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**RISK MANAGEMENT AT COMMERCIAL CREDITS AND
ALTERNATIVE CREDIT SCORING MODEL**

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**RISK MANAGEMENT AT COMMERCIAL CREDITS AND
ALTERNATIVE CREDIT SCORING MODEL**

**TİCARİ KREDİLERDE RİSK YÖNETİMİ VE ALTERNATİF
KREDİ SKORLAMA MODELİ**

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- 1) Credit Scoring
- 2) Logistic Regression
- 3) Commercial Credits

ABSTRACT

In this thesis a credit scoring model is suggested in order to predict probability of default of bank's client companies. By using real data obtained from one of the Turkey's largest commercial banks about manufacturing firms, default prediction logistic regression model was built. After credit scoring model was built, cut off values are used to map probability of default obtained from logistic regression. Cut off point is a score where credits with risk scores smaller than this point are predicted as good credit and others beyond this point are predicted as bad credit. In order to define optimum cut off point, bad credit ratio of prediction curve is constructed where actually bad credit ratio is plotted against the good credit percentage of prediction for all cut off values. Bad credit ratio of prediction curve used in order to show the trade off between risk and volume.

Finally, Receiver Operating Characteristic (ROC) curve and Gini coefficient are used to test the result.

Keywords: Credit Scoring, Logistic Regression, Commercial Credits

ÖZET

Bu çalışmada banka müşterisi olan firmaların kredilerini ödeyememe olasılıklarını tahmin eden bir skorlama modeli önerilmektedir. Üretim firmaları hakkında Türkiye'deki bir bankadan elde edilen gerçek veri seti kullanılarak borcu ödememe tahmini yapan bir lojistik regresyon modeli oluşturulmuştur. Model oluşturulduktan sonra, kesim noktaları kullanılarak, model sonucu hesaplanan kredilerin ödenmeme olasılıkları sınıflandırılmıştır. Her kesim noktası için bu noktanın üzerinde kalan krediler kötü kredi, altında kalan krediler iyi kredi olarak belirtilmiştir. En uygun kesim noktasını bulmak amaçlı, her kesim noktası için iyi kredi olarak tahmin edilen kredi yüzdesi ve gerçekte kötü kredi olup iyi kredi olarak tahmin edilen bu kredilerin içinde kalan kredi oranından oluşan grafik çizilmiştir. Bu grafik risk ve hacim karşılaştırması yapmak amaçlı kullanılmıştır.

Sonuç olarak ise ROC doğrusu ve Gini katsayısı ile modelin sonuçları ve performansı değerlendirilmiştir.

Anahtar kelimeler: Kredi Skorlama, Lojistik Regresyon, Ticari Krediler

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I. INTRODUCTION

According to BIS (Bank for International Settlements), credit risk is most simply defined as the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms. The goal of credit risk management is to maximize a bank's risk-adjusted rate of return by maintaining credit risk exposure within acceptable parameters. Banks need to manage the credit risk inherent in the entire portfolio as well as the risk in individual credits or transactions. Banks should also consider the relationships between credit risk and other risks. The effective management of credit risk is a critical component of a comprehensive approach to risk management and essential to the long-term success of any banking organisation¹[1].

Commercial banks use various scoring models to evaluate financial performance of client firms for managing credit risk. The purpose of this thesis is to present an alternative credit scoring model which was built by using historical data. This scoring model can also help banks to develop their own credit scoring model to determine capital requirements for credit risk according to internal ratings based approach (IRB approach) which was created as a part of Basel-II replacing the original Basel Accord of 1988 (Basel-I) in an effort to create a better framework for regulating bank capital. Because under Basel-II foundation IRB approach, banks are allowed to develop their own empirical model to estimate the PD (Probability of Default) for individual clients or groups of clients by using their historical data. For further information about Basel-II, International Convergence of Capital Measurement and Capital Standards: A Revised Framework by Basel Committee on Banking Supervision can be read.[19]

In Turkey, the study for Harmonizing the Capital Measurement and Capital Standards in International Level, known as Basel-II was conducted in accordance with EU (European Union) regulations. Pursuant to the Banking Regulation and Supervision Board Resolution (BRSA) dated February 24, 2011 number 4099, it was announced that a parallel implementation process with Basel-I was introduced as from July 1st, 2011 until June 30, 2012, within the aim of ensuring that both banks and credit customers are accommodated

¹ Principles for the Management of Credit Risk – final document. Basel Committee on Banking Supervision, <http://www.bis.org/publ/bcbs75.html>

healthily to the innovations brought by Basel-II to capital adequacy measurement and especially to the calculation of credit risk. Following the termination of the parallel implementation process on June 30, 2012, the “definitive” implementation process has begun as of July 1st, 2012 and the final Basel-II regulations were published in the Official Gazette number 28337 dated June 28, 2012. [20]

Basel-II “definitive” implementation process has begun as of July 1st, 2012 in Turkey, and as far as credit risk is concerned, Basel-II allows banks to choose between two approaches for determining their capital requirements: 1- The standardised approach, which basically refines the old set of risk weights proposed in the 1988 Capital Accord (Basel-I), introducing the use of external ratings and leaving essentially unchanged the capital charges for loans to unrated firms; and 2- The internal ratings based (IRB) approach, which allows banks to use their own internal estimates of the credit risk components. Specifically, there are two variants of the IRB approach: the foundation IRB approach, where banks only provide estimates of each borrower’s PD (Probability of Default), and the advanced IRB approach, where banks estimate also LGD (Loss Given Default) ie the loss that the bank would face for a specific loan facility in case the borrower defaults, EAD (Exposure at Default) and M (Loan Maturity). [19]

According to Banking Sector Basel II Progress Report-October 2012 prepared by Turkey Banking Regulation and Supervision Agency (BRSA), 64% of banks are in harmonization with foundation IRB approach and 47% of banks are in harmonization with advanced IRB approach between the ratio of 50% and 100%. And also 92.9% of banks aims to use advanced IRB approach but only 65% of banks calculates PD for corporate companies and small and medium size enterprises.[18] In this thesis, credit scoring model was built by using historical data in order to calculate PD and after some enhancement this can help banks about harmonization with IRB approach.

