6. INCREASING FINANCIAL AUDIT QUALITY USING A NEW MODEL TO ESTIMATE FINANCIAL PERFORMANCE

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Abstract

Establishing the performance of the companies is one of the facts that influence the shareholders' attitude. As a fact, a framing category could further affect the evolution of the company and could influence the audit opinion. As creditworthiness should be given to audit, a performance function score was computed for the companies listed on the Bucharest Stock Exchange. Four performance categories were established, while the validation was done using not only companies from RASDAQ, which is Romania's secondary market, but also their next stock price evolution. The model developed is trustworthy, as more than 70% of the companies were properly framed.

Keywords: Zscores, Bucharest Stock Exchange, going concern, RASDAQ, financial analysis

JEL Classification: G17, M40, M42

1. Introduction

Ever since the pattern recognition technique has been implemented, it has been used in several areas starting with statistical applications, followed by artificial intelligence, engineering, medical diagnosis, credit scoring, selection of projects or the importance of computer progress.

Considering the above mentioned, when the pattern recognition technique is analyzed, both the unsupervised method and the supervised one are considered. Fukuhama (1990) points out that the problem regarding the supervised pattern recognition deals with the estimation of the density function of explanatory variables in

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a space with n dimensions and its distribution in subspaces, categories and classes. In fact, the supervised pattern recognition technique is used to reveal the performance obtained by a company when its financial and economic performance is measured, even though models that use locally linear embedding and support vector machines have been recently applied to predict bankruptcy (Lin *et al*., 2013). Moreover, the discriminant analysis can be used in the evaluation stage of the company's goodwill which can influence its financial performance (Ioniță, Stoica, 2009).

The main reason for selecting this technique is based on the fact that there is a fundamental need for estimating the economic and financial performance of a company and to predict its evolution. Consequently, when the practical issue is analyzed, financial problems can be detected as they could also influence the report and the opinion of the audit team (Haron *et al*., 2009). The importance of the audit report is first pointed out by Altman and McGough (1974), who reveal that approximately half of the bankrupt companies that they analyzed had a proper "going concern" opinion. The authors compared bankruptcy prediction models with auditors' opinion and concluded that bankruptcy prediction models have higher accuracy than the auditors' opinion. On the other hand, the audit opinion can affect the evolution of stock prices as the investors would manifest a reserved attitude towards investing in a company with improper audit opinion (Hoti *et al*., 2012). Other researches such as Anvarkhatibi (2012) or Farzinfar (2013) provide mixed evidence on the relationship between audit report and the evolution of stock price. Studies like Koh and Killough (1990), Hopwood *et al*. (1994), Lenard *et al*. (2001), Gaeremynck and Willekens (2003), Carey and Simnett (2006), Martens *et al*. (2008) point out the importance of data mining techniques in influencing the auditor's going concern opinion. For example, Mutchler (1985) applied discriminant analysis in order to test the going concern of financial auditors and concluded that the results obtained by using it have higher accuracy. Similar analysis was conducted by Gaganis, Sochos, Zopounidis (2010), who developed a model by which better classification accuracy is obtained when variables like auditor opinion are taken into consideration. Other studies involving both the discriminant analysis and the auditor's opinion are conducted by Moradi *et al*. (2013) or Carlo et al. (2014).

While the financial auditor's opinion can impact the attitude of several shareholders or the relationship with the bank (Feldmann and Read, 2013), the financial performance of firms can influence the decision of the bank regarding financial approval - higher performance facilities bank loans (for example S&P credit ratings is positively related to return on assets, EBITDA and total assets (Hung *et al*., 2013)) - or can present the areas where major problems occur.

The present research tries to present a new model for scoring the Romanian companies that are listed on the Bucharest Shock Exchange (BSE). The innovative element of the scoring is firstly the form, by the classification criteria and secondly, by the way the validation was done - using data from RASDAQ, which is considered the secondary market and where companies have, in general, lower financial performance. The RASDAQ companies have not applied the IFRS accounting measure before 2012, which could be an element that can significantly influence their performance. Framing the financial performance can also influence the auditors' opinion as they are going to adjust their resource allocation and they are going to provide more detailed information considering the degree of risk that the audited company presents.

The paper is structured into three parts; the first one reveals the theoretical background, the second one emphasizes the methodology applied and correlates it with the mathematical approach, while the third one presents the results obtained in order to illustrate the performance of the companies from the Bucharest Stock Exchange. The paper ends with conclusions and recommendations.

