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**PHD DISSERTATION  
THESIS STATEMENTS**

**Application of bankruptcy models  
on companies from Harghita County**

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# 1. INTRODUCTION

The empirical and methodological approaches have developed a lot nowadays mainly due to social sciences which led to methodological development in finance too. The main part of financial research is still based on capital markets, however corporate finance research has evolved a lot as well.

## 1.1. Background and relevance of the topic

In the past few years, financial modelling and financial predicting developed a lot in the domain of corporate finance research. Free capital movement made it possible for many investors to invest in high expected return fields. *The limited existence of capital* and rational thinking made investors put their money with minimal risk. They expect to get their money in a given construction and with interest. Because of the risk, investors follow their money closely. Economic and financial crises and economic downturns have a major impact on companies. Companies go bankrupt, in this way investors lose their money, thus the bankruptcy of companies has a high cost on social life too. *The bankruptcy of a company* is a costly phenomenon for all economic actors. Money lenders lose their money, companies bear liquidation costs, employees get no salaries, owners get money under their value or they get nothing. In the case of big companies, bankruptcy has deeper effects because it involves that many suppliers lose money as well, and due to open economies this produces a contagious effect. Starting from the unregulated mortgage legal system in the United States of America, a financial crisis appeared in 2007 which reached Europe and Romania too in August 2008. The financial crisis was followed by a longer economic crisis. Due to the economic crisis and partly because of the new Basel agreement, the bankruptcy prediction evolved a lot and many researchers pointed out the importance of bankruptcy predictions inside the small and medium sized enterprises (SME) too. Until that point research on bankruptcy has been mainly carried out on big companies and financial institutions such as banks. Bankruptcy research on SME has been neglected (Bellovary et al., 2007).

Research on bankruptcy has been greatly influenced by the evolution of empirical research and the development of information technology. Furthermore, the growing value of debts and their repayment risk encouraged bankruptcy modelling and application to develop. Much of the research has been carried out on big companies and banks, however after the Basel agreement bankruptcy and financial failure research of SME became more frequent in the United States of America and Western European countries.

## 1.2. Aims of the dissertation

The aim of my dissertation is to test bankruptcy models with financial ratios and see if they are applicable on the SME data sample from Harghita County. Following a theoretical research on the literature about bankruptcy, it has become clear that the Romanian financial research is highly oriented towards capital markets and macro finance modelling. Corporate finance and the application of statistical modelling based on financial ratios offers many opportunities for researchers. The research on bankruptcy is based on a small data sample of big companies, as well as testing Altman's Z model on these companies. Lizal and Schwarz (2012), Karas and Režňáková (2013) signal clearly a lack of empirical research in Central and Eastern European countries. The early recognition of financial failure and bankruptcy is the interest of all the actors of economic life. In this group the most interested ones are capital lenders, owners and the government.

Owners of SME tend to neglect the use of these bankruptcy prediction models because of two reasons: the lack of their knowledge on these models or because they do not consider these models important. We must mention that these models could become outdated in time; new research could be needed and they might have to be adapted to economic trends too. With the development of information systems, these models can be incorporated in complex information decision systems, because in this way they can be used in decision making in daily business life: decision makers can see their effect on company finance and liquidity. Empirical and theoretical models which have been elaborated in the past do not provide an exact answer on the perfect model. A great number of publications use the definition of bankruptcy on companies that are not bankrupt; the bankruptcy definition is often confused with financial failure. The definition of bankruptcy is described in my dissertation in a distinct chapter, and my research is carried out on bankrupt companies. Bankruptcy and financial failure must be used separately and applied separately in statistical models. A financially failed company is not always bankrupt, in this way the financial ratios can predict another financial state of a company.

Firstly, my aim was to develop bankruptcy prediction models based on SME data sample from Harghita County, which could be used by financial institutions. Secondly, I wanted to complete the SME bankruptcy research in Romania on regional level. Regarding the structure of companies, Harghita County is characterized by small and medium sized enterprises. The research on SME bankruptcy has become a priority in the past few years due to the Basel II. Capital Agreement applied from 2005. When it became active, a lot of criticism was formulated by governments and SME associations, since the high capital cost affected negatively these companies which represent the main pillars of a country's economy.

Altman and Sabato (2005), also Berger (2006) take into consideration the effects of the capital agreement on the SME sector. However, up until 2005, research on bankruptcy of SME can be considered very poor (Altman–Sabato, 2005). SME crediting is considered riskier (Altman–Sabato, 2005) as it is exposed to economic changes and shocks, contrary to big corporates. In the same time SME crediting is riskier for the returns and profitabilities of banks and financial crediting institutions (Kolari et al., 2006, Berger, 2006).

In my dissertation I formulated the following hypotheses.

*H1: The size of the small and medium enterprises does not influence the probability of bankruptcy. There is no significant relation between the size of the company and bankruptcy probability. The size characteristics of a company will not improve the model accuracy.*

According to the literature, big companies are more diversified in their activities, and because of that, they can get crediting easier (in many cases with less credit rate). As such, the probability of their bankruptcy is lower than in the case of SME. This fact is supported by several articles (for example Ohlson, 1980). In the case of SME, it is possible that fewer liquidation procedures are started. This is true because in many cases the receivables are smaller than the procedure costs. Contrary to my opinion, Altman et al. (2010) have concluded that company size matters. They even established a lower asset value, above which the liquidation procedure was started more than once (Altman et al., 2010). In Berger's (2006) opinion, crediting big corporates has greater risks as opposed to crediting SME. We must also mention the fact that the SME sector is an important part of an economy and their crediting is important for financial institutions. There is no clear evidence that the size of a company influences the probability of bankruptcy. In my research, the size of a company is measured using the logarithmic value of total sales and total assets. I wanted to see whether these variables appear in the models, and if they did, were they significant and could they give a better accuracy to the model.

*H2. The bankruptcy of the SME in Harghita County can be predicted with the working capital and financial ratios which are related to this such as the turnover rate of accounts payable and accounts receivable. The cause of the SME's bankruptcy in Harghita County is circular debt.*

In bankruptcy prediction models the most frequent variable is the negative capital and the small value of liquidity. However, throughout time many articles have pointed out that the liquidity ratio is a static variable and cannot accurately predict bankruptcy. In the same time, dynamic cash flow ratios and the return on ratios included in the models can predict financial failure or bankruptcy. In my opinion, bankruptcy of companies in the county is due to economic relations, transactions of companies, and as such, a high circular debt is the main cause. Taking all this into consideration, I assumed that only those variables would be selected which were connected to the working capital management of a company; cash flow based ratios and long term debt ratios would be insignificant. The latter one is because statistical data shows that company loan behaviour is poor in the county. Company finances are based on short term financing. The hypothesis will be tested by the presence/absence of these variables, ratios in the models. In the mean time, I use as ratios the arithmetic average value of balance sheet values. I wanted to test if these average ratios have a better accuracy in predicting bankruptcy contrary to the general ratios.

