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FACTORS INFLUENCING THE CREDIT RATIONING ON THE COMMERCIAL LENDING PROCESS

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ABSTRACT
Adverse selection and moral hazard problem that arise due to asymmetry of information is often observed in banking sector. Accordingly, banks use credit rationing mechanism in order to mitigate the losses that arise due to asymmetric information. In this study the concept of credit rationing mechanism applied by banks is examined by exploring the manufacturing firms from various sectors which applied for a corporate loan in 2103. Logistic regression and discriminant analysis were employed in order to estimate the credit rationing. The results indicate that morality, credit history, and liquidity variables have significant impact in the commercial lending process.

1. INTRODUCTION

An important feature of financial markets is the asymmetry of information that is defined as a situation in which one party –generally a borrower- in a transaction has more or superior information than another (mostly lender) party. The concept of asymmetric information was first introduced through Lemon Theory which was developed by George Akerlof (1970), who was later awarded with the Nobel Prize. Afterwards, this theory was studied in various contexts including labor, insurance, loan and capital markets. Asymmetric information in credit markets arises due to the failure of lenders and borrowers to exchange complete and correct information between each other. In a financial transaction, borrowers will have more information than lenders about their past default and likelihood of subsequent default, ability to repay, and the use of loan. This situation will lead to credit rationing where lenders either will not issue the loan or reduce the amount of loan. According to Frederic Mishkin, asymmetric information in financial markets leads to two primary problems that are Adverse Selection and Moral Hazard.

In financial markets, adverse selection is an *ex-ante* problem that occurs between lenders and borrowers where banks or financial institutions issue a loan to a risky customer. Adverse selection occurs when a borrower with a high credit risk and low credibility is willing to borrow loan and pay the high interest rate.

For example, a bank sets one price (interest rate) for all of its loans and the adversely selected customers are those who are risky ones and have a low potential for repayment of the loan. Adverse selection problem in credit markets can be mitigated through collateral requirements and credit rating services. Moral Hazard is an *ex-post* problem that arises between lenders and borrowers after a transaction occurs. It arises because an individual or institution does not consider the full consequences and responsibilities of its actions and hence has a tendency to act less carefully. In credit markets, moral hazard problem refer to a situation where borrowers do not use the fund for the specified purpose. Moral hazard problem occurs as a result of the inability on part of the lenders in monitoring the operations of borrowers and can be mitigated by close monitoring of the borrowers after a loan is issued (Atiyas et al, 1993:2).While adverse selection problem occurs before the transaction, moral hazard problem is seen after entering into a contract.

Credit rationing is limiting the supply of additional credit (loan) to the borrowers who are even willing to repay with higher interest (Jaffe and Russell, 1976:651). Credit rationing happens when demand for loans exceeds the supply. If lenders limit credits, due to adverse selection and moral hazard, for borrowers who have agreed to repay them, credit (loan) is rationed (Er,2011:311) In the literature, there are two types of theories in credit rationing. The first type of theory about credit rationing was developed by Jaffee and Russell (1976). According to their theory, the credit rationing occurs if lenders issue the credit less than what was demanded by borrowers. The second type of credit rationing theory was developed by Stiglitz and Weiss in 1981. In this theory, they argued that lenders implement credit rationing by declining (denying) the credit application entirely. The rest of this paper is organized as follows; the second part of this paper provides an empirical literature review on credit rationing, in the third part the dataset and methodology are presented, in the fourth part, the empirical result and findings are explained, and the last part concludes the study.

2. LITERATURE REVIEW

The modern literature on credit rationing dates back to John M. Keynes`s studies on Money. Hodgam (1960, 1962) was the first who actually studied the modern credit rationing in his researches. He explained the causes of credit rationing through economic reasons rather than institutional factors. The following researches are conducted in credit rationing from different perspectives. According to Petersen and Rajan, 1994, banking relationships seem to lessen credit rationing because banks can easily monitor and access information regarding borrowers' history and actions. Similarly, Berger and Udell (1995) found that the length of relationship lowers both the loan rate premiums and the likelihood of collateral requirements. Cole (1998) concludes that a previous experience with a lender increases the likelihood of credit availability and thus decreases the credit rationing.

