ORIGINAL PAPER

EMPIRICAL MODEL OF ASSESSING FIRM FINANCIAL PERFORMANCE - AN ECONOMETRIC PERSPECTIVE

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Abstract. *Present paper consists of a qualitative research on firm financial indicators. Firms included in our sample are Romanian firms within tourism sector. By using information gathered from financial statements, we performed a principal components analysis for a number of eight financial indicators. These financial indicators were: turnover growth rate, liquidity, solvency, return on assets, turnover gross margin, leverage, return on equity and debt. The aim was to select most relevant indicators which best reflect financial performance. Three aggregate financial indicators were extracted, which were further used for calculation of firm financial performance.*

Keywords: *econometric model, scores, principal component analysis, aggregate indicators.*

1. INTRODUCTION

Firm financial performance represents a measure of overall firm activity. It usually refers to financial indicators that result from analysis of firm financial statements. There is no unanimous opinion regarding type or number of indicators that should be observed in order to evaluate firm financial performance. Hence, previous literature refers to profit margin, earnings per share, return on equity, return on assets, return on capital employed as possible measurements of financial performance [1-4]. Moreover, return on investment and net income after tax is also used in this latter sense [5]. Other indicators include liquidity, debt ratio [6] or wage to turnover ratio, wage to expenditure ratio or operational expenditure to turnover ratio [7].

Principal component analysis aims at finding a linear combination of the original variables - a main component, which expresses maximum variation of the original variables. The following represents an exploratory study on a sample of 185 Romanian tourism firms. Research was conducted in order to extract several conclusions on firm financial performance measured throughout financial indicators. Within this research, method used was principal component analysis. Database was formed of 8 categories of financial indicators, named variables hereinafter, respectively return on assets - ROA, return on equity - ROE, return on sales - ROS, Solvency - SOLV, liquidity - LIQ, debt ratio - DEBT, Leverage - LEV, and turnover gross margin - TGM. Observed period was that of four years (2010 - 2014).

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Information was collected from firms' financial statements. Research was performed by using principal component extraction procedure in SPSS. The aim was to reduce data complexity and to evidence latent variables (components) that are behind measured variables - financial indicators.

Objectives of present analysis aimed at:

- ✓ restricting the number of financial indicators used in assessing firm financial performance and reflecting it at the same extent;
- ✓ discover the most relevant indicators for assessing firm financial performance.

2. PRELIMINARY ASPECTS

In order to achieve factor analysis, sample size must be large. Statistical surveys referring to sample size [8, 9] established the need for an absolute minimum number of cases of 100. Moreover, it was demonstrated [8] that in case of use of more than 20 variables, sample must consist of minimum 100 valid cases. Other studies [10, 11] revealed the need for reporting at least 5 valid cases for one variable. However, some authors [12] showed that ratio of subjects to variables should be 20 to 1. Based on these considerations, we consider that sample size is large enough for principal component analysis, whereas the 185 firms included in our sample stand on both minimum absolute number of cases and minimum ratio of valid cases:

$$\mathrm{RVC} = \frac{185}{8} = 23.125$$

where: RVC = ratio of valid cases, as absolute number of cases related to absolute number of variables.

Principal component analysis is based on the following assumptions:

- ✓ variables are normally distributed;
- ✓ variables are linear (no multicollinearity or singularity) and homoscedastic;
- ✓ correlations between variables are larger than 0.3 - factorability;
- ✓ sample is homogeneous.

These assumptions were tested in order to ensure sample validity. Normality tests were performed, separately for each variable, to test whether distributions are similar to normal distributions. For this purpose, statistical method used included both numerical and graphical representation. To characterize data series, we analyzed:

- ✓ descriptive statistics: mean, median, module, standard deviation, Skewness, Kurtosis, minimum and maximum data series;
- ✓ histograms.

Within performed analysis, we took into consideration following practices related to normality tests:

1) A series of data is normally distributed when kurtosis coefficient is 3. In this case, the distribution is considered mesokurtic. In other cases, distribution is either platykurtic - kurtosis coefficient is below 3, or leptokurtic - kurtosis coefficient exceeds 3 thresholds.

2) Normal distribution of data series is given by the existence of symmetry that has a skewness coefficient equal to 0. However, statistical practice has shown that it is unlikely to obtain a skewness coefficient equal to 0. Therefore, we considered that skewness coefficients between -1/2 and +1/2 reflect approximately symmetric distributions [13].

3) Histograms reflect summary descriptive statistical analysis, plotting distributions of analyzed variable. In this case, we considered useful graphical representations of distribution of values in comparison with normal distribution - Gauss.

