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Credit rating and preparing risk transition matrix for legal clients of banks with Markov chain approach

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ABSTRACT

Since most of the country's financial resources are in the banking industry and one of the main activities of the banking industry is to provide credit (facilities) to its customers, so many factors can lead to increased customer default in repaying credit received from the bank, which Lead to an increase in the credit risk of banks and ultimately the bankruptcy of the industry. The purpose of this article is to reduce the risk of default and prevent the bankruptcy of banks. Accurate credit rating leads to the facilities granted by the bank to its legal clients. The statistical population of the present study is active stock exchange companies that have used banking facilities. In this regard, using the Markov regime change model (MS), the factors affecting the probability of default of customers were estimated and the probability matrix of default was calculated. The results showed that the effect of debt-to-assets and debt-to-equity ratios on the probability of default was positive and significant, leading to an increase in the probability of default of companies. As can be seen, the shock of financial ratios in the two regimes did not have the same effects, indicating asymmetry.

Keywords:

Credit risk, Credit rating, transition matrix, Markov chain, Value at risk.

1. Introduction

Todays, all industries encounter risks that if not addressed, will have harmful consequences. Banks, as fund intermediaries, are in charge of collecting the excess liquidity of the society and directing it to the economic units in need, in the form of credit allocations. One of the important factors which affects the economic health of the society is the regular and accurate function of money circulation cycle between the bank and credit customers, because in case of confinement of resources by the customers, the money circulation cycle will be a dysfunctional cycle without any proper returns. Although for banks, default on a debt risk of the Loan (credit risk) is one of the most important risks, other risks such as operational risk, liquidity risk, market risk, etc. also have a major impact on the bank's activities. Due to the intense and increasing competition of banks and financial institutions, as well as the significance of other risks, the financial life of banks is at crucial danger. As in the recent economic crisis, the lack of attention to major risks in the banking industry and lack of serious concentration on comprehensive risk management led to the bankruptcy of a large number of small and medium-sized banks, which is a warning to the other industry activists. There has been a dramatic shift in risk management in recent years. This transformation began with the creation of a new indicator called VAR, or " value at risk"

VAR is an apprehensible way to quantify market risk. After G. P. Morgan's company introduced the risk assessment model in 1994 in order to measure value at risk, this model emerged as a benchmark method to measure market risk. In the following years, other models such as volatile data theory, final value, heterogeneous variance conditional models such as GARCH model were introduced in the researches such as Danilson and Veres (2002) to measure value at risk. Since a large part of the economy and financial resources of the country is placed on the banking industry and there are several factors which are able to increased credit risk and consequently to the bankruptcy, the purpose of the paper present aims to contribute to the enrichment of the credit risk calculation research area and as well as the banks' credit rating in order to manage credit risk and default risk.

2. Literature Review

Risk

Risk can be explained as uncertainty about the outcome of an event or incident in the future or unexpected events which is usually in the form of a change in the value of an asset or liability (Bernicker Hoff, 1999).

Credit risk

Credit risk is the highest risk associated with the financial and banking activities. Customer lending facilities are the largest source of credit risk for most banks. Due to the low capital of banks in relation to the total value of their assets, even if a small percentage of loans to customers are not receivable, the bank will face the risk of bankruptcy. In other words, credit risk is the possibility that some of the bank's assets - especially the granted facilities - will be reduced or devalued in terms of value (Bugs, 1967).

Credit rating

Credit rating is a scale for calculating credit risk that is extracted and calculated from credit report using standard formulas.

Adequate credit rating is obtained as a result of timely payment of bills and facilities received and indicates the willingness of individuals to repay the installments of facilities received.

Inadequate credit rating, on the other hand, is characterized by delays in repaying credit facility installments, a negative record including bankruptcy, a history of bounced checks, a negative track record of tax debt, and a negative track record in the database of external information providers.

The term credit rating refers to a quantified assessment of a borrower's creditworthiness in general terms or with respect to a particular debt or financial obligation. A credit rating can be assigned to any entity that seeks to borrow money—an individual, a corporation, a state or provincial authority, or a sovereign government.

Individual credit is scored by credit bureaus such as Experian, Equifax, and TransUnion on a three-digit numerical scale using a form of Fair Isaac Corporation (FICO) credit scoring. Credit assessment and evaluation for companies and governments is generally performed by a credit rating agency such as S&P Global, Moody’s, or Fitch Ratings. These rating agencies are paid by the entity seeking a credit rating for itself or one of its debt issues.

