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Efficiency of externally adjusted bankruptcy prediction patterns by bankruptcy prediction of Iranian organizations

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Abstract

The aim of this study is the effectiveness of prediction models adjusting for foreign bankruptcy to bankruptcy prediction organizations in Iran. This study is applied and descriptive in nature of the relatives who would try to model bankruptcy, through models, model risk In their book, Dan and Broadstreet use the term "failure" to refer to companies that are shutting down due to divestiture or bankruptcy, or abandoning loss-making business activities, or which are subject to change. Are legal by law. But in general, when a company's active business fails demands (demands) of creditors to satisfy, as the company failed to consider and if the debtor fails with its creditors to somehow reach an agreement should be based on the provisions of the Code of bankruptcy petition economy.

Keywords: Bankruptcy, Financial Crisis Stock Exchange.
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1 Introduction

The consequences of financial failure for financial creditors, managers, shareholders, investors, employees and even a country's economy are enormous. For this reason, over the past five decades, the forecast of corporate bankruptcy has become a significant concern for various corporate stakeholders. Accurate bankruptcy forecasting usually has many benefits, including reduced costs of credit analysis, better oversight, and increased debt collection rates. Therefore, bankruptcy forecasting has received a great deal of attention and is now more important [23]. The question today is not whether we should use bankruptcy prediction models, but how to increase the effectiveness of prediction models.

Alaka et al [2] stated that bankruptcy models are mainly used by financial institutions, e.g., banks are required. Their advantage is especially in their ability to provide clear information about potential risks and eliminate such problems in a timely manner and are important for current and future decisions [18]. Bankruptcy prediction is a very real issue in worldwide [11]. Thus, information about the threat of imminent bankruptcy fundamental aspects of decision - making managers, financial institutions and government organizations [31]. Bankruptcy issue, problem which it claims, demands separate set of assets that are not can be met together [14]. The impact of high business failure rates can be devastating for the company owner, partners, society and the economy [2].

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Extensive research and thus the creation of bankruptcy prediction models undoubtedly justifiable for companies. The performance of these models, among other factors, depends on the choice of tool chosen to build it. Apart from a few studies (such as Altman, [4] and Ohlson, [27]), tool selection in many studies of bankruptcy prediction models is not based on the capabilities of this tool. But also chooses based on popularities (like Abidal and Harris, [1]; Koyungogil and Ozgolbas,[24]), or based on professional backgrounds (e.g. Altman, Marco, and Varetto, [6]; Beaver, McNichols and Rhie [12]; Lin and McClean [25]) [2]. The reasons for the growing attention to this area can be pointed out that the projected bankruptcy of the Group of direct and indirect impacts of different economic. In general, a small part of the effects of a company's bankruptcy is the unemployment of labor, financial problems for company owners, the financial crisis of debtors and also the negative effects created in the supply chain [16].

Must be acknowledged to avoid loss huge flows through bankruptcy and emerge, academic research and many studies in this field, the imperative is the model and patterns bankruptcy with the highest prediction accuracy. It is very important that the information provided by the accounting system plays a significant role in this regard.

2 A review of the literature

In their book, Dan and Broadstreet use the term "failure" to refer to companies that are shutting down due to divestiture or bankruptcy, or abandoning loss-making business activities, or which are subject to change. Are legal by law. But in general, when a company active business fails demands (demands) of creditors to satisfy, as the company failed to consider and, if the debtor fails with its creditors to somehow reach an agreement should be based on the provisions of the Code of bankruptcy petition the. There is usually a difference between economic failure and financial failure. In general, business failure is the same as economic failure, because the institution has not been able to obtain the same return on investment as is available elsewhere. Failure by law is not the inability to meet obligations at maturity. Failure to define the rules that total assets are not sufficient to pay the total debt. Consultants for various reasons causing bankruptcy is the main reason for bankruptcy, mismanagement organizations. Management errors, high costs, weak financial activities, ineffective activities, sales and high production costs, will be used alone or a combination of them to be alert for bankruptcy. Economic activity can be another reason for bankruptcy. Economic recession, changes in interest rates, rising inflation, fluctuations in raw material prices and international economic conditions are some of the reasons for bankruptcy [7].