Given our sample, tests enabled us to conclude that distribution of values registered by all eight variables is normal distributions, so all variables fit to principal component analysis.

3. RUNNING PRINCIPAL COMPONENT ANALYSIS

Due to method used within present research, we started from the assumption that variables are moderately correlated using Pearson formula (r > 0.3) [14].

$$r = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{n(\sum x^2) - (\sum x)^2}\sqrt{n(\sum y^2) - (\sum y)^2}}$$

Demonstrating the contrary, leads us to the conclusion that principal component analysis is not suitable for our sample. Hence, we started by analyzing adequacy of variables to proposed method. In order to determine existence of correlations between variables, we analyzed coefficients correlation matrix, reflecting Pearson r correlation coefficient (parametric coefficient) - Table 1. Test of significance is two-tailed. In case some variables register insignificant correlation coefficient (below 0.01), these variables need to be excluded.

Table 1. Correlation matrix.

		ROA	LIQ	ROS	SOLV	ROE	DEBT	TGM	LEV
Correlations	ROA	1.000	.384	.330	.305	.382	-.504	.410	.432
	LIQ	.384	1.000	-.418	.505	-.432	-.486	.387	.374
	ROS	.330	-.418	1.000	-.301	.508	.304	.553	-.461
	SOLV	.305	.505	-.301	1.000	-.362	-.400	.441	-.366
	ROE	.382	-.432	.508	-.362	1.000	.324	.596	.631
	DEBT	-.504	-.486	.304	-.400	.324	1.000	-.382	.529
	TGM	.410	.387	.553	.441	.596	-.382	1.000	-.392
	LEV	.432	.374	-.461	-366.	.631	.529	-.392	1.000
Sig. (2-tailed)	ROA		.084	.135	.163	.030	.005	.078	.116
	LIQ	.084		.019	.005	.016	.007	.085	.093
	ROS	.135	.019		.168	.005	.165	.121	.039
	SOLV	.163	.005	.168		.038	.024	.042	.137
	ROE	.030	.016	.005	.038		.141	.056	.098
	DEBT	.005	.007	.165	.024	.141		.061	.019
	TGM	.078	.085	.121	.042	.056	. 061		.103
	LEV	.116	.093	.039	.137	.098	.019	.103	

Analyzing correlation coefficients matrix - Table 1 - we noticed that there are moderate and strong correlations between variables. Moderate correlations are those indicated by Pearson r correlation coefficients in the range [0.3; 0.5], and strong correlations are those reflected by Pearson r correlation coefficients in the range [0.5; 0.7]. Moreover, all correlations are statistically significant ($p < .05$ for 2-tailed test). Consequently, all considered variables are suitable for principal component analysis. None of these variables were excluded.

At the same time, by studying correlation matrix, multicolinearity analysis was possible. Thus, multicolinearity hypothesis was rejected because there were no cases of highly correlated variables (no correlations between variables were larger than 0.7). Rejection of multicollinearity assumption is confirmed by recorded value of correlation matrix determinant. This value (0.114) is significantly greater than 0, so that existence of multicolinearity is rejected. Using the same matrix, we concluded that singularity hypothesis is rejected (i.e. perfectly correlated variables). This hypothesis is rejected because there were no correlation coefficients with values equal to 1.

To verify that principal component analysis is an appropriate method for our sample, we also performed two types of statistical tests: KMO sampling adequacy test and Bartlett's test (test of sphericity). For this purpose, covariance and anti-image correlation matrices were analyzed.

Kaiser-Meyer-Olkin test (KMO) highlights sample adequacy for principal component analysis. KMO test, calculated as an aggregate value, recorded value of 0.703 (see Table 3). This value indicates that sample is adequate for component extraction. Since KMO test is calculated both for testing whether all variables fit within the model, and separately, for each variable, we analyzed in this latter sense the anti-image correlation matrix - Table 2. Anti-image correlation matrix reports, on diagonal, Kaiser-Meyer-Olkin coefficients of sampling adequacy. They highlight variable correlations to partial coefficients, and, as Table 2 shows, these values are significantly higher than 0.500 for each variable. Therefore, none of the variables were removed from our analysis, as only values lower than 0.500 highlight that such variables should be excluded from principal component analysis.

Anti-image covariance matrix - Table 2 - also tests sampling adequacy to principal component analysis. In this respect, values recorded on diagonal of anti-image covariance matrix were compared to 0.600 threshold. We concluded that our sample is adequate principal components analysis, as all values exceeded the above threshold, and only contrary would lead to sample inadequacy.

