COMPARING FINANCIAL DISTRESS PREDICTION MODELS BEFORE AND DURING RECESSION

Nataša Šarlija
University of J.J. Strossmayer in Osijek, Faculty of Economics, Osijek, Croatia
Trg Ljudevita Gaja 7, 31000 Osijek, Croatia
Phone: ++ 385 31 224400; E-mail: natasa@efos.hr

Marina Jeger
University of J.J. Strossmayer in Osijek, Faculty of Economics, Osijek, Croatia
Trg Ljudevita Gaja 7, 31000 Osijek, Croatia
Phone: ++ 385 31 224400; E-mail: mjeger@efos.hr

Abstract:

The purpose of this paper is to design three separate financial distress prediction models that will track the changes in a relative importance of financial ratios throughout three consecutive years. The models were based on the financial data from 2000 privately-owned small and medium-sized enterprises in Croatia from 2006 to 2009, and developed by means of logistic regression. Macroeconomic conditions as well as market dynamic have been changed over the mentioned period. Financial ratios that were less important in one period become more important in the next period. Composition of model starting in 2006 has been changed in the next years. It tells us what financial ratios are more important during the time of economic downturn. Besides, it helps us to understand behavior of small and medium-sized enterprises in the period of pre-recession and in the period of recession.

Key words: *Financial distress prediction, SMEs, logistic regression, financial ratios*

1. INTRODUCTION

Financial distress prediction models have been developed and used for more than five decades for their ability to forecast whether a company will have certain financial problems or even go bankrupt in the next period, usually one year. Economic consequence of company failure is great. Therefore, creating a model by which it would be possible to identify financial distress is of great interest for entrepreneurs, investors, creditors, auditors and other stakeholders. In such a way it is possible not only to predict a probability that a company will default, but what is more important to make certain actions in order to prevent more serious consequences.

Making a model with high predictive power is a challenge. In the beginning of the effort for making distress prediction, financial analysis technique was used. It has evolved from a qualitative type of information assessing to a development of quantitative measures and various bankruptcy and financial distress models. In complex business conditions, mathematical and statistical models have become a necessity.

Financial distress prediction models are usually composed on financial information – financial ratios of solvency, activity, profitability, investment, and leverage. Despite the fact that many studies reported high predictive power for their ratios, a unique perfect combination of financial ratios hasn't been found. Models' composition and precision depend on data sample, data availability, data quality, methods of analysis. Besides, financial distress models developed on a specific sample can only be applied to the firms with the same characteristics as those included in the sample. However, a progress has been made toward selecting financial ratios that turned out to be significant in multi-ratio models. Chen and Shimerda (1981) reviewed 26 articles that classified 65 financial ratios incorporated in predictive studies between 1966 and 1975, and reported 41 financial ratios that were considered to be important given citation in one or more of the 26 articles. In addition to that, the authors referenced a study conducted by Pinches, Mingo, and Caruthers (1973) and classified those useful ratios in seven factors: Return on Investment, Capital Turnover, Financial Leverage, Short-Term Liquidity, Cash Position, Inventory Turnover, and Receivables Turnover. Besides separating financial ratios according their usefulness in predicting financial distress, researchers have studied the validity of different methodology used in model development. Balcean and Ooghe (2004) separated four types of classical statistical methods that have been applied in corporate failure prediction studies (univariate analysis, risk index models, multi distriminant analysis, and conditional probability models) and identified several issues related to the usage of a particular methodology in prediction model development.

Most of the models are composed on financial information for publicly-owned firms from developed countries in a specific time frame. Although they extracted some common and most predictive financial ratios, it is the combination of them that makes a difference. All of that emphasizes the need for developing different models that will fully reflect the changes in internal and external environment of privately-owned small and medium-sized enterprises (SMEs) for a specific country, and the ways those changes influence firm’s financial health.

All of this makes us research to what extent the models that were effective during the prosperity would be useful during the recession. In practice, there is a possibility to change cut-off while applying model and in such way make sure that default rate will not go up. But, as a researcher or practitioner you are aware that macroeconomic conditions as well as market dynamic have been changed over time and financial ratios that were important in one period might become less important in the next period. So, this paper has two aims. First, to compare three separate financial distress prediction models developed for three consecutive years that capture time of prosperity and time of recession. The models are based on the financial data from 2000 privately-owned small and medium-sized enterprises in Croatia from 2006 to 2009 and developed by means of logistic regression. Models are compared according to hit rates and their composition. It is our goal to find out which financial ratios are stronger predictors during recession and which during times of prosperity.

