

DESIGNING THE MODEL FOR EVALUATING FINANCIAL QUALITY OF BUSINESS OPERATIONS – EVIDENCE FROM CROATIA

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The main objective of the paper includes designing a model for evaluating the financial quality of business operations. In that context, for the paper purposes, the financial quality of business operations is defined as an ability to achieve adequate value of individual financial ratios for financial position and performance evaluation. The objective of the model is to obtain comprehensive conclusion about the financial quality of business operation using only value of the function. Data used for designing the model is limited to financial data available from the annual balance sheet and income statement. Those limitations offer the opportunity for all sizes of companies from the non-financial business economy sector to use the designed model for evaluation purposes. Statistical methods used for designing the model are multivariate discriminant analysis and logistic regression. Discriminant analysis resulted in the function which includes five individual financial ratios with the best discriminant power. Respecting the results obtained in the classification matrix with classification accuracy of 95.92% by the original sample, or accuracy of 96.06% for the independent sample, it can be concluded that it is possible to evaluate the financial quality of business operations of companies in Croatia by using the model composed of individual financial ratios. Conducted logistic regression confirms the results obtained using discriminant analysis.

1. INTRODUCTION

Making subjective decisions using objective information represents an inevitable element of strategy analysis (David, 2011, p. 174). Management of a company implies business decision making in each of its stages (Tušek, 2001, p.

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18). Decision making process includes identifying problems and opportunities in order to resolve them (Daft, 2008, p. 272). Decision making is fundamental component of planning process which includes choice between several alternatives directed towards achieving company's objective (Buble, 1993, p. 87). The decision-making process should be rational and based on available information. Information available for decision-making purposes can be qualitative (e.g. human resources, customer satisfaction, business environment, processes) or quantitative. Certain authors when evaluating business quality more often use qualitative information, over quantitative ones. Kanji (1998) presented a possible model for evaluating business excellence which represents averages of performed measurements for qualitative indicators as customer satisfaction, employees and equity owners.

The most used model based on qualitative and quantitative information, which represents performance measurement framework, focused on the vision and strategy of the company, by combining non-financial measures (customers, learning and growth, internal business processes) and traditional financial metrics, was improved and promoted by Kaplan & Norton (1993). Balance scorecard is a strategic measurement system, and nota a measure of strategy (Kaplan & Norton, 1993, p. 147). Another model based on qualitative information for strategy evaluation is SWOT analysis used to evaluate the strengths, weaknesses, opportunities and threats of a company.

The most important form of quantitative information is financial information available from the accounting system of a company. Using quantitative information should be an essential element of the business decision-making process. Accordingly, annual financial statements, as an outcome of the accounting system, represent a reliable source of information for internal users and external stakeholders. Based on that information, financial statements analysis can be conducted. Financial ratios have an important role in determining an organization's strengths and weaknesses in the investment, financing, and dividend areas. They are usually used for detecting strengths or weaknesses in management, marketing, production, research and development, and management information systems activities (David, 2011, p. 107). To improve the quality of available information, synthetic ratios for evaluating financial quality of business operations or predicting instability of a business can be used.

It is important to emphasise that the concept *the financial quality of business operations* is composed and used for research purposes. It represents the ability of a company to achieve an adequate level of financial position and

performance of business operations, evaluated by using financial data available from financial statements. Financial information, and in that context individual and synthetic financial indicators, should be used to evaluate the financial quality of business operations. On the other hand, to obtain comprehensive evaluation of business quality, which primarily includes measurement of vision, mission and strategy of the company, qualitative and quantitative information, and for that purposes developed methods and models should be combined and used simultaneously.

2. THEORETICAL CONSIDERATIONS

2.1. Importance of financial information for the financial quality of business operations evaluation

The quality of financial information available in annual financial statements is mainly related to the applied accounting policies determined by specific assumptions, principles and standards. Principles, standards, concepts, and assumptions are infiltrated through accounting (Wild et al., 2011, p. 8). As it was previously stated, the objective of accounting is to provide information that will be used in a business decision-making process. That information has to be credible and reliable. Its objective is to inform stakeholders on business operations of a company. The purpose of annual financial statements is to give a certain summary of the overall business operations of a company. The quality of information available in financial statements represents a presumption of quality business decision making process.