*H3. The bankruptcy prediction models based on principal component analysis are more reliable than models based on simple financial ratios.*

Statistical models used in bankruptcy prediction have more assumptions regarding the variables used, assumptions which are not present in real economic life. In bankruptcy prediction research, based on financial ratios, we can construct models which predict financial failure or bankruptcy of a company. For this we use several financial ratios. However, it could be very hard for researchers to find the most reliable ratios that predict failure accurately if too many financial ratios are being used. Using less financial ratios can result in loss of information. The use of multivariable statistical analysis can be a golden way. The principal component analysis is a statistical method which combines the many variables into fewer new components with less information loss. In my opinion, the principal component analysis can help to elaborate new bankruptcy models which could predict the accuracy of the model. With the help of financial ratios and new components as new variables, I put this hypothesis under test, checking it with logistic regression models and the neural network model.

## 2. MATERIALS AND METHODS

Aziz and Dar (2006) compared articles on financial failure, pointing out the lack of information and data which is a common flaw signalled by researchers. In elaborating my thesis, getting the database from which the research could be conducted represented the biggest challenge. The problem is that in Romania financial data of companies is very hard to get. The database of the Ministry of Finance is an open resource, yet it contains quite summarized financial data which does not allow carrying out a research. The data used in my dissertation is from 2008, based only on financial data of Harghita County. It would be interesting to see the results of the same research carried out on regional level. Unfortunately, there is a lack of macro finance data on regional level as well.

The final database was put together using two main sources. One of the sources was the Ministry of Finance which provided the database on SME financial reports from Harghita County, containing coded data. The list of bankrupt companies was collected from the online page of the National Trade Register Office and it consumed a lot of time. The two databases were put together using special database techniques. Thus, the final database consisted of financial reports from 2009 to 2013, regarding companies from Harghita County.

In the mentioned 5 years, in Harghita County there were 1472 failed companies on the whole. From these I managed to identify 588 (39.95%) companies that went bankrupt. I had to take into consideration another factor, namely that these companies had to have financial reports in the two years prior their bankruptcy (balance sheet and profit-loss account). This proportion can be considered relatively good if we keep in mind that some of the bankrupt companies did not hand in annual financial statements to the official financial institutions. On national level this situation is the same and does not improve (Coface, 2015). Up until 2010, only 40.21% of the financially failed companies put down their report, in 2014 the rate improved to 49.46%, and a slow improvement was to be expected in the following two years. Based on the aforementioned data, we can conclude that only one out of two financially distressed companies puts down its financial report (Coface, 2013).

Following that, I excluded those companies which had no value in the total sales and total assets in the two years preceding their bankruptcy. The original list decreased to 255 bankrupt firms. In the meantime I excluded companies which were younger than 3 years old. I wanted to study active companies, not young enterprises. These companies went bankrupt because of mismanagement or because they did not have a correct market research on demand. As such, they represent another group, in my opinion. Certain articles characterize new and young companies as having poor or less effective control, their cash management is greater, in this way they are more likely to go bankrupt than others that survived 3 years of business (Charalambous et al., 2001). In other articles, the age of a company is considered a very important variable in predicting failure (Jovanovic, 1982, Pakes–Ericsson, 1998). Newcomers know partly the market, so there is a possibility that they overestimate/underestimate their capabilities. Consequently, their effectiveness will be surely known after a few years of activity. In my opinion, the first few years are about learning and developing or, in the worst case, going bankrupt. However, their characteristics are not similar to a company which has been active for more than 3 years. Similarly, there were left out from the data sample those companies in whose financial report the total sales were significantly less than the other incomes. I did this because I consider that these companies have already started to sell their assets, as a result they could have already been unhealthy financially speaking. Lastly, there were left out from the data sample all the companies that did not have a total asset value of 100,000€. I considered that in this way I could get rid of the companies that are inactive or aim for invoicing.

The healthy companies were selected based on three criteria:

1. the total asset of the company is bigger than 100,000€;
2. the net income is positive in the two consecutive years;
3. is compatible with the proportion of bankrupt group based on its activity code.

The final database contains two groups: one group of healthy companies and another group of bankrupt companies. The bankrupt companies had to have financial reports in the two years prior their bankruptcy. There are a great number of articles which claim that the period must be longer than 3 years. Others say that bankruptcy prediction can be used on short time data. There is no exact answer to this question (Laitinen, 1993). In my opinion, the evolution of bankruptcy in the case of active companies is a long term evolution, but if we take into consideration the accuracy of predicting bankruptcy, I consider that taking into account one year is better. Considering two or more years before bankruptcy has less discriminating power between the two groups, thus the prediction accuracy could be worse. In my case, the database made it possible to take into consideration only one year before bankruptcy.

Concluding, the final database consisted of 110 bankrupt and 965 healthy companies.

### **Financial ratios and variables used in the research**

After finalizing the data sample, I calculated 83 financial ratios from the balance sheet and profit-loss account. I took into consideration the financial ratios used in the literature about bankruptcy. In some cases I made changes on the ratios, I improved them with accounting, applying tax corrections. The financial ratios can be grouped in 6 groups. The market ratios in my case could not be used.

1. Return on ratios: I calculated 10 main financial ratios and other forms containing tax corrections and others, in total 22 financial ratios. For example, in the case of ROA I used 7 versions, from which only 4 remained in the final research as input.
2. Efficiency ratios (3 financial ratios and its versions, in total 5 variables).
3. Liquidity ratios (8 financial ratios and its versions, in total 12 liquidity ratios).
4. Debt ratios (9 debt ratios and its versions in total 13 financial ratios).
5. Cash flow ratios (11 cash flow ratios and further versions, in total 15 cash flow based ratios).
6. Other financial ratios (11 ratios). In this group there are included the size variables, the sales growing ratios and other financial ratios, in total 16 financial variables.

In the process of choosing the right financial ratios, I took into consideration the empirical research too (Belovary et al., 2007).