Table 2. Anti-image covariance and correlation matrices

		LIQ	ROS	SOLV	ROE	DEBT	TGM	LEV	ROA
Anti-image covariance	LIQ	.861	-.080	-.179	-.118	-.074	-.113	.026	.034
	ROS	-.080	.856	.010	.002	-.035	-.192	-.052	-.127
	SOLV	-.179	.010	.831	.081	.168	-.105	-.082	-.142
	ROE	-.118	.002	.081	.824	-.014	-.115	.100	-.166
	DEBT	-.074	-.035	.168	-.014	.872	-.023	-.145	.130
	TGM	-.113	-.192	-.105	-.115	-.023	.706	.164	-.106
	LEV	.026	-.052	-.082	.100	-.145	.164	.807	.135
	ROA	.034	-.127	-.142	-.166	.130	-.106	.135	.716
Anti-image correlation	LIQ	.684[a]	-.094	-.212	-.140	-.086	-.145	.031	.043
	ROS	-.094	.703[a]	.012	.003	-.040	-.246	-.062	-.163
	SOLV	-.212	.012	.605[a]	.098	.197	-.137	-.101	-.184
	ROE	-.140	.003	.098	.733[a]	-.017	-.151	.122	-.217
	DEBT	-.086	-.040	.197	-.017	.622[a]	-.030	-.173	.165
	TGM	-.145	-.246	-.137	-.151	-.030	.742[a]	.217	-.149
	LEV	.031	-.062	-.101	.122	-.173	.217	.704[a]	.177
	ROA	.043	-.163	-.184	-.217	.165	-.149	.177	.737[a]

**a = values of sampling adequacy.*

After applying Bartlett's test of sphericity, we obtained an approximate value of Chi-square (χ^2) of 69.526, large enough to reject hypothesis that variables are not correlated. Difference between the identity matrix and correlation matrix is statistically significant, so there is a chance close to 0 (sig. = 0.000) to obtain this value of Chi-square if variables were not correlated.

Table 3. Values of KMO and Bartlett's tests.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.703
Bartlett's Test of Sphericity	Approx. Chi-Square(χ^2)	69.526
	df	28
	Sig.	.000

Hence, it is relevant for principal component analysis to be conducted, as all tests on our sample show that results of such analysis are statiscally significant and several conclusions could be extracted regarding firm financial performance [15]. These are presented within next sections of the paper.

4. RUNNING PRINCIPAL COMPONENT ANALYSIS

To determine the number of principal components extracted from the factor analysis, we used several criteria in order to obtain valid results. The first criteria we analyzed were Kaiser criteria (Kaiser rule), according to which principal component extraction [16-19] will retain only those components which record initial eigenvalues greater than 1. As Table 4 shows, first component has an initial eigenvalue of 1.645, second component has an initial eigenvalue of 1.467, and third component has an initial eigenvalue of 1.365. Starting with fourth component, initial eigenvalues are significantly lower than 1 threshold. Hence, we concluded that extraction of more than 3 components is not recommended, given Kaiser criteria. Thus, only the first three components satisfy this rule, and, accordingly, number of relevant components to be extracted is limited to 3.

Another criteria used for determining number of components to be considered for analysis is cumulative percentage criteria. Under this criteria, extracted components should explain at least 70% of the total variation in initial variables (Table 4). Third column of Table 4 shows percentage of variation explained by each of the extracted components. Hence, by extracting a single component a major percent of the initial variation is explained, respectively 31.934%. Extraction of a second component explains further 21.642% of the initial variation, hence, by extracting two components 53.576% of the variance in the original variables is explained. Continuing the extraction procedure, a third component explains another 19.566% of the initial variation, reaching to a total of 70.066% of variance explained. Finally, the process leads to maximum percentage of variance explained, that of 100%. We limited extraction to three main components, as only these three components recorded eigenvalues over 1 threshold and they explain together a high percent of the initial variance, above the recommended threshold of 70%.

Table 4. Variance explained by initial, extracted and rotated components.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	2.395	31.934	31.934	1.645	26.563	26.563	1.431	24.893	24.893
2	1.371	21.642	53.576	1.467	23.335	49.898	1.396	22.454	47.347
3	1.185	19.566	73.142	1.365	20.168	70.066	1.383	19.719	70.066
4	.882	11.030	78.172						
5	.732	9.147	81.667						
6	.661	8.268	89.365						
7	.568	7.104	95.274						
8	.505	6.310	100.000						

In order to determine the optimal number of principal components that can be extracted Cattell criteria [20, 21] can also be used - scree plot. We used this criteria to validate conclusions derived from the above discussed criteria, namely to ensure that number of components to be extracted for the purpose of our research is 3. Scree plot confirmed that extraction of only 3 components is recommended, as plotted eigenvalues of first three components are on the steep slope of the curve.