Another important factor that mitigates the credit rationing is the age of the firms. Diamond, 1991, and Oliner and Rudebusch, 1992, have found that in credit rationing firm age is an indicator of firm's quality, since longevity may contain a signal for survival ability and quality of management, as well as the accumulation of reputational capital.

Moreover, the information gap is relatively smaller for older firms given their longer track record (Petersen and Rajan, 1994; Cressy, 1996). In addition; recent studies have indicated that the likelihood of credit rationing increases for more innovative firms. In particular, when the loan applicant requires funding for specific, intangible and highly innovative investment, such as those in R&D, rationing may be more likely (Freel, 2007 and Piga and Atzeni, 2007). External auditing and international accounting standards are also thought to reduce firm denseness by increasing the transparency of financial accounts. Dharan (1993) points out that the auditor's opinion is assumed to convey, without error, the risk characteristics of the firm to the lenders. Given that external auditing is costly, firms that choose to do so actually send a quality signal to potential lenders (Konstantinos and Nicholas 2011). According to Cole, 1998; Rajan and Zingales, 1998; Beck and Levine, 2002; Cowling and Mitchell, 2003, industrial heterogeneity has considerable impact on the credit rationing mechanism. Another factor that affects the credit rationing is the managerial ability (Cavalluzzo et al., 2002). In his study, Hubbard (1998) states that a firm's investment opportunity set may also affect the likelihood of rationing.

3. DATA AND METHODOLOGY

In this study, we obtained data from a state bank (bank-level data) that operates in Gaziantep region in Turkey. The data set includes quantitative and qualitative factors for 100 firms operating in manufacturing sector which applied for a corporate loan in 2013. We were only able to include 77 firms to the analysis due to the missing data of firms. All firms are classified into two groups; non-rationed and credit rationed firms based on loan approval. Accordingly, if a loan application is approved and granted in full then the firm is considered non credit rationed firm. However, if the loan application was rejected or partially granted then the firm is regarded as credit rationed. Thus, the depended variable here takes binomial value 1 for rationed firm and 0 for non-rationed firm. The factors that might influence the credit rationing are indicated as follow, firm size (x1), firm age and ownership structure (x2), bank relations (x3), foreign trade status (x4), the administrative structure (x5), morality (x6), liquidity (x7 (A)), the asset structure (x7 (B)), the capital structure and leverage (x7 (C)), profitability, and productivity (x7 (D)), the performance ratios (x7 (e)) and the credit history (x8). Each factor is scored between 1 and 4 by the bank where 1 indicates lower risk measure and the score of 4 specifies higher risk measure. The variables, abbreviations and codes used in the study are shown in appendix 1.

Firm size is one of the independent variables which defined as total annual net sales of the firms in the sample. As total net sales increases, the credit risk hence probability of credit rationing is expected to decreases. The next independent variable is firm age which indicates the history of the company which is indicator of firm's reputation and livability. Bank relationship variable defined as firm's past experienced with banks and the variable is expected to have negative relationship with credit rationing. Foreign trade (export and import) status; the variable specify whether or not the firm has any international business relationship. Foreign trade variable is expected to have negative impact on the credit rationing. If a firm does not involve any foreign trade, either by exporting or importing, the variable was not used in the analysis.

Administrative structure; the variable indicates the type of management and total experience of the professionals in the firm. Morality is classified as firm's past borrowing experience (how a firm fulfilled its obligations) and higher morality indicates lower credit rationing. Liquidity variable explains the power of firms to meet the short-term liabilities. The higher the liquidity of a firm the lower credit rationing will be. Asset structure variable explains how firm's assets are allocated and effectively utilized? Capital structure and indebtedness; defined as the total debt level and leverage ratio. Profitability and efficiency variable indicate the relationship between firm's sales, profitability and credit rationing. Performance ratios: the ratio measures impact of performance ratio on the credit rationing. Credit history is the last variable in the analysis provides information about a firm's past loan growth and credit information.