2. Literature Review

The first who initiated the research in the field is considered to be FitzPatrick (1932). His study upon 38 companies, half with high performance and half with a bad reputation, points out that, three years before the bankruptcy occurs, important financial ratio changes can be detected. A similar research was implemented by Winakor and Smith (1935), as they discovered that while the financial performance declined the main ratio also decreased sharply. The same conclusion regarding the close connection between the trend rate and the continuity of the company's activity was identified by Merwin (1942), 6 years before the moment of bankruptcy.

However, the scientific concern in this area started with the research by Beaver (1967). A univariate analysis was developed taking bankrupt and non-bankrupt companies into consideration. The idea was to predict the inability of a company to make payments and the moment when the bankruptcy occurs using liquidity, profitability and solvency indicators.

In 1966, the risk was introduced into the pattern recognition technique by Tamari (1966) and then by Mosesand Liao (1987). Altman (1968) emphasized the gap between the univariate models and multi-variate ones, and it is considered to be the initiator of discriminant analysis as he decided to use five financial indicators for quantifying the financial performance of a company. Several studies have been done in order to improve its model by other researchers, such as Deakin (1972), Blum (1974), Sinkey (1975), Altman, *et al*. (1977), Conan and Holder (1979), Lincoln (1984), Poston, Harmon, and Gramlich (1994), Grice and Ingram (2001), Lugovskaya (2010), Li and Rahgozar (2012), etc. The multiple discriminant analysis has been also applied to the Romanian market, as it offers better financial prediction than that obtained by the classic models and it can impact on the detection of the factors that have caused the financial crisis.

Mânecuta and Nicolae, (1996), Ivoniciu and Băicuşi (1998), Baileşteanu (1998) are the authors of the first pattern recognition approach, while Anghel (2002), Statev (2006), Sajin (2010) and Moscalu (2012) applied this technique to several areas, each study being conducted on a larger sample by using different ways of estimation. For example, Anghel (2002) analyzed the companies that were in default, while Moscalu (2012) presents the financial performance of small and medium companies.

An important study was conducted by Bărbuță-Mişu (2009), who identified that the reinvested profit ratio and the weight of financial debts in total debts were the indicators that had the most influence in establishing the financial performance of the company, followed by return on equity. The results were obtained using discriminant analysis. The data are important as some of the indicators are accounting measures, to which an auditor should pay higher attention. The literature introduces the importance of audit when financial performance is analyzed, as financial ratios frequently appear not only in the internal management report, but also in the auditor's one. Green (1978) stated the importance of financial ratios as they were generally used for reporting liquidity, leverage, activity and profitability. The investors would use these elements in order to detect the company's performance and to predict its future evolution. The study conducted by Mironiuc, Robu, Robu (2012) reveals the importance of auditors in detecting the financial fraud which can be committed by manipulating financial information for obtaining the fixed threshold of performance.

3. Methodology

Discriminant analysis is a classification algorithm which has the ability to predict in which category a new element, with similar characteristics, can be placed (Soeyoshi, 2006).

The main hypothesis of the discriminant analysis is that the population (Ω) is formed from K classes ($\omega\_1,\omega\_2 \ldots \omega\_K$) which are included in the population, are not totally different and form the entire population.

The purpose of discriminant analysis is to detect an efficient way to form the K classes, which are called prediction classes, that are mutually two by two exclusive, different from the initial classes, included in them and which form the entire population. In discriminant analysis, it is considered that *a priori* classes are known and are used in order to frame a new object with similar features. The distinction between classes is made by the discriminant scores.

In order to determine the discriminant scores, optimal set variables (descriptive variables) have to be identified (Ruxanda, 2009, pp. 94-101). Consequently, the idea is to detect the discriminant functions and to identify their eigenvalues. In order to create the final equation of discriminant function, the values associated with separation criteria (used to frame the classes) are established.

The idea of the research is to identify a way of dividing the companies that are listed on the Bucharest Stock Exchange based on their financial performance using discriminant analysis. In order to achieve this objective, the discriminant functions which separate the companies with a higher performance from the companies with a lower performance were estimated. For the companies listed on the Bucharest Stock Exchange, financial information was collected for 2010 from their financial statements. The validation was realized for two periods of time, 2011 and 2012, for the RASDAQ listed companies. For the validation model, firstly, a Z score was also calculated and, secondly, the results were compared considering the RASDAQ companies' stock price fluctuation. The validation is important as it is conducted on a different sample than the one upon which the discriminant functions were constructed. In order to conduct the study, the hypothesis of the discriminant analysis had to be validated; otherwise the results could be questioned. In fact, the multivariate normality hypothesis and the fact that the covariance between groups was equal were tested. The first hypothesis points out that each predictor should be normally distributed or at less close to a normal distribution. Consequently, the estimated residuals of dependent variables should have a normal distribution or each variable should be tested for normality using the statistical validation tests. The assumptions of multivariate normality were validated using the Kolmogorov-Smirnov or Shapiro Wilks' tests. The selection of the test depends on the dimension of the analyzed sample. The variables were adjusted using the methodology recommended for obtaining the normal distribution.