Although different type of techniques have been used to build credit scoring model in order to predict PD (probability of default), discriminant analysis and regression based models are the most widely used methods in this area.

One of the most important study using ratio analysis was done by Beaver in 1966[2]. Beaver developed indicators that discriminate failed and non-failed firms using univariate

discriminant analysis. Beaver used cash flow / total debt, net income / total assets, total debt / total assets, working capital / total assets, current assets / current liabilities ratios and he concluded that when financial ratios are used to assess likelihood ratios, the cash flow / total debt ratio produces large likelihood ratios, even five years before failure.

In 1968, Altman[3] used a multivariate discriminant analysis with 5 variables that are working capital / total assets, retained earnings / total assets, earnings before interest and taxes / total assets, market value equity / book value of total debt, sales / total assets. The discriminant function with this ratios was called as Z-Score model. Altman obtained 94% and 97% classification accuracy among failed and non-failed firms with the Z-Score model that was built with matched sample data, and he concluded that 95% of the data was correctly predicted.

The multivariate discriminant analyses applications continued with Deakin[4] in 1972. Deakin used cash flow / total debt, net income / total assets, total debt / total assets, current assets / total assets, quick assets / total assets, working capital / total assets, cash / total assets, current assets / current liabilities, quick assets / current liabilities, cash / current liabilities, current assets / sales, quick assets / sales, working capital / sales, cash / sales ratios. Deakin also tested the model on an independent sample consisting of 11 failed and 23 nonfailed firms selected at random from the 1964 and 1963 Moody's Industrial Manual and he indicated that application of the second year's discriminant function correctly classified 90% of all firms that failed or did not fail in the next one to three years.

In 1974, Blum[5] applied multivariate discriminant analysis for 115 failed and 115 non-failed companies by using liquidity and profitability accounting data. He concluded that the predictive accuracy of his model was 93-95% at the first year before default, 80% at the second year, 70 % at the third, fourth and fifth years before default. One year later, Sinkey[6] used multivariate discriminant analysis to present statistical analysis of the balancesheet and income-statement characteristics of problem banks.

Altman and Lorriss[7] applied multivariate discriminant analysis for 40 failed and 113 non-failed companies and they indicated that accuracy ratio of a six variable model exceeds 90% in 1976. Another paper on discriminant analysis was published by Dambolena and Khory[8]

in 1980, their model validated correct percent classifications for years 1, 3, and 5 were 87%, 85% and 78% respectively.

Also regression based models was used during 1970's. Orgler[9] used regression analysis for commercial credits in 1970, in the hold-out sample he classified 75% of bad loans as bad and 35% of good loans as good.

In 1980, Ohlson[10] investigated a logistic regression analysis, he used data collected from the period 1970-76. At the cut off point which minimizes the sum of errors, 17.4% of non-failed firms and 12.4% of 105 failed firms were misclassified.

Srinivasan and Kim[11] compared logistic regression with other methods in 1987. Also Tam and Kiang[12] applied discriminant analysis, logistic regression and neural networks with 18 explanatory variables in 1992.

This was followed by Coats and Fant[13] in 1993, by using Altman's (1968) variables they applied discriminant analysis and neural network approach. Rosenberg and Gleit (1994) analyzed neural network technique in corporate credit decisions[14]. In 1999 Laitinen and Kankaanpaa[15] discussed 6 alternative methods that have been applied to failure prediction: linear discriminant analysis, logistic regression, recursive partitioning, survival analysis, neural networks and the human information processing approach. They used the Finnish data and examined all the methods from one, two and three years prior to failure. Their results indicate that with the three variables employed in this study, that no superior method has been found.

In this paper, logistic regression analysis technique which is a suitable method to build credit scoring model implemented to sample data. The use of a discriminant model to measure credit risk has not been considered here because of several problems that can occur when using this method as Eisenbeis mentioned in his survey.[21] Logistic regression requires less restrictive statistical assumptions so the use of logistic regression analysis essentially avoids all of the problems discussed with respect to discriminant analysis. And also logistic regression model is used because of the data specifications. In the data, dependent variable is a dummy variable and the explanatory independents are in different types and variables are not normally distributed. The sample data includes 1144 credits totally, 1110 of them are good credits, 34

of them are bad credits. Total number of good credits are much more than bad credits, so we expect that our scoring model should predict most of the good credits correctly rather than bad credits. In this study, good credit term is used to refer to a credit which is paid successfully and bad credit term is used to refer to a credit which is defaulted. For commercial credits, "default" means that credit is not paid in 90 days after maturity with agreed conditions. In the next two chapters more details about the data and the logistic regression model we used in our study is described.