Transition matrix

A Transition Matrix, also, known as a stochastic or probability matrix is a square (n x n) matrix representing the transition probabilities of a stochastic system (e.g. a Markov Chain).

The size n of the matrix is linked to the cardinality of the State Space that describes the system being modelled.

This article concentrates on the relevant mathematical aspects of transition matrices.

Aspects related to the use of the concept in the specific context of Credit Risk are discussed in the Rating Migration Matrix entry.

Discrete versus Continuous Time

A fundamental choice of the modelling framework is whether the stochastic system is assumed to evolve in continuous time or in discrete time steps. Continuous time frameworks may be more accurate and/or more mathematically tractable versus discrete time frameworks yet computational representations involve always some form of discrete time approximation.

A Markov transition matrix is a square matrix describing the probabilities of moving from one state to another in a dynamic system. In each row are the probabilities of moving from the state represented by that row, to the other states. Thus, the rows of a Markov transition matrix each add to one

Markov chain

Markov chain is a time-discrete random process with Markov property. Markov property states that the conditional probability distribution for the system in the next step depends only on the current state of the system and not the previous states, however the statistical properties of the system are predictable in the future. In many applications, the important issues are these statistical properties which is called Transition system state and the probabilities attributed to these state changes are called the probabilities of Transition. A Markov chain is completely determined by a set of modes and the probability of transitions.

3. Research background

Altman (1968) strongly attempted to find a significant relationship between a company's accounting variables and the probability of inability to repay its debts in the future, and provided a relationship known as the Z-Score. This method was based on the analysis of linear separation between good and bad companies, according to which there was only the possibility of distinguishing good companies from bad ones. The usage of this model in the banks is as the following: if the borrower's Z score is below the critical level, the loan application will be rejected or more control will be applied to increase the security of the loan and minimize the losses caused by the non-payment. Although this method was very rudimentary, it could predict the status of bad companies to some extent, and by 1980 it was the dominant method of most studies.

Bogess (1967) was the first researcher to use a computer to examine large data sets and using complex multivariate statistical tools improved credit scoring models. Beaver tried to estimate the successes and failures of companies using a number of indicators and multivariate logistic regression model.

Dokri Wafentakis (2008) in his paper "Experimental Comparison of Different Models for Estimating Value at Risk" evaluates a number of selected value at risk methods using the daily data of the London Stock Exchange of a period of ten years.

Manesme and Barthelemy (2012) examined the possibility of using the CF extension to determine the value at risk of assets and showed the way that Cornish-Fisher approximation performs more accurate and faster measurements than previous methods.

4. Methodology

Since the purpose of the current study is credit rating and preparing the risk Transition matrix for legal customers of the banks with Markov Chain approach, this study is considered as an applied research. For this purpose, using a multiple logit model, the default probability of the statistical population is estimated. Then, using Markov Regime Switching Model, the default Transition probability matrix between legal clients is calculated.

5. Results

The present article aims to study about the credit rating and preparing risk transition matrix for legal clients of banks with Markov chain approach. The statistical population of this study include active stock exchange companies that used banking facilities. The time span of this study is between 2003-03-20 and 2020-03-17.

5.1. Descriptive statistics review

Since the performance of different time series models can be affected according to different data, first of all, we review the descriptive statistics of the variables of this research in table 1. Descriptive statistics and statistical tests are carried out on the logarithm of the research variables including cash flow, best selling and buying price, return, total assets, quick and current ratio, total debt, net profit, equity, operating profit and average stock prices.

According to the table above, it can be seen that the fluctuations of the variables are relatively high and also based on their skewness and kurtosis as well as Jarque- Bera test their distribution is not normal.

