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Investigation of the Joint Effect of Economic Cycles and Industry Specific Sector on Credit Scoring Models

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Abstract

One of the most important risks that the banks and financial institutes face, is credit risk which is related to not-paid instalments or the instalments paid with delay by borrowers. Banks use credit scoring models In order to prevent this type of risk. The goal of this research is to investigate the joint effect of economic time cycles and the industry sector on credit scoring models we are seeking to answer the key question: “when should bank change their credit scoring models based on economic time cycles and for which industry sectors?”. The dataset of the research involves all companies that were applied for a loan in one of the Iranian major banks during the years 2008-2011. The companies have been divided into four industry sectors including “Industry and Mine”, “Oil and chemical”, “Service and Infrastructure” and finally “Agriculture”. Based on the sector of the industry and year, 54 explanatory variables, both financial and non-financial, 12 distinct industry sectors and time-specific data sets are built then classification methods were used to classify customers into two groups of defaults and non-defaults. Finally, we compared the results by Wilcoxon Test. The results show that the companies that are in the groups of Industry and Mine and Agriculture, need their own special credit scoring based on industry type model and time but two other groups don’t need of course in the studies dataset duration. Finally, the study concluded by introducing the credit scoring strategies for different four-cycle of economies.

Keywords: Industry sectors; Economic Time Cycles; Credit Scoring; Corporate customers; Classification.

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Introduction

In today's competitive economy credit scoring is widely used in the banking industry. Every day, individual's and company's records of past borrowing and repaying actions are gathered and analyzed by information systems and manual application forms. Banks use this information to determine the individual's and company's profit and credit risk. Credit scoring is one of the main cases in the bank lending process (Van Gestel & Baesens, 2009). It is usually used to answer the key questions that what is the probability of default and discrimination of creditworthy from non-worthy applicants within a fixed period of time, usually one year. Credit scoring uses banks historical loans and external credit scoring/rating bureaus reports data to classify customers as good or bad.

There are three main techniques suggested to perform classification in credit scoring including mathematical programming, statistical and intelligent techniques. Mathematical programming is used to minimize the sum of the deviations of misclassified applicants from the discriminant function. Statistical discriminant analysis (DA) and logistic regression (LR) are the most recognized statistical method used to assess the credit score(Wiginton, 1980). In a study linear DA is applied and it shows that it is as efficient as logistic regression (Harrell & Lee, 1985). There are also many intelligent techniques applied to the problem including decision trees (DT), case-based reasoning (CBR), Bayesian networks (BN), neural networks (NN), support vector machines (SVM), etc. There are also many studied which developed their contribution by building improvement points on the previous techniques weaknesses. Malhotra et. Al. used the adaptive neuro-fuzzy inference systems(ANFIS) for rule induction and showed that its superior results compared to DA on their study credit scoring dataset (Malhotra & Malhotra, 2002). Baesens et.al. use and evaluate Neurorule, Trepan, and Nefclass neural network rule extraction techniques on German credit database, Bene1 and Bene2 credit database. They showed Nero rule and Trepan yield performs better on accuracy compared to the C4.5 and the LR, they also visualize the extracted rule sets (Baesens, Setiono, Mues, & Vanthienen, 2003). Hoffmann et.al used evolutionary algorithms as a new learning function for fuzzy rule induction (Hoffmann, Baesens, Mues, Van Gestel, & Vanthienen, 2007). Martens et al used the support vector machine for rule induction in the credit scoring problems(Martens, Baesens, Van Gestel, & Vanthienen, 2007). A new method for rule pruning is provided by Ben-Davide and showed better performance on his studies credit scoring data set(Ben-David, 2008). As mentioned there are some studies of all kind which shows the superiority of some techniques but there is not a technique which is dominantly the best performer among all other techniques in the literature.