4. EMPIRICAL RESULTS

In this study, we first performed a correlation analysis in order to test whether or not there is a significant correlation among the variables. Correlation analysis proves the multicollinearity problem by measuring the linearity of the relationship between variables. Multicollinearity occurs when two or more variables in a model are correlated and provide abundant information about the response. As indicated in appendix 2, no significant correlation was found among the variables. Tolerance and Variance Inflation Factor (VIF) were also examined to test whether or not there is a significant Multicollinearity problem between the variables. Menard (1995) indicates that if the tolerance value is <0.1, then there is a serious multicollinearity problem in the model, and if it is <0.2, then there is a potential multicollinearity problem. According to Myers (1990), the multicollinearity problem appears in a model if the VIF value is greater than 10. Field (2005) states that the average VIF score that is close to 1 indicate that multicollinearity problem does not exist in a model. According to Cokluk (2010), the standard error of regression coefficients (β) should be evaluated in order to figure out the multicollinearity problem. If the standard error of all variables is less than 2, it is considered that multicollinearity problem does not exist.

Table 1: The test of Multicollinearity Problem with Standard Error, Tolerance and VIF Values.
Coefficients(a)

Model		Unstandardized Coefficients		Collinearity Statistics	
		B	Std. Error	Tolerance	VIF
1	(Constant)	-4,218	1,561		
	Size	0,047	0,119	0,668	1,496
	Age	-0,010	0,125	0,734	1,363
	Relation	-0,100	0,207	0,471	2,121
	Export	0,194	0,140	0,729	1,372
	Admin	0,408	0,404	0,494	2,024
	Character	1,201	0,737	0,784	1,276
	Liquidity	0,133	0,090	0,547	1,827
	Asset	-0,129	0,130	0,710	1,408
	Leverage	0,228	0,130	0,454	2,204
	Profit	0,016	0,061	0,768	1,302
	Performance	0,063	0,092	0,823	1,215
	History	0,128	0,068	0,830	1,205

As seen in Table 1, the standard error of the independent variables was found to be less than 2; the tolerance value for all variables was found to be more than 0.2 and the VIF value for all variables appears to be less than 10. Therefore, the problem of multicollinearity between the independent variables does not exist. Durbin–Watson (DW) statistics test is used to identify the presence of autocorrelation problem in the regression analysis. The value of DW statistics lies between 0 and 4. The value close to 0 indicates positive serial correlation, the value close to 4 indicates negative autocorrelation problem and the DW value around 2 indicates no autocorrelation. As seen in Table 2, the DW value was found 2,373 and the result concludes that there is no autocorrelation problem in the model.

Table 2: Autocorrelation Problem
Model Summary(b)

Model	Durbin-Watson
1	2,373

a. Predictors: (Constant), History, Export, Character, Leverage, Performance, Asset, Profit, Age, Size, Admin, Liquidity, Relation

b. Dependent Variable: Rationing

4.1. Discriminant Analysis and Results

Discriminant analysis is one of multivariate statistical techniques which aim to predict the relationship between the categorical variables and metric independent variables (Kalaycı, 2008: 335). Discriminant analysis has two main objectives: separation and classification. If the first objective (seperation) was used in an analysis the model is called Descriptive Discriminant Analysis for the second objective the model is specified as Predictive Discriminant Analysis (Özdamar, 1999:320).

SPSS 18.0 statistical analysis program was used to analyze the data. 12 different variables included in the analysis and only 3 variables found as significant determinants of credit rationing. In disciriminant method there are three assumptions to minimize the misclassification and provide optimal analysis: equal covariance, the lack of multiple connections and normal distribution. In order to apply the discriminant analysis for the data, group must have equal covariance matrix. Equal variance assumption is tested by Box's M statistic. The significant Box’s M statistics show the deviation from normality or unequal covariance matrix or both (Albayrak, 2006: 63). Although homogeneity of variance and covariance matrix is the main assumptions, discriminant analysis still can be performed where the covariance matrix is not equal. When the data tested by Box-M Statistic, the results indicate that Box’s M=35,117, F=5,595, $p<0,01$, the covariance matrix is not homogenous.

