## THE USING FACTOR ANALYSIS METHOD IN PREDICTION OF BUSINESS FAILURE

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**Abstract:** After the great financial crisis of 2008 many companies all over the world was facing with bankruptcy or insolvency, because it were not able to face to the all challenges and the unexpected changes in the economy. Literature review and study demonstrated that the prediction of the risk of bankruptcy of firms is imperative. However, the lack of a comprehensive theory of business failure has led to the selection of a variety of financial variables in insolvency prediction. Most researchers started with a large set of variables and then applied different statistical techniques or stepwise procedures in order to reduce the number of predictors. This study highlights the utility of factor analysis in prediction of business failure.

## JEL classification: C38, G01

## Key words: business; company; Factor Analysis; failure; Principal Components Analysis

### 1. INTRODUCTION

Nowadays, there is also an increasing concern with the cross-border contagion triggered by the recent financial crisis and its domino effect in the global market. Not surprisingly, bankruptcy prediction has been a topic of active research for business and corporate organizations since past decades. Different methodologies in bankruptcy literature were created for modeling prediction of trading disability.

Although the interest in financial distress prediction has long been confined to academics, it ended to capture the interest of more and more professionals, including practitioners and regulators. Corporate bankruptcy not only incurs serious financial loss to its creditors but also has a high cost to the society and the country's economy.

A study made by Coface Romania based on the data provided by the National Trade Register Office, showed that 25.842 companies were forced into bankruptcy by the end of the year 2012. The year 2013 brought a big number of insolvencies in the Central and Eastern Europe and Romania registered a record number of insolvencies in the whole CEE region (Table no.1).

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Country	Total number of active companies*	Total Insolvencies	Insolvency rate
Bulgaria	400.000	834	0,21%
Croatia	150.000	3.186	2,02%
Czech Republic	1.471.000	10.653	0,72%
Estonia	139.000	514	0,37%
Hungary	595.000	13.489	2,27%
Latvia	229.600	818	0,36%
Lithuania	Lithuania 90.800		1,67%
Poland	1.795.000	883	0,05%
Romania	421.900	27.145	6,44%
Serbia	Serbia 111.700		7,61%
Slovakia	Slovakia 540.000		0,09%
Slovenia 185.500		994	0,54%

Table no.1 Insolvencies of CEE region in 2013

\*(expert organisations' estimation, average)

Source: www.coface.ro/Stiri-Publicatii/Publicatii/Insolvente-Coface-CEE-2013

#### 2. OBJECTIVES

The main objective of this study is the importance to identify issues that cause business failure and understand the causes behind the collapse of a company. The company managers and financial analysts are concerned more than ever, to identify issues that cause business failure. The economic reality of a company can be described through a set of variables and the problem appears when the number of variables is significant. Most of business failure prediction models are based on financial ratios as predictors.

#### **3. METHODOLOGY**

The selection of the predictors that carry out the most significant predictive accuracy in a classification model has been intensively addressed in numerous studies. Most commonly, the financial ratios selected as predictors in the bankruptcy prediction models should adequately cover three fields: profitability, management efficiency, and solvency. Literature review and study performed on the situation of Romanian firms in an unstable period, affected by global financial crisis triggered during 2007 and in Romania since 2008, demonstrated that the prediction of the risk of bankruptcy of firms is imperative. A comprehensive theory of business failure has led to the selection of a variety of financial variables in insolvency prediction and most researchers started with a large set of variables and then applied factor analysis in order to reduce the number of predictors. This study emphasizes an factor analysis technique, called Principal Components Analysis

(PCA). PCA represents a powerful tool for analyzing a large set of data. It is a modality of identifying patterns in data of large dimension where graphical representation of them is not possible, compressing the data by reducing the number of dimensions, without loss of information (Smith, 2002). By reducing the number of dimensions we kept only those important characteristics of the data set which contribute most to its variance obtained by linear combinations of the initial variables. For this type of analysis, we chose SPSS software, which is an accessible statistical software. The results indicate the utility of eliminating variables from a large set of data with a minimum influence in order for manager to take a better decision to avoid collapse of the company.

## 4. ANALYSES

For this study we use a sample of 100 Romanian companies listed on Bucharest Stock Exchange (BSE) in an unstable period year 2012, where 85 are distressed company and 15 undistressed company. Financial results for the selected companies were collected from the 2010 year-end Balance Sheet and Profit and Loss Account, and were taken from the official website of BSE, www.bvb.ro. We have presented in the below figure the evolution of the companies admitted to trading according to annual reports issued by BSE since 1995 (the year of the re-establishment BSE) until 2013 when it was issued and posted on the website in the last report www.bvb.ro so far.

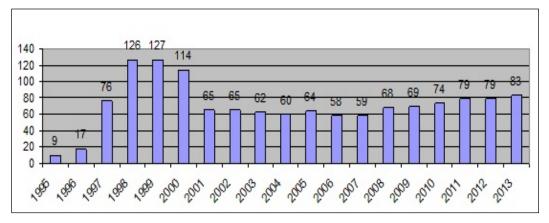


Figure no.1 Number of companies admitted to trading in the period 1995-2013

For this study there were calculate the following eight financial ratios: Current ratio (CR); Quick ratio (QR); Return on Assets (ROA); Return on Equity (ROE); Return on Capital Employed (ROCE); Net Profit Margin (ROR); Turnover Rate of Fixed Assets (FATR); Receivables Turnover Ratio (RTR). After completing the data base structure (see Figure no.1), using PCA we obtained the following results: Descriptive Statistics; Correlation Matrix; KMO and Bartlett's Test; Total Variance Explained; Scree Plot; Rotated Component Matrix. Descriptive Statistics table supplies the number of analyzed cases for each variable, the average across each dimension and the standard deviation (see Figure no.2).