Following extracted matrix component, we noted that some variables are highly positively correlated with certain components, while others are highly negatively correlated with other components. Therefore, for a relevant analysis and a correct interpretation, we proceeded by investigating component matrix obtained by rotation of axis. We used Varimax rotation with Kaiser normalization, which does not allow extracted components to be intercorrelated.

Table 5. Extraction of components using Varimax rotation

	Component		
	1	2	3
LIQ	.007	.520	.065
ROS	.187	**.616**	-.036
SOLV	-.150	.433	**.742**
ROE	**.668**	.248	-.152
DEBT	-.280	.249	**-.757**
TGM	.492	**.758**	.120
LEV	-.554	.056	-.143
ROA	**.781**	.243	.389

After a Varimax rotation axis type (see Table 5), results show that there are strong correlation coefficients between each component and some variables, but lower correlation coefficients for remaining variables, so that these components are not intercorrelated. Given these new findings, it is further possible to interpret components in terms of financial indicators. Discussion of results is presented in detail in section 4 of the paper.

5. RESULTS AND DISCUSSION

Principal component analysis lead to extraction of a total of three components, interpreted as follows:

- First component is interpreted in terms of financial indicators return on equity and return on assets - as it is strongly, positively correlated to these indicators, respectively 0.668 and 0.781 correlation coefficients. Therefore, we considered that first component is a synthetic indicator of firm profitability.
- Second component is interpreted in terms of return on sales and turnover gross margin - as it is strongly, positively correlated to these two indicators, respectively 0.720 and 0.616 correlation coefficients. Consequently, second component is a synthetic indicator of firm activity.
- Third component is interpreted through financial indicator of solvency - to which it is strongly, positively correlated (0.742), and in terms of leverage indicator - to which it is strongly, negatively correlated (-0.757). Accordingly, we considered that third component reflects firm financial structure.

Results of principal component analysis can be summarized as shown in Figure 1. As seen, the three components extracted were named according to their significance throughout the above interpretation:

- Component 1 was called aggregate indicator of firm profitability (AIFR);
- Component 2 was called aggregate indicator of firm activity (AIFA);
- Component 3 was called aggregate indicator of firm financial structure (AIFFS).

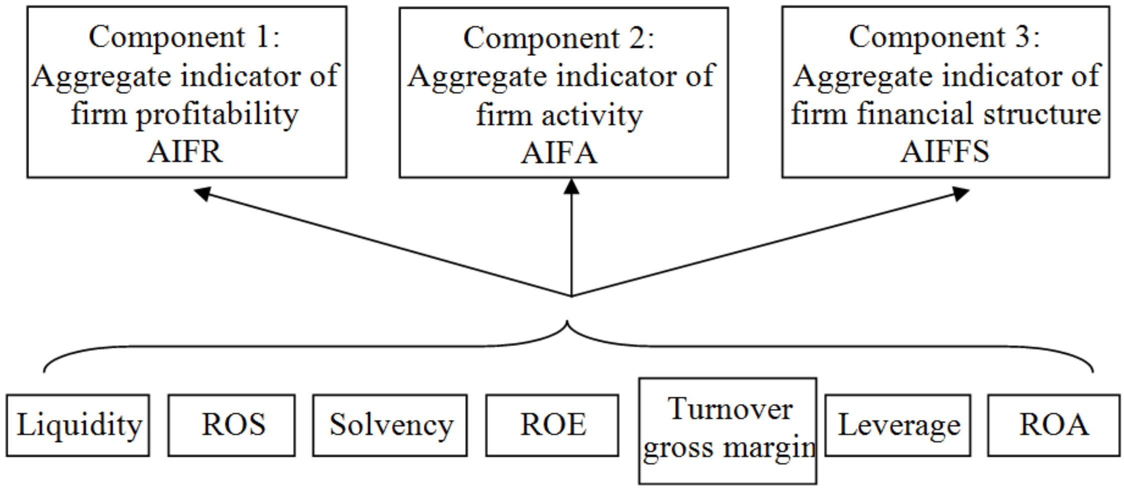

Figure 1. Extracted components.

In order to calculate average score of each variable - financial indicator - that is included within the three extracted components, we used a credit scoring model, similar to the ones used by banks in financial assessment of firms. Thus, it was possible to convert values of financial indicators in scores from 1 to 5 (where 1 represented lowest score and 5 represented highest score) based on the model described in Table 6.