Second, to calculate error rate that would be made if the model created in 2006 would be applied in the following years.

The structure of the paper is the following. In the next section provides overview of previous research. Data and variables are described in section 3, methodology and results in section 4. The last section provides conclusion and discussion.

2. PREVIOUS RESEARCH

Ever since William H. Beaver (1966) demonstrated that financial ratios can be useful in the prediction of an individual firm failure, financial distress and bankruptcy prediction models have become increasingly popular among academic researchers. Numerous failure prediction models have been developed (Altman, 1968; Ohlson, 1980; Zmijewski, 1984; Zavgren, 1985) using various modeling techniques. In the light of summarizing work on prediction models, several issues have been noted. Firstly, financial distress prediction models lose their predictive power over time. Moyer (1977) tested the temporal and the firm size validity of Altman's model, and found only modest predictive ability when the original model parameters were applied to the new data. Zavgren (1985) and Holmen (1988) showed that, in the course of time, prediction models have performed less well to a certain extent. Secondly, certain methodological issues in terms of ignoring economic idiosyncrasies of the observed period were found in many studies. Mensah (1984) warned that, in addition to the selection of different ratios in the final prediction model, researchers typically analyze data across several years without considering the underlying economic events in those years. Besides, Mensah compared several bankruptcy prediction models developed by applying multiple discriminant analysis and concluded that "the best multivariate models would show some nonstationarity, with different ratios becoming important at different periods depending on the economic event that triggered the bankruptcies for the period examined" (p. 382 - 383).

The next question that needs to be answered is what financial ratios or groups of ratios become important when economic conditions change. Opler and Titman (1994) indicated that there is a positive relationship between financial condition and firm performance during economic downturns, and more highly leveraged firms tend to lose market share and experience lower operating profits than their competitors. The implication of their work would be that it is reasonable to expect that liquidity ratios and leverage ratios play important role in assessing firm's financial health during recession. Hendel (1996) argues that in recession non-liquid assets, such as inventories, is unnecessary since demand is low relative to inventories held. Therefore, during recession firms tend to deviate from the one-period profit maximizing behavior by depleting inventories in order to generate cash and improve their chances of survival. This implicitly assumes importance of liquidity and activity ratios that reflect changes in inventory and other short-term assets. Previously mentioned Mensah's study showed that the ratios that should be of most help in predicting bankruptcy in time of recession are related to short-term assets management (particularly inventory and receivables), liquidity and cash-flow-generating ability (Mensah, 1984).

3. DATA AND VARIABLES

There are three separated data samples for models' development and three for models' validation. Development samples are consisted of 1987 privately-owned small and medium-sized companies in Croatia. These companies were selected randomly from the population of Croatian companies that existed in 2009 in a way that the whole population of the companies was divided into two groups – financially healthy companies and financially distressed companies. If the firm wasn't able to pay a single obligation continuously over the period longer than 90 days in one year, than it is selected as financially distressed firm. In each group 1000 companies were randomly selected. After data cleaning, total sample of companies consists of 990 financially healthy and 997 financially distressed companies. Companies selected in 2009 with their financial statements in 2008 were analyzed over the period of 4 years where the status (healthy/distressed) might have changed during the period. Financial ratios are calculated from companies' financial statements. In developing first model, financial ratios were calculated for year 2006 and the financial state "distressed or healthy" is extracted from 2007. For the second model, financial ratios were calculated for year 2007 and the financial state "distressed or healthy" is extracted from 2008. And, for the third model, financial ratios were calculated for year 2008 and the financial state "distressed or healthy" is extracted from 2009.

Models are tested on validation samples which are created randomly for each year. For example, model developed for 2006 is tested on a validation sample created for the same year etc.

Samples distribution of the companies used for development and validation are given in table 1.

Table 1: Development and validation samples from 2006 to 2009.

