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THE RELATIONSHIP BETWEEN CREDIT RISK AND BAD DEBTS THROUGH OPTIMUM CREDIT RISK DETERMINATION INDICES IN REFAH-E KARGARAN BANK OF ZANJAN USING DATA EXPLORATION MODEL

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ABSTRACT

The present article investigates the relationship between credit risk and bad debts through optimum credit risk determination indices in Refah-e Kargaran Bank of Zanjan using data exploration model. To do so, 500 cases of square accounts in the mentioned bank from 2009 to 2013 and were analyzed using logistic regression analytical models, as well as variance analysis method. The results revealed that there was a significant relationship between pending claims and credit risk. The from investigated credit indices, the variables including working place status from possession points of view (rental and owned), type of pledge, monthly salary, eminence of the applicant, nominal capacity proportionality, all the indices' relationships with the repayment quality were verified, save for the relationship between working place status from possession points of view and repayment quality.

KEYWORDS: Credit Risk, Bad Debts, Credit Rating, Credit Indices, Logistic Regression

INTRODUCTION

Credit risk analysis is one of the key issues of financial risk management. Due to the recent financial crises, credit risk analysis is regarded as the primary focus banking and financial industry. Accurate estimation of the credit risk could be rendered as an efficient application of economic capital. One of the most important decisions made by the financial institutions as part of their daily functions is on the question that whether they should grant loan to a certain applicant or not. Large amount of data in respect to the repayment behavior of the past applicants could be stored thanks to the advent of large scale data storing facilities. The aim of credit rating is to analyze these data and establish models which differentiate good credit payers from bad ones using features such as eminence, types of gage, monthly salary and proportionality of the nominal capacity with commitment. Numerous methods have been proposed (decision on which specific learning method has to be opted is a complicated issue related to credit risk analysis. A favorable option in order to choose a method is to establish an eclectic prediction system which includes a number of possible solutions as elements. In so doing, the relation between these indices and credit risk was investigated utilizing logistic regression method and variance analysis.

Literature Review

In the financial risk management realm, credit risk analysis is an essential issue. The ability to different- iate between good and bad credit costumers is especially important in every credit granting institution such as commercial banks and specific retailers. It is, therefore, imperative to have specific models to predict failure in repayment accurately. In the real world, a person's background has to be assessed by a bank in order to decide on that person's qualification to be granted certain loans, and under what interest rate.

Due to the significance of financial risk analysis, there has been a great deal of research on this issue. Accordingly, many approaches such as individual models like linear discrimination analysis, logistic analysis, integer programming, classification tree, artificial neural networks, genetic algorithm, (GA) (Chen and Huang, 2003; Varetto, 1998)and support vector machine,(SVM) (Van Gestel*et al.*2003; Huang *et al.*, 2004), and some combinational models such as neuro-fuzzy system(Piramuthu, 1999; Malhotra and Malhotra, 2002) and fuzzy SVM(Wang *et al.*, 2005), have vastly been applied in credit risk analysis tasks. It is difficult to state that the efficiency of one certain model is invariably better than those of other models in all situations. Most often, the performance of the individual models depend on the problem. Some researchers have shown that the combinational categorizers in the combinational models, where two or more categorizing methods are combined, could reveal more accurate classifications compared with single models.

Credit rating refers to an action in which the credit of financial and credit institutions and banks' personal and legal person costumers is assessed based on the information gained from them and allows further insight into their current financial status in respect to the ability of repaying the received facilities and gaining further services. On the basis of this method, credit risks of the individuals are evaluated and the clients are classified and ranked based on their credit risk (Khodaverdi, 1388, 48).

Due to the necessity of utilizing costumer credit assessment starting from 2009 by Refah-e Kragaran Bank in all facility granting (save for retail facilities), unseasoned nature of the system, and lack of sufficient research on the efficiency of the system utilization in relation to credit risk reduction, the present study investigated the efficiency of the utilized qualitative indices in credit rating system with the purpose of gaining insight into the applicants' status and the relationship these credit indices with the quality of repaying the facilities.

Population and Statistical Society

All the real individual facility receivers from Refah-e Kargaran Bank of Zanjan Province from 2009 to 2011 constituted the population, yet since having access to all the files was difficult, 500 cases of facility granting were randomly selected and studied. Because of the credit rating system establishment since 2009, in Refah Bank, the investigated cases were about the applicants who had applied from early 2009 and had paid up by the end of 2011.

The Variables

The independent variables of this research include: a. ownership status of the working place from occupation point of view (rental and owned), b.the rate of eminence of the applicants, c. type of free and presentable pledge from the applicants, d. average salary of the applicant, and e. proportion of the nominal capacity (activity volume) proportionality with the amount of the facility demanded by the applicant.