For the second hypothesis, the covariance between matrices was tested. For this, the Box's M test was used.

The discriminant analysis was applied using financial information for the companies that were listed on the Bucharest Stock Exchange at the end of 2010. From the initial sample, the financial institutions were excluded, as their reporting manner is totally different from the other companies. Also, the financial companies were excluded as the close and funds hypothesis applies to them, so they can be undervalued on the market. The remaining sample consists of 59 entities. For each company, financial data has been collected from the financial statements and explanatory notes. Information regarding the financial components and information regarding the daily price of its stocks were also collected. 14 financial indicators were computed for each company, as they could predict the degree of performance of that entity.

The return on equity is calculated using the results obtained in a period divided by the resources that generated such results. Using this computation formula, a comparison with other elements such as the inflation rate or the interest rate can be done.

Indebtedness to equity or the financial leverage points out the ability of the company to pay its debts from its own resources. This ratio is recommended to be as small as possible, taking into consideration that the creditors have priority in obtaining their loans upon the shareholders when the company is in bankruptcy.

Companies' solvency reflects the way the companies can fulfill their payment obligations. It is recommended that more than a third should be formed from own resources in order to reflect a higher financial performance.

The quick ratio illustrates the possibility of current assets to be turned into cash in order to cover the current liabilities of the company. For a high financial performance, it is recommended that the indicator should be higher than unit.

Net profit per share is a financial indicator that generally is correlated with the dividend yield, as an increase in its value cumulated with a higher value of the dividend yield reflects high creditworthiness of the company.

The evolution of profit, calculated as the ratio of the difference of profit obtained between two consecutive financial years to the positive value of the profit from the initial period, is another financial performance measure.

Net profit divided by total assets reflects the efficiency of assets utilization, which could be similar to the ratio of net sales to total assets.

The floating capital was divided by total assets, as it represents a method of measuring the enterprise flexibility. A higher performance is expected as the value of floating capital is increasing.

The evolution of employment was considered as another element that can influence the performance of the companies. This element can also provide information about the social policy of the enterprise.

Another ratio that was calculated is the value of net sales divided by the number of shares, as this element points out some of the benefits that a shareholder should obtain.

The gross yield dividend was extracted for each company and it shows whether the shareholders of the company have been remunerated for their capital allocation.

Price-earnings ratio was also calculated for each company. It is the most frequently used ratio that quantifies the efficient placement. It also provides information on whether a company is overvalued or undervalued.

The gross profit divided by total assets was also calculated as it could provide a measure of performance without the influence of fiscal policy.

The last indicator that was calculated is the net profit margin, as its higher value can emphasize higher financial performance of the companies that were selected.

The justification for selecting these indicators is based on the fact that not only the performance of the company is shown by them, but also the risk idea has to be considered when performance is analyzed. In fact, in order to detect the bankruptcy risk there are at least two techniques that can be used: the empirical way, in which the probabilities for an event to occur are calculated, and the formal one, where a score function is determined, as Stancu (2007) emphasized.

The second method is frequently used nowadays, as it can eliminate the information redundancy and it can identify the ratios which provide reliable information about the probability of bankruptcy.

Taking the evolution of the companies into consideration, it has been demonstrated that there are some ratios by which some financial problems can be pointed out by their critical value. Onofrei (2007) considers that, among them, the most important are:

$$\frac{\text{Floating capital}}{\text{Total assets}}, \frac{\text{Current assets}}{\text{Current liabilities}}, \frac{\text{Equity}}{\text{Total liabilities}} \qquad (1)$$

Consequently, these ratios were included into the current research.

In order to provide information about which variables are significant, the principal component communalities table was analyzed. This table presents how much information is recovered from the initial variable. It is considered that at least 40% from the initial information has to be recovered, otherwise the variables are omitted and the analysis is conducted without them.