Thorburn [32] and Juliet and Hübner [19] argues that the bankruptcy of the company on various aspects of the economic environment negatively affect. The likely negative effects of bankruptcy on the company's position in product markets and capital, by spending more time in the process of bankruptcy, will - be. For example, a bankrupt company as much more time in the bankruptcy process pass, keep customers and employees, and attract capital investment, the more difficulty will be encountered [9].

Bankruptcy is a situation in which a debtor company is unable to repay its debts and can be the result of a company's inability to survive in the market, which is reflected in the loss of jobs, loss of assets and Productivity is low [3]. The risk of bankruptcy or bankruptcy indicates the probability that a company will not be able to meet its debt obligations, respectively the probability of bankruptcy of the company in the next few years. Bankruptcy risk assessment is especially important for investors when deciding on stocks or securities, but it is also important for managers in making financial decisions about budget, investment and distribution policy. Failure prediction models as well as are important tools for bankers, rating agencies and even the company itself [5].

Bankruptcy forecasting is essential for investors as well as business suppliers or retailers. Credit lenders and investors should assess a company's risk of financial bankruptcy before deciding whether to invest or grant credit to avoid significant losses for banks and other credit lenders. A company's suppliers or retailers always do credit transactions with the company, and they must also be fully aware of the company's financial situation and decide on a credit transaction. Accurate forecasting of the company's financial situation worries the various stakeholders of a company . Bankruptcy problems have necessitated studies to create various stressors to help investors make prudent investment decisions [26].

Designing reliable models to predict bankruptcy is crucial for many decision-making processes [28]. The approach used to predict bankruptcy over time, starting with the Beaver model (1966, 1968), is based on univariate analysis for selected ratios and has excellent predictive power. Then, Altman (1968) created a distinct multiple analysis model called the model Z-Score He took steps. Bankruptcy prediction models can be divided into two general categories depending on the variable used: static and dynamic models [11]. In the bankruptcy prediction literature, the models of Altman (1968), Olson (1980) and Zmejewski (1984) have the most citations based on accounting variables. These bankruptcy prediction models use various explanatory variables and statistical techniques. Therefore, the predictive power of these bankruptcy prediction models varies. However, when statistical techniques, the original is used, the accuracy of the model by Altman (1968), Olson (1980) and Zmejewski (1984) respectively 80.6% , 93.8% and 95.3% is [11]. Ashraf et al [8] found that both models by Altman (1968) and Zmejewski (1984) are still valuable for predicting emerging market financial distress and can be used by traders, financial professionals, managers, and other stakeholders. Are they thinking of investing in an organization or want to increase the performance of their organization, use it [8]. Elviani et al. [15] The validity of Altman models (1968), Olson (1980), Spring (1978) and predicted Zamiski (1984) in bankruptcy [15].

Most authors offered models tailored to their economic characteristics. Jouzbarkand et al., [20] developed an econometric forecasting model in US companies using three simple, correlated, and readily available financial ratios as explanatory variables, and their results showed a forecast accuracy of more than 80% . Gives Dakovich et al [13] developed statistical models for predicting the bankruptcy of Norwegian companies operating in the industrial sector. They modeled an unobserved heterogeneity between different segments through an industry-specific stochastic in the generalized linear mixture model . The developed models have been shown to perform better with Altman variables [13].

In addition, Two models have been collected for predicting bankruptcy related to Iran's economic situation. Using logistic regression, Olson (1980) and Shirata models (1995) examined and compared the performance of these models. Their results show that the created models are able to predict bankruptcy. To classify and rank companies, they use their business law to determine bankrupt companies and one Q-Tobin used simple to identify halal companies [20].

3 Research Method

This study is applied and descriptive in nature of the relatives who would try to model bankruptcy, through models. A) The risk (2001). This model has a logit model as equation (3.1) is. B) accounting model Koopayee Pour Heydari and that the relationship 3.2 and 3) the contingent claim BARS (2008) in relation (3.3) can be expressed.

A) Shamway model (2001)

$$\begin{aligned}P_{i.t}(Y_{i,t+1}) &= \\ &= Probability\ of\ bankruptcy\ i\ In\ the\ year\ t\ Is.If\ the\ company\ goes\ bankrupt\ 12 months \\ &\quad later,\ one\ is\ otherwise\ zero.\end{aligned} \tag{3.1}$$

$X_{i,t}$ Is the vector of the independent variables and β is the vector of the column of estimated coefficients and is the width of the origin.

