# THE RELATIVE IMPORTANCE OF FINANCIAL RATIOS AND NONFINANCIAL VARIABLES IN PREDICTING OF INSOLVENCY

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## Abstract

One of the most important decisions in every bank is approving loans to firms, which is based on evaluated credit risk and collateral. Namely, it is necessary to evaluate the risk that client will be unable to repay the obligations according to the contract. After Beaver's (1967) and Altman's (1968) seminal papers many authors extended the initial research by changing the methodology, samples, countries, etc. But majority of business failure papers as predictors use financial ratios, while in the real life banks combine financial and nonfinancial variables. In order to test predictive power of nonfinancial variables authors in the paper compare two insolvency prediction models. The first model that used financial rations resulted with classification accuracy of 82.8%, while the combined model with financial and nonfinancial variables resulted with classification accuracy of 88.1%.

**Key words:** *Insolvency prediction, Financial ratios, Nonfinancial variables*

## 1. INTRODUCTION

Prediction of business failure is very interesting topic for both practitioners and academics. Business failure in the current globally unstable business environment is becoming more important since large number companies are faced with decreased demand, reduced revenues/income, what in short term results with insolvency and bankruptcy in the long term. For the prediction of business failure are interested all stakeholders, particularly investors and creditors. In countries like Croatia which are bank oriented (i.e. banks are main sources of financing) the problem of business failure is particularly interesting from the perspective of the banks. Namely, every bank must control and manage credit risk (among other business risks) in order to survive and earn profit for the shareholders.

Business failure can be defined in different ways but from the perspective of banks credit risk management it is important to asses the probability of default for the each client. According to the Croatian regulations default is the situation in which client is failing to make obliged payments of any kind of debt in period longer than 90 days (Pervan, Filipović, 2010). Many banks develop internal tools for credit risk assessment, usually based on financial ratios, which are calculated from the historical financial statements. This kind of credit risk models are usually based on the Altman's (1968) methodology, in which selected financial ratios were compared for two groups of companies (healthy and bankrupted). Altman's analysis resulted with finding that only five financial ratios were enough to distinguish healthy from bankrupted companies. After Altman's seminal paper many later studies tried to upgrade methodology and models predictive power. But almost all studies were focused only on financial ratios, while nonfinancial variables (management, employees, clients, industry, etc) were excluded from the failure prediction models.

Empirical insights into the practice of banks have revealed that banks use financial and nonfinancial information when assessing clients credit risk. Since only a few papers used this kind of approach authors of this paper wanted to explore the relative importance of financial and nonfinancial information in insolvency prediction. Analysis was conducted on the sample of 825 clients of a Croatian commercial bank, where 15.39% of clients were insolvent, while 84.61% were solvent. Empirical findings indicate that combined insolvency prediction model (with financial and nonfinancial variables) has outperformed model with only financial variables. Namely, model that used only financial rations resulted with classification accuracy of 82.8%, while the combined model with financial and nonfinancial variables resulted with classification accuracy of 88.1%. This empirical finding indicates that prediction of insolvency and credit risk management can be improved by incorporating nonfinancial information in banks lending decisions.

## 2. PREVIOUS RESEARCH

Credit risk management in every bank requires detailed analysis of the client previous and expected financial position. Namely, bank must evaluate the risk that client will be unable to repay the principal and interest according to the contract. Empirical research in few Croatian banks (Pervan, Peko, 2008) has revealed that banks in practice use financial and nonfinancial variables for evaluation of client failure. Academics have been analyzing the issue of business failure for many years, while this stream of research has started in the 1930-es, when Fitz Patrick analyzed financial profile of companies with risk of business failure (Fitz Patrick, 1932).

