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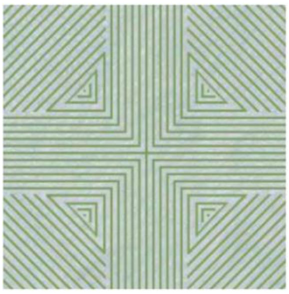

FINANCIAL RATIOS AND THE PREDICTION OF BANKRUPTCY

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Abstract

In this paper 10 financial ratios of 835 companies (48 companies were default and 787 companies were non-default) were used for prediction of bankruptcy. On the base of different combinations of these ratios which were formed by the taking one ratio from each financial factor such as financial leverage, capital turnover, cash position, etc., 16 z-score models estimated. Unfortunately, there was small compliance for predictability power of these bankruptcy models. On the other hand, we separately used all ratios (for example; X3 – cash/Total Assets, X6 – cash/Sales) classified by the same factor (for X3 and X6, cash position) in different models and found that it doesn't change the result of the predictability power of the bankruptcy models. Fortunately, this result shows the same pattern with most of the papers in this area.

Key words: *Kappa test, Altman's z-score, Edmister's z-score, predictability power, prediction of bankruptcy.*

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1. Introduction

The prediction of bankruptcy is very useful tool in finance, especially in banking for estimation of the credit risks. In the literature a credit risk is perceived as a disability or refusal for repayment of the granted loans in compliance with terms stipulated in the loan agreement as a result of default of the borrower or other reasons. The losses resulted from the credit risks are introduced in two forms: expected losses and unexpected losses. Although the credit risk arises between financial institutions and borrowers, other market participants also get involved. For example, employees getting the salary in different ways, the companies evaluating their funds and small traders can be considered as indirect elements of the market conjuncture. Before the appearance of the methods for credit risks assessment banks used to minimize potential risks by trying to know the customers closely and using other methods. Naturally, there were always subjective factors in decision making process. Measuring the credit risks has great importance from the perspective of debt management and taking preventive measures. By applying the methods of credit risk assessment, banks can respond to the question whether or not to grant the loan to the customer. In order to determine the credit risk both statistic and econometric methods can be used. It requires long time series or data network with a large volume. However banks have not shown the interest for this estimation before. By this necessity the adjustment in the Basel II framework intended to accumulate the necessary statistic data by banks. In this paper, we have tried to evaluate the prediction of bankruptcy for companies in Azerbaijan.

2. Literature review

We will begin to discuss the "bankruptcy model" which is assuming the linear relationship between dependent and independent variables. Usually, the dependent variable of such models (Z) is equal to 1 for non-bankrupt companies and is equal to 0 for bankrupt companies. Altman’s (1968) model is one of the most used models in this field. Altman (1968) has prepared z-score methodology based on the financial indicators of 66 main companies. In the following years Altman improved this research several times. In his research paper called “Zeta Analysis” (1977), he took 111 companies as research object over the period of 1962-1975. So, 53 of these companies had become bankrupt, of which 29 were companies but 26 were retail trade firms. Whereas 32 of companies that had not become bankrupt were industrial companies and 26 were retail trade firms. Altman (2000) also constructed research titled “Predicting financial distress of companies: revisiting the z-score and zeta models”. Z-score model introduced by Altman (1968) for determining the credit risk was significant and has been used widely since the middle of the 20th century. The explaining variables used in each of three models convey the same meaning. However, X_4 variable participating in Altman’s (1998) default model on non-production sectors is different from the same variable (X_4) of other two models.