The selection criteria was constructed by combining some financial ratios and by giving them a score between 1 and 4, as four classes of performance are considered to be relevant for the Romanian market. The first one represents the class of the most performing companies, the second one represents the category of well performing companies (above market average), the third category represents the less performing companies, while the last is formed from companies that could suffer from important financial distress.

The selection criterion is a combination of four elements and it represents one of the innovative parts of the research. The first component is the number of trading days, the second one is the percentage of the trading period when the values of the stock prices were above the average, the third one is a combination of the evolution of the net profit and the value of net profit from the analyzed period, while the last one is a criterion considering the dividend yield and the evolution of the total number of employees.

The scoring method conferred 4 points for the company with the highest performance, while 1 point was assigned to the company with the lowest one.

The number of trading days is the first component that was analyzed. It is considered that a company is traded over the entire year if the number of trading days is around 250. This value was divided into four parts, under 40% or approximately 100 days when the company was traded, between 40% and 60% or about 100-150 trading days, between 60% and 80% or a number of 150-200 trading days and above 80% or above 200 trading days. Four points were conferred to the category with a trading period above 200 days.

The second criterion points out the number of days when the closing stock price was above the average of the trading period. This element reflects the percentage when the performance of the company was above the average if the whole trading period is considered. Lowest limit was below 35%, while its increase was 5% and 10% for each performance category. As a consequence, the companies with over 50% of the closing price above the average price have obtained 4 points.

The third element was formed from a combination of the evolution of the net profit and the net profit from the period on which the analysis is conducted. If both had positive values, then the company was considered to have the highest performance degree, while their negative values show that financial distress can be revealed. Moreover, it was considered that a positive evolution correlated with a negative net result reflects a lower degree of financial performance than the performance formed with positive results, but a negative evolution.

The last selection criterion was also a combination between the evolution of the number of employees and the existence or inexistence of the dividend yield. The judgment was similar to that applied to the previous selection criteria, considering the existence of dividend yield is the performance criterion. In fact, when both indicators had positive values, the company was considered to have the highest performance, while the negative values suggested the lowest one. After establishing the splitting criteria, the scores for each category were added. The breakpoint for each category was established at 8, 11, and 14. The companies that obtained a score below 8 (below half of the maximum value) were considered as having a high degree of financial distress and were included in the fourth class of performance. The score increased by 3 points, so a company was considered to have higher performance if at least two of the four elements had received a maximum value.

In order to estimate the probability of a proper allocation, the leave one out principle was used. In fact, to estimate the discriminant function, this is fitted to select n-1 samples (58 in the present research) from the original population. Each time the discriminant function is calculated, it is used to determine the proper class of the remaining observations that were not considered in the analysis.

After the critical score was fixed, a method that considers that the four classes of performance do not have the same number of observations was used. Due to this aspect, the Ramayah *et al*. (2010) formula could be applied when there are only two groups (N represents the number of elements of a group, while z represents the centroid for the corresponding group).

$$Z_{cs} = \frac{N_A * Z_B + N_B * Z_A}{N_A + N_B} \qquad (2)$$

Otherwise, the score is calculated using the sum of the products between each coefficient and the corresponding normalized variable value, as shown in equation 3.

$$S_f = sum_i(zscore_i * Coefficient_{f,i}) \qquad (3)$$

Then, distances to function centroid C_(f,g) were calculated, and the company was included in the category with the lowest value. We used the formula from equation 4.

$$d_g^2 = sum_f(S_{f,i} - C_{f,g}) \qquad (4)$$

For a reliable validation of our model, the same technique was applied to companies that are listed on RASDAQ. The financial data was extracted from the Bucharest Stock Exchange site. A total number of 90 companies which had the highest trading values were selected, some with financial information from 2011, and some with financial information from other period. For each company, the same financial indicators were computed.

The idea is to validate the discriminant functions and to provide information that they are time invariant. For establishing if the framing criteria present creditworthiness, the stock price of RASDAQ companies was used in order to try to forecast the company's evolution when its financial performance is analyzed. The average price and the number of trading days from the next year were calculated and the results were compared with the values from the previous year and with those obtained by the discriminant function.

It has to be mentioned that there are two ways of making the discriminant analysis. The first one involves the independent variables together, while the second one (the stepwise method) is used to determine which of the variables has a more important discriminant power. Variables can be entered or removed from the model according to their discriminant power. Both techniques are used, which confers a higher degree of confidence to the model that was developed.