Table 3: Eigenvalue

Function	Eigenvalue	Variance	Cumulative	Canonical Correlation
1	0,388a	100,0	100,0	,529

As shown in Table 3, since initially two groups were determined one discriminant function was derived. The higher Eigenvalue indicate that the larger part of the variance in the dependent variable is explained by the function. Canonical discriminant function explains 100% of the total variance. The resulting function is statistically significant. Eigen value of this function is 0.388.

Table 4: Wilk’s Lambda Value

Function Test	Wilks' Lambda	Ki-Square	Sd	Anl.
1	,721	24,082	3	,000

Table 4 indicates the ratio that was not explained by the total variance of discriminant scores of Wilk's Lambda statistics. In the test conducted by Wilks’ Lambda, the first function Wilks' Lambda value of 0.721 (i.e. 72.1% of the total variance) cannot be explained by the groups.

Table 5: Canonical Discriminant Coefficients

	Function
	1
Character	6,093
Liquidity	1,124
History	,567
Constant	-16,089

As seen Table 5, among 12 factors 3 variables namely Character, Liquidity and History were found statistically significant and included in the model. The discriminant equation result is given below. The morality variable is the most effective variable for the Z-score value in the discriminant equation.

$$Z_{score} = -16{,}089 + 6{,}093 \text{ Character} + 1{,}124 \text{ Liquidity} + 0{,}567 \text{ History}$$

Table 6: Average Group Discrimination Function Values

	Function
	1
No Credit Rationing	-0,561
Credit Rationing	0,673

In Table 6, the average separation function scores for each company (group) are presented. In other words it is found that $Z = \frac{N_a Z_b + N_b Z_a}{N_a + N_b} = 0{,}112$. Accordingly the following classification was carried out; if Z score value is greater than > Z, then there was found credit rationing or vice versa.

Table 7: Discriminant Analysis Classification Success

Discriminant Analysis		Estimated Group			
		0	1	Total	Accuracy Percentage
Observed Group	0	30	12	42	71,4
	1	8	27	35	77,1
	Total	38	39	77	74,0

In table 7, the classification value of the 77 companies obtained from discriminant analysis is presented. The model estimated the credit rationing with 71.4 % (30 out of 42) and 77.1 % (27 out of 35) accuracy for the non-credit rationed and credit rationed firms respectively. The total correct classification success for 77 companies is recorded as 74 %.

4.2. Logistic Regression Analysis and Results

We also employed in order to identify the factors that affect the credit rationing in a loan approval process. Logistic regression or *logit* regression as a statistical modeling technique is used to predict the outcome of a categorical dependent variable, such as class or label, based on one or more independent variables. The purpose of this method is to build the most appropriate model which identifies the relationship between independent and dependent variable with minimum input (variable) (Çokluk, 2010:1359). In general, multivariate logistic regression model is defined as follows (Ozdamar, 2004:590);

$$P(Y) = \frac{e^{Z}}{1 + e^{Z}}$$

where Z is a linear combination of independent variables.

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p$$

where$\beta_0, \beta_1, \beta_2$ and β_n are regression coefficients.

In logistic regression method, binary logistic regression analysis is used if the dependent variable consists of categorical variable with two options (Cokluk, 2010:1362-1363). Since the dependent variable is a categorical variable with two different outputs, we used Binary Logistic Regression Analysis in this study.

The hypotheses of the model can be constructed as follows;

$H_0: \beta_0 = \beta_1 = \beta_2 = \cdots = \beta_p$
$H_1: \beta_0 \neq \beta_1 \neq \beta_2 \neq \cdots \neq \beta_p$

Table 8: Omnibus Tests of Model Coefficients

	Chi-square	df	Sig.
Step	3,963	1	0,047
Block	29,729	4	0,000
Model	29,729	4	0,000

In Table 8, the omnibus test which measures whether or not they explained variance in a set of data is significantly greater than the overall unexplained variance is presented. The model is found to be significant at the 0.95 confidence level.