Other prevailing method had been introduced by Edmister (1972). He examined 19 financial ratios in his work and used previous empirical researches for ratio selection. Edmister (1972) had suggested the following financial ratios: inventory/net working capital, net working capital/total assets, current assets/total debt, total debt/equity, fixed assets/equity, cash flow/current liabilities, current liabilities/equity, equity and long-term debt/fixed assets, inventory/sales, fixed assets/sales, total assets/sales, net working capital/sales, equity/sales, earnings before taxes (EBT)/sales, EBT/total assets, EBT/equity, and EBT plus depreciation/total debt. Edmister (1972) had used 7 financial ratios in his model. While establishing z-score values as a dependent variable in the model he coded zero 0 for those companies which considered as default case, otherwise it was coded as 1. So, in accordance with this model the companies are classified to be not default case if z-score of these ones equal to 0.530 and more. Whereas the cases less than 0.530 are considered to be default case. We will discuss largely Edmister's (1972) approach in the next sections.

Sprcic et al. (2013) have used Edmister's approach in their research work which is called "The applicability of the Edmister model for the assessment of credit risk in CROATIAN SMEs". They estimated the Kappa test to define agreement for I and II type errors. Sprcic et al. (2013) found that there is very little compliance between predicting financial difficulties according to Edmister and the real bank sample.

Ohlson (1980) is one of the authors who have investigated the prediction of bankruptcy using the logit model. He observed 105 default and 2058 non-default companies to develop his bankruptcy model and used **the maximum likelihood** approach as the estimating method.

3. Financial ratios

Chen and Shimerda (1981) effectively summarized the financial ratios which have been used by other authors. Here, we use their table (see Chen and Shimerda (1981), page 57) and believe that it will be helpful to choose our financial ratios.

Table 1
Chen and Shimerda's (1981) table

Factor	**Ratio**	**Beaver**	**Altman**	**Deakin**	**Study by Edmister**	**Blum**	**Elam**	**Libby**
Return on Investment	Net Income/Sales*						X	
	Funds Flow/NW						X	
	Funds Flow/TA						X	
	Net Income/TA	X		X				X
	Net Income/NW							
	EBIT/Sales						X	

	EBIT/TA		X				X	
	NI/Common Equity**					X		
Capital Turnover	QA/TA			X				
	Funds Flow/Sales						X	
	Current Assets/TA			X				X
	Net Worth/Sales				X			
	Sales/TA		X				X	
	WC/TA*	X	X	X				
Financial Leverage	Total Liabilities/TA	X		X			X	
	Total Liabilities/NW					X	X	
	Long-Term Debt/CA**						X	
	Funds Flow/TD**	X		X		X	X	
	Funds Flow/CL**				X			
	Retained Earnings/TA**		X					
Short-Term Liquidity	Current Assets/CL	X		X			X	X
	Quick Assets/CL			X	X		X	
	Current Liabilities/NW				X			
	Current Liabilities/TA						X	
Cash Position	Cash/Sales			X				
	Cash/Total Assets			X				X
	Cash/Current Liabilities			X			X	
	No Credit Interval**	X						
	Quick Flow**					X		
Inventory Turnover	Current Assets/Sales			X				X
	Inventory/Sales				X			
	Sales/Working Capital			X	X			
Receivables Turnover	Quick Assets/Inventory**					X		
	Quick Assets/Sales			**X**				

*Ratio not included in the final factors of the PEMC studies.
**Ratio not in the 48 ratios included in the PEMC study.

In addition, we will consider Chen and Shimerda's (1981) result when choosing the financial ratios of our z-score model. They said: "….The ratios classified by the same factor are highly correlated, and the selection of one ratio to represent a factor can account for most of the information provided by all the ratios of that factor. Inclusion of more than one ratio from a factor leads to multicollinearity among ratios and distorts the relationship between the dependent and independent variable…" (See Chen and Shimerda's (1981), page 59). Altman and Sabato's (NA) paper is another useful source on the classification of the financial ratios. They grouped the financial ratios over 5 factors as following:

Leverage: Short Term Debt/Book Value of Equity, Book Value of Equity/Total Liabilities, Liabilities/Total Assets.

Liquidity: Cash/Total Assets, Working Capital/Total Assets, Cash/Net sales, Intangible/ Total Assets.

