-90

- Pampel, Fred C. (2000), "Logıstıc Regressıon: A Prımer", *University Of Colorado, Boulder, Sage Publıcatıons International Educational And Professional" Publisher Thousand Oaks London New Delhi*,1-25

- Sori, Zulkarnain Muhamad Ve Jalil, Hasbullah Abd (2009), "Financial Ratios, Discriminant Analysis And The Prediction Of Corporate Distress", *Journal Of Money, Investment And Banking*, 11: 5-15.

- Tae Kima, Yoon. Ohb, Kyong Joo. Sohnc, Insuk (2004), Changha Hwang , "Usefulness Of Artificial Neural Networks For Early Warning System Of Economic Crisis", *Expert Systems With Applications* 26 583–590 University Of Colorado, Boulder,

- Thawornwong,Suraphan. Enke ,David (2004), "The Adaptive Selection Of Financial And Economic Variables For Use With Artificial Neural Networks" , *Neurocomputing.*56, 205 – 232

- Tucker, Jon (1996), "Neural Networks Versus Logıstıc Regressıon In Fınancıal Modellıng:A Methodologıcal Comparıson", *University Of Southern California, Usa -,Plymouth Business School University Of Plymouth, Drake Circus, Plymouth, Devon, Pl4 8aa, United Kingdom*.1996 s.1-6

- Wallace, Martin P. (2008), "Neural Networks And Theır Applıcatıon To Fınance", *Business Intelligence Journal* ,67-76

- Wong, James M.W. Ve Ng, S. Thomas (2010), "Company Failure İn The Construction Industry: A Critical Review And A Future Research Agenda", *Xxıv Fıg International Congress*, Sydney, Australia, 11-16 ,April 2010

APPENDIX 1

FINANCIAL STRUCTURE RATIOS	LIQUIDITY RATIOS
Financial Leverage Ratio	Current Ratio
Short Term Foreign Funds (STFF) / Total Funds	Acid Test Ratio
Long Term Foreign Funds / Total Funds	Stock Dependence Ratio
STFF / Equity Capital	Currency Ratio
KSVD / Total Foreign Funds	Floating Assets / Foreign Funds Ratio
Long Term Foreign Funds / Total Foreign Funds	
Financing Rate (Equity Capital/Total Foreign Funds)	
Real Assets (RA) / Equity Capital Stock	
Fixed Assets/ Equity Ratio	
Equity Ratio	
Debt Equity Ratio	
OPERATING RATIOS	**PROFITABILITY RATIOS**
Inventory Turnover Ratio	Net Profitability Ratio
Avarage Number of Days Inventory on Hand	Operating Profit Margin
Receivable Turnover Ratio	Net Profit for the Period / Net Sales
Avarage Collection Period	Equity Dividend Rate
Asset Turnover	Asset Profitability
Real Assets Turnover Rate	Net Sales / STFF (Financial Rantability)
Current Assets Turnover Rate	Cost of Mechandise Sold / Net Sales

APPENDIX 2

Appendix 2. Experiment/Training Set Logit Models

Models	Variables	Coefficients (Standard Error)	Model Results	Classification
1.MODELS	Liquidity Rate (Acid test rate) STFF/Total Funds STTF /Total Foreign Funds Constant	4.4679** (1.8616) -23.9162*** (6.9182) 9.7472*** (3.8538) -2.5076 (2.7360)	LR = 95.34*** Log Likelihood= -14.7147 Pseudo R^2 = 0.7641 n=90	SC : % 93.33 CC : %95.56 FPDER: %4.44 FNDER : %6.67 TDC : %94.44
2.MODELS	LTFF/Total Funds Operating Profit Margin Constant	4.8394* (2.5512) 21.7856*** (6.3956) -0.5750 (0.6065)	LR = 33.14*** Log Likelihood= -38.8804 Pseudo R^2 = 0.2988 n=80	SC : %77.50 CC: %75.00 FPDER : %25.00 FNDER : %22.50 TDC: %76.25
3. MODELS	LTFF/Total Funds LTFF/ Total Foreign Funds Constant	-35.2801 8.8579 17.2189*** 4.5417 -0.1120 *** 0 .5315	LR = 40.72*** Log Likelihood= -32.3210 Pseudo R^2 = 0.3865 n=76	SC : % 84.21 CC: %84.21 FPDER : %15.79 FNDER: %15.79 TDC: %84.21

(i)*,** and *** indicate significance at the level 1%,5% and 10%, respectively. (ii) n: is the number of observations (iii) SC: Sensitivity criterion gives the values of the correctly determined observations of the successful companies (1) .CC: Certainty criterion gives the values of the correctly determined observations of the unsuccessful companies (0) .FPDER: False positive discrimination error rate is the rate showing that the successful companies are discriminated as unsuccessful. FNDER: False negative discrimination error rate is the rate showing that the unsuccessful companies are discriminated as successful. TDC: Total discrimination criterion is the value showing the total correct estimation rate of the model. It gives the total discrimination rate of the successful and unsuccessful companies.