Given matrix of extracted components (see Table 5 in section 3), each of the three components is expressed as a linear combination of financial indicators, as follows:

AIFR = .007*LIQ + .187*ROS - .150*SOLV + .668*ROE - .250*DEBT +.482*TGM - .554*LEV + .781*ROA.

AIFA =.520*LIQ +.416*ROS + .433*SOLV +.248*ROE +.249*DEBT +.758*TGM + .056*LEV + .243*ROA.

AIFFS =.065* LIQ -.036*ROS +.742*SOLV - .152*ROE -.757*DEBT + .120*TGM - .143*LEV + .389*ROA.

Table 6. Credit scoring model used.

Indicator / Points	1	2	3	4	5
TGM	TGM < 0	10 ≥ TGM > 0	20 ≥ TGM > 10	30 ≥ TGM> 20	30 ≥ TGM
SOLV (S)	S < 100	105 > S ≥ 100	120 > S ≥ 105	150 > S≥ 120	S ≥ 150
LIQ	LIQ < 60	80 > LIQ ≥ 60	90 > LIQ ≥ 80	110 > LIQ ≥ 90	LIQ ≥ 110
DEBT (D)	D >350	350 > D ≥ 300	300 > D ≥ 250	250 > D ≥ 200	200 > D
ROA	ROA < 0	5 > ROA ≥ 0	8 > ROA ≥ 5	10 > ROA ≥ 8	ROA > 10
ROE	ROE < 0	5 > ROE ≥ 0	8 > ROE ≥ 5	10 > ROE ≥ 8	ROE > 10
LEV	LEV < 0	1,5 ≥ LEV > 0	2 ≥ LEV > 1,5	3 ≥ LEV > 2	LEV > 3
ROS	ROS < 0	10 ≥ ROS > 0	20 ≥ ROS > 10	30 ≥ ROS > 20	ROS > 30

Consequently, using the above linear combinations and obtained scores of each variable, we were able to calculate average scores for each of the three extracted aggregate indicators. As Table 7 shows, highest average score was that of aggregate indicator of firm profitability - 3.781 points, followed by the aggregate indicator of firm activity, respectively 3.234 points, and lowest score was that of aggregate indicator of firm financial structure - 2.825 points. This result recalls the fact that extending firm activity and registering positive results are possible only in case of using borrowed financial resources, as firms' resources are, in most cases, insufficient to achieve such objectives. Average financial performance of our sample is significantly higher than half of the possible score, respectively 3.280 points, out of 5 possible.

Table 7. Average scores of extracted components.

Indicator	**Average score**
Aggregate indicator of firm profitability	3.781
Aggregate indicator of firm activity	3.234
Aggregate indicator of firm financial structure	2.825
Financial performance	**3.280**

Based on these results we conclude that, on average, firms within investigated sample have acceptable financial results, with positive impact on their financial performance. However, results indicate that financial performance of Romanian tourism firms is far from excellent, so several improvements are needed in order to increase average score, to bring it closer to the maximum one.

5. CONCLUSIONS

Principal component analysis made possible to reduce number of financial indicators that reflect firm financial performance. Consequently, it provided necessary framework to evaluate actual financial performance of Romanian tourism firms. In this latter sense, results showed that financial performance of Romanian tourism firms is medium, and several measures should be taken into account. Firstly, in order to improve aggregate indicator of firm profitability, firms should consider improving asset utilization and efficiency of capital employed. As assets and capital are main elements that ensure firm development, increasing their efficiency leads to significant improvements in ROA and ROE, main latent factors of firm profitability.

Secondly, improving aggregate indicator of firm activity refers to improving firm turnover. For this purpose, Romanian tourism firms should consider analyzing customer satisfaction, as customer complaints could offer useful information regarding future services developments. Nonetheless, conducting customer loyalty campaigns could also improve firm turnover. Such evolution of firm turnover will positively impact ROS and TGM, latent factors of firm activity.

Thirdly, aggregate indicator of firm financial structure could be enhanced by detailed analysis of firm possibilities to sustain capital costs. Many firms within this sector tend to expand their activity yearly, so costs of borrowed resources increase proportionally. Firms should evaluate risks in contracting additional capital (debt), as it could lead to solvency difficulties and deterioration of leverage, main two latent factors of firm financial structure.

Finally, we consider that future research could aim to extension of present analysis to other sectors, or even nationally. This way, results could provide a complete picture of Romanian economy and, of course, could allow conclusions to be drawn regarding other possibilities for increasing firm financial performance.

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