Beaver (1967) defined business failure as inability of a firm to pay its financial obligations. Research sample incorporated 79 listed failed firms in period 1954-1964. Each failed firm was matched with a non-failed firm from the same industry and with similar asset size. The best discriminator between failed and non-failed firms was ratio cash flow/total debt, where cash flow was calculated as net income plus depreciation, depletion and amortization. Altman (1968) has improved research methodology by usage of multiple discriminate analysis (MDA). Research sample incorporated 33 listed bankrupted firms and 33 listed "healthy" firms from manufacturing sector. The sample of nonbankruptcy firms was matched by industry, size and year. Obtained MDA model resulted with five ratios which were significant for bankruptcy prediction and discrimination between "healthy" and bankrupted firms. Classification accuracy of Altman's 1968 Z-Score model was 95%, while model error was 5%, when testing was done on estimation sample and with data one year before bankruptcy. Classification error has increased to 17% percent with data two years before bankruptcy, indicating classification accuracy of 83%.

The first research on SME business failure was done by Edminister (1972) who also used MDA as statistical technique to discriminate among loss and non-loss SME borrowers. Empirical analysis has resulted with MDA model with seven financial ratios. Classification accuracy of model was 93%. Research also revealed that models predictive power depends on ratios calculation approach. Namely, model with industry relativized ratios resulted with higher classification accuracy in comparison with model based on classical ratios. Ohlson (1980) was the first one who suggested usage of logit model instead of MDA. Namely, MDA has the following main characteristics: requirement for normality of predictors an requirement for the same variance-covariance matrices for both groups. The logit model does not have assumptions on a priori probabilities and distribution of predictors. Ohlson did not use match pair sample, but he used 105 listed bankrupted firms and randomly chosen 2,058 listed non-bankrupted firms. Classification accuracy of Ohlson's model was 96.3%. Bankruptcy prediction study for retail sector was done by Bhargava et al. (1998). Logit model for the retail sector indicated that Altman's Z-Score had better bankruptcy predictive power in comparison with cash flow and inventory turnover. Also, ROA outperformed cash flow and inventory turnover, while cash flow outperformed inventory turnover in terms of bankruptcy predictive power.

Nam and Jinn (2000) used logit model with data for 46 listed bankrupted companies and 46 matched (by industry and size) non-bankrupted listed companies from Korea. Authors used 33 financial ratios, while only the following three ratios have been significant in prediction of bankruptcy. Classification accuracy for estimation sample was 77.2%, while for holdout sample it was little lower (76.2%). Vuran (2009) in his study used data for 78 Turkish public and private failed companies in period 1999-2007. Failed firms were randomly matched with data for 91 non-failed firms (from the same industry and year). Classification accuracy of model with data one year before failure was 84.4%, while model with data for two years before failure had classification accuracy of 80.3%. Logistic regression resulted with finding that the same variables like in MDA models were significant for failure prediction. Classification accuracy of the logistic regression model with data one year before failure was 84.4%, while the model with data for two years before failure had classification accuracy of 82%.

Šarlija et al. (2009) developed model for prediction of insolvency on the sample of 4,213 insolvent firms and 55,903 solvent firms from Croatia. Insolvency prediction model was based on 14 financial ratios and two dummy variables (industry and county). Models predictive accuracy was 68.16% for solvent firms and 74.22% for insolvent firms, when tested on holdout sample. Pervan et. al. (2011) developed model for bankruptcy prediction based on the data for Croatian firms. Research was conducted on the sample of 78 bankrupted companies and 78 healthy companies from Croatian manufacturing and trade/wholesale industries. Use of MDA has shown to be problematic since two major assumptions were violated: data normality and equality of covariance matrices. MDA models accuracy in prediction of bankrupted companies was 79.5%. LR model had higher classification accuracy (85.9%) in comparison with MDA.

On the basis of listed and other similar research it is possible to conclude that historical financial information is useful for business failure prediction. Research from different countries has shown that all groups of financial ratios (profitability, liquidity, activity, solvency...) can effectively contribute in modeling of business failure. Also, here we must point out that statistical methodology has changed during the years. Namely, while early studies used MDA later studies used conditional probabilities model (logit, probit, logistic regression). All previously presented papers dealing with business failure prediction put focus only to financial ratios. Only a few papers used non-financial variables. Thus for example, Grunert et al (2005) used data from four German banks and compared six financial and two non-financial factors in calculation of credit score. As non-financial variables authors used management quality and market position. Research sample included 340 non-defaulted events and 69 defaulted events. Empirical research was based on the three models. The first model used only financial variables for calculation of credit score and its accuracy in predicting default was 88.75%. The second model was based on non-financial variables only and resulted with credit score and its accuracy in predicting default of 89.00%. The final, third model combined financial and non-financial variables resulted with credit score with highest accuracy in predicting default (91.69%). Findings suggest that predictive power of banks scoring models can be improved by incorporating non-financial variables.