Then, empirical results are presented and after score ranges are defined, cut off values are used to evaluate the prediction performance of the model. Cut off point is a score where credits with risk scores smaller than this point are predicted as good credit and others beyond this point are predicted as bad credit. The objective of credit scoring model is to optimize bank's risk and volume trade off. The sample data contains good credits more than bad credits, so optimum cut off point should predict most of the good credits correctly. Cut off point=4 maximizes our good credit prediction with minimum actually bad credit ratio. When we set $S=4$ as a cut off point, 59% of bad credits and 82% of good credits classified correctly. Finally, Receiver Operating Characteristic (ROC) curve methodology and Gini coefficient are used to test the discriminative power of the model.

1. DATA

The data used in this study is obtained from one of the Turkey's largest commercial banks. All of the credits used in the data are utilized between the year 2003 and 2011 by commercial manufacturing firms. The sample data consists of 1144 credits totally, 1110 of them are paid successfully, 34 of them are not. In this study, good credit term is used to refer to a credit which is paid in accordance with agreed conditions and bad credit term is used to refer to a credit which is not paid in 90 days after maturity with agreed conditions. Data includes 1110 good credits and 34 bad credits. Number of good credit is very high compared to number of bad credit, so data is not in equilibrium. Amount of these credits are greater than 100.000 TL/USD/EUR and maturities are greater than 3 months.

Financial ratios of each successful or unsuccessful year are used to predict repayment performance of customers. In order to compare the financial ratios appropriately, borrower firms which have net sales between 10 million-100 million TL are used. Total assets of firms are ranged from 1 – 450 million TL. Following financial ratios used as an independent variables for the model :

Liquidity ratio "*(Current assets - Inventories) / Current liabilities*" in other words quick ratio indicates liquidity of the borrower. Liquidity problems denote a higher default probability as Galil mentioned in his paper [24]. This ratio measures the ability of a company to use its near cash or quick assets to extinguish or retire its current liabilities immediately. Quick assets include those current assets that presumably can be quickly converted to cash at close to their book values so more liquid firm can pay its credits easier. Therefore, the higher liquidity ratio is better. Deakin[4], Srinivasan and Kim[11] used liquidity ratio in their studies to predict default probability. Gross margin "*Gross profit / Net sales*" indicates how much profit generated for every unit of revenue. The higher gross margin ratio means that firm covers its revenue from sales to profit effectively and in accordance with this Lennox (1999) found that a company is most likely to go bankrupt when it is unprofitable, highly leveraged, and has cashflow problems [23]. If "*Financial expenses / Net sales*" ratio is negative, it means that firms interest cost is higher than interest income. Tatlıdil and Özel[25] used this ratio in their studies and found it is significant. Debt ratio "*(Short + Long term debt) / Total assets*" indicates the percentage of assets that have been financed by borrowing. So, the lower

debt ratio means, the less risky firm. Beaver's[2], Deakin's[4] and Ohlson's[10] studies contain different analyse techniques by using debt ratio and they found that debt ratio has a positive relationship with default probability. In Turkey, textile sector has a large export volume and companies in this sector are more sensitive to foreign exchange rate. So, relationship between textile sector and repayment of credit is investigated. Textile sector variable is equal to 1 for borrowers which have operations in textile sector and 0 for another sectors.

All of the variables except textile sector are numeric variables. The descriptive statistics of this variables are given below.

Table 1.1. Descriptive Statistics

<u>Variables</u>	<u>Mean</u>	<u>Median</u>	<u>Maximum</u>	<u>Minimum</u>	<u>Std. Deviation</u>
Liquidity ratio	1.02	0.88	5.34	0.03	0.67
Gross margin	0.16	0.14	0.78	-0.08	0.11
Financial expenses / net sales	-0.03	-0.02	0.07	-0.85	0.05
Debt ratio	0.65	0.68	1.67	0.10	0.18

It can be seen from the above table that the maximum liquidity ratio is 5.34 and the minimum one is 0.03. So it can be said that our data has companies that are in more liquid position and also which are in nonliquid position, the average liquidity ratio is 1.02 and this ratio is acceptable for manufacturing firms. The average gross margin ratio of the data is 0.16, where the maximum one is 0.78 and the minimum one is -0.08. The minimum gross margin ratio shows that some of company's profit before tax is negative. In the data, maximum debt ratio is 1.67 and the minimum one is 0.10. The average of debt ratio is 0.68, this shows that some of the companies are financed by borrowing rather than capital stock.

At the beginning of this study more variables are used but high correlation between some of the variables caused insignificant probabilities. So, after insignificant variables have been removed, remaining 5 variables are used to build the model. The correlation matrix of variables are given below.

Table 1.2 Correlation Matrix

	Liquidity ratio	Gross margin	Financial expenses / net sales	Debt ratio	Textile Sector
Liquidity ratio	1.000000	0.117975	0.087756	-0.450832	0.039071
Gross margin	0.117975	1.000000	-0.206506	-0.122308	-0.011518
Financial expenses / net sales	0.087756	-0.206506	1.000000	-0.138102	0.002478
Debt ratio	-0.450832	-0.122308	-0.138102	1.000000	-0.074863
Textile Sector	0.039071	-0.011518	0.002478	-0.074863	1.000000

It can be seen from Table 1.2 that there is a high negative correlation between liquidity ratio and debt ratio. Debt ratio indicates the percentage of assets that have been financed by borrowing, and the higher debt ratio means more risky firm but more liquid firm means less risky firm, so negative relationship between debt ratio and liquidity ratio is normal.