Sample	2008/2009	2007/2008	2006/2007
Development – healthy companies	990	1307	1547
Development – distressed companies	997	681	439
Validation – healthy companies	894	917	949
Validation – distressed companies	99	81	46

There were 31 financial ratios together with region and industry used as predictors in logistic regression model. Initial group of 31 ratios was selected primarily based on previous research (see Chen and Simerda (1981), and Pinches, Mingo, and Caruthers (1973)) and covered all five main categories of ratios (liquidity ratios, profitability ratios, leverage ratios, operational or activity ratios, and solvency ratios). Descriptive statistics for 15 found significant in created models are given in table 2. Financial ratios that weren't significant are the following: Operating Revenues/Operating Expenses, Current ratio, Quick Ratio, Cash/Sales, Cast/Total Liabilities, Long-Term Assets Turnover, Inventory Turnover, Days Sales in

Inventory, Working Capital/Total Assets, Total Liabilities/Total Assets, Total Liabilities/Equity, Equity/Long-Term Assets, Total Liabilities/(Retained Earnings + Depreciation), Retained Earnings/Total Assets, Net Profit/Total Assets, and Net Profit Margin.

Table 2: Descriptive statistics for variables enter the models for healthy (H) and distressed (D) companies

Ratio	2006/2007	2007/2008	2008/2009
Operating Revenues/ Operating Expenses	H: 0,90 (0,39) D: 0,65 (0,47)	H: 0,93 (0,36) D: 0,64 (0,46)	H: 0,85 (0,41) D: 0,57 (0,46)
Net Profit/Equity	H: 0,19 (0,24) D: 0,07 (0,17)	H: 0,20 (0,24) D: 0,07 (0,16)	H: 0,17 (0,23) D: 0,05 (0,15)
Cash/Short-term Liabilities	H: 0,25 (0,35) D: 0,08 (0,21)	H: 0,30 (0,46) D: 0,09 (0,26)	H: 0,28 (0,36) D: 0,07 (0,20)
Equity/Total Assets	H: 0,28 (0,30) D: 0,14 (0,22)	H: 0,28 (0,30) D: 0,13 (0,21)	H: 0,31 (0,32) D: 0,12 (0,20)
Total Revenues/Total Assets	H: 1,31 (1,17) D: 0,60 (0,86)	H: 1,40 (1,22) D: 0,63 (0,88)	H: 1,36 (1,19) D: 0,57 (0,85)
Sales/Accounts Receivables	H: 15,03 (13,79) D: 9,19 (13,25)	H: 14,04 (13,33) D: 9,96 (13,55)	H: 14,07 (13,51) D: 9,90 (13,69)
Long-term Assets/(Equity + Long-term Liabilities)	H: 0,86 (1,20) D: 0,67 (1,11)	H: 0,85 (1,18) D: 0,69 (1,15)	H: 0,78 (1,09) D: 0,69 (1,13)
365/Receivables Turnover	H: 85,58 (94,92) D: 138,93 (138,07)	H: 83,84 (92,32) D: 125,72 (131,16)	H: 82,02 (94,41) D: 135,02 (137,77)
Equity/Sales	H: 2,80 (6,51) D: 6,05 (8,86)	H: 2,36 (5,98) D: 5,95 (8,83)	H: 3,74 (7,39) D: 6,73 (9,18)
Sales/Total Assets	H: 1,23 (1,14) D: 0,53 (0,82)	H: 1,31 (1,18) D: 0,55 (0,82)	H: 1,21 (1,15) D: 0,47 (0,77)
Long-term Liabilities/ Short-term Assets	H: 0,53 (1,25) D: 0,49 (1,22)	H: 0,57 (1,29) D: 0,61 (1,39)	H: 0,58 (1,33) D: 0,59 (1,31)
Short-term Liabilities/Total Assets	H: 0,57 (0,33) D: 0,74 (0,29)	H: 0,56 (0,33) D: 0,73 (0,30)	H: 0,53 (0,34) D: 0,73 (0,29)
Cash/Total Assets	H: 0,11 (0,17) D: 0,04 (0,10)	H: 0,11 (0,17) D: 0,04 (0,11)	H: 0,12 (0,17) D: 0,03 (0,11)
(Short-term Assets – Inventory) / Sales	H: 0,45 (0,46) D: 0,63 (0,62)	H: 0,44 (0,45) D: 0,58 (0,60)	H: 0,43 (0,47) D: 0,64 (0,64)
Total Revenues/Short-term Assets	H: 2,61 (2,65) D: 1,40 (2,15)	H: 2,83 (2,72) D: 1,55 (2,35)	H: 2,83 (2,72) D: 1,42 (2,28)

Note: first value in each cell is mean, and the value in parenthesis is standard deviation.