The mentioned variables were considered as the independent variables in relation with repayment quality of the clients (good credit and bad credit payers) which results in bad debts.

It has to be mentioned that the answers to all of the variables, except for monthly income, in credit rating system used in the banks were qualitative(field selection which has been illustrated in table 1), and were codified in order to be calculable.

Table 1: Codifying the Range of Qualitative Indices

Introduced Indices	Selected Fields in Rating System	Field Code
X8 (Free pledge, presentable by the applicant)	Securities(bearer bonds, time deposit, secured bonds) Combinational (partially owned accompanied with promissory note or other pledges) Promissory note on the third parties' bail Undisputable ownership	1 2 3 4
X9 (nominal capacity proportionality with the commitment rates)	nominal capacity proportionality of the applicant without proportionality with the requested amount Maximum capacity of the applicant as much as the previous commitments without excessive capacity Capacity of the costumer completely proportional to the total requested sum and the previous commitments Capacity of the costumer more than the requested amount of facility and the previous commitment	1 2 3 4
X10 (the status of the main work place of the costumer taking possession type into consideration)	Owned Rental	1 2
X11 (eminence of the costumer from general point of view)	Applicant with notoriety Applicant without good reputation Applicant approved by minority Applicant approved by majority Highly reputable applicant	1 2 3 4 5
X12 (monthly salary)	Below 10 million 10-30 million Rials 31-50 million Rials 51-100 million Rials 100+ million Rials	1 2 3 4 5

Logistic Regression

The logistic or algorithm of the possibility of failure in repayment, or bad debt (with allocation of the number "2") and the possibility of no failure in repayment, or promptness in repayment (with allocation of number "1"), for the current study is as the following models. Through the analysis (using logistic regression)the relationship of five independent variables, namely, nominal capacity proportionality, reputation, type of pledge , working place and income, with the dependent variable (repayment quality: being good credit or bad credit costumers) using quantitative and ordinal scale methods were studied. Since monthly income was a quantitative variable among the five variables, which was changed intoaordinal scale and entered the model, the coefficients of logistic function included:

Salary variable in quantitative form:

Logistic(p)=./695+/971fame(1)+/920fame(2)+/695fame(3)+20/098guranty(1)-2/011guranty(2)+19/563 guaranty(3)

Salary variable in scalar form:

Logi(p)=/564+/258income(1)1/459income(2)+1/100income(3)+/182income(4)+1/063fame(1)+/932fame(2)+20/030guranty(1)-1/965 guaranty(2)+19/055 guaranty(3)

Analysis regression-logistic method

Table 2: Total Coefficient of the Model

Salary Variable in Scalar Form					Salary Variable in Quantitative Form			
Sig.	**Df**	**Chi-Square**			**Sig.**	**df**	**Chi-Square**	
.006	4	14.545	**Step**		.002	2	12.454	**Step**
.000	9	42.798	**Block**		.000	5	28.253	**Block**
.000	9	42.798	**Model**		.000	5	28.253	**Model**

Table 3: Model Expression Coefficient

Salary Variable in Scalar Form					Salary Variable in Quantitative Form			
Nagelkerke R Square	**Cox & Snell R Square**	**-2 Log Likelihood**	**Step**		**Nagelkerke R Square**	**Cox & Snell R Square**	**-2 Log Likelihood**	**Step**
.049	.031	487.364[a]	1		.049	.03	487.364[a]	1
.087	.055	474.909[a]	2		.087	.055	474.909[a]	2
.129	.082	460.364[a]	3		-	-	-	-

Table 4: Included Variables in Model (Effective in the Model)

Salary Variable in Quantitative Form						
	B	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**
without good reputation			13.195	2	.001	
approved by minority	.971	.269	12.983	1	.000	2.640
approved by majority	.920	.492	3.503	1	.061	2.510
Highly reputable applicant	.695	.230	9.108	1	.003	2.003
note pledges			13.967	3	.003	
Securities	20.098	27878.954	.000	1	.999	534894881.910
Undisputable ownership	-2.011	.538	13.967	1	.000	.134
Combinational(partially owned accompanied with promissory note or other pledges)	19.563	28419.340	.000	1	.999	313291434.514
Constant	.695	.230	9.108	1	.003	2.003
Salary Variable in Scalar Form						
	B	**S.E.**	**Wald**	**Df**	**Sig.**	**Exp(B)**
Below 10 million			14.871	4	.005	
10-30 million Rials	.258	.252	1.055	1	.304	1.295
31-50 million Rials	-1.459	.480	9.229	1	.002	.233
51-100 million Rials	1.100	.869	1.604	1	.205	3.004
100+ million Rials	.182	.863	.044	1	.833	1.199
without good reputation			14.684	2	.001	
approved by minority	1.063	.279	14.519	1	.000	2.895
approved by majority	.932	.504	3.419	1	.064	2.539
Highly reputable			14.684	2	.001	
note pledges			9.918	3	.019	
Securities	20.030	28041.302	.000	1	.999	499881740.369
Undisputable ownership	-1.965	.624	9.918	1	.002	.140
Combinational(partially owned accompanied with promissory note or other pledges)	19.055	28119.479	.000	1	.999	188496883.290
Constant	.564	.256	4.867	1	.027	1.758