In my research I used multivariable statistical methods to discriminate between the two groups: the logistic regression model and the principal component analysis. In the same time I used the artificial neural network modelling in distinguishing between the two groups.

### 3. RESULTS

Before working out the final model, I performed the primary statistical tests on financial ratios. As a primary conclusion, I can summarize the following:

- The financial ratios calculated from balance sheets can distinguish between the two groups if the arithmetic average is used. There are few exceptions, such as the working capital ratio to total sales (variable – v7).
- Among the variables I had to exclude those which contained long term debt. The data sample and the SME in Harghita County are characterized by short term financing behaviour. The long term debt is not characteristic to the SME in Harghita County.
- Due to the above mentioned fact, the variables that consisted of the interest cost were excluded from the analysis.
- The variables that consisted of the number of employees were left out because they did not present any relevant differences between the two groups.
- From the analysis there were excluded the ROE ratio and all those financial ratios which consisted of the capital value or the cash flow of the working capital in the same variable. This was because two negative values in a fraction make the value positive, giving a false picture of the financial health of the company. These negative values were characteristic mainly to the bankrupt group. On the whole, a number of 4 ratios were left because of the double negative fraction.

In bankruptcy research the company size is frequently studied. *The size of a company* can be measured mostly by two values: the value of total sales and the value of total assets. Noticing the value of total assets in both groups, we can formulate the following conclusion: the bankrupt sample is characterized by 7.54% assets growing two years before bankruptcy, until the healthy group presented a 65% asset growing.

**Table 1: Total assets value**

Company group	Total assets n-2 year – lei, average value	Total assets n-1 year – lei, average value	Changes – % average value	decrease/increase – % from the total sample n-1 year
bankrupt	4 065 414	4 027 810	7.54%	50.90%
healthy	2 827 227	3 121 705	65.00%	24.50%

Source: own calculations

The decrease of assets is more frequent in the case of the bankrupt group. 50.9% of the companies had a decreased value in assets, while in the healthy group only 24.5% of the companies presented an asset decrease. From the data we cannot conclude that the assets value starts to decrease one year before bankruptcy.

The most important value that characterizes the activity of a company is *total sales*. A company can pay its obligations by total collected sales. If we compare the two groups according to the total sales, the following results occur: the bankrupt group has a 6.3% total sales decrease in average one year before bankruptcy, while the healthy group presented a 114% total sales growth in the same period. The decrease is frequent in the bankrupt group, 70.9% of the companies presented a decrease in total sales.

**Table 2: Total sales value**

Company group	Total sales n-2 year – lei, average value	Total sales n-1 year – lei, average value	Changes – % average value	Decrease/increase – % from the total sample n-1 year
bankrupt	4 072 474	3 314 114	-6.3%	70.9%
healthy	3 605 199	4 073 272	114%	25.9%

Source: own calculations



In the case of the healthy group, the decrease frequency in total sales was only 25.9% from the whole data sample. Looking at the financial data presented above, we can see that the negative downturn of the total sales can be an influential variable in bankruptcy prediction.

A further question we have to look into is the proportion of accounts receivable in total sales. This value shows the proportion of the sales that were collected. If sales were not collected, it means that the company does not get enough cash to continue its activity, it needs further financing which can lead to financial distress and even to bankruptcy.

Analyzing the data, we can conclude that the average accounts receivable rate from total sales was 47.37% two years before bankruptcy in case of the bankrupt group, and 21.9% in the case of the healthy group in the same time period. One year before bankruptcy this rate deteriorated to 62.22% in the case of the bankrupt group, while the average value of the healthy group changed positively, being established at 20.21%. In the same time we should examine the ratio between the money collected and the money paid (variable v51). The smaller the ratio, the more likely there are liquidity problems. If the value goes below 1 unit, it means that the company needs working capital financing. The data sample in the case of the bankrupt group presented an average value of 0.85, while the healthy group had an average value of 1.06. To understand the ratio better, we have to take into consideration the total income value as well. If the company had negative results in a year and the cash ratio was under one, it means that the company did not collect its financial results. This situation occurred in the case of 27.27% of the bankrupt group and 33.06% of the healthy one.

After analyzing *liquidity ratios*, we can conclude that the working cash flow ratio cannot be used in bankruptcy predictions. Negative working capital had a distortive influence on the results. Looking at the results, we can also conclude that, based on the liquidity ratio, both groups have values that are normal or close to normal values. As such, these ratios cannot be used to distinguish between the two groups. In the case of healthy companies, the liquidity ratio had a high value. When the accounts receivable rate in working assets was being analyzed, I could see the high proportion, which pointed out that the money was not being collected. In the case of the bankrupt group, the liquidity rate had been decreasing one year before bankruptcy; in other words they had already been facing financial problems. The value of liquidity which is normal between 0.8 and 1.8 (Borszéki, 2000) was close to the lower value in their case.

**Table 3: Average values for liquidity ratios**

	General liquidity		Liquidity ratio without stocks		Cash ration		Accounts receivable / Working assets	
	n-2	n-1	n-2	n-1	n-2	n-1	n-2	n-1
bankrupt	1.41	1.07	0.84	0.67	0.14	0.10	44.76%	47.06%
healthy	3.29	2.72	2.06	1.79	1.05	0.71	44.06%	47.82%

Source: own calculations

*Debt ratios* represent other important indicators which can predict financial failure or bankruptcy. After analyzing the data from Harghita County and comparing them to data available on national level, we can conclude that companies from Harghita County do not finance their activity from long term debt. The value of long term debt is very low in many cases. This is also confirmed by the data provided by the National Bank of Romania. The value of debt in Harghita County decreased constantly from 2008. The average decrease was 4.17% in the period ranging from 2009 to 2015, while the average decrease on long term debt was 1.93% on national level. The ratio of long term debt of county enterprises, as opposed to the national total, decreased from 0.80% to 0.56% in the 2009–2015 period. The negative trend seems to be changing, because in 2015 it increased significantly with 11.43%. Behind these facts there could be the behaviour of not taking risks after a financial crisis or the lack of guarantees for the loans.