Altman et al. (2008) on the sample of UK SME tested informational value of non-financial information for prediction of failure (default). Research sample included 2,237,147 nonfailed and 26,256 failed SME. The basic default prediction model included five financial ratios, while the total model besides financial included selected non-financial variables. Empirical findings indicated that total model had 9% better predicting power in comparison with the basic model. As statistically significant non-financial variables the following should be pointed out: legal actions by creditors, filling history, comprehensive audit report and some firm specific characteristics.

## 3. RESEARCH DATA AND METHODOLOGY

Research sample was based on the data-base of a Croatian commercial bank, which comprised financial and non-financial data about clients. Data base included data for 825 clients-firms, while financial ratios were calculated on the basis of 2010 financial statements i.e. one year before default. List of defaulted firms was obtained on 31 December 2011 and that list includes all firms which haven't been able to settle debts (principal and interest) in period loner than 90 days. Within the sample 127 firms (15.4%) were defaulted, while 698 firms (84.6%) were non-defaulted. Relatively high percentage of defaulted firms in the sample is result of economic crises which has reflected its negative effects on Croatian economy in 2010 and 2011. On the basis of financial statements from 2010 we have calculated the initial set of 15 financial ratios that were often used in business failure literature.

Obtained data-base included information about seven nonfinancial variables, which are binary and therefore for each observation (firm) can take value 1 or 0. Here we must notice that all non-financial variables are binary, while usage of five point's Liker scale would result with more precise measurement. But since obtained data-base provided by bank included only binary variables authors decided to use such data for default modeling. List of non-financial variables provided by bank data-base is the following:

- Firm age (if firm is older than two years than it is less risky - value 1, while firm operating less than two years is more risky - value 0).
- Size measured by number of employees (if firm has more than five employees than it is less risky - value 1, while firm with less than five employees is more risky - value 0).
- Quality of accounting information (if accounting information is accurate and reliable firm is less risky - value 1, otherwise if accounting information is not accurate and reliable firm is more risky - value 0).

- Dependence on key customers (if firm does not have client with more than 30% of sales it is less risky - value 1, while firm with client with more than 30% of sales is more risky - value 0).
- Firm owners' personal credit performance (if firm owners do not have unsettled private debt[1] firm is less risky - value 1, while if firm owners do have unsettled private debt firm is more risky - value 0).
- Management quality (if managers are experienced, educated and performed good business decisions firm is less risky - value 1, otherwise if managers are unexperienced, uneducated and performed wrong business decisions firm is less risky - value 0).

Variables Quality of accounting information and Management quality are measured on the basis of previous business relationship between bank and each client. Measurement is done by banks credit risk officers, but details on measurement methodology are not provided by the bank, since used methodology represents confidential information. Also, since banks original credit rating methodology was confidential information there was no possibility to compare default prediction accuracy of developed and original bank model.

As statistical method authors decided to use logistic regression due to its advantages over multiple discriminant analysis - MDA. Namely, MDA has assumptions for ratios normality and equal dispersion of covariance matrices for groups defined by dependent variable. Many studies reported that the mentioned two assumptions are violated and therefore results might be questionable. Although the evidence on the issue of sensitivity of MDA in case of violated assumptions is mixed, the results must be interpreted with potential impacts of violated assumptions. Especially in the case of small samples and unequal covariance matrices statistical significance of the estimation can be adversely affected (Hair, et. al, 2010). When MDA assumptions are violated a good alternative is LR. Namely, LR does not have requirements for data normality of equal dispersion of covariance matrices of groups. With fewer assumptions LR can be used more efficiently than MDA, when assumptions of data normality and equal dispersion of covariance matrices is not met.

