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Using Binary Logistic Analysis for Analyzing Bankruptcy

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Abstract: *All companies are the topic to the bankruptcy risks. If we look at the definition, a bankruptcy risk is the business' disability to deal with payable responsibilities. In the recent past, as a consequence of the dynamization of the financial and economic action of different firms, it has become essential to obtain precise information about bankruptcy. In order to summarize this analysis, I use a binary logistic regression because it is important to verify if some financial indicators could have an impact on bankruptcy. Binary logistic regression estimates the probability of an event occurring, in this case the probability of companies to become bankrupt or not. The software that I have used in order to express my findings is IBM SPSS Statistics.*

Keywords*: Bankruptcy, Statistical Analysis, Binary regression, Predictive Analysis.*

I. Introduction

Business bankruptcy is changing into a progressively significant subject in today's environment. The bankruptcy conclusion can be a matter of life and death for the companies, but the influence of the situation is upscaled by the diversity of business connections in which companies typically are implicated. We know that bankruptcy is not a favorable part for any type of business. If a business goes bankrupt, there will be damaged also a lot of other linked industries, not only the company itself.

Any firm that does business with customers will get itself in bankruptcy situation one day through the life of the company. However, owners know the situation and they need to understand how a client's bankruptcy instance will influence and effect the business. Consumer bankruptcy forms have risen drastically in the last 10 years. Companies have to realize the bankruptcy procedure from the perspective of a creditor dealing with a client debtor.

Bankruptcy is a legislative procedure that occurs within the national tribunal system. The aim of this paper is to serve business owners and businesses that are insolvent get remission from impossible-to-pay debts. Bankruptcy is supposed to be a last resource. When a debtor has experienced anything to produce money in order to carry on paying debts and sustain their business or essential living level, and collapsed, the debtor can get to the bankruptcy court for defense from creditors and to kick back their financial condition.

The threat of bankruptcy is concerned by plenty various aspects. For that reason, determining the elements influencing bankruptcy risks, particularly financial performance variables are significant and needed.

II. Review of the scientific literature

Bankruptcy is one of the subjects that have gained considerable awareness from many researchers. Principally, the variables that show the financial performance of companies are crucial and statistically significant in research. Eljelly et al. (2001), Bandyopadhyay (2006) and Ohlson (1980) elaborated models of bankruptcy probability forecasting using logistic models. They used variables like after-tax profit/total assets, net profit/total assets and total debt/total assets.

According to Fulmer et al., (1984) and Altman et al., (2007) studied the correlation between financial index and bankruptcy risks: ROE, ROA and TAT were statistically significant for previsioning the bankruptcy risks.

Business that has higher liabilities and low earnings before interest and taxes (EBIT) are less potentially to continue their businesses. Gu (2002)

III. Research Methodology

The database that I used in my research paper contains financial information about bankruptcy of different companies and was extracted from kaggle.ro. The dataset consists of approximately 6820 records.

In order to establish the determining factors of companies that could be bankrupt or not, I used a binary logistic regression because it is essential to identify what leads a company towards bankruptcy. The dataset was imported in IBM SPSS Statistics and all the variables were coded accordingly.

The independent variables that were in used in my analysis are: return on assets (ROA), Operating Profit Rate, Total Asset Turnover, Return on Equity, and the binary dichotomous dependent variable is Bankrupt.

Return on Assets (ROA) is a financial ratio that illustrate how profitable is an organization/company is in relation to total assets. ROA is a metric which determines if a company uses their assets in an efficient way in order to bring profits. As a formula, ROA is written:

$$\text{Return on Assets} = \frac{Net\ Income}{Total\ Assets} \quad (1)$$

Operating Profit Rate is a performance or a profitability indicator which shows the percentage of profit a business delivers from its operations before subtracting fees and interest charges. As a formula, Operating Profit Rate is written:

$$\text{Operating Profit Rate} = \frac{Operating\ Profit}{Total\ Revenue} \quad (2)$$

Total Asset Turnover (TAT) is a financial ratio that calculates the value of a business' revenue or sales corresponding to the value of its assets.

Return of equity (ROE) is a measure of financial performance and it is calculated by splitting the net income by shareholder's equity. So, the higher the ROE, the more successful a business's management is at producing income and growth.

$$\text{Return on Equity} = \frac{Net\ Income}{Average\ Shareholders\ Equity} \quad (3)$$

The binary variable "Bankrupt" describes if a company is bankrupt or not and was coded with 0 and 1. (1-Yes, 0-No).

IV. Results and discussion

Binary logistic regression estimates the probability of an event occurring, in this case the probability that companies will be bankrupt or not.

Table no. 1. Classification Table

	Observed		**Predicted**		
Step 0	**National Standards**		**Bankrupt**		**Percentage correct**
	Bankrupt		No	Yes	
		No	6599	0	100.0
		Yes	220		.0
	Overall Percentage				96.8

Source: Author own research results

According to the classification table (table no. 1), the model always assumes "no" because there are more companies that will not be bankrupt compared to those who will. (6599 compared with 220). The overall percentage tells us that this approach to prediction is correct with 96.8%, which is a very good approximation.