**Table 4: Company debt and its changes**

	mil.	2010	2011	2012	2013	2014	2015
Harghita County	RON	350.00	335.30	332.50	318.80	313.10	348.90
	<i>changes</i>	-10.08%	-4.20%	-0.84%	-4.12%	-1.79%	11.43%
	other currency	395.40	373.20	360.80	329.80	302.30	248.70
	<i>changes</i>	3.26%	-5.61%	-3.32%	-8.59%	-8.34%	-17.73%
Romania average	RON	976.71	1091.48	1198.99	1196.38	1221.67	1331.48
	<i>changes</i>	2.07%	11.75%	9.85%	-0.22%	2.11%	8.99%
	other currency	1603.83	1764.59	1748.72	1571.44	1391.70	1288.66
	<i>changes</i>	13.91%	10.02%	-0.90%	-10.14%	-11.44%	-7.40%
Romania total	RON	40 044.90	44 750.70	49 158.50	49 051.60	50 088.60	54 590.70
	<i>changes</i>	2.07%	11.75%	9.85%	-0.22%	2.11%	8.99%
	other currency	65 757.20	72 348.30	71 697.60	64 429.20	57 059.60	52 835.10
	<i>changes</i>	13.91%	10.02%	-0.90%	-10.14%	-11.44%	-7.40%

Source: National Bank of Romania, own calculations

Based these data, we can conclude that the SME sector has a low value on long term financing, the companies finance their activities on short term.

**Table 5: Short term finance in total finance – average value %**

	n-2	n-1
bankrupt	78.5%	79.7%
healthy	77.3%	78.9%

Source: own calculations

In their article, Altman et al. (2010) mentioned that in the SME sector the working capital is an important factor in the surviving financial collapse. The big rate of commercial loans or other short term financing is due to circular debt and increasing financial problems (Borszéki, 2008) which is characteristic to the SME sector in Harghita County.

The financial failure of a company is due to the lack of cash, this is why we need to analyze cash flow ratios. In the present research several variables were calculated. In this part of the paper I present only those cash flow ratios which involve short term financing, ratios that include total sales and total assets. The differences between the two groups can be seen in the primary results presented in what follows. The cash flow ratio in the case of the bankrupt group decreased and went down to negative values, while the healthy group showed an increase over time. This leads to the conclusion that the bankrupt group presented payment problems. The working cash flow could not be calculated on a two years term because the data set did not make it possible. The difference is still traceable because the working cash flow is double in the case of the healthy group one year before bankruptcy.

**Table 6: Average value of the cash flow ratios**

	Gross CF		Working CF
	n-2	n-1	
bankrupt	98 991	-3257	150 098
healthy	290 349	390 659	305 943

Source: own calculations

The gross cash flow rate from total sales shows that total sales are not enough to pay for obligations in the case of the bankrupt group (the average value was negative one year prior

bankruptcy). The gross cash flow rate in total sales was 11.93% in the case of healthy companies' group and -3.84% in the case of the bankrupt group. Another important ratio is the *working cash flow rate in short term liabilities*. A bigger value is desired because in this way there is enough cash to pay for short term liabilities. The difference between the two groups is significant. In the case of the bankrupt group the average rate was 2.96%, while in the case of the healthy group the average value was 41.59%.

The return on ratios has also been used in bankruptcy prediction. The return on assets (ROA) is the most frequent indicator from this group. I tested more variations of ROA to see which the best predictive variable is.

**Table 7: ROA ratio and its changes – average values**

%	ROA		ROA modified	
	n-2	n-1	n-2	n-1
bankrupt	-4.06%	-6.00%	-2.59%	-4.56%
healthy	6.56%	11.25%	7.67%	12.29%

Source: own calculations

Note: modified with tax and tax shield

The changes can be seen in the case of the both groups. The bankrupt group presents a decrease in value of the ROA, the other group almost doubled its value in a one year period.

### Result of the logistic model

In my thesis I compared and tested the probability of bankruptcy in Harghita County on SME data using multivariable statistical models and artificial neural network models. Since the dependent variable has two outputs, I have chosen the binary logistic modelling, where 1 represents the bankrupt company and 0 the healthy company.

The logistic regression modelling was conducted on the following criteria:

- The data analysis was made on final data set with the help of IBM Statistics SPSS software 19<sup>th</sup> version.
- For finalizing the model, more testing was needed. Hence, I used the FORWARD, the BACKWARD and the ENTER procedures. In the case of ENTER procedure, I have chosen the input variables according to my beliefs and I tested their relations and effects. I was also aware of the multicollinearity of variables. Multicollinearity is an unwanted phenomenon in logistic regression, because it can lead to mistaken results. According to Ramanathan's (2003) opinion this is not always true, multicollinearity can sometimes improve a model.
- As input, I have chosen 38 financial ratios as independent variables of the models. These variables were put to primary tests too.
- The input criteria of the model were established at the 5% probability value, the output criteria was established at 10% probability.
- The data set was split to 70% test sample and 30% hold out sample. It is important that in the case of the test sample, the number of observed items must be over 50 (Engelman et al., 2003) in order to apply a multivariable statistical analysis. This request has been fulfilled in the present research.
- The cut value was 0.5, but the model was also tested on other cut of values, the objective being the maximization of accuracy (Ooghe–Spaenjers, 2010).
- The accuracy of the models in the case of first error was between 58.2% and 75.8%.

The final logistic model is presented below:

$$P(\text{bankruptcy}) = \frac{e^{-1,946-21,134x_1 - 15,833x_2 - 1,197x_3 + 0,002x_4 + 1,880x_5}}{1+e^{-1,946-21,134x_1 - 15,833x_2 - 1,197x_3 + 0,002x_4 + 1,880x_5}}, \text{ where:}$$

- x1 ROA
- x2 CF/Total sales
- x3 Total sales changes
- x4 Turnover period of accounts payable
- x5 Debt/Total sales

The accuracy of the model was 95% in the case of the test sample and 96.5% in the case of the holdout sample at 0.5 cut value, which was also the best value for distinguishing between the two groups.

### Result of the neural network model

For the neural network planning I took in consideration the one and two hidden layers too, with different number of neurons. The most accurate model was the two hidden layer model with 7 and 5 neurons in each hidden layer. The activation functions of the layers were sigmoid. The learning process was multilayer perception form. In the case of the one hidden layer which consisted of 3 neurons, we can state that it was as good as the model that contained 7 neurons in the hidden layer. The accuracy of the 20-3-2 neuron network was worse with 3.1 pp. than the 20-7-5-2 neural network. The accuracy of the final neural network model (20-7-5-2) was 97.1% in the case of the hold out sample. The model contained mainly the debt rate from total sales ratio as the most important variable.