An important issue in application of LR can be the problem of multicollinearity of independent variables. Since some of financial ratios use the same variables in the calculation there is possibility of multicollinearity problem in the estimated model. The problem of multicollinearity in the estimated model causes inefficiently estimated parameters and high errors, which in turn results with many insignificant variables and high explanatory power of the estimated model. In order to control this problem we have decided to use two approaches. The first one is the usage of matrix of Pearson Correlation coefficients, where correlation higher than 0.8 indicates multicollinearity problem. The

[1] Unsettled private debt of firm owners is determined from Croatian register of credit obligations.

second test for multicollinearity can be done by Variance Inflation Factors – VIFs, where linear regression of one discriminating variable was run, while all other variables were used as explanatory variables.

## 4. EMPIRICAL FINDINGS

As mentioned before the basic aim of the research was to find out informational value of non-financial variables in default (insolvency) prediction. In order to solve the issue authors decided to develop and compare two models. The first model (Financial variables model) was based on financial variables only, while the second model (Combined model) combined financial and non-financial variables. Both models were evaluated on the data provided by a Croatian commercial bank and by usage of SPSS software. The first model was based on the financial variables[2] only and final version of the model was obtained by backward stepwise method. Variables that entered in the step final of LR model were D/A (Debt/Assets), E/FA (Equity/Fixed assets), CFO/A (Operating cash flow/Assets) and NI/A (Net income/Assets). Descriptive statistics for mentioned variables is given by Table 1:

*Table 1: Final step variables – Descriptive statistics*

| Variable | Minimum | Maximum | Mean | St. deviation |
|---|---|---|---|---|
| D/A | 0,01 | 916,62 | 1,96 | 31,91 |
| E/FA | -83,84 | 836,44 | 5,08 | 37,15 |
| CFO/A | -7,06 | 118,34 | 0,15 | 4,15 |
| NI/A | -216,16 | 12,67 | -29,60 | 75,89 |

In the final step for the financial variables model LR Chi-square was 108.975, with significance 0.001% indicating that the overall fitting of the estimated model is good. Another approach of measuring the model fitting is Nagelkerke R Square. In this case Nagelkerke R Square was 21.5% indicating moderate relationship between the used financial ratios and default prediction.

*Table 2: Final step variables - Financial variables model*

| Variable | B | S.E. | Wald | df | Sig. |
|---|---|---|---|---|---|
| D/A | 0.030 | 0.006 | 28.133 | 1 | 0.0001 |
| E/FA | -0.0064 | 0.024 | 6.930 | 1 | 0.0080 |
| CFO/A | -0.109 | 0.028 | 14.561 | 1 | 0.0001 |
| NI/A | -0.197 | 0.031 | 40.481 | 1 | 0.0001 |
| Constant | -1.460 | 0.109 | 179.815 | 1 | 0.0001 |

[2] List of all financial variables used in modeling is given in Appendix.

Table 2 indicates that only variable D/A has got the positive sign meaning that increase of leverage increases the probability of client being insolvent-defaulted. Other three statistically significant variables (E/FA, CFO/A and NI/A) have negative sign indicating that the increase of these variables decreases the probability of being bankrupted. This finding is logical since increase of coverage ratio, operating cash flow and profitability indicates better financial stability and performance and should result with lower probability of being insolvent. The financial variables model classification accuracy for healthy firms was 88.4%, for defaulted firms 52.0%, while total accuracy was 82.8%.

*Table 3: Classification Results – Financial variables model*

| | | Predicted group | | |
|---|---|---|---|---|
| | | Non-default | Default | Percentage Correct |
| Observed group | Non-default | 617 | 81 | 88.4 |
| | Default | 61 | 66 | 52.0 |
| Overall Percentage | | | | 82.8 |

The second model Combined model included both, financial and non-financial variables, while the final version of the model was obtained by backward stepwise method in two steps. In the final step for the Combined model LR Chi-square was 252.567, with significance 0.001% indicating that the overall fitting of the estimated model is good. Another approach of measuring the model fitting is Nagelkerke R Square. In this case Nagelkerke R Square was 45.8% indicating moderate strong relationship between combined variables and default prediction. It should be noticed that Nagelkerke R Square for Combined model was significantly higher than for Financial variables mode (21.5%), indicating that combined model has better data fitting. Non-financial variables that entered in the final LR model were Quality of accounting information (ACCQ), Firm owners personal credit performance (OFIN) and Management quality (MANQ).