From that point of view, information available from financial statements can be converted into a more concrete base by using different tools and techniques of financial statements analysis. Financial statements analysis takes into account business cycles and trends, as well as company's strengths, weaknesses, opportunities and threats (Catty, 2010, p. 165). Financial statements analysis involves using different methods for calculating individual, group and synthetic financial ratios and their interpretation in terms of evaluating financial quality of business operations. By using individual financial ratios, it is possible to evaluate financial position and business efficiency. By combining certain individual financial ratios, it is possible to expand conclusions on business operations of the company.

Studies related to financial statements analysis focus on improving information ability of financial ratios, which were, from their earliest stage, related to predicting failure, or evaluating financial quality of business

operations. The development of the model for evaluating financial quality of business operations is based on a need to improve communication and information value of existing individual financial ratios.

2.2. Review of commonly used methodology and financial ratios for evaluating the financial quality of business operations

Certain tendencies focus on developing various models taking into account different business activities, size of companies, or geographical position. For those purposes, researchers use different multivariate methods. The most commonly used methods are multivariate discriminant analysis and multivariate logistic regression. In addition, neural networks are also important within recent studies.

Previous studies resulted with numerous models composed of different types and numbers of individual factors, either accounting data or financial ratios. Bellovary et al. (2007) conducted a review of bankruptcy prediction studies which showed that the range of factors included into any model was between one and 57, i.e. the review showed that all in all 752 different factors were used (Bellovary, Giacominio, & Akers, 2007, p. 7). Average number of factors included in models during all analyzed periods was 10.

According to the review of bankruptcy prediction studies, conducted by Bellovary et al. (2007), multivariate discriminant analysis was the most efficient method of accurate prediction of failure probability, i.e. evaluating the financial quality of business operations. During the 1980s and 1990s, apart from discriminant analysis and logit analysis, neural networks model was popular for designing evaluation models.

The most used factors included in the financial quality of business operations evaluation models are different variations of profitability and liquidity ratios. The most used factor is total assets profitability calculated as the relationship of net income and total assets (54 models), then total assets profitability calculated as the relationship of earnings before interest and taxes and total assets (35 models). According to those results, it can be concluded that total assets profitability ratio represents the most important ratio in the existing models for financial quality of business operations evaluation. Additionally, important factors are liquidity ratios including current ratio (51 models) and quick ratio (30 models).

2.3. Literature review

The earliest attempts of assessing financial quality of business operations by using individual financial ratios can be traced back to the beginning of the 20th century. Development of well-known synthetic DuPont deductive ratio in 1920s represents foundation of using financial ratios for business efficiency assessment. (Aljinović Barać, 2008, p. 102). It is a system of ratios, used to assess the strategic orientation of a company and as such is a management tool. System efficiently evaluates the realization of the chosen strategy of the company.

First attempts of using financial ratios for the purpose of evaluating business failure were made in the 1930s (Altman, 1968, p. 590). Some of the first studies on the ability to evaluate and predict the financial quality of business operations by using financial ratios were directed to simple univariate methods that first and foremost focused on determining its average values and making conclusions based on trends. The most important authors that made contributions to that field were Patrick (1932), Winakor & Smith (1935), Merwin (1942) and Beaver (1966). R. F. Smith and A. H. Winakor (1935) studied changes within financing structure of unstable companies. In the early 1940s. Merwin (1942), in his research, based on a sample of 900 companies, compared different ratios of existing and failed companies (Altman, 1968, p. 590). Alexander Wall conducted the first research which focused on creating ratio index by using weighted average of different ratios. Although his attempts were unsuccessful, his research represents praiseworthy efforts to develop model by using discriminate analysis (Horrigan, 1968, p. 287).

Studies conducted at that time show that financial ratios differ between failing and continuing companies (Altman, 1968, p. 590). In the 1930s, there were two principal elements of financial ratios development. The first one included the creation of effective groups of ratios where the most important role was played by Roy A. Foulke (1933). The other one included more concrete studies on the ability to predict financial difficulties of companies by using financial ratios. Winakor and Smith also conducted a research in that field and determined that the most accurate and steady indicator of failure is net working capital to total assets ratio (Horrigan, 1968, p. 289). Merwin (1942) conducted the first sophisticated analysis of predictive power of ratios. His findings include net working capital to total assets, net worth to debt and the current ratio as the most accurate ones (Horrigan, 1968, p. 289).