### The results of the models based on principal component analysis

The new components resulted from principal component analysis can estimate better accuracy than the models with simple ratios. The principal component analysis (PCA) is a frequently used statistical method in finance. The advantage of the method is that between the components there is no multicollinearity, which is to be avoided in statistical analysis. As input for the PCA, I used 43 financial ratios from the total list of variables in the first step. The KMO value of the model was 0.833, which means that the variables could be used in principal component analysis. The components explained 83.78% of the total variance. The size component (containing the values that measured the size of the companies) was insufficient if we took into consideration the 0.5 MSA value. However, I still used it for further analysis. After leaving out 3 ratios, since they presented low sampling adequacy, the model KMO value increased to 0.860, explaining 79.94% of the total variance. The remaining 8 components were not satisfactory, so I reran the data reducing them to 7 components. This step proved to be better, because the KMO value changed to 0.863.

### Logistic regression model based on principal component analysis

For maintaining comparability between the models, I kept the same criteria on developing the logistic regression model based on principal component analysis. The results show that the accuracy is slightly better on the models based on principal component analysis. The hold out sample accuracy was 97.1% at 0.5 cut value. The accuracy is slightly better than the logistic regression model which contains only financial ratios.

The final equation model is the following:

$$P(\text{bankruptcy}) = \frac{e^{-8,713-3,037x_1 - 1,708x_2 - 1,419x_3 - 4,084x_4 - 0,848x_5 - 2,093x_6 - 0,355x_7}}{1+e^{-8,713-3,037x_1 - 1,708x_2 - 1,419x_3 - 4,084x_4 - 0,848x_5 - 2,093x_6 - 0,355x_7}}, \text{ where:}$$

x1 F1 component;                    x5 F6 component;  
x2 F2 component;                    x6 V11\_1 – total sales/average assets;  
x3 F3 component;                    x7 F7 component.  
x4 F5 component;

**Neural network model based on principal component analysis**

The neural network model based on principal component analysis had 45 input neurons (37 financial ratios and 7 components). The data set has been split as previously to test sample and hold out sample. At the first tests I took into consideration the one and two hidden layer networks with different number of neurons. I wanted to test the accuracy of principal component analysis based models as opposed to the models that contain only simple financial ratios. The model that contained only the 7 components as input and one hidden layer had an inferior accuracy as compared to the logistic regression model containing only financial ratios. The final model based on components had a better accuracy than the other models.

**Table 8: Classification table for neural network model based on principal component analysis**

Network construction	Test sample			Hold out sample		
	healthy	bankrupt	total	healthy	bankrupt	total
45-7-2	99.60%	68.80%	96.50%	99.30%	81.80%	97.40%

Source: SPSS output, own calculations

The one hidden layer network had the highest accuracy, furthermore, in these models there occurred the lowest type I errors (29.21%). If we take into consideration the accuracy of the models, the area under the ROC curve and the values of Gini coefficients, we can conclude that the principal component analysis improves the prediction power of the models. Table 10 shows the accuracy values of the 4 models, and as it can be easily seen, the neural network model based on PCA has the best predictive power. In this model, the bankruptcy prediction is the highest (81.80%) in the hold out sample. It must be mentioned that the neural network model containing only financial ratios had the same accuracy as the logistic regression based on PCA. Studying the area under ROC curve and the Gini coefficients, we can conclude that the neural network modelling is superior to the logistic regression. The PCA is time consuming if we take into consideration the time spent on testing and building up the model.

**Table 10: Accuracy and results of the final models**

	LR-model		NN-model		FLR-model		FNN-model	
	testing sample	hold out sample	testing sample	hold out sample	testing sample	hold out sample	testing sample	hold out sample
Total sample	95.00 %	96.50%	95.90 %	97.10 %	95.90 %	97.10 %	95.50 %	97.40 %
ROC value	0.954		0.964		0.961		0.971	
Gini coefficients	0.908		0.928		0.922		0.942	
Type I. error	41.60%	24.20%	36.40%	24.20%	35.10%	24.20%	31.20%	18.20%
Type II. error	0.90%	1.10%	0.40%	0.40%	0.60%	0.40%	0.40%	0.70%

Source: own calculations

*Note: LR – logistic regression model, NN – neural network model, FLR – logistic regression model based on PCA, FNN – neural network model based on PCA.*

The number of type I error is the lowest in the case of neural network model based on PCA: 18.20%. In the other models, the number of type I error is the same as in the hold out sample. After analyzing type II errors, we can conclude that the difference in accuracy is almost the same, although some differences can be seen. Analyzing the area under the ROC curve, it can be concluded that the neural network model based on PCA is the most accurate model. This model has an accuracy of 97.40% in the case of hold out sample. This model is followed by the neural network model with an accuracy of 97.10% on hold out sample. This result is surprising, because I have been expecting the PCA based models to be more accurate. As a final conclusion, I can say that the neural network modelling has a more accurate prediction power than the logistic regression. Models based on PCA have more accuracy than models containing only financial ratios.

The present research completes the research of Romanian bankruptcy and financial failure by testing the accuracy of different models based on SME data sample. Comparing it to the results of international research, we can say that the Romanian bankruptcy research offers wide opportunities for young researchers. Among articles published in Romanian, the paper written by Brîndescu and Goleţ (2013) can be considered large data research. The mentioned authors used the data from Timiș County, their final model having 5 variables from the 11 used in the first tests. Similarly to our data, the accounts receivable turnover period is present in their model. In their conclusions, the aforementioned authors point out the importance of working capital in the prediction of financial failure.

**In the prediction of bankruptcy, besides financial ratios, the macroeconomic and macro financial variables can improve the accuracy of the model.**

