Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development
Vol. 16, Issue 2, 2016
PRINT ISSN 2284-7995, E-ISSN 2285-3952

DISCRIMINANT ANALYSIS AS A METHOD FOR ESTIMATING THE PROBABILITY OF DEFAULT OF MOLDOVAN SMALL AND MEDIUM ENTERPRISES IN RURAL AREAS

Anatol RACUL, Dragoș CIMPOIEȘ, Alexandru GORGOS

State Agrarian University of Moldova, 44 Mirceşti Str., 2049, Chişinău, Republic of Moldova, Emails: anatol.racul@gmail.com

Corresponding author: anatol.racul@gmail.com

Abstract

This study tries to present a method for the estimation of the probability of default (PD) of Moldavian SMEs, which would be a parametric alternative to the expert-based models used nowadays. Discriminant analysis is the most widely used statistical based method for the estimation of PDs in the global financial industry and generally gives rather good estimations. Even with all the particularities of the Moldovan companies, the results obtained are promising and suggest that indeed, a statistical-based model would be very useful for Moldovan financial institutions.

Key words**:** *creditworthiness, Moldavian agriculture, rural development*

INTRODUCTION

Since 1991, when the Republic of Moldova became independent, the performance of the banking system continuously improved in order to be successfully integrated in the global financial system. The banking system became deeply integrated into the Moldavian economy due to its role of aggregation of firms' and households' savings and that of granting credits. [4]

This integration also made the banking system rather correlated to the macroeconomic situation of the national economy and a relative high degree of pro-cyclicality can be observed.

The problem of access to credit persisted during the transition period, despite the dynamic development of the banking system. According to several surveys performed by World Bank, the majority of entrepreneurs emphasize that this is one of the major barriers in the continuous development of Moldavian business. Local economists conclude that the lack of sufficient access to credit for local business is a fundamental constraint that hampers the economic development of the Republic of Moldova . [5]

The cost of attracted resources is the highest in the region for the past decade, as Moldova has one the highest real interest rates in the region. This circumstance has a tremendous effect on credit policy of all banks, which are constrained to pay high interests on the deposits they receive, thus seeking opportunities with very high expected return and low risk. In this way, agricultural activities or small production firms are not focused by the banks when seeking projects in which to invest. A high concentration of credits can be observed in some sectors of the economy that are exposed to exogenous shocks, thus determining the pro-cyclical characteristic of the banking system. A particular unpleasant effect has been attested during the 2008-2009 period, when the trade and construction sectors had much to suffer. The large exposures of many banks in this sectors produced losses that were unforeseeable, decreasing the already low degree of credibility of the population in the banking sector.

MATERIALS AND METHODS

At its roots, discriminant analysis is a classification technique which uses data obtained from a sample of companies to draw a boundary that separates the group of reliable one from the group of insolvent ones. [6]

The discriminant function is developed in order to perform this task. If

$$Z = w_1 \cdot X_1 + w_2 \cdot X_2 + \dots + w_n \cdot X_n$$

and

$$X = X_1, X_2, \dots X_n$$

is a linear combination of the characteristics of the companies, the weights w_i have to be selected to maximize the distance between the mean values of Z for "good" and "bad" companies. [1]

Assuming a common sample variance of the two distinct groups, the method of separation if defined as:

$$M = w^T \cdot \frac{m_g - m_b}{(w^T \cdot S \cdot w)^{\frac{1}{2}}},$$

where m_g represents the sample means of the "good" companies, as m_b represents the sample means of the "bad" ones. S is the common sample variance. Intuitively, M is the ratio between distance between the sample of means of the two groups and the square root of the sample variance of each group.

The value of M is maximized when

$$\frac{m_g - m_b}{(w \cdot S \cdot w^T)^{\frac{1}{2}}} - \frac{\left(w \cdot [(m]_g - m_b)^T\right)(S \cdot w^T)}{(w \cdot S \cdot w^T)^{\frac{3}{2}}} = 0$$

which is equivalent to

$$(m_g - m_b)(w \cdot S \cdot w^T) = (S \cdot w^T)\left(w \cdot [(m]_g - m_b)^T\right)$$

and finally to

$$w^T = \left(S^{-1}(m_g - m_b)^T\right).$$

The model finds the weights that applied in the initial linear combination present the best separator of the "good" and the "bad" companies in terms of maximizing the distance between means. After the calculation of all Z values (discriminant scores), a cut-off point is selected at the average distance between the means of the two groups. [2]

RESULTS AND DISCUSSIONS

The discriminant analysis will use 20 financial ratios that were computed. As the model uses the stepwise method to eliminate the variables with insufficient discriminatory power, we can afford to input as many variables as possible. [3]

Table 1 depicts the variables (in all cases the transformed version of the variables was performed using Wilk's Lambda, the ratio of the unexplained variance on total variance.

At each step of the iteration the variable that minimizes the overall Wilk's Lambda of the model.

Table 2 presents the evolution of these values during the addition of new indicators into the model.