Also debt ratio and gross margin ratio have negative correlation because high gross margin indicates less risky firm in contradistinction to debt ratio. Higher gross margin means that firm generates much profit from its sales, profitable firm can become more liquid easily. So there is a positive correlation between gross margin and liquidity ratio. Financial expenses to net sales ratio is negative when firm's interest cost is higher than interest income and higher debt ratio may cause higher interest cost, so there is a negative correlation between financial expenses to net sales ratio and debt ratio.

2. THE MODEL AND THE RESULTS

Logistic regression is a kind of regression which is used when the dependent variable is set up as a 0-1 dummy variable and the explanatory independents are any of type. Examples are the problem of explaining whether an individual will vote yes or no, whether a company will fail or not etc.

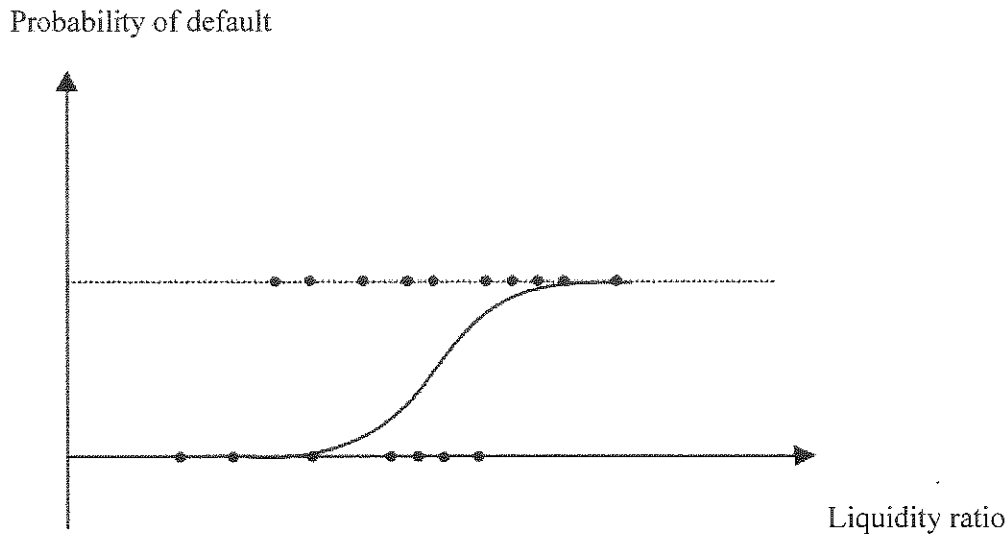
In this study logistic regression is performed on a sample of good and bad credits to build the model where the independent variables are 4 financial ratios and the sector. The dependent variable B_G has two categories, 0 indicates good credits (are paid successfully) and 1 indicates bad credits (are not paid successfully). Independent variables are Debt Ratio(DR), Financial Expenses/Net Sales(FE), Gross Margin(GM), Liquidity Ratio(LR) and Textile Sector(TS).

Logistic regression model produces estimated probabilities between 0 and 1. It does this by using a function that effectively converts to the regression model so that the fitted values are delimited within the (0,1) interval. Visually, the fitted regression model will come over as an S-shape rather than a straight line. This is shown in figure 2.1.

Also some other advantages of logistic regression can be summarized as follows;

The independent variables don't have to be normally distributed, or have equal variance in each group, so it is more robust. It does not assume a linear relationship between dependent and independent variables. The dependent variable need not be normally distributed. It does not require that the independents have to be interval. It does not require that the independents have to be unbounded.

Figure 2.1. The Logit Model



The logistic function F , which is a function of any random variable, z , would be,

$$F(zi) = \frac{e^{zi}}{1 + e^{zi}} = \frac{1}{1 + e^{-zi}}$$

where e is the exponential under the logistic regression model approach. The model is so called because the function F is in fact the cumulative logistic distribution. So the logistic model estimated would be,

$$Pi = \frac{1}{1 + e^{-(C+(\beta1*DR)+(\beta2*FE)+(\beta3*GM)+(\beta4*LR)+(\beta5*TS))}}$$

Coefficients are shown in Table 2.1. So the logistic model estimation is:

$$Pi = \frac{1}{1 + e^{-(C+(2.26*DR)+(-7.47*FE)+(-1.49*GM)+(-0.63*LR)+(0.85*TS))}}$$

For i=1 explanatory variables are, DR=0.39, FE=-0.06, GM=0.16, LR=0.54, TS=1

$$P_i = \frac{1}{1 + e^{-(-3.119)}} = 0.04$$

So, probability of default is 0.04. (P_i is the probability that $B_G=1$)

As it can be seen from Table 2.1. the signs of the logistic regression coefficients are consistent with our expectations about the effect of a each independent variable on credit default.

Table 2.1. The Results Of The Model

Dependent Variable: B_G

Method: ML - Binary Logit (Quadratic hill climbing)

Sample:1144

	Coefficient	Prob.
DEBT RATIO (DR)	2.264741 (1.057028)*	0.0321
FINANCIAL EXPENSES/NETSALES (FE)	-7.470793 (2.836956)*	0.0085
GROSS MARGIN (GM)	-1.486681 (1.804807)*	0.4101
LIQUIDITY RATIO (LR)	-0.635721 (0.465063)*	0.1716
TEXTILE SECTOR (TS)	0.854515 (0.507466)*	0.0922
C	-4.719065 (1.021682)*	0.0000
McFadden R-squared	0.086754	
Log likelihood	-139.7551	
Obs with Dep=0	1110	Total Obs 1144
Obs with Dep=1	34	

* Standart errors are in parenthesis.