4. Discussions and Results

Only 10 of the computed variables were used for the pattern recognition technique, as no more than 40% of the initial information could have been recovered from the other variables. The excluded variables were earnings per share, net sales divided by the number of shares, gross yield dividend and net profit divided by total assets. As one can see, the excluded indicators were, in general, accounting measures which present the static feature of financial performance. From the auditors' perspective, earnings per share are considered to be an indicator that can be easily controlled by managers in order to gain private benefits. The literature considers that larger audit companies can mitigate the negative impact of this indicator, but the results have been certified only for the United States of America. In order to realize the discriminant analysis, the multi-normality and the equality of the multi-variance hypotheses were tested. Literature points out that the multi-normality can be obtained by some mathematical tricks upon the initial variables, such as square roots, logarithmic and inverse transformations. For the first two cases, to the absolute value of financial indicator a minimum value or a small value was added in order to create positive values. For normalization, both the normality of each variable and the residual distribution were tested. The results regarding the normalization are presented in Table 1.

Table 1

The Normality Significance of the Variables

Variable	Modification	Kolmogorov-Smirnov		Shapiro-Wilks	
		Statistic	Significance	Statistic	Significance
Return to equity	Square roots	0.299	0.000	0.632	0.000
Indebtedness to equity	Decimal logarithmic	0.078	0.200	0.986	0.727
Solvency	Decimal logarithmic	0.123	0.026	0.938	0.005
Quick ratio	Decimal logarithmic	0.158	0.001	0.938	0.005
The evolution of profit	For values below 10, square roots For values above 10, decimal logarithmic	0.098	0.200	0.095	0.001
Floating capital divided by total assets	Square roots	0.132	0.012	0.965	0.092
The evolution of employment	Inverse	0.145	0.003	0.793	0.000
Price earnings ratio	For values below 10, square roots For values above 10, decimal logarithmic	0.099	0.200	0.934	0.003
The gross profit divided by total asset	Only the adjusted value	0.186	0.000	0.869	0.000
Net sales divided by total assets	Normal value	0.121	0.032	0.901	0.000

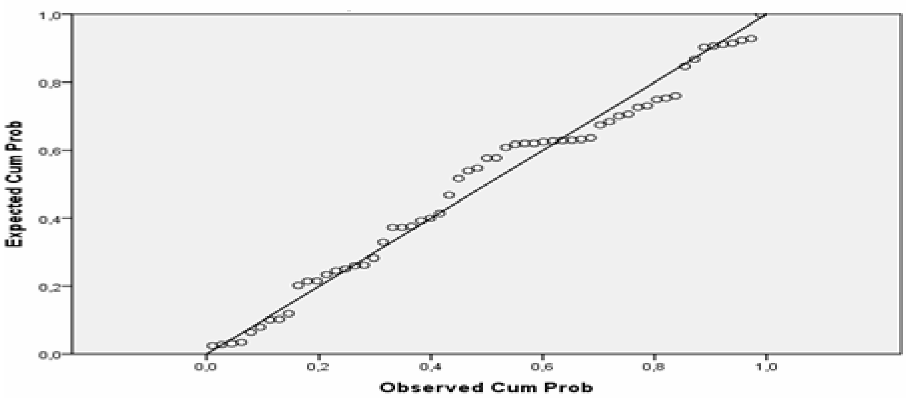
Source: Excel and SPSS output; authors' calculation.

One may see that almost each variable has a normal distribution. The acceptance of normality comes from the fact that the significant value should be lower than 0.001 in order to accept that the distribution is not normal. In general, both tests are statistically correct, as the Kolmogorov-Smirnov test may be used for big samples, while the Shapiro-Wilks test is generally used for samples besides 50 observations. The variables that are not normal are the gross profit divided by total assets and the return on equity ratio. While the first one is almost normal, the second one does not have a normal distribution. The influence of both returns on equity ratio and gross profit divided by total assets was tested and the indicators were included in the analysis only if the discriminant analysis hypotheses were validated.

The distribution of residuals is also normal, so all the variables were included in the discriminant function analysis - the literature points out that the normalization of the independent variables is not enough. The results obtained are presented in Figure 1.

Figure 1

The Normal Residual Distribution of the Dependent Variable: The Performance Score



Source: Authors' calculation.