Variance Analysis Test

In order to complete the obtained results, the response variable (repayment quality) was analyzed using Kruskal-Wallis and Mann-Withney methods. It has to be mentioned, however, that since there sponse variable was ordinal (1-Reggular, 2-Delayed Maturities, 3-Pending, 4-Doubtful debts), and the independent variables including presentable free pledge, average monthly salary, the ownership status of the working place from occupation point of view, nominal capacity proportionality to amount of commitments, were two or more than two groups, two-by-two comparisons were conducted using Mann-Withney method and comparison for more than two were implemented utilizing Kruskal-Wallis approach. Havingmade sure of the significance of the relations between groups, for accurate investigation of the data with more than two groups, they were investigated and analyzed once more using Mann-Withney method.

Table 5: Variance Analysis

Rank Mean	Type of Pledge		Type of Possession	Rank Mean
Securities	200.00		Rental	251.48
Combinational	200.00		Owned	249.36
note pledge	247.23		Sig:./816	
Undisputable ownership	361.31			
Sig:./000			eminence of the costumer	Rank mean
			approved by minority	287.98
monthly salary	Rank mean		approved by majority	241.75
Below 10 million	255.91		Highly reputable applicant	251.03
10-30 million Rials	239.74		Sig:./001	
31-50 million Rials	328.87			
51-100 million Rials	229.00			
100+ million Rials	271.45			
Sig:./001				

TESTING THE RESEARCH RESULTS

Mann-Withney Results revealed that there was no significant difference between the costumers with dissimilar working place in terms of possession status (owned/rental)from repayment quality point of view (level of possibility 0.816) which approves exclusion of the working place in logistic regression method (based on the results obtained from tables 5 and 6). The results gained from Kruskal-Wallis indicated a significant difference in costumers' levels of reputation concerning repayment quality (level of possibility 0.001), which verifies inclusion of reputation in logistic regression approach (presenting results in table 4 is due to inclusion in regression model and in table 5 because of the resulted significance at the level lower than 5%). Kruskal-Wallis suggested a significant difference between the costumers' pledge types in repayment quality (possibility level of 0.000). These results approve the inclusion of pledge type variable in logistic regression method. Kruskal-Wallis test suggested a significant difference between repayment quality of the costumers with different average monthly income (level of possibility 0.001), which verifies inclusion of reputation in logistic regression approach(presenting results in table 4 is due to inclusion in regression model and in table 5 because of the resulted significance at the level lower than 5%).Finally, according to Kruskal-Wallis test there was no significant difference between repayment quality of the costumers with different offered capacities (level of possibility 0.178). These results approve exclusion of the nominal capacity proportionality in logistic regression method.

CONCLUSIONS

There was no significant model between main working place of the applicant concerning the ownership status (owned/rental) and debts. That is, no relation was observed between the rental or owned nature of the working place and the nature of being good credit costumers.

The relationship between reputation and eminence of the applicant and the debts was significant in a way that here was a direct relationship between the majority of the applicants and the minority, who were famous for being good credit payers, and formed the basis. Yet the highly reputable group was ranked the same with the criterion group (the minority) and showed no significant relationship.

A significant relationship was observed between free and presentable pledges and debts in both methods (qualitative and ordinal) so that proprietary pledge had a negative relationship in both ordinal and quantitative methods in two months. In other words, proprietary pledges have had higher rates of bad debts compared with promissory pledges.

In the current study, in addition to bed debt investigations (more than a two-month delay in repayment), due to changing the two-month method to six-month(more than six-month delay in repayment)approach, according to the instructions of Central Bank of Islamic Republic of Iran, reduced the result by 50%, yet the results have not been included in the current article. That is to say that the wider the boundary between good and bad credit costumers grows, the lower the bad debt rates of the pledges have fallen. There was also a significant relationship between average monthly income and the debts. In the quantitative method, the variable was not entered the model, but in ordinal method, the third group (31-50 million Rials) a negative and significant relationship was observed with repayment quality. Other ranges were classified in one group, which were not significant. The proportionality of the proportion of the nominal capacity with the commitment rates were investigated yet were not included in model in neither quantitative nor ordinal mode.

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