Table 9: Model Summary

	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
	76,379	0,320	0,428

In Table 9, Cox & Snell R Square and Nagelkerke R Square scores indicate the amount of variance explained by the logistic model. Higher Nagelkerke R Square score indicates better model fit and the R square score that is equal to 1 shows perfect model fit (Cokluk, 2010:1386). Nagelkerke R Square was found to be 0.428 and the score indicates that 42.8 percent of the model is explained by the independent variables. The -2 log likelihood value is used for investigating the contribution of independent variables to the model and testing the significance of the regression coefficients (Avci, 2011:97). The -2 log likelihood is found to be 76.379 at 95 % confidence level. In the initial model that includes only the constant term, the -2 log likelihood value is found to be 106,107, but at the end of the fourth step, the value is found to be 76,379. The decreasing -2 log likelihood indicates improvement in model-data fit as independent variables are added to the model.

The Hosmer–Lemeshow test is used to measure the goodness of fit for logistic regression models. This test examines whether or not all logistic regression (logit) coefficients (except the constant) term is equal to zero.

H_0: There is no significant difference between observed and predicted value in the model.

H_1: There is significant difference between observed and predicted value in the model.

Table 10: Hosmer and Lemeshow Test

	Chi-square	df	Sig.
	14,771	8	0,064

As seen in Table 10, since the chi-square value of the model with 8 degrees of freedom (14,771) is found to be less than χ ^ 2 (0.05, 8) = 15.51,H_0 hypothesis is not rejected.

Table 11: Classification Table

Observed		Predicted		
		Rationing		Percentage Correct
		0	1	
Rationing	0	34	8	81,0
	1	9	26	74,3
Overall Percentage				77,9

In Table 11, the classification scores obtained from logistic regression model are presented. The ratio of the total correct classification of the model at 5% significance level is found to be 77.9%. The model correctly estimates 34 of 42 non-rationed companies and 26 of 35 credit rationed firms.

Table 12: Estimated Coefficients Variables in the Equation

	B	S.E.	Wald	df	Sig.	Exp(B)
Character	11,187	5,691	3,864	1	0,049	72.205,616
Liquidity	0,996	0,441	5,098	1	0,024	2,706
Leverage	1,148	0,605	3,602	1	0,058	3,152
History	0,843	0,389	4,704	1	0,030	2,324
Constant	-29,832	11,800	6,392	1	0,011	0,000

In Table 12, the standard error of coefficients of independent variables (SE), Wald statistics (Wald), significance levels (Sig) and Exp (B) statistics are given. In logistic regression, Wald statistic, which has a specific distribution known as chi-square, is a measure of the significance of β (Cokluk, 2010:1388). The variables including Character, Liquidity and History is found to be significant at 95 % confidence level. The Leverage variable is found to be insignificant at 5% significance level and is not included in the model. Eventually, the model is constructed as follows;

$$\mathrm{In}\left[\frac{\mathrm{P}}{1-\mathrm{P}}\right] = -29{,}832 + 11{,}187\ \mathrm{Character} + 0{,}996\ \mathrm{Liquidity} + \ 0{,}843\ \mathrm{History}$$

According to the model, as all three risk factors increases, the likelihood of a bank's credit rationing increases. Especially, the Character risk factor has significant impact on credit rationing compared to the other two factors.

5. CONCLUSION

In credit markets, asymmetric information problem causes two major problems that are adverse selection and moral hazard. From banking perspective, the problem of information asymmetry leads to increase in operating cost and decrease in productivity, and during the economic or financial crisis period, it causes the bankruptcy of banks. Banks that face the problem of asymmetric information use credit rationing mechanism to reduce the default risk of their non-performing loans. Credit rationing occurs when lenders either does not issue the loan or reduce the amount of loanable funds for the borrowers.