Shamway's (2001) model involves taking the independent variables as follows.

NITA= Ratio of net profit to total assets.

TLTA = Total debt to total asset.

EXRET= Equivalent to the logarithm of the company's excess return over the return of the Tehran Stock Exchange index.

SIGMA= Deviation of daily returns annually, three months before the portfolio.

RSIZE= Lgartm stock market value of the company's total stock market value of the Tehran Stock Exchange.

B) Accounting model of Pour Heidari and Kopai [29]

$$\begin{aligned}P = 20784/3K_1 + 80384/1K_2 + 61363/1K_3 + 50094/0K_4 + 16903/0K_5 + 39709/1K_6 \\ + 12505/0K_7 + 33849/0K_8 + 42363/0K_9\end{aligned} \tag{3.2}$$

Where:

P= Financial crisis in the company.

K_1 = Profit before tax asset.

K_2= Retained earnings to total assets.

K_3Working capital to assets.

K_4= Equity debt.
K_5= Profit before tax to sales revenue.
K_6=Current assets to current liabilities.
K_7=Net profit to sales.
K_8=Debts to assets.
K_9 =Firm size (log of net sales).
Separating point: 8907/15
f 8907/15 P Yes, the company has a financial crisis, otherwise the company has no financial crisis.

C) Bars & Shamway model (2008)

This model is a simple approach of Black and Schulzmurten structural model. In the simple model of Bars Shamway (2008) there is no need to solve two equations at the same time and equations (3.3) and (3.4) are used to calculate the distance to failure. They estimated debt fluctuations as described in Equation (3.3) and company fluctuations as a weighted average of equity value and debt fluctuations as described in Equation (3.4).

$$D.naive = 05/0 + 25/0E \tag{3.3}$$

$$D.naive = E + D \tag{3.4}$$

$$P_{nive} = N(-DD_{nive}) = N \tag{3.5}$$

P_{nive} =Probability of failure
E =Equal to the value of the stock
A =Total value of assets.
D =Equal to the value of current liabilities plus half of long-term liabilities.
N =Equal to the normal cumulative density function (whatever inside () is). T =The forecast horizon is one year, soT Is equal to one.= Company fluctuations. = Returns last year. =Deviation of equity returns. = Debt deflation calculated during Equation 3.4.
Bars and Dinner limited the previous year's return between the company's previous year's return and the risk-free rate.
To test the hypothesis of system performance characteristic curve (ROC) And logistic regression was used. Curve ROC In sauce software, SPSS and Aetta Applicable; But the difference below the surface of the curve is not applicable due to the correlation of the models. The following steps were performed to create the characteristic performance curve of the system.

1. The probability of bankruptcy of the sample companies obtained from each model was arranged for the whole sample from larger to smaller.
2. Depending on the number of samples and bankrupts, 10 to 100 portfolios are formed. In this research, due to the small sample size and bankrupt, the 10 portfolios formed was given.
3. The percentage of bankrupt companies per year was calculated for each portfolio (the number of companies that actually went bankrupt each year cumulatively for all years of each portfolio divided by the total number of sample bankrupts). Percentage of bankrupt companies cumulatively for all portfolios Y Formed.
4. The number of companies in each portfolio is cumulative X Formed
5. For each bankruptcy prediction model, the above steps were performed and a characteristic curve of the system performance was drawn.

In this study, following Henley and McNeill [17], the area under the curve using Wilcoxon statistics and the standard error was calculated from the area below the curve as described in Equations (3.6) and (3.7). Then test it as a relationship (3.6) was carried out. To compare the area under the curve, two different models (determined as 1 and 2) follow Henley McNeill (1983) of the statistical distribution. Z Naturally as the relationship (3.7) was used. Sobhart and Keenan (2001) argues that the area under the curve is a definite measure of the ability of nasal models.

$$\begin{aligned}(A) =& \textit{Level below the receiver operating indicators curve.}\\ =& \textit{Number of bankrupt companies.}\end{aligned} \tag{3.6}$$

$$\begin{aligned}Se\ (A) =& \textit{ Standard error of the area under the curve}\\ r =& \textit{ Correlation between two models}\end{aligned} \tag{3.7}$$

Information from the face of a major financial and notes by State Standard of Tehran Stock Exchange website and application software intercepts the modern extracted and analyze data from version 9 software application used Eviews.