4. METHODOLOGY AND RESULTS

Previous research of methods used in predicting financial distress are logistic regression (LR), multiple discriminant analysis (MDA), neural networks (NN), and genetic algorithms (Aziz, Dar, 2006; Balcaen, Ooghe, 2004). It has also been shown that the best methodology for modeling has not been extracted yet, since it depends on the dataset characteristics. Altman et al. (1994) showed the best result by using linear discriminant analysis. Desai et al. (1996) got the best results by multilayer perception. Desai et al. (1997) showed that LR outperformed NN. Yobas et al. (2000) produced the best results using NN, while Galindo and Tamayo (2000) using CART decision tree.

Traditionally, different parametric models are used for classifying input vectors into one of two groups, which is the main objective of statistical inference on the financial distress prediction problem. Logistic regression provides a powerful technique analogous to multiple regression and ANOVA for continuous responses. Since the likelihood function of mutually independent variables $Y_1,\ldots,Y_n$ with outcomes measured on a binary scale is a member of the exponential family with $\left(\log\left(\frac{\pi_1}{1-\pi_1}\right),\ldots,\log\left(\frac{\pi_n}{1-\pi_n}\right)\right)$ as a canonical parameter (π_j is a probability that Y_j becomes 1), the assumption of the logistic regression model is a linear relationship between a canonical parameter and the vector of explanatory variables $\mathbf{x}_j$ (dummy variables for factor levels and measured values of covariates):

$$\log\left(\frac{\pi_j}{1-\pi_j}\right) = \mathbf{x}_j^{\tau}\boldsymbol{\beta} \tag{1}$$

This linear relationship between the logarithm of odds and the vector of explanatory variables results in a nonlinear relationship between the probability of Y_j equals 1 and the vector of explanatory variables:

$$\pi_j = \exp\left(\mathbf{x}_j^{\tau}\boldsymbol{\beta}\right)/\left(1+\exp\left(\mathbf{x}_j^{\tau}\boldsymbol{\beta}\right)\right) \tag{2}$$

In order to extract important variables we used forward selection procedure available in SAS software, with standard overall fit measures. Detailed description of the logistic regression can be found in Harrel (2001).

Logistic regression resulted in three separate financial distress prediction models presented in the table 3. Predictive ability of each model is adequate: 2006/07 model – Sommers' D = 0,605, Percent Concordant = 80,1; 2007/08 model – Sommers' D = 0,579, Percent Concordant = 78,8; 2008/09 model – Sommers' D = 0,630, Percent Concordant = 81,4. C statistics of the models indicate adequate fit of the models: 2006/07 model c = 0,803; 2007/08 model c = 0,790; 2008/09 model c = 0,815.

Several regularities can be noticed in the table above. Firstly, five ratios are constantly present in all three models (marked with *), and those ratios represent measures of profitability, liquidity, leverage, business activity and efficiency. Secondly, while individual ratios within the models are changing, the structure of the model in terms of groups of ratios, as well as a number of individual ratios included in the model, is relatively stable. Ratios marked with (♣) in each year represents those ratios that are relevant only in corresponding model. Thirdly, activity ratios represent the majority group in case of all three models.

Table 3: Financial distress models for each period composed of financial ratios with their level of significance.

Financial distress model 2006/2007		**Financial distress model 2007/2008**		**Financial distress model 2008/2009**	
Financial ratio	**p-level**	**Financial ratio**	**p-level**	**Financial ratio**	**p-level**
↑ Operating Revenues/ Operating Expenses*	0.0392	↑ Operating Revenues/ Operating Expenses*	0.0497	↑ Operating Revenues/ Operating Expenses*	0.0360
↑ LT Assets/(Equity + LT Liabilities)*	0.0004	↑ Cash/ST Liabilities	0.0001	↑ Cash/ST Liabilities	0.0001
↓ ST Liabilities/Total Assets*	0.0001	↑ LT Assets/(Equity + LT Liabilities)*	0.0010	↑ LT Assets/(Equity + LT Liabilities)*	0.0270
↑ Cash/Total Assets♣	0.0001	↓ ST Liabilities/Total Assets*	0.0001	↓ ST Liabilities/Total Assets*	0.0008
↑ Sales/Accounts Receivables♣	0.0001	↓ 365/Receivables Turnover♣	0.0001	↑Total Revenues/Total Assets♣	0.0047
↓ Equity/Sales*	0.0043	↓ Equity/Sales*	0.0108	↓ Equity/Sales*	0.0110
↑ Sales/Total Assets	0.0087	↑ Sales/Total Assets	0.0001	↓ (ST Assets – Inventory)/Sales♣	0.0001
↑ Net Profit/Equity*	0.0083	↓ LT Liabilities/ ST Assets♣	0.0707	↑ Equity/Total Assets♣	0.0001
		↑ Net Profit/Equity*	0.0001	↑ Net Profit/Equity*	0.0001
				↑ Total Revenues/ST Assets♣	0.0109

Note: ↑means that the bigger the ratio, the higher is the probability that firm will be healty in the next period, while ↓ means that the smaller the ratio, the higher is the probability that firm will be healthy in the next period.