A small part represents those articles which are engaged in studying the effects of the macroeconomic and macro financial variables in corporate bankruptcy. The incorporation of the macroeconomic and the macro financial variables into corporate financial modelling is proposed by (Hernandez–Wilson, 2013), (Bottazzi et al., 2010), (Hol, 2007). In my research I have also studied whether the macroeconomic and macro financial variables can give a better predictive power to the models. I calculated the trend coefficient of every variable used in the 7 years data. These variables were the following: the national total sales value, the total sales value of the county, the inflation rate, the GDP and the medium sized credit rate. In the case of the last variable, I have also calculated the variation over time and I have used the 7-year trend coefficient as a variable. I used the total sales on national and on county level since I reasoned that if the SME from Harghita County had more business relation inside the county, then the national total sales variable would not give enough predictive power. I used a period of 7 years because I considered it long enough to have predictive power. Longer data set was not reachable. The data was collected from the Romanian National Institute of Statistics and the National Bank of Romania. My assumption was that the total sales have a negative influence on the bankruptcy probability (since in my models the bankrupt SME were noted with number 1). I supposed that the probability for a company to go bankrupt decreases if the total sales of an industry increase. The same assumption has been made in the case of GDP. It is expected that if the GDP of a county is growing, then its effect on the bankruptcy probability will be smaller. In the case of inflation, literature is divided (Hernandez–Wilson, 2013). There are some authors who claim that investors will lose the value of their money over time if inflation is growing. In this case investors take more risk when investing their money which has a beneficial effect, decreasing the probability of bankruptcy (Qu, 2008). Other specialists claim that if inflation is growing, then investors would expect the economy to be poor and this would have an effect on banking credit, which in its turn would affect corporate loans (Mare, 2013). In the case of credit rates, I expected that if the rate decreased, it would make investors' expectations become better, also increasing the entrepreneurial behaviour because of less costly credits, which can result in decreasing the

probability of bankruptcy. This assumption had to be made carefully as the credit-taking behaviour of the SME is reduced in Harghita County. This is why I tested only short and medium-term interest rates. The final variables have been tested with financial ratios, testing new models in which the new macroeconomic and macro financial variables are incorporated (test result are shown in Table 11).

In what follows, I have used the logistic regression test model. The macroeconomic and macro financial variables have been included in the final logistic model containing financial ratios. The assumptions made regarding the test have been the following:

- I have used the ENTER method for testing.
- The input criteria of the model have been established at the 5% probability value, the output criteria at 10% probability.
- The data set was split to 70% test sample and 30% hold out sample. It is important to notice that in the case of the test sample, the number of observed items is over 50 (Engelman et al., 2003).
- The cut value was 0.5, but the model has been tested on other cut of values as well, the objective being the maximization of the accuracy (Ooghe–Spaenjers, 2010).

The test results from the logistic regression can be summarized as follows. Firstly, all the macroeconomic and macro financial variables have been included in the original model. The results turned out worse as compared to the original model, and the new variables were not significant. As a result, I have retested the variables entering them one by one. The final results and the comparison of the models are shown in Table 11. The same table shows the accuracy of the test and hold out sample, the area under the ROC curve and the GINI coefficient, as well. The original logistic regression model which contains only financial ratios is the model 0. The models which contain the trend of the national and county total sales (model 1 and 2) have similar accuracy, but they are superior to the base model. The national and the county GDP variable (model 4 and 5) are significant in the model, yet they did not improve the accuracy of the model. The same results occurred in the model containing the inflation. Model 8, which contained the county GDP value and the county total sales, had the same predictive power as the original model at 0.5 cut value. However, at 0.55 cut value, accuracy became better (97.1%, namely the same accuracy as in the neural network model). It must be mentioned that type I errors did not improve at any of the models. The interest rate variable was not significant in the models. The inflation variable turned out to be significant (sig. = 0.003) and the value of beta was positive (beta value 21.366) showing that inflation increases the probability of bankruptcy. I consider that for further research it would be important to test all variables which include the inflation of different products that represent a high proportion in different industries. If we look at the Gini coefficients and the value under the ROC curve, we can summarize the following: (i) the most accurate model is the one which incorporates the GDP value of the county; (ii) the macroeconomic and macro financial variables have a contribution to the improvement of accuracy of the models.

In the case of neural network models, the results turned out to be similar. The most accurate model has been constructed from two hidden layers with 7 and 5 neurons. The accuracy was similar to the neural network model based on PCA, yet the ROC value was slightly higher. The results showed that the most important variables, beside the financial ratios, were the county GDP and the inflation.

The final model which contains the macroeconomic and macro financial variables is represented below:

$$P(\text{bankruptcy}) = \frac{e^{-18,395x_1 - 17,410x_2 - 1,487x_3 + 1,980x_4 - 0,002x_5 - 4,957x_6 - 14,209x_7}}{1 + e^{-18,395x_1 - 17,410x_2 - 1,487x_3 + 1,980x_4 - 0,002x_5 - 4,957x_6 - 14,209x_7}}, \text{ where}$$

x1 – ROA

x2 – CF/total sales

x3 – growth of total sales

x4 – debt rate to total sales

x5 – accounts payable turn on period

x6 – total sales trend of the county

x7 – GDP trend of the county

After carrying out the testing, my conclusion is that, besides financial ratios, macroeconomic and macro financial variables can improve the accuracy of the bankruptcy prediction models. Those variables which can be linked to the activity of an industry have a bigger effect on the models. In the case of neural network models, the accuracy improved slightly but the relative importance of macro variables were not significant.



**Table 11: The influence on macroeconomic and macro financial variables on the logistic regression model**

<i>cut value = 0.5</i>		<b>Model 0</b>	<b>Model 1</b>	<b>Model 2</b>	<b>Model 3</b>	<b>Model 4</b>	<b>Model 5</b>	<b>Model 6</b>	<b>Model 7</b>	<b>Model 8</b>
Variables		<i>5 financial ratios</i>	<i>5 financial ratios + national total sales trend</i>	<i>5 financial ratios + county total sales trend</i>	<i>5 financial ratios + inflation</i>	<i>5 financial ratios + national GDP</i>	<i>5 financial ratios + county GDP</i>	<i>5 financial ratios + interest rate trend</i>	<i>5 financial ratios + inflation rate yearly</i>	<i>5 financial ratios + county GDP and total sales trend</i>
Nagelkerke R <sup>2</sup>		0.683	0.703	0.701	0.702	0.704	0.706	0.702	0.698	0.717
Hosmer–Lemesow test		0.653	0.976	0.603	0.889	0.942	0.938	0.963	0.868	0.843
Test sample	healthy	99.10%	99.10%	99.00%	99.00%	99.30%	99.10%	99.30%	99.30%	99.40%
	bankrupt	58.40%	63.60%	63.60%	62.30%	62.30%	62.30%	61.00%	61.00%	63.60%
	total sample	95.00%	95.50%	95.40%	95.30%	95.50%	95.40%	95.40%	95.40%	95.80%
Hold out sample	healthy	98.90%	99.30%	99.30%	97.80%	98.60%	98.60%	98.60%	98.60%	98.90%
	bankrupt	75.80%	75.80%	75.80%	75.80%	72.70%	72.70%	72.70%	75.80%	75.80%
	total sample	96.50%	<b>96.80%</b>	<b>96.80%</b>	95.50%	95.80%	95.80%	95.80%	96.10%	<b>96.50%</b> <b>97.10%*</b>
ROC curve		95.4%	95.4%	95.3%	95.7%	<b>96.0%</b>	<b>96.0%</b>	95.9%	95.7%	95.8%
Gini-coefficient		0.9080	0.9080	0.9060	0.9140	<b>0.9200</b>	<b>0.9200</b>	0.9180	0.9140	0.9160

Source: SPSS output, own calculations

\*Changing the cut value to 0.55 improved the accuracy of the hold out sample to 97.1%.