Tamari (1964) conducted one of the first attempts to analyse failure of companies by using contemporary statistical methods (Altman & Narayanan, 1996, p. 81). In the mid-1960s, Beaver (1966) conducted a research on individual financial ratios from the aspects of assessment probability to predict bankruptcy. Beaver's "study will undoubtedly become a landmark for future research in ratio analysis" (Horrigan, 1968, p. 291). The application of complex multivariate statistical and mathematical methods at first did not result with applicable models (Beaver, 1966, p. 100). Soon after Beaver's study, E. I. Altman (1968) conducted his well-known research in which he created still the most popular model for predicting corporate bankruptcy by using contemporary multivariate discriminant analysis which provided multidimensionality of financial ratios.

As stated earlier, William H. Beaver (1966) was the first important researcher in the field of using financial ratios as a tool to predict bankruptcy. The primary objective of his research was to determine ability of the financial ratios as predictors of important events, including failure (Beaver, 1966, p. 72). Author's research refers to the period from 1954 to 1964 and includes data for 79 failing companies for which a set of 30 individual financial ratios were calculated. According to the obtained results, differences between failed and stable companies exist observing five years before bankruptcy.

Edward I. Altman (1968) was the most important researcher who significantly improved the usefulness of individual financial ratios by developing a model for predicting corporate bankruptcy. The initial sample included 66 manufacturer companies which were equally divided into failed companies and the one without difficulties in business operations. In the research, the author used 22 financial ratios classified in five categories including liquidity, profitability, leverage, solvency, and activity ratios. The final result of the research was a model consisting of five financial ratios with the best discriminating ability.

The first important research of the usefulness of financial ratio analysis for predicting failure of small companies was conducted by Robert O. Edmister (1970). The result of his research is the discriminant function based on tri-annual sample and includes seven variables. The author divided the results based on function value into "black-grey-white" sections, as a basis for determining failure probability. Developed function correctly classifies 39 of 42 cases (93 percent) (Edmister, 1972, p. 1.488).

Ohlson (1980) was the first author who successfully applied multivariate logistic regression instead of discriminant analysis for designing a model for predicting bankruptcy. He used a sample of 105 bankrupt and 2,058 non-bankrupt companies. By using nine independent variables and applying logit analysis three models were created. Using the three models designed within the research it was proven that the size of the company represents a significant variable for discrimination on bankrupt and non-bankrupt companies.

The authors from Croatia also made valuable efforts to develop models for evaluating financial quality of business operations. The requirement to have quality information at disposal for making decisions on investing in equity shares had resulted in 2007 with the creation of the business excellence model by Belak & Aljinović Barać. Authors' main goal was to create a model for assessing business excellence based on financial ratios calculated by using data available from financial statements and to all stakeholders (Belak & Aljinović Barać, 2008, p. 27). The model was primarily designed for companies, whose shares are publicly traded on the Croatian Stock Exchange. From large number of financial ratios including all categories, 14 ratios were chosen, along with 5 structural ratios, 5 ratios of financial performance and 4 efficiency of investing on the stock exchange (Belak & Aljinović Barać, 2008, p. 29).

Zenzerović (2008) conducted a research to emphasize the importance of instruments for predicting bankruptcy, i.e. evaluated the going concern assumption on business operations of the company (Zenzerović, 2008, p. 3). The research focused on transition economy and included business operations of 110 companies for the period from 1996 to 2006. Within the process of designing the model, a total of 50 different individual financial ratios divided into six categories were used: liquidity (6 ratios), solvency (1 ratio), activity (8 ratios), economy (5 ratios), profitability (9 ratios) and cash flow ratios (11 ratios) (Zenzerović, 2008, p. 129). The research conducted by using multivariate discriminant analysis and logit analysis resulted with several models focused on the size of companies and on their business activities. The final results according to the classification test show an accuracy of over 90%.

3. METHODOLOGY AND RESEARCH RESULTS

Quantitative based models designed in Croatia, in addition to accounting information, usually require knowing and using additional information such as the market value of the company. On the other hand, the mentioned models include using data from cash flow statement. The main emphasis in this paper is designing a model for evaluating the financial quality of business operations by

using only data available from balance sheets and income statements, i.e. data that are available for every company in Croatia which prepare their financial statements in accordance with the *Regulation on structure and content of annual financial statements* (NN¹no. 38/2008, 12/2009, 130/2010). Also, previously designed models were developed for only several specific business activities of companies, and most of them were large and quoted companies. This research includes all business activities of the *non-financial business economy* sector in Croatia and all companies' sizes according to the Accounting Law. In that context, it is necessary to limit input data to those that are available for all companies' sizes of non-financial business economy sector in Croatia. Due to the fact that small companies are not obliged to prepare cash flow statement, only data available from balance sheet and income statements are used for the research.