Few studies approached to investigate the economic cycles and industry-specific effects together on credit scoring. The financial characteristics of the companies in different sector and economic cycles including trough, expansion, peak and contraction differ, mainly because of distinctive operational behaviors of different Industry types in an economic cycle, therefore one can hypothesis that “economic cycle based industry-specific credit scoring models can predict the behavior of a company in a specific sector better compared to general traditional models. There are few studies in the field which approached the question but did not respond to it directly. Kim investigated the industrial characteristics and excluded the financial, transportation and utility companies because of their different financial structures to other companies (Kim, 2005). Samson discusses that although rating agencies use industry-specific determinants in their credit rating processes Industry-specific input variables have not been used (Samson SB, 2008). Hájek compares the selected fuzzy rule-based classifiers and indicates that it is possible to increase classification performance by using different classifiers for individual industries (Hájek, 2012). There is also some literature in the field of bankruptcy prediction. Lee et. Al. presented a multi-industry investigation of the bankruptcy of Korean companies using back-propagation neural network (BNN), The results indicate that prediction using industry sample outperforms the prediction using the entire sample which is not classified according to the industry by 6–12% (Lee, 2013). Sohn, Lim et al. introduced credit scoring for biotechnology industry loans using technology attributes (Sohn, Lim, & Lee, 2016). They also introduced technology credit scoring using fuzzy linguistic variables compared to logistic regression, which showed better performance (Sohn, Kim, & Yoon, 2016). Karas et al build a credit scoring model for construction companies on the sample of Czech companies, their models show 3.6 to 8 percent higher accuracy compared to traditional models (Karas, 2019).

It can be seen that although there are industry-specific models investigated, the time periods in terms of economic cycles and their effect on different industry sector credit scoring models are not investigated totally and there is a main research gap in the area that remained. Boom and recession cycles can occur for a whole of an economy in a country and also for an industry-specific sector individually. This leads to the question: “if a specific industry sector is in its boom or recession, do banks current credit scoring models which are built using previous years data efficiently work in these situations?”.Another question is: “can banks have prebuilt models for each industry-specific sector based on the industry sector’s situation in the economic cycle including trough, expansion, peak and contraction phase?”. In the other words for example: “can banks have for example a service sector credit scoring model in service economy trough, expansion, peak and contraction phases separately, and is it totally works better?”. If the bank can, then they could use these powerful models and rapidly change them by economic cycles boom and recession. This study tries to respond to the previous researches gap that the mentioned model building is necessary and effective. And it finally Introduces an economic cycle based industry sector-specific framework for better decision making on changing the credit scoring models in the area.

The rest of the paper is structured as follows: section two describes the research method used. Section three introduces the empirical results including data set introduction, main approaches for dealing with missing values, experiments settings and performance analysis approaches, and introducing the research framework for decision making on credit scoring model change during economic cycles, finally the study concluded in section four.

Methdology

This paper aims to investigate and Differentiate the industry-specific credit scoring models change during the time in terms of economic cycles. For this purpose, five steps are designed carefully. The development process of the models and experiments in this study are shown in Figure 1.