Table 4: Hit rates on the hold-out validation samples for three models

Hit rate	**2006/2007**	**2007/2008**	**2008/2009**
For healthy companies	85,14%	82,33%	80,09%
For distressed companies	67,39%	66,67%	70,71%
Total hit rate	84,32%	81,06%	79,15%

Table 4 gives hit rates on the hold-out validation samples for each model built. The 2006/07 model is tested on the validation sample for the same period and the same stands for the other two models. Table 5 gives hit rates on the hold-out validation samples for the model built in 2006/07. So, here we tested precision of the 2006/07 model on 2007/08 and 2008/09 data.

Table 5: Hit rates on the hold-out validation samples for the 2006/07 model

Hit rate	**2006/2007**	**2007/2008**	**2008/2009**
For healthy companies	85,14%	80,42%	78,90%
For distressed companies	67,39%	65,43%	63,63%
Total hit rate	84,32%	79,19%	77,40%

It can be noticed that precision of the 2006/07 model is declining over the years which is not the case if each year separate model is built. Although total hit rate for the 2008/09 model is little bit lower than in previous years, hit rate for distressed companies is higher compared to previous years.

5. DISCUSSION AND CONCLUSION

As in many other developing countries, global recession reached Croatia somewhat later than it was the case with the developed world. By the end of 2008, Croatian economy started to experience first signs of recession – reduction of foreign investments, increase in energy prices, and decrease in export of Croatian goods and services. Besides, some of the reactions of Croatian government to the global crisis, such as taxes increase, were unfavorable for Croatian firms, especially the small and medium-sized private firms. Faced with a reduction of available funding sources and contractions in market demand, Croatian entrepreneurs had to change the usual way of doing business in order to survive. Most of them started with cutting costs by reducing inventories, increasing efficiency and downsizing. Those who managed to adapt to changes in the market, were the ones who suffered the least from the economic downturn.

Some of those changes are visible in comparison of prediction models developed on data prior to the recession and during recession. Alongside the changes and adaptation of everyday business activities to signs of recession, activity ratios gained a bigger share in the prediction model. Besides, ratios that incorporate equity as a source of funding are more present in the 2008/2009 model. Perhaps even more interesting is the fact that leverage ratios were reduced in number going from the 2007/2008 model to the 2008/2009 model. This implies that the lack of funding sources didn't have a significant negative impact on companies that successfully redesigned their business activities and maintained good relationships with customers and suppliers.

As previously mentioned, five ratio are constant in all three models. Those ratios are comprehensive ones and as such they reflect most of the changes in a life of a firm. For instance, the net profit/equity ratio (ROE) is composed of turnover ratios and profitability ratios. The operating revenues/operating expenses ratio refers to total revenues and total expenses accrued from the primary business. The LT Assets/(Equity + LT Liabilities) ratio indicates to what degree long-term assets is financed from long-term sources such as equity and long-term liabilities. Financially healthy companies recorded a higher value of this ratio relative to financially distress companies, but that value was still lower than 1 which indicates that part of short-term assets should be financed from long-term sources. In line with that, the ST Liabilities/Total Assets ratio measures the percentage of totals assets financed with short-term sources, primarily accounts payable. Finally, the equity/sales ratio indicates the amount of revenues generated with certain equity investment.

The 2006/2007 model and 2007/2008 model are quite similar in a sense that both contain only one ratio that's not included in any other model. Furthermore, both models have very similar ratio structure which can be described as a reflection of very similar economic conditions in both periods. Nevertheless, economic conditions reflected in the 2008/2009 model were considerably different than in the two previous years. The 2008/2009 model includes a total of four new ratios - three activity ratios (Total Revenues/Total Assets, Total Revenues/Short-term Assets, (Short-term Assets-Inventory)/Sales) and one leverage ratio (Equity/Total Assets).