Liquidity ratio, has a negative coefficient which indicates that as the liquidity of the borrower increases, the probability of default decreases. We would expect a higher liquidity ratio to lead to a decrease in a company's default risk. The more liquid firm can pay its credits easier and this conclusion proves this assumption.

Gross margin, has a negative coefficient which indicates that profitable firms are less likely to default. A high return on sales is a positive signal that a company occupies a strong market position, which should reduce company's default risk. So we would expect that the profitability of the borrower has a positive effect on credit repayment and this result proves this assumption.

Financial expenses / net sales, has a negative coefficient and this means if firms interest cost is higher than interest income, it is more likely to default. This ratio gives an information about company's burden of interest arises from loans hence the credit worthiness of the company.

Debt ratio, has a positive coefficient which indicates that lower debt ratio means less risky firm. In other words, when percentage of assets that have been financed by borrowing increases, probability of default increases. So positive coefficient supports this hypothesis.

Textile Sector, variable is equal to 1 for borrowers which have operations in textile sector and 0 for another sectors. The positive coefficient means that firms in textile sector are more likely to default. In this study relationship between textile sector and repayment of credit is investigated and more independent variable can be added for another sectors. Because of a high percentage of foreign trade in textile sector, companies in this sector are more sensitive to foreign exchange rate.

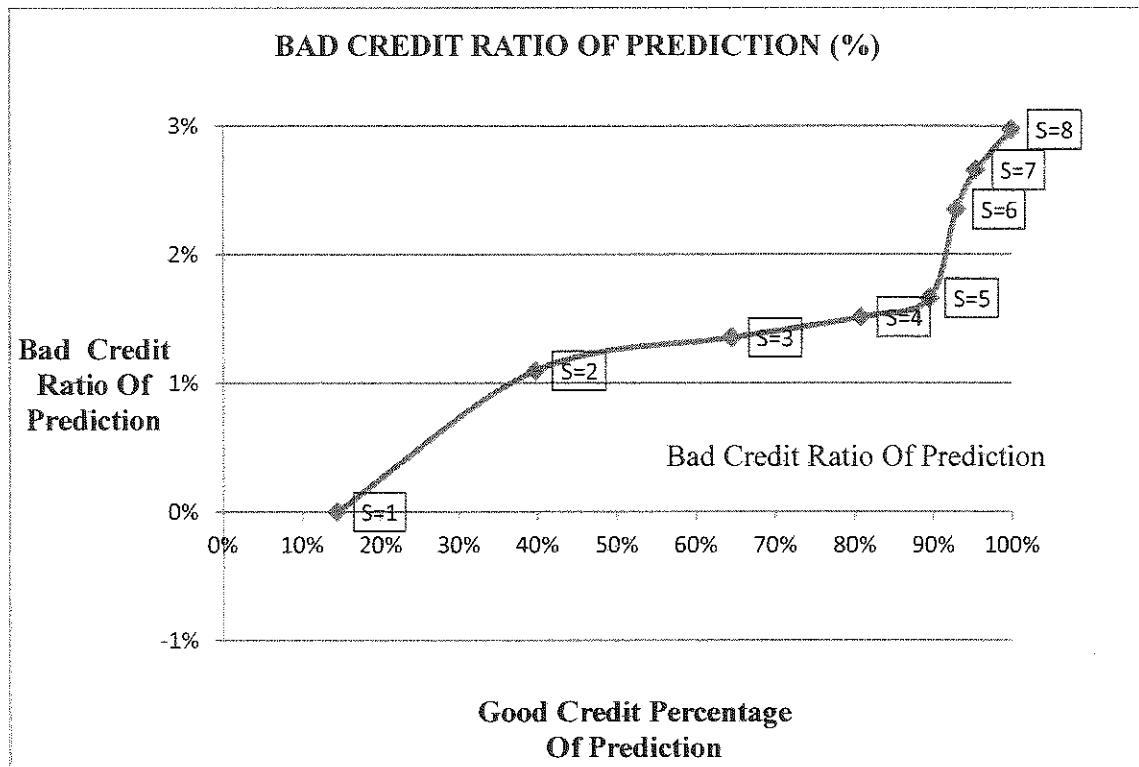
Defining the Score Ranges and the Cut off Point

After developing the model, score ranges are defined and then cut off values are used to evaluate the performance of the model. The scores we defined according to the results of the model are given below :

<u>Probability Of Default (PD)</u>	<u>Score</u>
0.00 < PD < 0.01	1
0.01 < PD < 0.02	2
0.02 < PD < 0.03	3
0.03 < PD < 0.04	4
0.04 < PD < 0.05	5
0.05 < PD < 0.06	6
0.06 < PD < 0.07	7
0.07 < PD	8

Cut off point is a score where credits with risk scores smaller than this point are predicted as good credit and others beyond this point are predicted as bad credit.

Figure 2.2. Bad Credit Ratio Of Prediction



It can be seen from figure 2.2 and table 2.2 that, at S=4, good credit percentage of prediction increases distinctly and also bad credit ratio of prediction has a minor increase. The objective of credit scoring model is to optimize bank's risk and volume trade off. So, S=4 as a cut off point maximizes our good credit prediction with minimum bad credit ratio.