Table 1. Stepwise Statistics

Variables Entered/Removed[a,b,c,d]

Step	Entered	Wilks' Lambda							
						Exact F			
		Statistic	df1	df2	df3	Statistic	df1	df2	Sig.
1	Receivables_Period3	.918	1	1	769.000	68.841	1	769.000	.000
2	ROS3	.875	2	1	769.000	55.055	2	768.000	.000
3	Inventories_Period3	.864	3	1	769.000	40.241	3	767.000	.000
4	Commercial_WC_Period3	.858	4	1	769.000	31.642	4	766.000	.000
5	CashSTAssets3	.853	5	1	769.000	26.447	5	765.000	.000

At each step, the variable that minimizes the overall Wilks' Lambda is entered.

a. Maximum number of steps is 82.

b. Maximum significance of F to enter is .05.

c. Minimum significance of F to remove is .10.

d. F level, tolerance, or VIN insufficient for further computation.

Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development
Vol. 16, Issue 2, 2016
PRINT ISSN 2284-7995, E-ISSN 2285-3952

Table 2. Evolution of Wilk's Lambda

Wilks' Lambda

Step	Number of Variables	Lambda	df1	df2	df3	Exact F			
						Statistic	df1	df2	Sig.
1	1	.918	1	1	769	68.841	1	769.000	.000
2	2	.875	2	1	769	55.055	2	768.000	.000
3	3	.864	3	1	769	40.241	3	767.000	.000
4	4	.858	4	1	769	31.642	4	766.000	.000
5	5	.853	5	1	769	26.447	5	765.000	.000

The most tangible result of the discriminant analysis is providing canonical coefficients for the variables in the model. These coefficients, presented in Table 3, if multiplied by the respective variables and computing the sum will result in the final discriminant score of each company.

Table 3. Canonical discriminant function coefficients

Canonical Discriminant Function Coefficients

	Function
	1
ROS3	.010
Receivables_Period3	-.004
Inventories_Period3	-.002
Commercial_WC_Period 3	.000
CashSTAssets3	.033
(Constant)	.621

Unstandardized coefficients

The score that is obtained for each firm can be computed using:

Discriminant Score= 0.621+0.10 * *Return on Sales*-0.004 * *Receivables Period*-0.002 * *Inventories Period*+0.000 * *Commercial Working Capital Period*+0.33 * *Cash/Short Term Assets*

In order to be able to rank the firms using the obtained scores, Figure 4 is useful, as it compares the means of the scores of "good" and "bad" subcategories. In this case, a high score for a firm means lower probability of default.

Table 4. Comparison of the means

Functions at Group Centroids

Risk Category Transformed	Function
	1
Performing	.129
Default	-1.335

Unstandardized canonical discriminant functions evaluated at group means

As Table 5 suggests, a firm that is positioned in the first rating class will have 32.6% probability of default.

This study has demonstrated that discriminant analysis model is suitable to be implemented on Moldovan data and can indeed be used in real-life decision making processes of the risk departments of banks. The implementation of this model as an alternative to the already used expert system would provide a great added value to the final decisions of the risk management divisions. As demonstrated, the model is able to replicate the ratings assigned by the bank's expert and in this sense the most important features that would improve with the implementation this statistical based model would be in terms of measurability and verifiability. Also, the final decisions will tend to become more objective and homogenous. All these elements will greatly impact the lending policy of the bank and would prove a valuable asset in terms of "know-how" in comparison to the competition.

Table 5. Rating of discriminant analysis

Risk Category Transformed * Rating_Discriminant3 Crosstabulation

% within Rating_Discriminant3

		Rating_Discriminant3									Total
		1	2	3	4	5	6	7	8	9	
Risk Category Transformed	Performing	67.4%	85.9%	89.5%	90.7%	94.1%	96.5%	98.8%	98.8%	98.8%	91.2%
	Default	32.6%	14.1%	10.5%	9.3%	5.9%	3.5%	1.2%	1.2%	1.2%	8.8%
Total		100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

CONCLUSIONS

In order to present the main conclusions of this study, the discriminant score computed by the discriminant analysis model has to be transformed into probabilities of default. For this, the whole range of the discriminant score variable was divided into nine equal intervals. These intervals can be interpreted as rating classes and the percentage of defaulted firms from each class represents the estimated PD.

ACKNOWLEDGEMENTS

This research work was carried out with the support of The Academy of Sciences of Moldova and also was financed from Project partnership 15.817.05.31A "Sustainable development of rural areas of the Republic of Moldova in the context of integration within European Union" for the years 2015-2018.

REFERENCES

[1]Altman, E. I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. Journal of Finance, 23(4): 589-609
[2]Eisenbeis, R. A., 1978, Problems in applying discriminant analysis in credit scoring models. Journal of Banking and Finance, 2(3): 205-219
[3]De Laurentis, G., Maino, R., Molteni, L., 2010, Developing, Validating and using Internal Ratings. United Kingdom: John Wiley & Sons
[4]Lupusor A., 2011, De ce creditele bancare sunt scumpe în Moldova și care sunt soluțiile? Chisinau: Expert-Grup
[5]Opurenco, A., Popa, A., 2010, Analiza constrângerilor. Chisinau: Expert-Grup
[6]Resti, A., Sironi, A., 2007, Risk Management and Shareholders' Value in Banking: From Risk Measurement Models to Capital Allocation Policies, United Kingdom: John Wiley & Sons