Table 1: Descriptive statistics of research variables

variable	Average	Standard deviation	Skewness	kurtosis	Jarque-Bera Test	probability
Operating profit Log	1/254	0/589	0/85	3/425	15/68	0
Net profit Log	2/66	0/183	0/43	4/56	13/65	0/002
Equity	2/98	0/23	0/55	3/87	12/6	0/001
Cash flow Log	2/23	0/283	0/18	5/48	14/54	0/003
Best buy price	1/57	0/198	0/23	4/29	10/87	0
Best sell price	1/87	0/87	0/39	5/83	15/87	0
Return	0/23	0/374	0/41	6/09	8/98	0/014
total assets Log	2/98	0/098	0/58	3/28	16/44	0
Instant ratio	0/83	0/173	0/65	4/59	10/34	0/002
Current ratio	0/98	0/228	0/38	6/99	11/56	0/004
Total debts Log	2/85	0/487	0/58	3/85	19/73	0
Average share price Log	1/37	0/556	0/63	4/08	20/34	0

Source: Research results

5.2. Estimating logit model and calculating the default probability

Regression models can be used to test the fitting of binary dependent variables to the other independent variables. If these models are used as methods of accreditation, the purpose is to classify customers into two groups: able to repayment and unable to repayment by using the credit characteristics of borrowers. The use of nonlinear models, such as the maximum likelihood method to optimize those functions means that regression models make it possible to calculate membership probabilities as well as default probability directly from the model. These properties are suitable for calibrating the ranking model. Among the regression models, we can recall logit and probit which in this section, the logit model is used as follows:

In the first part of this article, we will discuss the usage of financial ratios to estimate the multiple logit model in order to calculate the ranking of companies and their default probability.

Related field	Variable type	Related field	Variable type
Total Debt	Debt	Total current asset	Sassets
Total assets	Totalassets	Total current debt	Sdebt
Total Equity	Equity	Cash balance	Cash
Long-term financial facilities	Ldebt	Accumulated profit (loss)	Pland
Gross profit	Profit	Capital	Capital
Net profit	Netprofit		

According to the input components of the model, the variables are defined based on financial ratios as follows:

According to the introduction of financial variables in the table above, the first model estimated in the structure of the logit model, according to the introduced variables, the probability of non-repayment of facilities is calculated based on the following relationship:

$$P_i = \frac{e^{\beta_0+\sum_{i=1}^{n}\beta_i X_i}}{1+e^{\beta_0+\sum_{i=1}^{n}\beta_i X_i}}$$

If the structure of the model can be in k possible states, the number of k-1 regression models will fit. In this equation P, there are two states of default and non-default probability for the borrowers (facility recipients). In this regard, for each of the sample companies, a multiple logit model is estimated and its credit risk is calculated, which the estimated coefficients for sample companies are given in the table below, and based on that structure the companies are rated in Table 3.

Table 2: Introduction of research variables

Denominator	numerator	variable name
Total assets	Total Debt	X1=(Debt/Totalassets)
Total Equity	Total Debt	X3=(Debt/Equity)
Total assets	Long-term financial facilities	X4=(Ldebt/Totalassets)
Total current debt	Total current asset	X11=(Sassets/Sdebt)
Total assets	Total current asset– Total current debt	X14=((Sassets-Sdebt)/ Totalassets)
Total assets	Total current debt	X15=(Sdebt/Totalassets)
Total assets	Cash balance	X16=(Cash/Totalassets)
Total current debt	Cash balance	X20=(Cash/Sdebt)
Total assets	Net profit	X27=(Netprofit/Totalassets)
Total Equity	Net profit	X30=(Netprofit/Equity)
-	total assets Log	X34=(Log(Totalassets))

Table (3): Customer ranking model

First level		Second level	
variable	Coefficient	variable	Coefficient
Width of origin	0/266	Width of origin	0/888
X1	0/987	X1	0/435
X3	1/009	X3	1/007
X15	1/226	X15	1/268
X27	-0/815	X27	-0/788
X34	-0/97	X34	-0/934

Source: Research results

Table 3 is the result of estimating a two-level model that according to the default and non-default probability of customers to their commitments the model is estimated in two parts and the coefficients of the first and second parts are presented to manifest the effect of each independent variable on the dependent variable. In this equation, the variable X1 indicates that the debt-to-assets ratio has a direct relationship with the customer default probability, X3 indicates that the equity-debt ratio has a direct relationship with the customer default probability, X15 indicates that the current debt-to-current asset ratio has a direct relationship with the customer default probability, X27 indicates that net profit-total asset ratio is inversely related to customer default probability and X34 logarithm of assets is inversely related to customer default probability. For example, in the model above, the coefficient of variable X1 (ratio of total debt to total asset) is positive and significant. This ratio is used to study the capital structure of the firm. According to the theory of capital structure, there is a direct relationship between the default probability and debt of the company because the capital structure of the firm affects in the success of the company's financing from external sources. The ratio of total debt indicates the degree of confidence of creditors in the receipt of their claims from the economic enterprise of the study.