Also it can be seen from table 2.2 that, when S=4 is defined as the cut off point, good credit percentage of prediction is 80.86 % and bad credit ratio of this prediction is 1.51 %. This means that when S=4 is defined as the cut off point, 925 of 1144 credits are classified as good credit and 14 of them are defaulted actually.

Table 2.2. Good Credit Percentage Of Prediction & Bad Credit Ratio Of Prediction

SCORE	PREDICTION		ACTUAL		GOOD CREDIT PERCENTAGE OF PREDICTION	INCREASE	BAD CREDIT RATIO OF PREDICTION	INCREASE
	GOOD	BAD	GOOD	BAD				
1	165	979	165	0	14.42%	-	0.00%	-
2	456	688	451	5	39.86%	25.44%	1.10%	1.10%
3	739	405	729	10	64.60%	24.74%	1.35%	0.25%
4	925	219	911	14	80.86%	16.26%	1.51%	0.16%
5	1024	120	1007	17	89.51%	8.65%	1.66%	0.15%
6	1064	80	1039	25	93.01%	3.50%	2.35%	0.69%
7	1092	52	1063	29	95.45%	2.44%	2.66%	0.31%
8	1144	0	1110	34	100.00%	4.55%	2.97%	0.31%

When we set the cut off point at S=4 we can see that 14 of actually bad loans were classified as good and 20 as bad. So it means that 59% of bad credits classified correctly. And also 82% of actually good credits predicted as good.

Table 2.3 Cut Off Point At Score 4

		PREDICTION		TOTAL	ACCURACY
		BAD	GOOD		
ACTUAL	BAD	20	14	34	59%
	GOOD	199	911	1110	82%

The Model Performance

Receiver Operating Characteristic (ROC) curve methodology which is a widely used validation technique for credit scoring models is applied to test discriminative power of the model. [22]

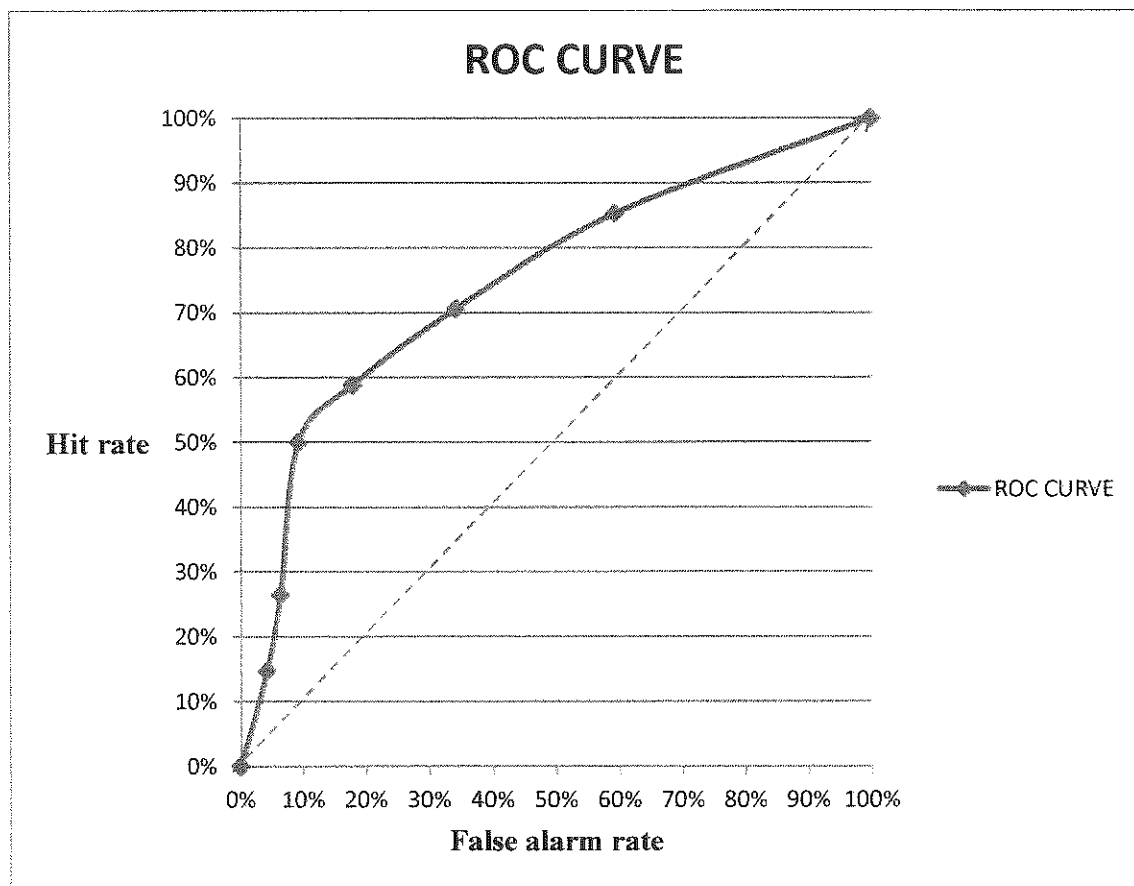
The construction of a ROC curve can be explained by two possible distributions of continuous scores for good credits and bad credits. For well-designed scoring models, the distribution of good credits should have better scores on average than the distribution of bad credits. To decide which credits will survive during the next period and which credits will default a value C has to be introduced. Each credit with a score lower than C is classified as a good credit and each credit with a higher score is classified as a bad credit. C can be called cut off point and in other words cut off point is a score where credits with risk scores smaller than this point are predicted as good credit and others beyond this point are predicted as bad credit. If the score is beyond this cut off point and the credit later defaults, the classification was correct. Otherwise, a good credit was incorrectly classified as a bad credit. The same procedure applies to the group of good credits. We define the hit rate $HR(C)$ as $H(C)/N_b$ where $H(C)$ is the number of correctly classified bad credits with the cut off point C and N_b is the total number of bad credits in the sample. The false alarm rate $FAR(C)$ is defined as $F(C)/N_g$ where $F(C)$ is the number of false alarms, that is, the quantity of good credits that were mistakenly classified as bad credits according to their scores and cut off point C . The total number of good credits in the sample is denoted by N_g . Hence, the ROC curve is constructed as follows. For all cut points C that are contained in the range of the scores, the quantities $HR(C)$ and $FAR(C)$ are calculated. The ROC curve is a plot of $HR(C)$ versus $FAR(C)$. For an example, Table 2.4 summarizes all possible decision results for score 4 as a cut off point;