The second hypothesis reveals that the variance-covariance between groups is similar or equal. For this, the Box's M test was used. Its major premise is based on the fact that if the significance value of Box's M test is greater than 0.001, then the null hypothesis of equal population covariance matrix is valid. For establishing this, the correlation between variables was tested. The return on equity and the company's solvency variables were removed from the study, as their correlation with other variables was really high. For example, the correlation between the return on equity and the floating capital ratio was -0.871 and the correlation between the return on equity and the indebtedness ratio was 0.658, while the solvency ratio was 0.942 correlated with return on equity. The value of Box's M is translated by taking the log determinant of each group into consideration. In order to estimate the Box's M value, all combinations between the remaining variables without return on equity and solvency ratio (that were highly correlated with other variables) were estimated. The result was chosen from 247 scenarios (sum of combinations of 8). Table 2 reveals the elements.

Table 2 shows that the covariance between groups is considered to be equal - the assumption was validated by the Box's M test. The validation is, however, sensitive to the number of elements in the sample, and it improves when the dimension of the sample increases.

Table 2

The Equality of Covariance Matrix

Group	Log determinant	Box's M value and significance
1	-16.865	
2	-16.692	
3	-16.324	
4	-13.317	
Pooled within groups	-14.243	
		99.518 with 0.002 significance

Source: SPSS output, authors' calculation.

As the hypotheses of discriminant analysis are now valid, a reliable analysis was conducted taking the classification criteria into consideration. The first group had 10 elements, the second one had 14 elements, the third one had 22 companies, while the last one had 13 firms that could exhibit important financial distress. As four groups of performance were considered, 3 discriminant functions were estimated for the model. In the model, 5 of the 10 variables (indebtedness to equity, quick ratio, the evolution of profit, floating capital divided by total assets, gross profit divided by total asset) were included. The other variables, which were not omitted due to their correlation, negatively influenced the hypotheses of discriminant analysis (they were not valid any more) or affected the classification rate which was below the value of significance. The first analysis points out that 59.3% of the companies are correctly classified when the probabilities of group membership and the predicted membership were analyzed. The result has creditworthiness wherever the difference between the predicted membership group and the initial classification was beyond 5%, as the dimension of the sample is quite small. The results offer a higher relevance to the developed model after the adjustment of the classes. Consequently, 9 companies were framed into the first class, 17 into the second, 24 into the third, and 9 into the last one.

As four classes of performance are considered, 3 discriminant functions are generated. An optimum problem is solved and the coefficients of the discriminant function are estimated. The significance of the estimated discriminant functions is presented in Table 3.

Table 3

The Significance of Discriminant Functions

Discriminant function number	Eigenvalue	% of variance	Canonical correlation	Function significance
1	0.673	87.3	0.634	0.005
2	0.093	12.1	0.292	0.756
3	0.005	0.6	0.071	0.966

Source: SPSS output, authors' calculation.

Table 3 presents the canonical correlation coefficients (0.634, 0.292 and 0.071), which measure the association between the discriminant score and the set of independent variables. In fact, the first discriminant function cumulates 63.4% of the variance within the group. However, although this is an indicator of the strength of relationship between the companies, it does not provide information about a reliable relationship of the classification accuracy. In order to establish the discrimination power of the functions, the eigenvalue elements are analyzed – the functions with the largest eigenvalues are those with maximum significant discriminatory power. The results reveal that the first function is the most important one.

It can be observed that the first canonical function is significant, which means that a credible classification between companies with high performance and companies with medium upon average performance can be correctly made. The second and the third significance functions probabilities point out that a proper framing classification cannot be conducted with the other discriminant functions. However, they could be valid as half of the variance is explained by the first discriminant function (Wilk's Lambda results). It has to be revealed that the prior probabilities of elements were considered equal, as a company could be included in any category of performance. The explanation is that the performance of a listed company cannot be anticipated, so the proper classification accuracy can be achieved by using these framing assumptions.

One important aspect consists in identifying which elements affect each discriminant function (some elements may have a higher influence upon a certain function than the others). The significance of discriminant functions is provided as all variables are measured on the same scale.

Table 4

The Importance of Factors in Establishing the Discriminant Function

Variable	Function		
	1	2	3
Indebtedness to equity	0.382	-1.103	-0.503
Quick ratio	-0.013	1.720	0.290
The evolution of profit	0.441	-0.406	0.786
Floating capital divided by total assets	0.464	1.527	0.290
The gross profit divided by total assets	-0.897	-0.673	0.053

Source: SPSS output (authors' calculation).

According to Table 4, it can be assumed that the first discriminant function is more influenced by the gross profit divided by total asset; the second one is a combination of financial distress indicators, while the last one is made from net profit evolution and the indebtedness ratio of the company. Table 4 illustrates the impact of each independent variable, which can be a measure of the relative importance of each variable of the original predictors. The discriminant function equation can be subtracted from the analysis, so the classification function coefficients are extremely important.