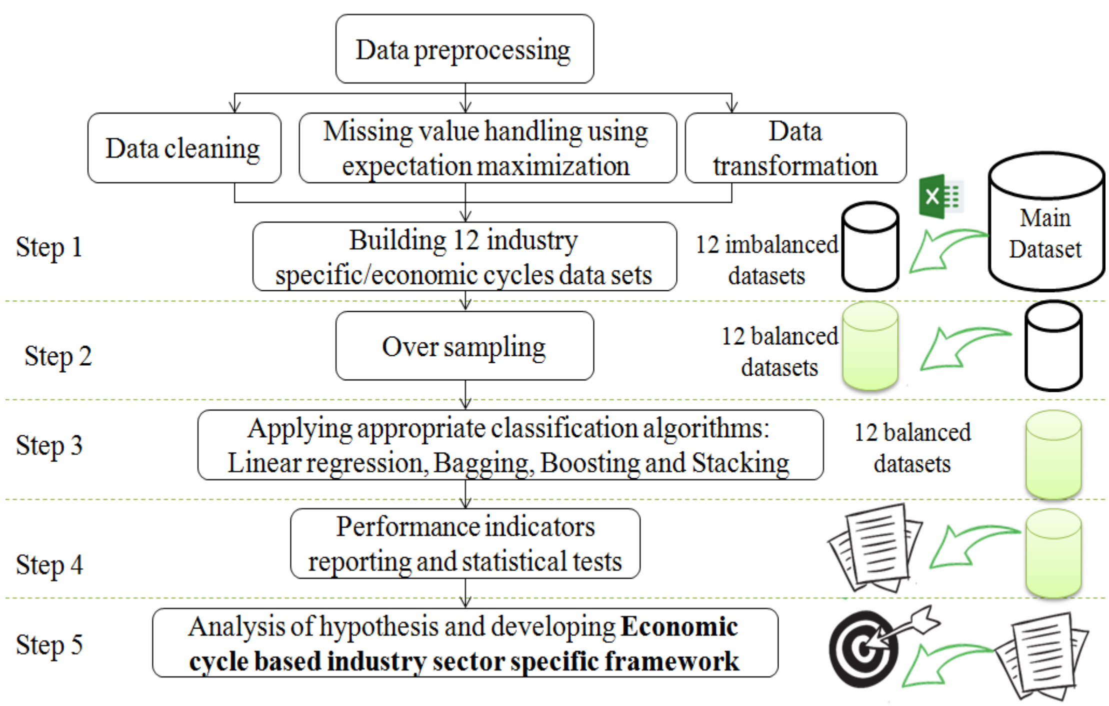

Figure 1. Research steps of the study

A brief description of the steps used in this paper is presented below.

Results and Descussion

Step 1: Data preprocessing

In this step, the bank's internal data for existing customers are collected and engage in data cleaning, data integration, data transformation, data reduction and finally generation of 12 different industry and economic cycles specific datasets are done in order to respond to the research question.

Step 2: Oversampling

In order to avoid sample biases which are usual in slight imbalance credit scoring datasets because of bad/good ratios, the oversampling of bad applicants are done for every 12 datasets separately.

Step 3: Applying appropriate classification algorithms

To reach reliable results appropriate classification algorithms which were used in previous credit scoring researches including linear regression, bagging, boosting and stacking is applied for all 12 datasets separately due to their superiority is shown in recent studies (Guo, 2019 and Ribeiro, 2020). Then the tuned classification model is tested using the next year data sets as the test sets to evaluate that "are credit scoring models of the previous year work for the future years?" and if yes for "how many years?". For example, a model for agriculture dataset using 2009 year data is built using: 70% training and 30% test of agriculture dataset for the year 2009; then the model is tested on the agriculture dataset for the year 2010 and 2011 separately, and the performance results are reported. This process is done also for all other 12 datasets and we have 36 model building and testing processes.

Step 4: Performance indicators reporting and statistical tests

For all four industries, specific credit scoring models based on three-year economic cycles (Time) Wilcoxon test is used to report the significance of the difference between each industry-specific model change during time. Therefore we have 4 pairs of hypotheses which can be described as follows:

H_0: The industry-specific credit scoring models for agriculture sector performance indicators do not have significant differences during the 2009 year compared to 2010 and the bank can use the 2009 model for 2010.

H_1: The industry-specific credit scoring models for agriculture sector performance indicators have significant differences during the 2009 year compared to 2010 the bank cannot use the 2009 model for 2010.

It can be formulated as mathematically follows:

$$\begin{cases} \mu_{Ag^{2009}} = \mu_{Ag^{2010}} \\ \mu_{Ag^{2009}} \neq \mu_{Ag^{2010}} \end{cases} \quad (1)$$

We can also formulate the 2010 and 2011 years for agriculture as follows:

$$\begin{cases} \mu_{Ag^{2010}} = \mu_{Ag^{2011}} \\ \mu_{Ag^{2010}} \neq \mu_{Ag^{2011}} \end{cases} \quad (2)$$

There are also other three pairs of hypotheses for the service and infrastructure sector, oil and chemical sector and industry and mine sector and totally the number of hypotheses reaches eight separated hypotheses.