Profitability: Earnings before Interest and Taxes/Sales, Earnings before interest, taxes, depreciation and amortization/Total Assets, Net Income/Total Assets, Retained Earnings/Total Assets, Net Income/Sales.

Coverage: Earnings before interest, taxes, depreciation and amortization/Interest Expenses, Earnings before Interest and Taxes/Interest Expenses.

Activity: Sales/Total Assets, Account Payable/ Sales, Account Receivable/ Liabilities.

To define the financial ratios of our z-score model, we observed 835 companies (48 companies were default and 787 companies were non-default) and collected their several financial indicators for the period 2006 - 2012. These financial indicators have been used to calculate 10 financial ratios and constructed a cross-section data base. Three of them were chosen on the base of Altman and Sabato (NA) while seven financial ratios were chosen on the base of Chen and Shimerda (1981). All of them are given in table 2

Table 2

Our financial ratios

Marks	**Ratios**	**Factor**	**Source**
X_1	Book Value of Equity /	Financial	Altman and Sabato

	Total Liabilities	leverage	(NA)
X_2	Sales / Total Assets	Capital turnover	Chen and Shimerda (1981)
X_3	Cash/ Total Assets	Cash position	Chen and Shimerda (1981)
X_4	Total Liabilities/ Total Assets	Financial leverage	Chen and Shimerda (1981)
X_5	Working Capital / Tot. Assets	Capital turnover	Chen and Shimerda (1981)
X_6	Cash/ Sales	Cash position	Chen and Shimerda (1981)
X_7	Intangible/ Total Assets	Liquidity	Altman and Sabato (NA)
X_8	Net Income / Total Assets	Return on Invest.	Chen and Shimerda (1981)
X_9	Net Income / Sales	Return on Invest.	Chen and Shimerda (1981)
X_{10}	Account Payable / Sales	Activity	Altman and Sabato (NA)

4. Methodology

As mentioned above, dependent variable (Z) of this type model (z-score model) is equal to 0 when observed company is default; otherwise it is equal to 1. We know that such models are called model with binary dependent variable. Suppose that our z-score model is as following:

$$Z_i = \beta_0 + \sum \beta_j X_{ij} + u_i \qquad (5.1)$$

Where, Z_i is a dependent variable of the model which is coded as 0 for default companies and coded as 1 for non-default companies, X_{ij} are financial ratios of the model which have been introduced in section 3, u_i is disturbances of (5.1) model, i = 1,2,….,42 (see section 3) and j = 1,2,…,10.

It is clear that, (5.1) type linear models have two major fundamental problems: Non-normality of the disturbances $u_i$and Heteroscedastic variance of the disturbances u_i. The assumption of normality for u_i is no tenable for (5.1) model because dependent variable (Z) of this model takes only two values: 1 and 0. Therefore u_i is equal to $1 - \beta_0 - \sum_{j=1}^{11} \beta_j X_{ij}$ when $Z_i = 1$ and u_i is equal to $-\beta_0 - \sum_{j=1}^{11} \beta_j X_{ij}$ when $Z_i = 0$. Under this phenomenon, we can argue that u_i follows the binomial distribution. But it is not be so critical. Because OLS point estimates still remain unbiased. In other hand, as simple size increases OLS estimators tend to be normally distributed. From the statistics, we already know that the mean is equal to P_i (the probability of $u_i = 1 - \beta_0 - \sum_{j=1}^{11} \beta_j X_{ij}$) and variance is equal to $P_i(1 - P_i)$ for the binomal distribution. Therefore, we see that the variance is a function of the mean in binomial distribution. Meaning that, the disturbances are always heteroscedastic in (5.1) model. But heteroscedastic models like (5.1) can be transformed to homoscedastic model as following:

$$Z_i^* = \beta_0^* + \sum \beta_j X_{ij}^* + u_i^* \qquad (5.2)$$

Where,$Z_i^* = \frac{Z_i}{\sqrt{h_i}}$, $\beta_0^* = \frac{\beta_0}{\sqrt{h_i}}$, $X_{ij}^* = \frac{X_{ij}}{\sqrt{h_i}}$, $u_i^* = \frac{u_i}{\sqrt{h_i}}$,$h_i = var(u_i) = P_i(1 - P_i) = \hat{Z}_i(1 - \hat{Z}_i)$. We can get $\hat{Z}_i$ from the equation (5.1).