Table 5

Canonical Discriminant Functions Coefficients

Variable	Function		
	1	2	3
Constant	-0.791	0.658	-1.883
Indebtedness to equity	0.637	-1.841	-0.840
Quick ratio	-0.029	3.844	0.647
The evolution of profit	0.967	-0.890	1.724
Floating capital divided by total assets	1.603	5.277	1.372
The gross profit divided by total assets	-12.087	0.658	-1.883

Source: SPSS output (authors' calculation).

Consequently, the first function discriminant could be formed as presented in equation 1 (the BDB model).

$$F_1 = -0.791 + 0.637 * \text{indebtednes}_{\text{ratio}} - 0.029 * \text{quick}_{\text{ratio}}\text{all } 0.967 * \text{Profit}_{\text{evolution}} + 1.603 * \text{floatingcapital}_{\text{ratio}} - 12.087 * \text{grossprofit}_{\text{ratio}} \quad (5)$$

Moreover, the discriminant scores for each company were calculated, as they are important when the companies are framed into categories of performance. If all the functions contribute to the classification result, then each function has its own score; otherwise, if only one function is valid, then the scores represent a linear dimension and different scores are calculated. As only the first function is relevant for the study, the specific discriminant scores were calculated. They are presented in equations (6), (7), and (8).

$$S_1 = 0.382 * \text{indebtedness}_s - 0.013 * \text{quick}_s + 0.441 * \text{profit}_{\text{evolution}_s} + 0.464 * \text{floating}_{\text{capital}_s} - 0.897 * \text{gross}_{\text{profit}_s} \quad (6)$$

$$S_2 = -1.103 * \text{indebtedness}_s + 1.720 * \text{quick}_s - 0.406 * \text{profit}_{\text{evolution}_s} + 1.527 * \text{floating}_{\text{capital}_s} - 0.673 * \text{gross}_{\text{profit}_s} \quad (7)$$

$$S_3 = -0.503 * \text{indebtedness}_s + 0.290 * \text{quick}_s + 0.786 * \text{profit}_{\text{evolution}_s} + 0.397 * \text{floating}_{\text{capital}_s} + 0.053 * \text{gross}_{\text{profit}_s} \quad (8)$$

In equations (6), (7) and (8) the values that were used for each company were standardized.

The relevance of the discriminant function can be pointed out by analyzing the values of centroids, which represent the unstandardized canonical discriminant function evaluated at group averages, as revealed in Table 6.

As one may see, when function 2 and function 3 are used, the difference between each class is not very clear, so misclassification can be assumed when framing a company into a category of performance. For example, the separation between classes cannot be properly made when the third discriminant function is used, as the value of centroids is close to zero.

Table 6

Values of Discriminant Functions Centroids

Performance class	Function		
	1	2	3
1	-0.872	-0.546	0.065
2	-0.651	0.370	0.031
3	0.203	-0.060	-0.079
4	1.561	0.008	0.088

Source: SPSS output (authors' calculation).

Taking the report over classification accuracy into consideration, about 71.2% group cases from original variables where correctly classified. As a fact, each group had more than 65% of elements correctly classified and only a few elements were incorrectly classified. When the cross validation value is analyzed, about 47.5% of the initial companies were correctly classified. This value is reliable, as it has to be compared with the squared sum of prior probabilities index with a 25% value for performance. The results could be summarized in Table 7.

Table 7

Probability of Predicted Group Membership

Performance class	Probability of predicted group membership				Total
	1	2	3	4	
1	66.7%	22.2%	11.1%	0%	9
2	11.8%	76.5%	5.9%	5.9%	17
3	8.3%	20.8%	66.7%	4.2%	24
4	11.1%	11.1%	0%	77.8%	9

Source: SPSS output (authors' calculation).

Using the stepwise method, the gross profit to total assets ratio is the one with the highest discriminant power.

The model was validated using companies from RASDAQ. The sample was formed from 90 companies, as it represents one and a half of the original sample.

Consequently, both the discriminant scores and the distance from each one to the centroid of the group were calculated. The classification for each company is made considering the minimum of the square distance calculated between the score and the centroid. As the companies from RASDAQ frequently have a lower number of trading days than the companies from BSE and they often do not offer any dividend, the classification criterion was modified to 6, 8, and 10 values (12 points represent the maximum).The results are shown in Table 8.