Table no. 2. Variables in Equation

		B	S.E.	Wald	df	Sig.	Exp (B)
Step 0	**Constant**	-3.401	.069	2462.664	1	.000	.033

Source: Author own research results

The variables in the table of the equation show us the coefficient for the constant (). According to the table, the model with this constant has a statistically significant predictor of the result, because Sig = 0.000. The model has a high accuracy of almost 97%.

Table no. 3. Omnibus Test of Model Coefficients

		Chi-Square	df	Sig.
Step 1	**Step**	385.623	4	.000
	Block	385.623	4	.000
	Model	385.623	4	.000

Source: Author own research results

Omnibus tests of the model coefficients (table no. 3) are used to check if the new model (with explanatory variables included) is an improvement of the basic model. The Chi-Square test was used to see if there was a significant difference between the -2Log likelihood of the base model and the new model. In this case, Chi-Square=385.623 and Sig=000, which means that the null hypothesis is rejected. Because Chi-Square is significant, means that the new model is significantly better. The "Model" row always compares the new model with the original one. The Step and Block rows are important only if the explanatory variables are added to the model in a gradual or hierarchical manner. If the model was built in stages, then these rows would compare -2 Log likelihood of the newest model with the previous version to determine if each new set of explanatory variables determined improvements or not. In this case, I added all four explanatory variables in a single block and therefore there is only one step. This means that the Chi-square values are the same for step, block and model. Sig values are equal to 0.000 which indicates improved model accuracy when the explanatory variables are added.

However, the most important of all the results is the table Variables in the table of equations. This table needs to be studied very closely, as it is at the heart of the answer to our questions about the common association of ROA, Operating Profit Rate, Total Asset Turnover and ROE.

		B	S.E.	Wald	df	Sig.	Exp (B)
Step 1	-17.799	-17.799	1.138	244.589	1	.000	.000
	180.560	180.560	61.878	8.515	1	.004	2.607E+78
	-3.680	-3.680	.993	13.725	1	.000	.025
	-6.633	-6.633	3.719	3.182	1	.074	.001
	-169.540	-169.540	61.899	7.502	1	.006	.000

Table no. 4. Variables in the Equation

Source: Author own research results

This table provides the regression coefficient (B), Wald statistics (to test statistical significance), and (Exp (B)) for each variable category.

The variables "ROA", "Operating Profit Rate" and "Total Asset Turnover" are statistically significant because Sig is less than 0.05. Wald for ROA is equal with 244.589, for Operating Profit Rate is equal with 8.515 and for Total Asset Turnover is 13.725.

The classification chart answers a similar question as the classification table which is "How accurate is our model in classifying individual cases"? However, the rating chart provides some finer details. This graph shows the frequency of categorizations for different predicted probabilities and whether there were "yes" or "no" categorizations. This provides a useful visual guide to how accurate the model is by showing how many times the model would predict a "yes" result based on the predicted calculated probability when in fact the participant's result was "no".

Figure no. 1. Observed Groups and Predicted Probabilities

```
              Observed Groups and Predicted Probabilities

    2000                                                                  +N
+
         INN
I
         INN
I
F                                                                        INN
I
R                                                 1500                   +NN
+
E                                                                        INN
I
Q                                                                        INN
I
U                                                                       INNN
I
E                                                1000                  +NNN
+
N                                                                       INNN
I
C                                                                       INNN
I
Y                                                                      INNNN
I
     500                                                               +NNNN
+
         INNNNN
I
         INNNNNN
I
         INNNNNNNNY
I
Predicted  ---------+---------+---------+---------+---------+---------+----
-----+---------+---------+----------
  Prob:    0        .1        .2        .3        .4        .5        .6
.7        .8        .9         1
  Group:
NNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNYYYYYYYYYYYYYYYYYYYYYYYY
YYYYYYYYYYYYYYYYYYYYYYYYY

          Predicted Probability is of Membership for Yes
          The Cut Value is .50
          Symbols: N - No
                   Y - Yes
          Each Symbol Represents 125 Cases.
```

Source: Author own research results

It is observed according to figure 1 that the model is good for predicting the result for individual cases, because there are a lot of observations towards the left and right ends of the graph. Such a diagram shows that where the event took place (on the 0.4th place - indicated by the letter Y on the graph), the predicted probability was also high and that where the event did not occur (letter N on the graph) the predicted probability was low. The graph shows that there are quite a few cases with the letter Y on the graph, which means that the model predicts a 90% probability that the event will happen.

The regression equation is written:

Log(p/1-p) = -169.540 -17.799 * ROA -+ 180.560 * Operating Profit Rate – 3.680 * Total Asset Turnover – 6.633 * ROE.

V. Conclusion

Business bankruptcy is changing into a progressively significant subject in today's environment. The bankruptcy conclusion can be a matter of life and death for the companies, but the influence of the situation is upscaled by the diversity of business connections in which companies typically are implicated. We know that bankruptcy is not a favorable part for any type of business. If a business goes bankrupt, there will be damaged also a lot of other linked industries, not only the company itself.

In my research I used a binary logistic regression estimates the probability of an event occurring, in this case the probability that companies will be bankrupt or not.

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