Step 5: Analysis of hypothesis and developing Economic cycle based industry sector-specific framework

By analyzing the results of the hypothesis, the bank's credit scoring model building strategy is developed in a framework.

Empirical Analysis

In this section, the five steps of model building and experimental results are described carefully.

Step 1: Data preprocessing.

An Iranian bank dataset is used to build the credit scoring models. Table (1) shows the characteristics of the datasets. The initial dataset includes 1109 corporate applicants and 46 financial and non-financial features in the period of 2009 to 2011 are collected, from which 90.9% are creditworthy and the other 9.1% is non-worthy. Default was defined by Basel definition and used to generate a 1/0 target variable for modeling purposes (creditworthy = 1, non-worthy = 0. Descriptions of the variables and their missing values percentage are shown in Table 6 in Appendix 1. There are a few missing Values for some corporate, where 33 features (71.7%) have complete data and 813 (81.3%) applicants data records are complete. Table 1 summarizes the dataset characteristics before and after cleaning steps and a brief description of data preprocessing done on the data set. To recognize the datasets better in the research, each one of them is labeled with a data set code which is shown in the first column of Table 1. maximum likelihood (ML) performed well on credit risk missing data compared to other missing data handling methods, therefore SPSS statistics 25.0 ML function is used to handle the missing data (Florez-Lopez, 2010). Then the data set is normalized by scaling attribute values to fall within a specified range using SPSS modeler 18.0 functions.

Table 1. Dataset description

Data set code	Description	Data size	Inputs variables				Complete features%	Complete applicant records%
			Total	Continuous	Categorical	Features with		
1	Initial dataset	1109	46	38	8	13	NA	NA
2	Dataset (1) with variables converted	1109	46	38	8	13	NA	NA
3	431 records from Dataset (2) are eliminated because their loan is the current process of repay	753	46	38	8	13	71.7	81.3
4	Data set (3) variables are changed and categorical variables are converted to dummy variables	753	54	34	20	13	75.93	81.3
5	Data set (4) missing values are replaced using maximum likelihood	753	54	34	20	13	100	100

Step 2: Oversampling

In order to avoid sample biases which are usual in credit scoring datasets because of bad/good ratios, the oversampling of bad applicants are done using the random oversampling method for each 12 training credit scoring data sets (The ratio of training data is set to 70% and the test dataset is therefore 30%). The worthy/non-worthy ratio for each data set and the size of the data set before oversampling and the oversample coefficient is shown in Table 2.

Table 2. Datasets description by worthy/non- worthy ratio and datasets size after oversampling

Industry type	year	Data size	non-worthy	creditworthy	Worthy/non-worthy ratio
Industry and mine	2009	85	11	74	6.73
Industry and mine	2010	106	12	94	7.83
Industry and mine	2011	73	7	66	9.43
Oil and chemical	2009	53	10	43	4.30
Oil and chemical	2010	57	5	52	10.40
Oil and chemical	2011	46	3	43	14.33
Service and infrastructure	2009	40	10	30	3.00
Service and infrastructure	2010	40	4	36	9.00
Service and infrastructure	2011	51	3	48	16.00
Agriculture	2009	53	12	41	3.42
Agriculture	2010	73	12	61	5.08
Agriculture	2011	76	3	73	24.33

Step 3: Applying appropriate classification algorithms

In order to reach reliable results appropriate classification algorithms which were used in previous credit scoring researches including linear regression, bagging (10 logistic regressions), boosting (AdaBoost 10 logistic regressions) and stacking (firstly logistic regressions + secondly K nearest neighbors feed to the decision trees) are applied separately for all 12 datasets using rapid miner Studio 9.3 software. Then the tuned classification model is tested using the next year data set as the test set. For example, a model for agriculture dataset for the year 2009 is built using 70% training and 30% test of agriculture dataset for the year 2009; then the model is tested on the agriculture dataset for the year 2010, and the performance results are reported. This process is done also for other 12 datasets and we have 36 model building and testing processes.

Due to the high volume of the results and lack of space in the paper, just 12 runs among 36 model buildings for the “oil and chemical” industry sector results are presented and 10 different classifiers performance indicators including Gini, the area under the curve (AUC) and accuracy rate are reported in Table 3.