One of the main disadvantages of using individual financial ratios is their focus on a specific business segment. Individual financial ratios are used for the partial evaluation of different aspects of business operations including liquidity, solvency and activity on the one side, or economy and profitability on the other. Finally, it is necessary to conduct a comprehensive analysis that will relate specific conclusions into a general overview of the overall financial quality of business operations of a certain company. Due to this complexity and fragmentation of the evaluation process, the idea of designing a comprehensive single indicator was proposed. Using that single indicator will lead to conclusions about financial quality of companies' operations. As a result, the following research hypothesis is developed:

Hypothesis: It is possible to evaluate the financial quality of business operations by using a model based on financial ratios.

3.1. Characteristics of the sample

The pre-phase of designing a model for evaluating the financial quality of business operations includes determining the characteristics and size of the research sample. Studies on the prediction of failure, bankruptcy, and insolvency, and those on evaluating the financial quality of business operations, include using *categorical variable* which usually have two modalities (e.g. good/bad, stable/unstable, successful/unsuccessful). Stratified samples formatted by taking into account categorical variable, prerequisite the same number of units in both sub-samples. The estimation of the discriminant

¹ NN is the abbreviation for *Narodne Novine*, i.e. the Official Gazette of the Republic of Croatia.

function and the classification of observations is impacted by variations in groups' size (Hair et al., 2010, p. 353). The categorical variable includes two modalities, stable and unstable companies.

Furthermore, considering that the research will include the entire non-financial business economy sector in Croatia, companies are divided according to size and groups of business activity. Statistical Classification of Economic Activities 2007 in Croatia includes a total of 21 fields of business activities based on which those activities included into the research (Table 1) are chosen.

Table 1. Chosen fields of business activity used, according to the Statistical Classification of Economic Activities 2007 in Croatia

A	INDUSTRY	
	B	Mining and quarrying
	C	Manufacturing
	D	Electricity, gas, steam and air conditioning supply
	E	Water supply; sewerage, waste management and remediation activities
B	CONSTRUCTION	
	F	Construction
C	TRADE	
	G	Wholesale and retail trade; repair of motor vehicles and motorcycles
D	NON-FINANCIAL SERVICES	
	H	Transportation and storage
	I	Accommodation and food service activities
	J	Information and communication
	L	Real estate activities
	M	Professional, scientific and technical activities
	N	Administrative and support service activities
	S95	Repair of computers and personal and household goods

Source: Croatian Bureau of Statistics, 2014.

Croatian Bureau of Statistics regularly publishes information on non-financial business economy sector which is divided into four groups of activity, including: *Industry* (B, C, D, E), *Construction* (F), *Trade* (G), and *Non-financial services* (H, I, J, L, M, N, S95) (Croatian Bureau of Statistics, 2014). Second

classification includes size of companies according to the Accounting Law which includes small, medium-sized and large companies (NN, 109/2007, Article 3). This study is based on a random, triple stratified sample. The total number of companies from the specified segment that prepared and disclosed their annual financial statements for 2011 was 84,421 (Croatian Chamber of Economy, 2014). Those companies represent the population for forming sample size needed for the research (Table 2). The sample includes secondary data available from public database of the Registry of annual financial statements managed by FINA (Croatian Financial Agency). The obtained data refer to the year of 2012.

Table 2. Number of companies of chosen business activities that prepared and disclosed their annual financial statements in 2011 in Croatia

Analysed fields	Group of activities	Total			Total
		Small companies	Medium-sized companies	Large companies	
Industry	B	212	13	3	228
	C	10,261	406	114	10.781
	D	363	14	11	388
	E	490	78	12	580
Total		11,326	511	140	11,977
Construction	F	11,461	129	32	11.622
Total		11,461	129	32	11,622
Trade	G	25,278	325	81	25.684
Total		25,278	325	81	25,684
Non-financial services	H	3,132	59	27	3.218
	I	5,038	80	18	5.136
	J	4,092	34	13	4.139
	L	4,400	5	4	4.409
	M	13,189	37	13	13.239
	N	3,630	15	2	3.647
	S95	610	3	0	613
TOTAL		34,091	233	77	34,401
TOTAL		82,156	1,198	330	83,684

Source: Croatian Chamber of Economy, 2011.