Example including two group companies go bankrupt Successful and Unsuccessful can be. The main criterion for selection company insolvent, Article 141 of the Commercial Code can be. Accordingly, the company of " bankrupt " is that two consecutive years are eligible for this article. In general, the sample includes 100 companies, including the companies listed in the Tehran Stock Exchange during the year in 2007-2019 (1287 View contains 215 View bankrupt and in 1072 observed Unsuccessful) selected by the ROC The system is a method for assessing the appropriateness of forecasting parameters. Then, using the accrual earnings management and real variables through a logit regression model before the nose bankruptcy is estimated to be. In the end, the performance in terms of accuracy the nose and error checked out.

4 Model estimation and analysis And The analysis of

Investigating the significance of research variables

As mentioned in Chapter 3, it is necessary to examine the significance of its variables before estimating the model. A variable is when the mean, variance, and covariance remain constant over time. In general, if the temporal origin of a variable changes and the mean, variance, and covariance do not change, then the variable is mana, and otherwise the variable will be anonymous. Hypothesis of the stationary variables is as follows:
The variable is unknown
Is a variable
The significance of the variables can be examined in three modes: "at the level","on the first difference" and "on the second difference". Variables whose probability of being tested "at the level" is less than 5%. The null hypothesis about it is rejected and that variable is at the mana level. If it is more than 5%, it is unknown.
Viability test results in table 1 inserts have been shown. In any case, "Dickey Fuller" because of the possibility of all the variables under Was 5%, all variables were independent, dependent on the research period at a stable level were reliability means that the mean and variance and covariance parameters between the variables over different time has been fixed. As shown in Table 1, all variables are meaningful and do not require a collective test. does not exist. So the problem of spurious regression coefficients in the regression estimate there will be no false sense of multipliers to be false.

Model estimation and analysis of results

After examining the significance of the variables, it is time to estimate the research model. Due to the binary (zero and one) of the research dependent variable in the research model, in order to estimate this model, the logit regression technique is used. In order for linear regression coefficients in the linear regression model to be the best estimators without linear bias, it is necessary that the variance is part of the fixed model error and there is no alignment between the explanatory variables. Therefore, in the following, this issue is investigated and then the results of the estimates are explained. In the same direction of the softwareEviews Used to identify the relationship between variables.

Error component variance constant test (residuals)

One of the assumptions of linear regression is that all remaining sentences have equal variance. In practice, this assumption may not be very true and for various reasons such as: incorrect shape of the model function, the presence of outliers, structural failure in the statistical community, etc. we see the phenomenon of variance inequality. To test

Table 1: Results of mana test of research variables

Results	Generalized Dickey Fuller test		Variables
	Possibility	Statistics	
Mana	0.0000	22,598	K1
Mana	0.0000	22,597	K2
Mana	0.0000	15,065	K3
Mana	0.0000	7,711	K4
Mana	0.0000	23,295	K5
Mana	0.0000	11,188	K6
Mana	0.0000	7,714	K7
Mana	0.0000	6,239	K8
Mana	0.0000	22,781	K9
Mana	0.0000	10,069	EXRET
Mana	0.0000	13,176	NITA
Mana	0.0000	14,432	RSIZE
Mana	0.0000	12,112	SIGMA
Mana	0.0000	21,511	TLTA

Table 2: Results of the test of variance constant of the error sentence

Result	Possibility	Statistics F	Model
Variance heterogeneity component of the error	0/0146	3/3190	First
Variance heterogeneity component of the error	0/0179	3/3099	Second
Variance heterogeneity component of the error	0/0183	3/2098	Third

this problem, various tests have been introduced by economists. In this study, the residual variance homogeneity is assumed through the White test was examined. The results in Table 2 show that in both models, the null hypothesis that there is homogeneity of variance is rejected. In other words, there is an error component in both models of variance heterogeneity research. Therefore, in order to solve the problem of error variance heterogeneity, when estimating the logit regression model, the White option has been selected to solve the problem of heterogeneity.

Test for no alignment between explanatory variables

Alignment means that there is a strong relationship between the independent and control variables in the model. According to Tables 3 show the results of this test. The rate of variance inflation of independent variables of research models is within its allowable limit and therefore there is no problem in this regard.