Table 3. Performance measures on different models for each of four industry-specific data sets and general data set Linear Regression(LR), Bagging(BA), Boosting(BO) and Stacking(ST)

year	Classification techniqe	Data set	Gini	FPR	TPR	AUC	Precision	Accuracy	TN	FN	FP	TP
2009	LR	Train70% / Test 30%	0.28	0.67	0.92	0.64	0.5	0.81	1	1	2	12
	BA	Train 70% / Test 30%	0.66	0.33	0.77	0.83	0.4	0.75	2	3	1	10
	BO	Train 70% / Test 30%	0.48	0.80	1	0.74	1	0.84	2	0	8	43
	ST	Train 70% / Test30%	0.32	0	0.62	0.66	0.37	0.68	3	5	0	8
2010	LR	Train 70% / Test30%	0	1.00	0.94	0.5	0	0.88	0	1	1	15
		Train 2009 / Test 2010	-0.08	0.40	0.52	0.46	0.1	0.52	3	25	2	27
	BA	Train 70% / Test30%	0.86	0	0.88	0.93	0.33	0.88	1	2	0	14

year	Classification techniqe	Data set	Gini	FPR	TPR	AUC	Precision	Accuracy	TN	FN	FP	TP
		Train 2009 Test 2010	-0.02	1	0.99	0.49	0.16	0.84	0	1	10	72
	BO	Train 70% Test 30%	0.40	0.60	1	0.7	1	0.94	2	0	3	52
		Train 2009 Test 2010	0	0.80	0.88	0.5	0.14	0.82	1	6	4	46
	ST	Train 70% Test30%	-0.50	1	0.69	0.25	0	0.64	0	5	1	11
		Train 2009 Test 2010	-0.26	1	0.96	0.37	0	0.87	0	2	5	50
2011	LR	Train 70% Test30%	0.68	1	0.92	0.84	0	0.85	0	1	1	12
		Train 2009 Test 2011	0.20	1	0.91	0.6	0	0.84	0	4	3	39
		Train 2010 Test 2011	0	1	0.91	0.5	0	0.84	4	4	3	39
	BA	Train 70% Test30%	0.88	1	0.94	0.94	0	0.88	0	1	1	16
		Train 2009 Test 2011	0.20	0.67	0.93	0.6	0.25	0.89	1	3	2	40
		Train 2010 Test 2011	0.28	1	0.95	0.64	0	0.89	0	2	3	41
	BO	Train 70% Test30%	0.92	0.67	0.98	0.96	0.5	0.93	1	1		42
		Train 2009 Test 2011	0	1	0.88	0.5	0	0.82	0	5	3	38
		Train 2010 Test 2011				0.5	0	0.82	0	5	3	38
		Train 70%										

year	Classification techniqe	Data set	Gini	FPR	TPR	AUC	Precision	Accuracy	TN	FN	FP	TP
		Test30%	0	1	1	0.5	0	0.92	0	0	1	13
	ST	Train 2009 Test 2011	-0.44	0.67	0.56	0.28	0.05	0.54	1	19	2	24
		Train 2010 Test 2011	0.24	0.67	0.91	0.62	0.2	0.86	1	4	2	39

Step 4: Performance indicators reporting and statistical tests

The paper's hypotheses are evaluated at a 95% confidence level using IBM SPSS statistics 23 Wilcoxon function and reported in Table 4.

Table 4. Hypothesis test results

Hypothesis	Hypothesis first phrase	H_0 status	
		2009 vs 2010	2010 vs 2011
H_1	The agriculture credit scoring model does not have a significant difference compared to the general credit scoring model.	Rejected	Accepted
H_2	The Oil and chemical credit scoring model does not significantly differ compared to the general credit scoring model.	Accepted	Accepted
H_3	The Service and infrastructure credit scoring model do not have significant differences compared to the general credit scoring model.	Accepted	Accepted
H_4	The industry and mine credit scoring model does not have significant differences compared to the general credit scoring model.	Rejected	Accepted

It can be seen from the results that the agriculture time-specific based credit scoring models and industry and mine time-specific credit scoring models have significant differences from their previous models. It can also be seen that the service and infrastructure and oil and petrochemical time-specific credit scoring models do not change in the time interval of the study which is from 2009 to 2011. Totally we can conclude and add this knowledge to previous studies that the change of the special industry sector credit scoring models based on time is inevitable.