### 3. NEW RESULTS

Based on my research, I have formulated the four main results below:

- 1. The size of the SME in Harghita County does not influence the probability of financial failure or bankruptcy of companies. Company size is not a significant variable from the point of view of bankruptcy.***

This assumption is based on a number of reasons. Companies with high asset value can get financing easier and on lower costs as opposed to SME. The 'too big to fail' principle is valid in the company sector as well. The assumption is true based on the test results too. None of the size variables had major influence or were significant; furthermore they did not improve any of the models. In the case of PCA, variables did not reach the 0.25 MSA value which means that they did not correlate with any other factor. However, I used them in the PCA analysis, logistic regression models and neural network models, yet with no significant result. In many cases, results referring to the size of the company were insignificant, while the variables were significant only in a proportion of 10%. The relative importance of size variables was low in the case of neural network models.

In the literature it is often disputed whether the size of a company, as variable, influences bankruptcy or financial failure. There are a number of researchers who claim that the size of the company influences bankruptcy probabilities, while others think that there is no relation between them. I think that size is relevant only when a company grows over a point and its structure is not effective, furthermore no changes are made and the economic downturn starts. The size must be handled differently in the case of SME and corporations. In the case of corporations the control is more severe and the risk of bankruptcy is lower. In my research I have come across many articles in which the sample was not divided into SME and big corporations and the authors found the size as a significant variable for bankruptcy prediction.

- 2. The bankruptcy of the SME in Harghita County can be predicted by analysing the working capital and financial ratios which are related to this, such as the turnover rate of accounts payable and accounts receivable. The cause of the bankruptcy of some SME in Harghita County is circular debt.***

After running several models during the research, this hypothesis became true. The bankruptcy of the SME in Harghita County can be predicted using financial ratios related to working capital and to short term financing. These ratios have a major impact on the prediction accuracy as well. Many international researchers who studied the bankruptcy and financial failure of SME claim that the working capital and its financing are vital. In my opinion, this is true also because the SME sector of the county does not finance its activity with long term debt, contrary to other companies. The bank loan in the county is insignificant as compared to the value of the national average in 2015 (only 0.56% of loans from the total country loan).

The gross loan value of the SME sector decreased in average with 4.30% in the period between 2010 and 2015, while in the country the average value of the company loans increased by 0.50%. The final results of the models described show the same facts. The variables in these models are related to working capital or to turnover times. In all four models the accounts payable turnover period is preset, while in the neural network model all three turnover period variables are considered important in predicting bankruptcy. In the PCA based model the working capital component is determinant in the model.

My assumption that the SME sector in Harghita County is characterized by circular debt turned out to be true. One of the facts that must be mentioned here is the sign of the rate of total sales to total assets, which turned to be exactly the opposite as expected. Following a closer analysis, it turned out that more than half of the bankrupt companies have their sales in accounts receivable.

Two years before bankruptcy the accounts receivable rate from total sales was 47.37% in the case of the bankrupt group. This value deteriorated to 62.22% one year before bankruptcy. If we compare to the healthy group, we can see that two years before the base time, the same variable had a value of 21.59% and the value decreased to 20.21%.

***3. The bankruptcy prediction models based on principal component analysis are more reliable than models based on simple financial ratios.***

The accuracy of the models can be compared with the help of the ROC area and the Gini coefficient. We can conclude that the neural network model based on PCA is the most accurate. The accuracy of the hold out sample turned out to be 97.40%. In this model there was the smallest number of type I errors. We must mention that the neural network model based only on financial ratios turned out to be better than the logistic regression model based on principal component analysis. It can definitely be concluded that the PCA had increased the predictability of the models, yet this increase in accuracy was held back by the long testing and preparing of the data.

***4. In the prediction of SME bankruptcy the macroeconomic and macro financial variables can give a better accuracy to the models.***

Beside the basic logistic regression model, the effects of economic and macro financial variables have been tested. I used a 7-year trend coefficient as variable for the national GDP, national industry total sales, county GDP, county industry total sales, inflation and interest rate for medium term. As expected, it turned out that there are macro economic variables that improve the accuracy of the models. It was shown that the total sales based on county industry data have an impact on model accuracy. The county GDP trend also improved the accuracy of the model. In conclusion, the macroeconomic and macro financial variables slightly improved the logistic regression model. In the case of neural network, this improvement was not obvious from the results. The accuracy was the same and the results connected to type II error were slightly better. However, among the variables only the county GDP (0.302) and the inflation (0.347) relative turned out to be significantly important.

#### 4. SUCCESSIONS AND RECOMMENDATIONS

Based on the review on relevant literature and empirical research based on SME data from Harghita County, I have formulated some successions and recommendations for further research. Research on bankruptcy has become more and more important nowadays for creditors, economic decision makers and commercial partners as well. Research on bankruptcy and financial failure is still underrepresented in Central and Eastern Europe, and this is true to Romania too. The situation could be easily improved if financial data would be open sourced for researchers. A major part of articles have been based on big company data, while the SME sector has been neglected. Most articles are still searching for the best ratios and more accurate models (Altman and Hotchkiss, 2006). This is true in Romania, too. What is more, both SME financial modelling and research in this field need more attention.

In the future I consider it important to look for company datasets which contain information about companies that went financially distressed but survived over time. It would be interesting to see which ratios changed, what the causes which made the company survive the financial collapse were and whether they are still active after a period of three years. Which are the ratios that changed between the two groups, what could possibly affect them? Which are the factors that powered up bankruptcy? I am sure that companies in Harghita County do not make decisions on a planned strategy; the financial planning and the ability of modelling the decision from a financial point of view are still missing. I am also interested to observe how the lack of planning, as a habit, affects bankruptcy.