1. There is a significant relationship between the efficiency of foreign adjusted bankruptcy forecasting models and bankruptcy forecasting of Iranian organizations.
   In order to test this hypothesis, the estimation results of the model presented in Table 4 have been used. Value ratio statistic value (LR) A confidence level of 95% reflects the overall model is significant. The results of McFadden's coefficient of determination show that approximately 11.3% of the dependent variable changes (bankruptcy) are explained by the model independent variables. In general, according to the above, the first hypothesis can be considered confirmed at 95% confidence level. This means that the efficiency of foreign adjusted bankruptcy forecasting models has a significant relationship with the bankruptcy forecasting of Iranian organizations.
2. the parameters (coefficients) of failing to predict the bankruptcy of organizations in Iran there is a significant relationship.
   In order to test this hypothesis, the estimation results of the model presented in Table 5 have been used. Value ratio statistic value (LR) A confidence level of 95% reflects the overall model is significant.

Table 3: Results of the test of no alignment between the explanatory variable of the first model of research

Inflation factor variance	Coefficient of variance	Variable
	0.000832	K1
	0.000420	K2
	0.105722	K3
	0.000320	K4
	0.000198	K5
	0.000111	K6
	0.000640	K7
	0.013178	K8
	0.018292	K9
	0.000834	EXRET
	0.002108	NITA
	0.001697	RSIZE
	0.105998	SIGMA
	0.000322	TLTA

Table 4: Results of estimating the first research model

Significance level	z Statistics	standard error	Coefficient	Variables
0.0321	2.36909	0.717546	0.26484	NITA
0.0363	2.24518	0.421172	0.20326	TLTA
0.0344	2.68326	0.069984	0.24782	EXRET
0.0362	2.66375	0.028729	0.2478	SIGMA
0.0389	2.774033	0.049763	0.238519	RSIZE
0.115	1.576077	0.708293	1.116324	C
0.572271	Mean dependent var		0.113935	McFadden Rsquared
0.495602	SE of regression		0.495115	SD dependent var
165.0574	Sum squared resid		1.377655	Akaike info criterion
461,025	Log likelihood		1.417648	Black criterion
922.0504	Deviance		1.393138	HannanQuinn criter.
462,846	Restr. log likelihood		925.6926	Restr. deviance
0.67998	Avg. log likelihood		33.64224	LR statistic
			0.031982	Prob (statistical LR)

Table 5: Results of estimating the second research model

Significance level	z Statistics	standard error	Coefficient	Variables
0.0137	2.58159	1.819066	0.47701	K1
0.0433	2.93227	1.111779	0.14826	K2
0.0028	2.91007	1.482791	0.349444	K3
0.0085	2.014377	1.695977	0.024383	K4
0.0061	2.206847	1.370479	0.283479	K5
0.0048	2.764037	1.350242	0.031635	K6
0.0464	1.99186	0.573979	0.14328	K7
0.0453	2.00146	0.401075	0.302736	K8
0.0087	2.99167	0.040195	0.31775	K9
0.0093	1.97097	0.177713	0.10906	NITA
0.0074	2.8284	0.096373	0.17984	RSIZE
0.0344	2.78169	0.000235	0.16018	SIGMA
0.0379	2.07608	0.332714	0.69074	TLTA
0.0068	2.705935	0.102451	0.277225	EXRET
0.4383	0.775014	121.4513	94.12652	C
0.572271	Mean dependent var		0.410125	McFadden Rsquared
0.496452	SE of regression		0.495115	SD dependent var
163.6525	Sum squared resid		1.392802	Akaike info criterion
458.16	Log likelihood		1.486118	Black criterion
916.3198	Deviance		1.428927	HannanQuinn criter.
462,846	Restr. log likelihood		925.6926	Restr. deviance
0.67575	Avg. log likelihood		69.37289	LR statistic
			0.004234	Prob (statistical LR)

The results of McFadden's coefficient of determination show that the dependent variable changes (bankruptcy) are almost explained by the model independent variables. In general, the results show that according to the above, the third hypothesis can be considered confirmed at 95% confidence level. This means that the effective parameters (coefficients) of bankruptcy have a significant relationship with the prediction of bankruptcy of Iranian organizations.