Now let's discuss how we can use the financial ratios which have been given in table 2. For Altman and Sabato's (NA) and Chen and Shimerda's (1981) classifications, we can't use (X_1, X_4), (X_2, X_5), (X_3, X_6), (X_8, X_9) pairs together in (5.2) model. In this context, we are planning to estimate (5.2) model for all combinations of the financial ratios. These are as following:

Model (1): $X_7^*, X_{10}^*, X_1^*, X_2^*, X_3^*, X_8^* \rightarrow Z^*$

Model (9): $X_7^*, X_{10}^*, X_4^*, X_2^*, X_3^*, X_8^* \rightarrow Z^*$

Model (2): $X_7^*, X_{10}^*, X_1^*, X_2^*, X_3^*, X_9^* \rightarrow Z^*$ Model (10): $X_7^*, X_{10}^*, X_4^*, X_2^*, X_3^*, X_9^* \rightarrow Z^*$

Model (3): $X_7^*, X_{10}^*, X_1^*, X_2^*, X_6^*, X_8^* \rightarrow Z^*$ Model (11): $X_7^*, X_{10}^*, X_4^*, X_2^*, X_6^*, X_8^* \rightarrow Z^*$

Model (4): $X_7^*, X_{10}^*, X_1^*, X_2^*, X_6^*, X_9^* \rightarrow Z^*$ Model (12): $X_7^*, X_{10}^*, X_4^*, X_2^*, X_6^*, X_9^* \rightarrow Z^*$

Model (5): $X_7^*, X_{10}^*, X_1^*, X_5^*, X_3^*, X_8^* \rightarrow Z^*$ Model (13): $X_7^*, X_{10}^*, X_4^*, X_5^*, X_3^*, X_8^* \rightarrow Z^*$

Model (6): $X_7^*, X_{10}^*, X_1^*, X_5^*, X_3^*, X_9^* \rightarrow Z^*$ Model (14): $X_7^*, X_{10}^*, X_4^*, X_5^*, X_3^*, X_9^* \rightarrow Z^*$

Model (7): $X_7^*, X_{10}^*, X_1^*, X_5^*, X_6^*, X_8^* \rightarrow Z^*$ Model (15): $X_7^*, X_{10}^*, X_4^*, X_5^*, X_6^*, X_8^* \rightarrow Z^*$

Model (8): $X_7^*, X_{10}^*, X_1^*, X_5^*, X_6^*, X_9^* \rightarrow Z^*$ Model (16): $X_7^*, X_{10}^*, X_4^*, X_5^*, X_6^*, X_9^* \rightarrow Z^*$

5. Empiric results

We estimated combinations (model (1)-model (16)) of equation (5.2) by OLS and summarized the results in table 3.

Table 3

Performance of the bankruptcy models

	X_1^*	X_2^*	X_3^*	X_4^*	X_5^*	X_6^*	X_7^*	X_8^*	X_9^*	X_{10}^*	C	R^2
Model (1)	-0.63^{a}	-0.00^{c}	-0.80^{a}	------	------	------	-1.90^{a}	0.00^{a}	------	-0.00^{a}	5.44^{a}	0.48
Model (2)	-0.72^{a}	0.00^{a}	-0.86^{a}	------	------	------	-1.86^{a}	------	1.28^{a}	-0.00^{a}	5.38^{a}	0.39
Model (3)	-0.63^{a}	-0.00	-------	------	------	0.00^{b}	-1.65^{a}	0.00^{b}	------	-0.00^{b}	4.97^{a}	0.39
Model (4)	-0.69^{a}	0.00	-------	------	------	0.00^{b}	-1.61^{a}	------	0.89^{a}	-0.00^{b}	4.91^{a}	0.44