*Table 4: Final step variables – Combined model*

| Variable | B | S.E. | Wald | df | Sig. |
|---|---|---|---|---|---|
| D/A | 0.023 | 0.007 | 11.875 | 1 | 0.0010 |
| E/FA | -0.040 | 0.018 | 4.791 | 1 | 0.0290 |
| NI/A | -0.129 | 0.041 | 9.617 | 1 | 0.0020 |
| CFO/A | -0.085 | 0.032 | 6.857 | 1 | 0.0090 |
| ACCQ | 1.083 | 0.250 | 18.747 | 1 | 0.0001 |
| OFIN | -1.930 | 0.316 | 37.263 | 1 | 0.0001 |
| MANQ | -1.132 | 0.361 | 9.833 | 1 | 0.0020 |
| Constant | -3.270 | 0.254 | 166.043 | 1 | 0.0001 |

The Combined model classification accuracy for healthy firms was 92.4%, for defaulted firms 64.6%, while total accuracy was 88.1%. Classification results indicate that Combined model has outperformed Financial variables model for both groups of observations. Namely, in the segment of non-default companies the financial variables model had accuracy 88.4%, i.e. 4 percentage points lower than Combined model. Similarly, in the segment of defaulted firms the Financial variables model had accuracy 52.0%, i.e. 12.6 percentage points lower than Combined model.

*Table 5: Classification Results - Combined model*

| | | Predicted group | | |
|---|---|---|---|---|
| | | Non-default | Default | Percentage Correct |
| Observed group | Non-default | 645 | 53 | 92.4 |
| | Default | 45 | 82 | 64.6 |
| Overall Percentage | | | | 88.1 |

Obtained results, which confirmed that model with financial and non-financial variables outperformed model with financial variables in default prediction, are in line with previous similar research (Grunert et al. 2005 and Altman et al. 2008). Such finding indicates that prediction of default for the purpose of credit risk management can be improved by usage of nonfinancial information.

## 5. CONCLUSION

In recent years when economic crisis has spread all over the world many banks have increased portion of bad debt. Namely, due to fall of economic activity many firms are faced with decreased demand, fall in revenue/cash flow and therefore have problems with paying off the loans. In Croatia according to the latest data around 40,000 firms (50%) has problems with insolvency, while 13.3% of approved loans is classified as bad debt. In such business environment banks must be very cautious when make lending decisions. From the banks perspective it is necessary to evaluate the risk that client will be unable to repay the obligations according to the contract. According to the empirical insight into the practice of Croatian banks it is clear that they develop internal tools for credit risk assessment, usually based on financial ratios, which are calculated from the historical financial statements. Besides financial variables in the practice banks also use non-financial variables which are relevant for lending decisions.

Most of academic research on business failure if focused on financial variables while only few papers explored the usage of non-financial variables. In order to test predictive power of non-financial variables we have developed and compared two insolvency prediction models (Financial variables model and Combined model). Testing of both models on the data from a Croatian commercial bank has resulted with finding that Combined model has outperformed Financial variables model. This was especially true in the segment of defaulted firms, where Financial variables model had accuracy of only 52.0%, while Combined model had accuracy of 64.6% (12.6 percentage points higher). This empirical finding indicates that prediction of insolvency and credit risk management can be improved by incorporating nonfinancial information into default prediction models.

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**APPENDIX:**

List of all financial variables used in modeling:

1. Debt/Assets
2. Equity/Fixed Assets
3. EBIT/Annual Interests
4. Sales/Assets
5. Sales/Current Assets
6. Receivables period (days)
7. Current Assets/ Current Liabilities
8. Net Income/Sales
9. Net Income/Assets
10. Net Income/Equity
11. CFO/Sales
12. CFO/Assets
13. CFI/Annual Interests
14. CFO/Total Liabilities
15. CFO/ Current Liabilities.