3. There is a significant relationship between the comprehensive model of forecasting companies in Iran based on the prevailing conditions with the forecast of bankruptcy of Iranian organizations.
   In order to test this hypothesis, the estimation results of the model presented in Table 6 have been used. Value ratio statistic value (LR) A confidence level of 95% reflects the overall model is significant.
   The results of McFadden's coefficient of determination show that approximately 19.9% of the dependent variable changes (bankruptcy) are explained by the model independent variables.
   In general, the results show that according to the above, the second hypothesis can be considered confirmed at 95% confidence level. This means that the comprehensive model of forecasting companies within Iran based on the prevailing conditions with the forecast of bankruptcy of Iranian organizations there is a significant relationship.

5 As a result and Suggestion

The results, as described above, confirm the hypothesis that the comprehensive model of forecasting companies in Iran based on the prevailing conditions has a significant relationship with the forecast of bankruptcy of Iranian organizations and the stage of the economic cycle. Affects the financial condition of companies. A worse financial situation is expected in the recession and better financial conditions in the development phase. This finding has a significant effect on bankruptcy forecasting models related to forecasting companies' financial situation. If bankruptcy prediction models are applied, users must respect the general economic conditions, including macroeconomic development and industry. The stage of recession further leads to lower final bankruptcy rates . Conversely, the expansion phase leads to the highest scores. The evaluation of a company, according to the models predicting bankruptcy, should consider the stages of the economic cycle. It is not necessary to macroeconomics.

In financial bankruptcy analysis, it is important to identify companies at risk of bankruptcy and prepare to avoid any financial loss [22]. According to Rybárová, et al. [31] are bankruptcy models of early warning systems that are able

Table 6: Results of estimating the second research model

Significance level	z Statistics	standard error	Coefficient	Variables
0.0199	2.26645	0.10969	0.29567	K1
0.0019	7.03242	0.702181	0.52494	K2
0.0427	2.861006	0.63417	0.180194	K3
0.0001	5.16097	0.455138	0.689372	K4
0.0386	2.190931	1.67618	0.320034	K5
0.0347	3.72413	0.201986	0.34825	K6
0.4233	0.800776	0.058355	0.046729	K9
0.04969	1.971351	0.330097	0.225487	K8
0.0416	2.225493	0.357242	0.306049	K7
0.3396	0.95505	0.512394	1.44441	C
0.572271	Mean dependent var		0.199253	McFadden Rsquared
0.495245	SE of regression		0.495115	SD dependent var
163.8387	Sum squared resid		1.382194	Akaike info criterion
458,564	Log likelihood		1.448848	Black criterion
917.1272	Deviance		1.407997	HannanQuinn criter.
462,846	Restr. log likelihood		925.6926	Restr. deviance
0.67635	Avg. log likelihood		48.565448	LR statistic
			0.028314	Prob (statistical LR)

to identify a topic for a company's financial health based on the analysis of selected indicators. Kiaupaite-Grushniene [21] stated that the establishment of reliable models for predicting bankruptcy is essential for various decision-making processes. Purvinis et al [30] argue that an unfavorable business environment, risky business managers' decisions, and unexpected and unpleasant events may affect a company in bankruptcy and lead to bankruptcy. Baran [10] believes that financial bankruptcy prediction models allow for the adoption of timely strategic measures to prevent financial distress. The results of the Barbitota Monsieu et al. [11] study among European countries showed that there is a constant effort to use developed models for enterprises in different countries, even if decision makers know or at least need to know the assumptions that are appropriate for them. The original models used are probably no longer valid . There is constant concern about designing models to predict bankruptcy risk. Bankruptcy models based on macroeconomic variables do not seem to be stable over time because they are not used frequently and are not scrutinized over longer time horizons. It seems that the life cycle of forecasting models containing macroeconomic variables is not long enough and can not be used for further economic periods.

The main problem with bankruptcy prediction models presented in research is that they cannot be generalized because they are generated using a specific sample of a specific sector, specific time period, and specific region or country. As the above statistics show, there are other specific factors that increase bankruptcy in a country: changes in the economic environment, the legal framework, the incomparability of the population of interest, and so on. That is why it is necessary to analyze these models with the properties of the sector, country or time period and use the combined estimation techniques in the design of these specific models.

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