Model (5)	-0.57^{a}	-------	-1.08^{a}	------	-1.03^{a}	------	-4.02^{a}	0.00^{a}	------	-0.00^{b}	7.52^{a}	0.88
Model (6)	-0.57^{a}	-------	-1.28^{a}	------	-0.93^{a}	------	-3.79^{a}	------	1.65^{a}	-0.00^{b}	7.19^{a}	0.85
Model (7)	-0.53^{a}	-------	-------	------	-0.64^{a}	0.00^{a}	-2.89^{a}	0.002	------	-0.00^{c}	6.11^{a}	0.74
Model (8)	-------	-------	-------	------	-0.86^{a}	0.00^{b}	-3.24^{a}	------	1.26^{a}	-0.00	6.30^{a}	0.90
Model (9)	-------	-0.00	-0.51^{a}	0.35^{a}	------	------	-1.26^{a}	0.00^{b}	------	-0.00^{c}	3.35^{a}	0.46
Model (10)	-------	0.00^{b}	-0.50^{a}	0.39^{a}	------	------	-1.15^{a}	------	0.69^{a}	-0.00^{c}	3.08^{a}	0.57
Model (11)	-------	-0.00	-------	0.34^{a}	------	0.00^{c}	-1.10^{a}	0.00	------	-0.00	3.08^{a}	0.34
Model (12)	-------	0.00	-------	0.34^{a}	------	0.00	-1.07^{a}	------	0.33^{a}	-0.00	3.03^{a}	0.35
Model (13)	-------	-------	-0.61^{a}	0.31^{a}	-0.46^{a}	------	-2.20^{a}	0.00^{a}	------	-0.00	4.43^{a}	0.76
Model (14)	-------	-------	-0.53^{a}	0.50^{a}	-0.45^{a}	------	-1.83^{a}	------	0.97^{a}	-0.00	3.50^{a}	0.94
Model (15)	-------	-------	-------	0.31^{a}	-0.41^{a}	0.00^{a}	-1.91^{a}	0.00^{c}	------	-0.00	3.94^{a}	0.86
Model (16)	-------	-------	-------	0.27^{a}	-0.38^{a}	0.00^{a}	-1.89^{a}	------	0.51^{a}	-0.00	3.98^{a}	0.79

a – significant at 0.01
b – significant at 0.05
c – significant at 0.10

It is clear that from table 3, R^2 value imply model (5), model (6), model (7), model (8), model (13), model (14), model (15) and model (16) has better performance than others. But it is not enough to say that these models are able to classify the companies correctly. To say this, we need to define the predictability power of these models by calculating the I type and II type errors.

6. Total errors and predictability power

In section II, we note that 48 of 835 are default enterprises and 787 are operating enterprises in fact. Now we discuss the error of our estimation. As always I type error is considered to be more dangerous than II type error. Here, because classifying the non-default enterprises like default isn`t risky for bank.

Although in this case, bank may face losing its durable customers for sure, but is it possible to forecast the default case in order to avoid the credit risk in presence of I type error and II type error? To respond this question it is necessary to define the possibility of making I type error and II type error. Concretely, **I type error** means that the enterprises are classified as non-default however it is of default status. **II type error** means that the enterprises are classified as default however it is of non-default status. To minimize I type error, we will choose a combination which provides the correct classification of 95 percent of default companies. So, in table 4, have been given percentiles of II type error in condition of the correctly classification of 95 percent of default companies and we can easily see that, all models have very low performance. In other words, all models in table 4 have more than 85% total error. The classification on the base of the model (14) which has best performance (see table 3) caused 89% II type error.