APPENDIX 3

Appendix 3. Control/Test Set Logit Models

Models	Variables	Coefficients (Standard Error)	Model Results	Classification
1.MODELS	Liquidity Rate (Acid test rate) STFF/Total Funds STTF /Total Foreign Funds Constant	4.8912* 2.9111 -28.4957 ** (12.1293) 20.2803** (9.5321) -10.3663* (6.0406)	LR = = 42.24*** Log Likelihood = -6.60601 Pseudo R^2 = 0.7617 n=40	SC : % 90.00 CC : %95.00 FPDER : %5.00 FNDER : %10.00 TDC : %92.50
2.MODELS	LTFF/Total Funds Operating Profit Margin Constant	-7.4094** (3.4342) 7.0854 * (3.9506) 0.8629 (0.6993)	LR = 15.36*** Log Likelihood = -38.8804 Pseudo R^2 = 0.3078 n=36	SC : % 77.78 CC : % 77.78 FPDER : %22.22 FNDER : %22.22 TDC: %77.78
3. MODELS	LTFF/Total Funds LTFF/ Total Foreign Funds Constant	-53.2720*** (20.0269) 25.8079** (11.2886) 0.05239 (1.0965)	LR = 25.11*** Log Likelihood = -8.2370 Pseudo R^2 = 0.6039 n=30	SC : % 93.33 CC : % 93.33 FPDER : %6.67 FNDER : %6.67 TDC: %93.33

(i)*,** and *** indicate significance at the level 1%,5% and 10%, respectively. (ii) n: is the number of observations (iii) SC: Sensitivity criterion gives the values of the correctly determined observations of the successful companies (1) .CC: Certainty criterion gives the values of the correctly determined observations of the unsuccessful companies (0) .FPDER: False positive discriminationerror rate is the rate showing that the successful companies are discriminated as unsuccessful. FNDER: False negative discrimination error rate is the rate showing that the unsuccessful companies are discriminated as successful. TDC: Total discrimination criterion is the value showing the total correct estimation rate of the model. It gives the total discrimination rate of the successful and unsuccessful companies.

APPENDIX 4

Appendix 4. Experiment/Training Set Neural Network and Control/Test Set Neural Network

Models	**Type of network**	**Learning Algorithm**	**Number Of Nodes Input Layer**	**Number of Hidden Layers**	**Number of Nodes Output Layer**	**Classification**
1.MODELS	Multilayer Perceptron	Back Propagation	30	2 *1.* Number of Hidden Layers *:5* *2.* **Number of Hidden Layers:** *:1*	*1*	*SC : %68.89* *CC : %86.67* *FPDER : %13.33* *FNDER : %31.11* *TDC : %77.78*
	Multilayer Perceptron	**Back Propagation**	**30**	**2** **1.** Number of Hidden Layers *:5* *2.* **Number of Hidden Layers: Sayısı :1**	**1**	**SC : % 90.00** **CC : %95.00** **FPDER : %5.00** **FNDER : %10.00** **TDC : %92.50**
2.MODELS	Multilayer Perceptron	Back Propagation	30	2 *1.* Number of Hidden Layers *:2* *2.* **Number of Hidden Layers:** *:1*	1	*SC : %75.00* *CC: %70.00* *FPDER : %30.00* *FNDER: %25.00* *TDC: %72.50*
	Multilayer Perceptron	**Back Propagation**	**30**	**2** *1.* Number of Hidden Layers *:2* *2.* **Number of Hidden Layers:** *:1*	**1**	**SC : %94.44** **CC : %88.89** **FPDER : %11.11** **FNDER : %5.56** **TDC: %86.84**
3. MODELS	Multilayer Perceptron	Back Propagation	30	2 *1.* Number of Hidden Layers *:3* *2.* **Number of Hidden Layers:** *:1*	1	*SC : %97.37* *CC: %92.10* *FPDER : %7.90* *FNDER: %2.63* *TDC: %94.74*
	Multilayer Perceptron	**Back Propagation**	**30**	**2** *1.* Number of Hidden Layers *:2* *2.* **Number of Hidden Layers:** *:1*	**1**	**SC : % 100** **CC : %100** **FPDER : %0** **FNDER : %0** **TDC: %100**

Notes: (i) Italic Information Experiment/Training Set Neural Network and dark green information Control / Test Set Neural Networks results
(ii)SC: Sensitivity*;* *CC*: Certainty criterion *ölçütü*, FPDER: False positive discrimination error rate, FNDER: False positive discrimination error rate and TDC:Total discrimination rate