Step 5: Analysis of hypothesis and developing the Economic cycle based industry sector-specific framework

There are four cycles for industrial sectors including trough, expansion, peak and contraction which are continuously happens and each of them have their own duration. The results of models build for agriculture and industry and the mining sector shows the probable change in the economic cycle in which happens from 2009 to 2011. The other two sectors can have the change in a time which is probably out of the range of our research data, for example, 2012 or 2013.

Figure 2 shows the concepts which further used to develop a credit scoring model building strategy.

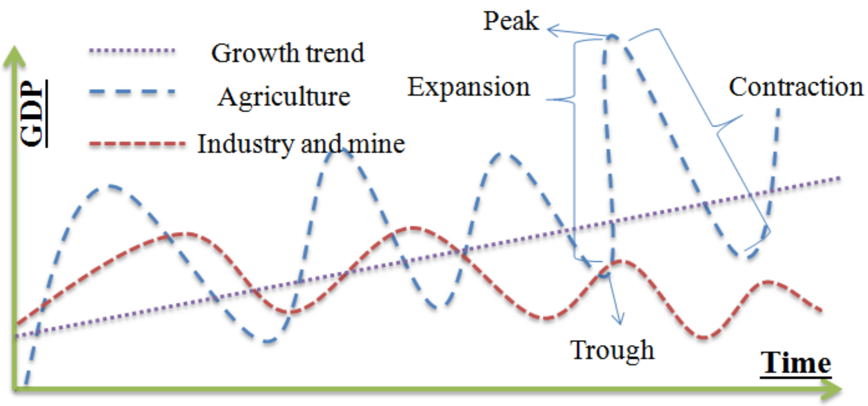

Figure 2. Four different economic cycles of two industrial sectors are shown (example), total economic growth is shown by a line with a constant slope

Table 5 formulated the credit scoring model change strategy using expert opinions.

Table 5. Economic cycle based industry sector-specific framework as an assistant tool for deciding when to change the credit scoring models

The economic cycle of the industrial sector	**Credit score card change decision**	**Strength/weakness**	**Credit scoring model change strategy**
Trough	If you build your model when the industrial sector is in its contraction then it's ok to use it for short term loans and of course, for long term loans, some adjustments are needed.	Using The models build by trough or expansion data may increase Type II error (false negative).	Make some adjustments to the models used contraction data.
Expansion	If you build your model when the industrial sector is in its trough then it’s ok to use it in expansion	Type I error (false positive) increases, Marketing costs for commercial banks increases as customer churn to other banks and can achieve their requested loan	Accept the applicants in the gray sector or change the credit scoring model.
Peak	If you build your model when the industrial sector is in its trough or expansion then it’s ok to use it just for short term loans	Type II error (false negative) increases especially for long term loans, also the wrong estimation of peak time leads to increase type II error	Reject the applicants in the gray sector or change the credit scoring model as fast as you can.
Contraction	If you build your model when the industrial sector is in its trough it’s probably ok to use it just for short term loans with some adjustments, but the models built in the expansion and peak cannot be used.	Type II error (false negative) increases by using models build which applied expansion and peak data.	Use the scorecard build through data, or change the credit scoring model totally.