Table 2.4 Decision Results For Score 4

		PREDICTION		
		BAD	GOOD	TOTAL
ACTUAL	BAD	20 (correct prediction) Hit!	14 (wrong prediction) Miss!	34
	GOOD	199 (wrong prediction) False alarm!	911 (correct prediction) Correct rejection!	1110

Accordingly, if the score of a credit is beyond 4, it is predicted as bad credit and if it is a bad credit actually, this means model's decision is correct. This situation is called an hit. Otherwise, the decision is wrong and called as false alarm. Number of correctly classified bad credits $H(4)$ equals to 20 and the total number of bad credits in the sample N_b is 34. So hit rate for cut off point 4 equals to $HR(4)=20/34=59\%$. The quantity of good credits that were mistakenly classified as bad credits according to their scores for cut point 4 is $F(4)$ and $F(4)=199$, the total number of good credits in the sample N_g is 1110. So false alarm rate for cut off point 4 equals to $FAR(4)=199/1110=18\%$. Similarly, if the score is below 4 and the credit does not default, the correct prediction made. Otherwise the decision is wrong. As a result for cut off point 4, hit rate is 59% and the false alarm rate is 18% . As mentioned before, to construct the ROC curve, hit rate and false alarm rate are calculated for all cut off points.

Figure 2.3. Roc Curve



The ROC curve is defined as a plot of Hit Rate (this can be also called as true positive rate or sensitivity) with respect to False Alarm Rate (this can be also called as false positive rate or 1-specificity) for all values of cut off scores. Figure 2.3 shows ROC curve of the model. The larger the area under the ROC curve the better the model's performance in predicting defaults. For a random model without discriminative power, the area under the ROC curve is 0.5 (the dotted line in (Figure 2.3), it is one for an ideal model and between 0.5 and one for any scoring model in practice. The Gini statistic is a linear combination of the area under the trade off curve. $Gini\ statistic = 2 * (ROC\ area - 0.5)$. A high Gini value means that the model is separating goods from bads better than the random model. Area under the ROC curve is 0.8001, so $Gini\ statistic = 0.6002$. However, Hamerle, Rauhmeier and Rösch[26] stated that this measure can not be compared between underlying portfolio and rated portfolio in their study, our model seems well-calibrated and also it has a relatively high sharpness (see Figure 2.2). Another, more qualitative argument arises from the review of several studies comparing rating systems that include qualitative variables (for example, sector) with those that do not. For example Grunert, Norden, and Weber[27] compared the accuracy of two internal rating systems, one using only quantitative data and the other additionally using qualitative data. They found that combined use of quantitative and qualitative variables results in significantly more accurate default predictions than the inclusion of only quantitative data. Frerichs and Wahrenburg[28] stated that banks with a small data set face several problems in building an internal rating system of their own and in 2007 Behr and Güttler[29] used a huge data set from more than one bank to build their scoring model. They used both financial ratios and qualitative variables to build a model for German small and medium-sized enterprises, and they found that area under the ROC curve is 0.8516. As compared with this, our data set is not huge and obtained from only one bank, but area under the ROC curve is 0.8001. So it can be said that both quantitative and qualitative assessments suggest that our model has discriminative power on a borrower's default risk.

II. CONCLUSION

In order to manage credit risk effectively, banks need a sophisticated decision support system backed by statistical methods. Credit scoring models are used as decision support system to measure, monitor, manage and control credit risks.

Risk management and profitability are very closely related so banks try to optimize their risk-return trade off. Conscious scoring model provides the bank early warnings for predicting potential business failure of borrowers. Thus, an effective risk monitoring supports managers' decisions and judgments, hence the profitability of the bank.

This study presents a scoring model to predict probability of default by measuring the financial performance of client firms. The sample data used in this study is obtained from one of the Turkey's largest commercial banks and data consists of 1144 credits totally, 1110 of them are paid successfully, 34 of them are not. The sample data contains good credits more than bad credits, so optimum cut off point should predict most of the good credits correctly and it should provide banks to balance their risk and volume. Liquidity ratio, gross margin, financial expenses/net sales, debt ratio and sector explanatory variables are used to predict repayment performance of customers.