Looking at hit rates, it can be concluded that if economic conditions are stabile, the same model can achieve adequate precision over the years. If the conditions are changing the first step is changing the cut-off policies after which development of the new model follows. However, the more adequate solution would be to include macroeconomic variables in financial distress prediction model which is the guidelines for the further research.

REFERENCES

1. Aziz, A. M., Dar, H. A., (2006), "Predicting Corporate Bankruptcy: Where We Stand?" *Corporate Governance*, Vol. 6, Issue 1, pp.18 – 33.
2. Altman, E. I. (1968), "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy" *The Journal of Finance*, XXIII.
3. Altman, E.I., Marco, G., Varetto, F., (1994), "Corporate Distress Diagnosis: Comparison Using Linear Discriminant Analysis and Neural Networks (the Italian experience)", *Journal of Banking and Finance* 18, pp. 505-529.
4. Balcaen, S., Ooghe, H., (2004), "35 Years of Studies on Business Failure: An Overview of the Classical Statistical Methodologies and Their Related Problems," Working Papers of Faculty of Economics and Business Administration, Ghent University, Belgium 04/248, Ghent University, Faculty of Economics and Business Administration.
5. Beaver, W. H. (1966), "Financial Ratios as Predictors of Failure" *Journal of Accounting Research*, Vol. 4, Empirical Research in Accounting: Selected Studies 1966, pp. 71-111.
6. Chen, K. H., Shimerda, T. A. (1981), "An Empirical Analysis of Useful Financial Ratios" *Financial Management*, pp. 51-60.
7. Desai, V.S., Crook, J.N., Overstreet, G.A., (1996), "A Comparison of Neural Network and Linear Scoring Models in Credit Union Environment", *European Journal of Operational Research 95*, pp. 24-35.
8. Desai, V.S., Conway, D.G., Crook, J.N., Overstreet, G.A., (1997), "Credit Scoring Models in Credit Union Environment Using Neural Network and Generic Algorithms" *IMA Journal of Mathematics Applied in Business & Industry 8*, pp. 323-346.
9. Galindo, J., Tamayo, P., (2000), "Credit Risk Assessment Using Statistical and Machine Learning: Basic Methodology and Risk Modeling Applications", *Computational Economics 15*, pp. 107-143.

10. Harrel F. E. Jr. (2001), "Regression Modeling Strategies with Applications to Linear Models, Logistic Regression and Survival Analysis". Springer: Berlin.
11. Hendel, I. (1996), "Competition under Financial Distress" *Journal of Industrial Economics*, Blackwell Publishing, vol. 44(3), pp. 309-24.
12. Holmen, J. S. (1988), "Using Financial Ratios to Predict Bankruptcy: An Evaluation of Classic Models Using Recent Evidence", *Akron Business and Economic Review,* Spring, Vol. 19, No. 1, pp. 52 – 63.
13. Mensah, Y. M. (1984), "An Examination of the Stationarity of Multivariate Bankruptcy Prediction Models" *Journal of Accounting Research*, Vol. 22, No. 1, pp. 380-395.
14. Moyer, R. C. (1977), "Forecasting financial failure: A re-examination" *Financial Management* 6 (1), pp. 11–17.
15. Ohlson, J. (1980), "Financial ratios and the probabilistic prediction of bankruptcy" *Journal of Accounting Research*, Spring, pp.109-131.
16. Opler, T. C., Titman S. (1994), "Financial Distress and Corporate Performance" *The Journal of Finance*, Vol. 49, No. 3, Papers and Proceedings Fifty-Fourth Annual Meeting of the American Finance Association, Boston, Massachusetts, January 3-5, 1994, pp. 1015-1040.
17. Pinches, G. E., Mingo, K. A., Caruthers, J. K. (1973), "The Stability of Financial Patterns in Industrial Organizations" *Journal of Finance*, pp. 389 – 396.
18. Yobas, M.B., Crook, J.N., Ross, P., (2000), "Credit Scoring Using Evolutionary Techniques" *IMA Journal of Mathematics Applied in Business & Industry*, 11, pp. 111-125.
19. Zavgren, C. V. (1985), "Assessing the Vulnerability to Failure of American Industrial Firms: A Logistic Analysis" *Journal of Business Finance and Accounting,* Vol. 12, pp. 19–45.
20. Zmijewski, M. E. (1984), "Methodological Issues Related to the Estimation of Financial Distress Prediction Models" *Journal of Accounting Research* 22 (Suppl.), pp. 59–86.