Examining this ratio answers the question of how much of total debt at the balance sheet date includes the shareholders' equity. Obviously, the larger this ratio is, the less collateral the creditors will have, and when this ratio exceeds one, it indicates unfavorable conditions for the creditors which means that the creditors will not be able to meet their claims in case of bankruptcy of the enterprises. This ratio can also be used to measure the shareholders' interest in the economic entity. For example, the banks should be more careful when granting facilities to the companies that despite having high professional capabilities possess low shareholders' equity and consequently provide a large part of the firm's assets from e debt creation. Because, although the conditions are favorable if the firm's operations are profitable, the bank has a low security margin.

5.3. Estimation of Transition probability matrix with MS model

The Markov regime switching model is based on the fact that events may occur over time that cause the parameter to change over time. For example, the relationship between two variables may vary in different regimes, i. e. positive in regime 1 and negative in regime 2. In this case, it is better to use nonlinear models to estimate the parameters of the population. In nonlinear models, the model parameters are not constant over time. Markov switching model is also one of these models. Because the parameters change according to the regime switching. In the vector auto-regression model based on the Markov model, the model parameters are considered as a function of the s-t variable. The important point in these models is that the residual depends on regime switching. This is due to the change in the variance of the estimated equation in the low and high fluctuation regimes. The results of the classical regression model estimation with two regimes are given in the table below. Assume that s-t is a random variable that can take only the integer values {1,2,…, N}. Also assume that the probability that the random variable s-t takes the value j at time t depends only on past values.

$$P\{s_t = j | s_{t-1} = i. s_{t-2} = k. \ldots\} = P\{s_t = j | s_{t-1} = i\} = P_{ij}$$

In this case, the above process is called n-state Markov chain, that's Transition functions are $\{P_{ij}\}\ i.j = 1.2. \ldots .N$ The transfer function P_{ij} indicates the probability of Transition from state i. to state j. Also, the following relationship is always established.

$$P_{i1} + P_{i2} + \cdots + P_{iN} = 1$$

The transfer functions are represented in a matrix N × N called P.

$$P = \begin{pmatrix} P_{11} & P_{21} & \ldots & P_{N1} \\ P_{12} & P_{22} & \ldots & P_{N2} \\ \vdots & \vdots & \ldots & \vdots \\ P_{1N} & P_{2N} & & P_{NN} \end{pmatrix}$$

The ξ_t vector is in a form of a random vector $N \times 1$ whose j-th entry is equal to one if $s_t = j$, otherwise the j-th entry takes the value zero. As a result, when $s_t = 1$, ξ_t vector is equal to the first column of the matrix I_N (unit matrix N × N) and when $s_t = 2$ is equal to the second column of the matrix I_N. And so on we continue until the vector ξ_t is obtained as follows.

$$\xi_t = \begin{cases} (1.0.0. \ldots .0)' \\ (0.1.0. \ldots .0)' \\ \ldots \\ (0.0.0. \ldots .1)' \end{cases}$$

If $s_t = i$, ξ_{t+1} takes a value of one with a probability of P_{ij}. As a result, the conditional hope ξ_{t+1} at the condition of $s_t = i$ can be written as follows.

$$E(\xi_{t+1} | s_t = i) = \begin{pmatrix} P_{i1} \\ P_{i2} \\ \vdots \\ P_{iN} \end{pmatrix}$$

The vector above is the column i of matrix P. In addition, when $s_t = i$, the vector ξ_t is column i of the matrix I_N. In this case, the above equation can be written as follows:

$$E(\xi_{t+1} | \xi_t) = P\xi_t$$

And according to Markov's feature which mentioned at the beginning of the discussion, the above equation can be written as follows:

$$E(\xi_{t+1} | \xi_t . \xi_{t-1} . \ldots) = P\xi_t$$

According to regression theory, the equation above is a regression equation. As a result, we can write it as follows.

$$\xi_{t+1} = P\xi_t + v_{t+1}$$
$$v_{t+1} = \xi_{t+1} - E(\xi_{t+1} | \xi_t . \xi_{t-1} . \ldots)$$