It is equally important to study the companies in the grey zone and their characteristics. In my opinion, in this case the financial ratios can be hardly separated between the two groups. They need a more complex and dynamic modelling. Thus, the need for data is much deeper. In the prediction models variables which characterize management habits or variables that can measure the decision effects must be incorporated. This type of data could be obtained only from interviews. These variables could improve the accuracy of models. The use of variables connected to management behaviour types can also improve accuracy. There have already been attempts to use such variables, such as Laitinen and Suvas (2016) who claim that, beside financial ratios, leader and cultural characteristics can improve accuracy.

In my research on available literature, it has turned clear that new model developing with higher accuracy can be obtained only if, beside financial ratios and macro economic factors, the model is upgraded with soft variables. Models must include other factors which come from outside (e.g. economic trends, regional conditions). Accuracy can be also improved by including other internal factors (e.g. financial politics, strategy and others) (Katits, 2010). Making a model general, it results in losing its accuracy capability. It is equally important to carry out research involving companies on regional level. This could result in creating better models. These models should incorporate variables that show the economic independency in the activity of a company, the independency of these companies from certain economic centres.

A considerable amount of research in model building does not take into consideration the shock effect of the economic crisis. The incorporation of time series could be important, yet they must be taken into account carefully: time series must not be split erroneously and data should characterise the economic fluctuation as a whole. It is interesting to see models resulted after and before an economic crisis. The results can point out the cause of the bankruptcy of SME. The models can react differently if they contain variables which characterise the economic crisis. Its shock has different effects in each industry, thus they must be treated separately.

The accuracy of financial failure models is situated below the result of bankruptcy prediction models. This is due to the structure of financially distressed companies which appear in the sample. Many publications neglect the fact that companies facing financial failure and those going bankrupt are part of the same data sample. If financially distressed companies are overrepresented in the data sample, the result could show similarities with companies from the healthy group. Consequently, this can lead to a decrease in accuracy. As a result, the financially distressed sample must be divided into successful/surviving and bankrupt groups.

Bankruptcy prediction models can be improved with variables that characterize the activity diversification of a company. If a company is presented in more than two markets the probability of going bankrupt is lower. Another variable could be the quality of a supplier. If the supplier depends heavily on a market, the probability of bankruptcy is higher. In order to achieve these, a more dynamic modelling is needed, completed with results from interviews.

## LIST OF PUBLICATIONS

### I. JOURNALS

#### 1.1. Foreign language journals

1. FEJÉR-KIRÁLY GERGELY - TÁNCZOS LEVENTE JÓZSEF: THE ANALYSIS OF PLANNING HABIT EFFECTS ON BUSINESS EFFICIENCY, International Conference on Business and Management, 26-27 April 2013, Izmir, Turkey, 202-211, INTERNATIONAL JOURNAL OF BUSINESS AND MANAGEMENT STUDIES Vol. 5, No 1, 2013, ISSN: 1309-8047.

2. Gergely FEJÉR-KIRÁLY (2015): Bankruptcy prediction: A survey on evolution, critiques, and solutions, *Acta Univ. Sapientiae, Economics and business*, 3, pp. 93-108, DOI: 10.1515/auseb-2015-0006.

#### 1.2. Articles in Hungarian Journals

1. FEJÉR GERGELY: A TELEPÜLÉSFEJLESZTÉSI INFRASTRUKTÚRA HELYZETE ROMÁNIÁBAN, KÜLÖNÖS TEKINTETTEL A KÖZLEKEDÉSI HÁLÓZATFEJLESZTÉRE, *Közgazdász Fórum*, 2006. - 5. KOLOZSVÁR, ISSN 1582-1986, 48-59.

### II. CONFERENCE PRESENTATIONS

#### 2.1 Foreign language

1. CSATA ANDREA - FEJÉR-KIRÁLY GERGELY - GYÖRGY OTTILIA - KASSAY JÁNOS: Competitive or developed region? 9<sup>th</sup> World Congress of Regional Science Association International, 9–12 May 2012, Temesvár – presentation, abstract – English

2. OTTILIA GYÖRGY, ANDREA CSATA, GERGELY FEJÉR-KIRÁLY, ZOLTÁN ANDRÁS: Entrepreneurial situation analysis of the development regions [Analiza situației antreprenoriale la nivelul regiunilor de dezvoltare], *Regionalizare și politici regionale*, editor: Roxana Demetra Stratulat, Lumen, 2014, 393-406, ISBN 978-973-166-373-9 – Romanian

3. SZŐCS ATTILA, CSATA ANDREA, F. KIRÁLY GERGELY: Conceptual model of the structural effect of brand equity on brand value, International Conference NATURA-ECON, Environmental Dynamics under the impact of Economic Trends - Realities and Perspectives, 7 March 2014, Szentgyörgy, 350-361, ISSN 2359-9081 – English

4. FEJÉR-KIRÁLY GERGELY: Factor analysis with financial ratios in the construction industry in Harghita County, 11th Annual International Conference on Economics and Business, CHALLENGES IN THE CARPATHIAN BASIN, Global challenges, local answers, 16-17 May – English

5. FEJÉR-KIRÁLY GERGELY - TÁNCZOS LEVENTE-JÓZSEF: Total revenue analysis of SMEs in Harghita County, 11th Annual International Conference on Economics and Business, CHALLENGES IN THE CARPATHIAN BASIN, Global challenges, local answers, 16-17 May, 2014 – English

## 2.2 Hungarian

1. FEJÉR-KIRÁLY GERGELY: Kockázati tőke finanszírozás a kis- és középvállalkozások esetében, *Gazdasági és Üzleti Kihívások a Kárpát-medencében Konferencia, 2011*, 248-256. ISBN: 978-606-8052-52-6.

2. FEJÉR-KIRÁLY GERGELY – Gáspár Bencéné dr. Vér Katalin: A helyi pénz és az informatika, *Vállalkozói és gazdasági trendek a Kárpát-medencében Konferencia, 2012*. Státus Kiadó, Csíkszereda, 73-84. ISBN 978-606-8052-79-3.

### III. OTHERS

Conference book editing:

1. FEJÉR-KIRÁLY GERGELY – LÁZÁR EDE: Vállalkozói és gazdasági trendek a Kárpát-medencében I–II–III kötet, Státus Kiadó, Csíkszereda, ISBN 987-606-8052-76-2.

Book:

2. VARGA JÓZSEF - FEJÉR-KIRÁLY GERGELY - SZÓKA KÁROLY - KOVÁCS TAMÁS: Nemzetközi pénzügyek, elektronikus tananyag, II. fejezet: Értéktőzsdék működése, under publication.