Table 8

Probability of Predicted Group Membership for Companies Listed on RASDAQ

Original criteria			Modified criteria		
Performance class	Number of companies	Number of companies correctly classified	Performance class	Number of companies	Number of companies correctly classified
1	0	0	1	11	4
2	1	0	2	22	6
3	32	25	3	45	34
4	57	1	4	12	3

Source: Authors' calculations.

The accuracy of the criteria is high for the companies of class 3 of performance, as generally the companies from RASDAQ have a lower performance than the companies listed on the Bucharest Stock Exchange. Moreover, the RASDAQ companies are constrained to report their financial statements through IFRS, which can affect their performance. In fact, the audit should pay higher attention when the financial statements of the RASDAQ companies are audited in order to report any possible mistakes. Each error could generate financial distress not only for the audited company, but also for the company that performs the audit services. The second criteria confers higher confidence to the discriminant function - about of 52.2222% of companies are correctly framed.

Considering the evolution of stock price of the companies that were correctly classified, it can be assumed that about 20% of the analyzed companies had superior values than the others, as they obtained both an average and a number of trading days superior to the previous situation. Table 9 illustrates this fact.

Table 9

The Evolution of Companies that Were Considered Relevant for the Applied Model

Performance class	The average is higher than in the previous year	The number of trading days is higher than in the previous year
1	3	0
2	0	2
3	17	13
4	0	0

Source: Authors' calculations.

It can be pointed out that a good framing for the companies of classes 1, 2, and 3 was achieved and it can be said that the companies framed into class 3 of performance could obtain higher performance than the developed model foresees.

Taking the auditors' opinion into consideration, it may be affirmed that even if a company has not a proper going concern, sometimes it can obtain good performance as its evolution is strongly influenced by the macroeconomic environment. Moreover, the shareholders should pay credit to the audit report, as the evolution of stock price on the Romanian market is difficult to be properly established (the Romanian capital market is sensitive to speculative international inflows and to adverse financial shocks - Anghelache *et al*., 2014). On the other side, it is considered that in this situation the managers should apply a cautious financial policy in order to avoid financial distress. The model presents a way of framing the companies listed on BSE or RASDAQ, for which auditors can better manage their resource allocation and can provide detailed audit reports in case an audited company suffers from financial distress.

5. Conclusions

The present research tries to establish a score function for framing companies that are listed on the Bucharest Stock Exchange. The function had been defined using financial data for the companies listed in 2010. A validation using RASDAQ companies and the evolution of the stock prices was implemented. The validation was conducted for 2011, while the stock price evolution was observed for 2012.

Regarding the model used, it is considered that it confers a high degree of confidence to the stakeholders, as more than 71.2% of the companies were correctly framed. The model is important not only for shareholders, but also for the auditors whose opinions can influence the attitude of shareholders. The auditor should pay high attention when the function score places the company into a lower performance category. It was proven that framing the companies can help the auditors to form their opinion (Hoti *et al*., 2012). In fact, particular attention should be paid when the financial situation of these companies is audited. Otherwise, even with a proper going concern given to the audited company in order to conceal the real financial situation, the company would suffer important financial distress.

The problems regarding the model that was constructed and the research undertaken are related to the fact that the number of companies on the Bucharest Stock Exchange is still small as compared to other countries (Yao *et al*., (2014) consider that an alternative to the linear discriminant analysis is to estimate the subspaces for each element and not for the entire sample), the companies do not have always a transparent financial reporting, and few elements about the audit process are mentioned on the individual site. As a fact, no proper analysis about company financial statements could be conducted as there is no standardized way of realizing them.

When the validation is encountered, it has to be said that the Romanian market is sensitive to the financial macroeconomic evolution and, consequently, the value of the stock prices and the annual average could be affected. On the other hand, the model shows that a proper farming is realized even for the RASDAQ companies, which is secondary market. Consequently, it can be said that the function is a reliable estimator of the framing category of such entities. The audit should pay a higher attention to the companies that are listed on RASDAQ when they are required to report their financial statements through IFRS. The audit can properly manage their own resources when a higher risk is encountered due to the framing operations.

Further research is based on constructing an audit index that could be correlated with the Zscore of the company. In fact, a higher degree of creditworthiness would be insured for audit companies, as the value of the index established should be correlated with the value of the Z score.

Other research objectives are looking at applying the model to other samples and at establishing a proper cut off score based on the results obtained by using several sample sizes.

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