As can be seen in the above equation, the above equation is a first-order autoregressive equation. In the second step, after determining the customer default probability, the risk Transition matrix of companies is calculated. The results of model estimation are given in Table 3. As can be seen, the effects of financial ratios on default during the specified time period of the research can be divided into two regimes that shock coefficients are also statistically significant. Considering that the y-intercept of the regime 1 is less than the y-intercept of regime 2, so it can be said that in regime 2 the credit default is more than the credit default in regime 2. The effect of debt-to-assets ratio and debt-to-equity ratio on the default probability is positive and significant, leading to an increase in the default probability of companies. The sum of interval ratios of debt-to-assets ratio and debt-to-equity ratio in regime 1 is 0.187 and 0.197 and in Regime 2 is 0.265 and 0.198, respectively. The effects of the variable intervals of net profit to total assets ratio and the logarithm of assets in regime 1 are equal to 1.263 and 0.979, and in regime 2 are equal to 1.285 and 1.319, respectively. As can be seen, the shock of financial ratios in both regimes does not have the same effects which indicates asymmetry. Estimated standard deviation in the both regimes also show that the variance of regime 1 is less than regime 2. In order to evaluate the regimes' stability as well as the probability of Transition of each regimen to another, the Transition probability matrix is created. As shown in the table, regimes 1 and 2 have a stability probability of 0.72 and 0.79, respectively which are relatively high. Also, the probability of Transition from regime 1 to regime 2 is about 42% and the probability of Transition from regime 2 to regime 1 is about 38%. Probability values indicate that regime 2 is more stable than regime 1.

Table 4: model estimation results

	Regime1		Regime2	
Variable	**Coefficient**	**significance level**	**Coefficient**	**significance level**
Width of origin	1/325	0	3/415	0
Debt to asset ratio	0/124	0/001	0/178	0
first interval of debt-to-assets ratio	0/112	0/002	0/164	0
second interval of debt-to-assets ratio	0/075	0	0/101	0/004
Debt to equity ratio	0/154	0	0/147	0/002
first interval of the debt-to-equity ratio	0/11	0/002	0/109	0
second interval of the debt-to-equity ratio	0/087	0/001	0/089	0/001
Ratio of current debt to current assets	0/092	0/002	0/096	0
first interval of current debt to current assets ratio	0/078	0	0/073	0
second interval of current debt to current assets ratio	0/058	0/001	0/081	0/003
net profit to total assets Ratio	-0/875	0	0/932-	0
first interval of net profit to total assets Ratio	-0/731	0	-0/739	0/004
second interval of net profit to total assets Ratio	-0/532	0/004	-0/546	0/001
Asset logarithm	-0/876	0	-0/943	0
first interval of the asset logarithm	-0/634	0/001	-0/854	0/001
second interval of the asset logarithm	-0/345	0/005	-0/465	0/006
Standard deviation	0/684		1/12	
P_{11}	0/5812			
P_{22}	0/6245			
Akaike statistics	5/654			
Schwartz statistics	6/351			

Source: research results

In the following, diagnostic tests regarding the disruption sentences of the estimated regression model are discussed, the results of which are reported in Table 5.

In the estimated model, the results of Portman-Tao test indicate the nonexistence of autocorrelation in the model disruption sentences. The reported normality test also indicates that the distribution of disturbance sentences is normal. Also, the results of ARCH test indicate the absence of heterogeneity variance in regression model disruption sentences. According to the estimation, the default correlation matrix of the sample companies is calculated:

Table 5: Results of diagnostic tests of regression model disruption sentences

Test	Test statistics	significance level
Portman-Tao	12/45	0/198
Jarque-Bera (Normality)	1/11	0/571

ARCH	0/039	0/824

Source: Research results

Table 6: Results from the default correlation matrix of sample companies

khesapa	seshargh	chekaren	mamasani	segharb	dehdasht	vaazar	ghedam	kasram	
0.477	0.481	0.342	0.565	0.709	0.823	0.751	0.504	1.000	kasram
0.363	-0.211	-0.387	0.108	0.248	0.480	0.286	1.000	0.504	ghedam
0.300	0.294	0.047	0.287	0.908	0.794	1.000	0.286	0.751	vaazar
0.397	0.342	0.190	0.392	0.868	1.000	0.794	0.480	0.823	dehdasht
0.425	0.443	0.225	0.309	1.000	0.868	0.908	0.248	0.709	segharb
0.700	0.731	0.647	1.000	0.309	0.392	0.287	0.108	0.565	mamasani
0.928	0.904	1.000	0.647	0.225	0.190	0.047	-0.387	0.342	chekaren
0.916	1.000	0.904	0.731	0.443	0.342	0.294	-0.211	0.481	seshargh
1.000	0.916	0.928	0.700	0.425	0.397	0.300	0.363	0.477	khesapa

Source: Research results

The results of the emission Transition matrix based on actual and predicted values is reported as follows.