The Logistic regression method is used to build the model because of its advantages and data specifications. After building the model, score ranges are defined to classify model's predictions. Then cut off values are used to evaluate the prediction performance of the model. Cut off point is a score where credits with risk scores smaller than this point are predicted as good credit and others beyond this point are predicted as bad credit. As a result, when cut off point equals 4, 59% of bad credits and 82% of good credits classified correctly. Finally the ROC curve is plotted and Gini coefficient is calculated to measure the discrimination power of the model.

For future projects, similar study can be done according to commercial loan types (installment, spot, revolving) or short term and long term loans. Foreign exchange rates are important for foreign currency loans, so TL and USD/EUR credits can be separated. And also this study can be done for each sector separately, this may give more detailed estimates

because every sector has different balance sheet dynamics. Companies which makes import and export are more sensitive to foreign exchange rate, so these company's credit risk is different from companies that have domestic trade. Different financial ratios or macroeconomic variables can be added to the model's explanatory variables.

REFERENCES

- [1] Principles for the Management of Credit Risk - final document. Basel Committee on Banking Supervision, <http://www.bis.org/publ/bcbs75.htm>
- [2] Beaver W. Financial ratios as predictors of failure. *Journal of Accounting Research* 1966;4:71–102.
- [3] Altman EI. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance* 1968;XXIII(4):589–609.
- [4] Deakin, E. B. (1972), A discriminant analysis of predictors of business failure, *Journal of Accounting Research*, 10-1, 167-179.
- [5] Blum, M., (1974) Failing company discriminant analysis, *Journal of Accounting Research*, 1-25.
- [6] Sinkey, J. F. (1975), A multivariate analysis of the characteristics of problem banks, *The Journal of Finance*, 30, 21-36.
- [7] Altman, E.I. and Loris, B. (1976), A financial early warning system for over the counter broker dealers, *Journal of Finance*, 31, 4, 1201-1217.
- [8] Dambolena, I. G. and Khoury, S. J. (1980), Ratio stability and corporate failure, *The Journal of Finance*, 1017-1026
- [9] Orgler, Y.E., Credit scoring model for commercial loans, *Journal of Money, Credit and Bank* 2: (1970) 435:445
- [10] Ohlson, J. A. (1980), Financial ratios and probabilistic prediction of bankruptcy, *Journal of Accounting Research*, 18, 109-131.
- [11] Srinivasan, V. and Kim, Y. H. (1987), Credit granting: a comparative analysis of classification procedures, *Journal of Finance*, 42, 665-683
- [12] Tam, Y. K. and Kiang, Y. M. (1992), Managerial applications of neural networks: the case of bank failure predictions, *Management Science*, 38, 926-947.
- [13] Coats P. And Fant L. Recognizing financial distress patterns using a neural network toll, *Financial Management* 22 (1993) 142-155.
- [14] Rosenberg, E. and Gleit, A. (1994), Quantitative methods in credit management - a survey. *Operations Research* 42, 589-613.
- [15] Laitinen, T. and Kankaanpaa, M. (1999), Comparative analysis of failure prediction methods: the Finnish case, *The European Accounting Review*, 8:1, 67-92

- [16] Bernd Engelmann, Evelyn Hayden, Dirk Tasche, Measuring the Discriminative Power of Rating Systems (2002)
- [17] Chris Brooks, Introductory Econometrics for Finance (2008)
- [18] http://www.bddk.org.tr/websitesi/turkce/basel/11342ilerlemeraporu_06_12.pdf
- [19] Basel Committee on Banking Supervision (2006) 'International Convergence of Capital Measurement and Capital Standards. A Revised Framework', June, available at: <http://www.bis.org/publ/bcbs128.pdf>
- [20] http://www.bddk.org.tr/WebSitesi/english/Announcements/Press_Releases/11035basel_ii_press_release.pdf
- [21] Eisenbeis, Robert A. (1977). "Pitfalls in the Application of Discriminant Analysis in Business, Finance, and Economics," *The Journal of Finance* 32(3), 875–900
- [22] Sobehart, J., and S. Keenan, 2001, Measuring Default Accurately, *Credit Risk Special Report*, 31–33.
- [23] Lennox, Clive (1999). "Identifying Failing Companies: A Re-evaluation of the Logit, Probit and DA Approaches," *Journal of Economics and Business* 51(4), 347–364.
- [24] Galil, Koresh, (2002). "The Quality of Corporate Credit Rating: an Empirical Investigation," Working Paper, Tel-Aviv University, Tel Aviv.
- [25] http://www.tbb.org.tr/Dosyalar/Arastirma_ve_Raporlar/Derecelendirme_Eylul2005.pdf
- [26] Hamerle, Alfred, Robert Rauhmeier, and Daniel Rösch (2003). "Uses and Misuses of Measures for Credit Rating Accuracy," Working Paper, University of Regensburg, Regensburg.
- [27] Grunert, Jens, Lars Norden, and Martin Weber (2005). "The Role of Non-Financial Factors in Internal Credit Ratings," *Journal of Banking and Finance* 29, 509–531.
- [28] Frerichs, Hergen, and Mark Wahrenburg (2003). "Evaluating Internal Credit Rating Systems Depending on Bank Size," Working Paper Series: Finance and Accounting, University of Frankfurt, Frankfurt, 115.
- [29] Behr B. and Güttler A. (2007). "Credit Risk Assessment and Relationship Lending: An Empirical Analysis of German Small and Medium-Sized Enterprises" *Journal of Small Business Management* 2007 45(2), 194-213