Conclusion

In this paper, 36 different credit scoring classification models for 12 time and industry sector-specific companies are built and the significant difference of time and industry-specific credit scoring models are investigated against the time for the first time in the research area of credit scoring as authors know by their comprehensive search of the worlds famous paper banks. Based on statistical tests, “agriculture” and “industry and mine” specific models show significant differences compared to others in the time horizon of 2009-2011 for which the study is done. In fact, it shows the influence of economic patterns in credit scoring models reliability for these two sectors and we can interpret that the credit scoring model built by 2009 data cannot be used for 2010 and 2011 for these two sectors but the credit scorning model of 2010 can be used for 2011 in which the patterns significant stability from 2010 to 2011. On the other hand for “service and infrastructure” and “oil and chemical” sectors the patterns do not change significantly totally and we can conclude that the model built using 2009 data can be used for 2010 and 2011 and the model built using 2010 data can be used for 2011.

Because of lack of access to comprehensive time-based credit data internally and internationally we cannot conduct a comprehensive analysis for a larger interval of years for example 15 years in which we probably can have two cycles for each industry sector. So far our findings show that the banks can achieve better results when they built "economic cycle based industry sector-specific" credit scoring models. In order to better interpret and generalization of the results, we introduced an "economic cycle based industry sector-specific framework" which, the decision-makers can use to assist them to decide to change their credit scoring model.

Future works can be done in three directions including assessing the time and industry type effect on credit limits of companies, investigating the lifetime of credit scoring models for each industry type which need long interval credit dataset and finally using external credit bureau data in order to better evaluate the industry-specific credit scoring models.

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Conflict of interest

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Appendix (1)

Table 6. list of variables in Iran bank credit dataset

Variable	Type	Complete%	Variable	Type	Complete %
Net profit	Continuous	100	Type of industry: industry and mine (=1, other =0)	Categorical	100
Active in the internal market	Categorical	100	Type of industry: agricultural (=1, other =0)	Categorical	100
number of countries that the company export to	Categorical	100	Type of industry: oil and petrochemical (=1, other =0)	Categorical	100
Sales growth	Categorical	97.95	Type of industry: infrastructure and service(=1, other =0)	Categorical	100
Target market risk (from 1 to 5)	Categorical	99.56	Type of industry: chemical (=1, other =0)	Categorical	100
Seasonal factors	Categorical	100	Year of financial ratio	Continuous	100
Company history(number of years)	Categorical	100	Type of book: Tax declaration(=1,other=0)	Categorical	100
Top Mangers history	Categorical	100	Type of book: Audit Organization (=1,other=0)	Categorical	100
Type of company: Cooperative (=1, other =0)	Categorical	100	Type of book: Accredited auditor (=1,other=0)	Categorical	100
Type of company: Stock Exchange(LLP) (=1, other =0)	Categorical	100	Inventory cash	Continuous	100
Type of company: Generic join stock(PJS) (=1, other =0)	Categorical	100	Accounts receivable	Continuous	100
Type of company: Limited and others (=1, other =0)	Categorical	100	Other Accounts receivable	Continuous	100
Type of company: Stock Exchange (=1, other =0)	Categorical	100	Total inventory	Continuous	100
Experience with Bank(number of years in 5 categories)	Categorical	100	Current assets	Continuous	100
Audit report Reliability	Categorical (binary)	93	Non-current assets	Continuous	100
Current period sales	Continuous	100	Total assets	Continuous	100
Prior period sales	Continuous	98.98	Short-term financial liabilities	Continuous	100
Two-Prior period sales	Continuous	97.52	Current liabilities	Continuous	100
Current period assets	Continuous	100	Long-term financial liabilities	Continuous	100
Prior period assets	Continuous	98.83	Non-current liabilities	Continuous	100
Two-Prior period assets	Continuous	98.1	Total liabilities	Continuous	100
Current period shareholder Equity	Continuous	100	Capital	Continuous	100
Prior period shareholder Equity	Continuous	98.68	Accumulated gains or losses	Continuous	100
Two-Prior period shareholder Equity	Continuous	96.94	shareholder Equity	Continuous	100
Checking accounts creditor turn over	Continuous	99.56	Sale	Continuous	100
Checking Account Weighted Average	Continuous	99.41	Gross profit	Continuous	100
In last three years average exports	Continuous	99.56	Financial costs	Continuous	100
Last three years average imports	Continuous	91.98	worthy/nonworthy) y)	Categorical (binary)	100

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