Actual Value		Value	
Bad	Good		
244	147,562	Good	Predicted Value
2,538	4,248	Bad	

Source: Research results

The results obtained from the model indicate the model is accurate in terms of actual and predicted values. Finally, according to the estimated models, the Transition matrix for credit risk is calculated in the table below.

Using the obtained results, the probability of risk Transition between different credit ratings for different time periods can be observed, for example, if a company has an AA credit rating for a period and its rating is reduced to BB, it will be equal to 0.252

Table 7: Results from the annual default matrix of sample companies

Credit rating	AAA	AA	A	BBB	BB	B	CCC	CC	C
AAA	1	0	0	0	0	0	0	0	0
AA	0	0/099	0/149	0/161	0/252	0/339	0	0	0
A	0	0/04	0/089	0/118	0/125	0/131	0/218	0/277	0
BBB	0	0/083	0/145	0/241	0/175	0/104	0/109	0/143	0
BB	0	0	0/05	0/098	0/125	0/138	0/293	0/301	0
B	0	0	0/056	0/096	0/131	0/194	0/235	0/288	0
CCC	0	0/03	0/03	0/067	0/146	0/219	0/235	0/273	0
CC	0	0	0/03	0/03	0/110	0/222	0/288	0/318	0
C	0	0	0	0	0	0	0	0	1

Source: Research results

6. Discussion and Conclusions

Today, banks, financial institutions and other financial service companies, due to the nature of activities and having a diverse portfolio of assets, face different types of risks that due to the constant changes in environmental factors and economic systems over time, the dimensions of risks affecting They are becoming more widespread day by day.

The purpose of this paper is to classify credit and prepare risk transfer matrices for legal clients of banks with Markov chain approach. The statistical population of the present study is active stock exchange companies that have used banking facilities. The period of this study is related to the period of 12/29/1381 to 12/27/1398. In this regard, using the Markov regime change model (MS), the factors affecting the probability of default of customers were estimated and the probability matrix of default was calculated.

In order to credit rating and prepare risk transfer matrix for legal clients of banks with Markov chain approach, the following steps were performed in this article:

1) Companies that have defaulted on the status of their received credits were examined.
2) The financial ratios of these companies were extracted.
3) The credit rating and probability of default of these companies were calculated using a Markov regime change model.
4) The transfer probability function was calculated in order to spread and transfer the default between companies.

According to the results of model estimation in Table (3), the results show that among the variables (Table 2) of financial ratios that are defined from the input components to the model, the effect of variables "= X1 ratio" Debt to assets "and" X3 = debt to equity ratio "has been positive and significant on the probability of default and leads to an increase in the probability of default of companies.

According to Table:(٤)

- ✓ The sum of the interval coefficients (first interval and second interruption) of the debt-to-assets ratio and the debt-to-equity ratio in Regime 1 is 0.187 and 0.197, respectively.
- ✓ The sum of the interval coefficients (first interruption and second interruption) of the debt-to-assets ratio and the debt-to-equity ratio in regime 2 is equal to 0.265 and 0.198.
- ✓ The effects of the intervals of the variables of the ratio of net profit to total assets and the logarithm of assets in regime 1 were equal to 1.263, respectively.
- ✓ The effects of the intervals of the variables of the ratio of net profit to total assets and the logarithm of assets in Regime 2 were equal to 1.285 and 1.319.

As can be seen, the shock of financial ratios in the two regimes did not have the same effects, indicating asymmetry.

Based on the results, it is suggested that having an up-to-date financial database plays an important and fundamental role in creating, developing and improving credit risk models, so having a customer financial database as one of the tools It is considered as a basis and it is suggested that banks create a financial database dedicated to their legal clients. Undoubtedly, the development of this thinking at the level of the whole economy will lead to the establishment of an extensive financial database in the country, which on the one hand will help expand financial transparency and on the other hand will facilitate financial studies and research, including modeling various credit risks. Also, designing and establishing a Markov chain model in credit risk forecasting and connecting it to the financial database to determine the degree of credit risk of each customer at any time of time is another suggestion presented in this article.

Resources

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