In this study, the factors that affect the credit rationing in commercial loan markets have been investigated by using quantitative and qualitative decision parameters for 77 firms that operate in manufacturing sector. Logistic regression and discriminant analysis were employed in order to estimate the credit rationing. When correlation coefficients between variables, tolerance and VIF scores are examined, it is found that multicollinearity problem does not exist between the variables. The Durbin- Watson test result (DW = 2.373) indicates that there is no autocorrelation problem. The Omnibus test result supports the relationship between the dependent and independent variables.

In this study, we examined probability of credit rationing with 12 different factors and found that morality, liquidity and credit history play significant role in loan approval procedure, as well as in credit rationing. Based on the methods, logistic regression and disciriminant analysis, there is a positive relationship between credit rationing and character, liquidity and credit history. In particular, the character variable, which is used as a morality risk, is a very important factor for decision makers in banks. In addition, compared to logistic regression, discriminant analysis yields better results on credit rationing estimation. The study can further be developed by using large sample that represents the whole commercial lending process in Turkey along with multiple periods.

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APPENDIX 1: Dependent and Independent Variables

Variables	Definition	Abbreviations	Codes / Value
Y	Credit Rationing	Rationing	1=Yes 0=No
X_1	Firm Size	Size	1= Total Sales >40.000.000 2= Total Sales <40.000.000 3= Total Sales < 8.000.000 4= Total Sales < 1.000.000
X_2	Firm Age and Ownership Structure	Age	1 = Risk Free 2 = Low Risk 3 = Risky 4 = High Risk
X_3	Bank Relations	Relation	1 = Risk Free 2 = Low Risk 3 = Risky 4 = High Risk
X_4	Foreign Trade Status	Export	1=1 = Risk Free 2 = Low Risk 3 = Risky 4 = High Risk
X_5	The Administrative Structure	Admin	1 = Risk Free 2 = Low Risk 3 = Risky 4 = High Risk
X_6	Morality	Character	1 = Risk Free 2 = Low Risk 3 = Risky 4 = High Risk
$X_{7(A)}$	Liquidity	Liquidity	1 = Risk Free 2 = Low Risk 3 = Risky 4 = High Risk
$X_{7(B)}$	Asset Structure	Asset	1 = Risk Free 2 = Low Risk 3 = Risky 4 = High Risk
$X_{7(C)}$	The Capital Structure and Leverage	Leverage	1 = Risk Free 2 = Low Risk 3 = Risky 4 = High Risk
$X_{7(D)}$	Profitability, and Productivity	Profit	1 = Risk Free 2 = Low Risk 3 = Risky 4 = High Risk
$X_{7(E)}$	The Performance Ratios	Performance	1 = Risk Free 2 = Low Risk 3 = Risky 4 = High Risk
X_8	Credit History	History	1 = Risk Free 2 = Low Risk 3 = Risky 4 = High Risk

APPENDIX 2: Correlation Coefficients between Variables

	Size	Age	Relation	Export	Admin	Character	Liquidity	Asset	Leverage	Profit	Performance	History
Size	1,00											
Age	0,26	1,00										
Relation	0,10	0,33	1,00									
Export	0,33	-0,07	0,01	1,00								
Admin	0,05	0,30	0,60	0,08	1,00							
Character	0,20	-0,03	0,17	0,02	0,19	1,00						
Liquidity	0,05	0,17	0,29	0,16	0,27	0,13	1,00					
Asset	0,24	0,22	0,10	0,21	0,27	-0,11	0,16	1,00				
Leverage	0,16	0,34	0,49	-0,09	0,35	0,07	0,53	0,14	1,00			
Profit	0,17	0,09	0,13	0,12	-0,04	0,10	0,11	0,28	0,25	1,00		
Performance	0,03	0,02	-0,01	0,09	-0,11	-0,14	0,23	0,06	-0,06	-0,08	1,00	
History	0,13	0,20	0,33	0,01	0,20	0,05	0,11	0,02	0,07	-0,04	-0,05	1,00