Table 4
Predictability power in condition of the correctly classification of 95 percent of default companies

	I type error	II type error	**Total error**	**Z score**	**Cohen's Kappa test**	
					Value	Result
Model (1)	0.40%	92.93%	93.33%	5.44	-0.006	Very small compliance
Model (2)	0.40%	87.65%	88.05%	6.03	0.001	Small compliance
Model (3)	0.40%	86.21%	86.61%	5.28	0.003	Very small compliance
Model (4)	0.40%	86.20%	86.60%	4.90	0.003	Small compliance
Model (5)	0.40%	92.60%	93.00%	7.52	-0.001	Very small compliance
Model (6)	0.40%	86.20%	86.60%	7.88	0.003	Small compliance
Model (7)	0.40%	93.20%	93.60%	6.13	-0.010	Very small compliance
Model (8)	0.40%	87.30%	87.70%	6.56	0.001	Small compliance
Model (9)	0.40%	87.90%	88.30%	6.11	0.001	Small compliance
Model (10)	0.40%	90.00%	90.40%	5.98	-0.002	Very small compliance

Model (11)	0.40%	87.90%	88.30%	3.08	0.001	Small compliance
Model (12)	0.40%	86.10%	86.50%	3.11	0.003	Small compliance
Model (13)	0.40%	92.90%	93.30%	4.43	-0.010	Very small compliance
Model (14)	0.40%	88.97%	89.37%	3.91	-0.001	Very small compliance
Model (15)	0.40%	88.13%	88.53%	3.94	0.000	Small compliance
Model (16)	0.40%	86.69%	87.09%	4.15	0.002	Small compliance

For the measuring of the predictability power of the bankruptcy models we use Cohen's (1960) Kappa[3] test. As it seems, the computed value of Kappa test falls to the first and second intervals (see footnote 1). It means that we have obtained only small and very small compliance. However, in order to use this classification in forecasting the default status and non-default status of enterprises, the computed result of test should be more than 0.81. Otherwise there is not any significance to use this classification in forecasting. We made an effort to provide classification for operating enterprises in the country through conducting the observations. It should be expedient if we use the available data of banks regarding default and non-default case of enterprises.

7. Conclusion

Z-score approach was used to predict the credit risk on the basis of Altman`s and Edmister`s approaches in this research. There were some results obtained through analyzing the implementation of this method in forecasting the credit risks in banking system. Financial ratios of 835 companies which selected on

[3]The value of this test is as follow:

$$k = \frac{\sum f_0 - \sum f_e}{N - \sum f_e}$$

Where, k – the value of kappa test, $\sum f_0$– sum of frequency on both observed classification, $\sum f_e$ – sum of frequencies on both expected classification, *N*– size of observation. The computed value of Kappa test is examined within 6(six) significance interval: $k \leq 0$(Very small compliance), $0 < k \leq 0.20$(Small compliance), $0.21 < k \leq 0.40$ (Acceptable compliance), $0.41 < k \leq 0.60$ (Medium strong compliance), $0.61 < k \leq 0.80$ (Significant compliance), $0.81 < k$ (Almost perfect compliance). We also found the application of this test in some papers which have been introduced by Cohen (1968), Cecilia and Joseph (1993), Helena (1980), Sprcic, Klepac and Suman (2013).

random were used to estimate the Z value. We looked through the problem by using the financial ratios as explanatory variables in estimating the function Z as dependent variable. Dependent variable Z is taken as 0 (zero) for default enterprises. Whereas it is taken for an operating enterprise as 1 (one). Finally, we get the regression which gives an opportunity to classify Z-score for financial system of Azerbaijan. We have fulfilled the classification of randomly selected 835 companies by using this regression. However, because the result of kappa test wasn't statistically significant, we couldn't use this classification to predict the bankruptcy.

On the other hand, we separately used all ratios (for example; X_3 – cash/Total Assets, X_6 – cash/Sales (see table 2)) classified by the same factor (for X_3 and X_6, cash position) in different models and found that it doesn't change the result of the predictability power of the bankruptcy models. Fortunately, this result shows the same pattern with the paper which has been introduced by Chen and Shimerda (1981).

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