Descriptive Statistics				
	N	Mean	Std. Deviation	
CR	100	3,3182	5,77083	
QR	100	2,3636	5,19890	
ROA	100	2,3417	3,70832	
ROE	100	3,4127	5,28922	
ROCE	100	5,3168	8, <mark>1517</mark> 0	
ROR	100	4,5067	10,63453	
FATR	100	1,2997	1,18188	
RTR	100	5,9972	7,71747	
Valid N (listwise)	100			

Figure no.2 Descriptive Statistics

The Correlation Matrix is the starting point for factor analysis techniques the correlation and show the intercorrelations between the financial indicators (see Figure no. 3). Value 0 for correlation coefficient indicates the absence of statistical correlations between variables.

Correlation Matrix									
		CR	QR	ROA	ROE	ROCE	ROR	FATR	RTR
	CR	1,000	,969	,226	,124	-,071	, <mark>550</mark>	-,078	-,137
Correlation	QR	,969	1,000	,249	,150	-,060	,623	-,101	-,155
	ROA	,226	,249	1,000	,934	,537	, <mark>562</mark>	,317	-,042
	ROE	,124	,150	<mark>,</mark> 934	1,000	, <mark>633</mark>	,451	,380	-,034
	ROCE	-,071	-,060	, <mark>537</mark>	,633	1,000	,131	,578	,017
	ROR	, <mark>550</mark>	,623	, <mark>562</mark>	,451	,131	1,000	-,080	-,112
	FATR	-,078	-,101	,317	,380	,578	-,080	1,000	,053
	RTR	-,137	-,155	-,042	-,034	,017	-,112	,053	1,000

Figure no.3 Correlation Matrix

KMO (Kaiser-Meyer-Olkin) index is 0.640 and this statistic test indicates the degree of correlations of the variables. Bartlett's test of sphericity is a test statistic used to examine if each variable correlates perfectly with itself, but has no correlation with the other variables. So, we know that this value let the application of a factor reduction procedure (see Figure no.4).

KMO	and	Bartlett's T	est
MINU	anu	Dalitetta i	COL

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		, <mark>6</mark> 40
	Approx Chi-Square	670,784
Bartlett's Test of Sphericity	df	28
	Sig.	, <mark>000</mark> ,

Figure no.4 KMO and Bartlett's Test

The Total Variance Explained table offers the factor analysis informations and present the eigenvalues in order from highest to lowest and proportions of variance for the eight components (see Figure no.5). Only two components respect the selection criterion (the cumulated percent in variation should be higher than 50% and the variance should be higher than 1, for each retained factor.

	Total Variance Explained								
Compo		Initial Eigenvalu	es	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
nent	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,170	39,623	39,623	3,170	39,623	39,623	2,794	34,928	34,928
2	2,281	28,513	68,136	2,281	28,513	68,136	2,657	33,208	68,136
3	,962	12,024	80,160				13636		
4	,833	10,413	90,573						
5	,351	4,387	<mark>94,960</mark>						
6	,325	4,059	99,019						
7	,053	,664	99,683						
8	,025	,317	100,000					_	

Extraction Method: Principal Component Analysis.

Figure no.5 Total Variance Explained

The Extraction Sums of Squared Loadings columns, contained eigenvalue, explained variance and the cumulative variance, before rotation. The explained variance by each factor is 39.623% for the first factor and 28.513% for the second factor and both factors explain 68.136% from variance. The Rotation Sums of Squared Loadings columns present a new distribution of explanatory variance with the same variance 68.136%, after rotations, such as: 34.928% for the first factor and 33.208% for the second factor. So, the first factor decreases in benefit of the second factor. The Scree Plot presents graphically the eigenvalues for all the principal components obtained and the number of factors is chosen where the plot levels begin a linear decline (see Figure no.6).

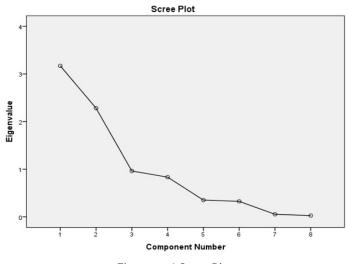


Figure no.6 Scree Plot

The Rotated Component Matrix table, contains the data obtained after application of factors rotation with the most used method of factors rotation named varimax, which is a transformation of the components in order to minimize the complexity of them. The results of the analyzed variables after rotation indicate that the first principal component has a good correlation with variables ROE, ROA, ROCE, while the second component has a good correlation with variables OR and CR (see Figure no.7).

Rotated Component Matrix <sup>a</sup>						
	Component					
	1	2				
ROE	,904	,224				
ROA	,850	,350				
ROCE	,843	-,125				
FATR	,662	-,247				
QR	-,009	,948				
CR	-,026	,920				
ROR	,323	,775				
RTR	,034	-,249				

Rotated Component Matrix <sup>a</sup>	8
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Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. a. Rotation converged in 3 iterations.

Figure no.7 Rotated Component Matrix

## 5. CONCLUSIONS

In our case study, we applied PCA on eight variables describing financial ratios and we obtained only two factors that concentrate more than 68% of the information provided by the eight original variables

This article highlights application utility of PCA method in the business domain, identify those factors which influence the economic development of a company. Using this type of factor analysis method, we can obtain useful information about this factors giving to the managers the possibility to pursue evolution of their company's financial condition.

In our case study, we presented how useful is PCA method in the business domain to reduce dimension of data related to the problems of companies distressed, we applied PCA on eight variables describing financial indicators and we obtained only two factors that concentrate more than 68% of the information provided by the eight original variables.

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