The sample size is specified by a significance level of 5% and a confidence interval of 10%. For each modality of a categorical variable, it is necessary to

obtain data for the total of 417 companies, i.e. the total planned number of companies in the initial sample was 834 (Table 3). Several criteria were imposed in order to classify a company as stable or unstable. The criteria for stable companies included *net income* and the existence of *retained earnings* in the year of obtaining data. If a company was registered as a limited liability company, its equity value should be at least HRK 20,000, and for a joint-stock company at least HRK 200,000.

Table 3. Sample size for stable and unstable companies

Analysed fields	Required number of companies			Total
	Small companies	Medium-sized companies	Large companies	
Industry	48	41	29	118
Construction	48	28	12	88
Trade	48	37	22	107
Non-financial services	48	34	22	104
TOTAL				417

Source: Author's calculations using: <http://www.macorr.com/sample-size-calculator.htm>

Unstable companies are those that had *loss* and *accumulated loss* in 2012. Data for the total number of *stable* companies included in random stratified sample were obtained. However, there was no adequate amount of *unstable* companies for medium-sized *Construction* (B) companies, and for large companies within all business activity groups. The initial sub-sample of unstable companies includes fewer elements than it was required and consists of 339 companies (Table 4).

Table 4. The initial number of stable and unstable companies in the sample

Analysed fields	STABLE COMPANIES			Total
	Small companies	Medium-sized companies	Large companies	
Industry	48	41	29	118
Construction	48	28	12	88
Trade	48	37	22	107
Non-financial services	48	34	22	104
Total number of stable companies in sub-sample				417
Industry	48	41	5	94
Construction	48	10	7	65
Trade	48	37	6	91
Non-financial services	48	34	7	89
Total number of unstable companies in sub-sample				339

Source: Financial agency, 2012.

For the specified sample elements, data available from balance sheet and income statement, referring to 2012, was gathered. Obtained data includes positions from annual financial statements that are necessary for calculating chosen individual financial ratios (Table 5).

Table 5. Positions from the annual financial statements needed for conducting the research

AOP mark	Positions from financial statements
AOP002	Fixed Assets
AOP034	Current Assets
AOP035	Inventory
AOP043	Receivables
AOP045	Accounts Receivable
AOP058	Cash
AOP059	Prepaid Costs
AOP060	Total Assets
AOP062	Shareholders' Equity
AOP063	Share Capital
AOP072	Retained earnings/Transferred losses
AOP083	Long Term Liabilities
AOP093	Current Liabilities
AOP098	Accounts Payable
AOP106	Deferred Costs
AOP111	Sales (revenue)
AOP114	Expenses from Operations
AOP121	Net Salaries and Wages
AOP124	Depreciation and Amortization
AOP131	Financial Revenues
AOP137	Financial Expenses
AOP146	Total revenues
AOP147	Total expenses
AOP148	Gross Income or Loss
AOP152	Net Income or Loss

Source: Financial agency, 2013.

Conducted analysis included all relevant individual financial ratios, which are most commonly used for evaluating business safety and efficiency of the non-financial business economy sector. Chosen ratios were assessed as relevant by their occurrence in the relevant literature (Table 6).

Table 6. Individual financial ratios used in the research

Abbreviation	Financial ratio	Numerator	Denominator
KTrL	Cash Ratio	Cash	Current Liabilities
KUL	Quick ratio	Current Assets - Inventory	Current Liabilities
KTL	Current ratio	Current Assets	Current Liabilities
KFS	Financial stability coefficient	Fixed Assets	Shareholders' Equity + Long Term Liabilities
RK/KO	Working Capital and Current Liabilities ratio	Net Working Capital	Current Liabilities
KZ	Debt-to-assets ratio	Total Liabilities	Total Assets
KVF	Debt-to-equity ratio	Shareholders' Equity	Total Assets
KF	Debt-to-capital ratio	Total Liabilities	Shareholders' Equity
PTK	Interest Coverage Ratio	Gross income + Financial Expenses	Financial Expenses
FZ	Indebtedness Factor	Total Liabilities	Retained earnings + Depreciation and Amortization
SPI	Degree of Coverage I	Shareholders' Equity	Fixed Assets
SPII	Degree of Coverage II	Shareholders' Equity + Long Term Liabilities	Fixed Assets
KOUI	Total assets turnover	Total revenues	Total Assets
KOKI	Current assets turnover	Total revenues	Current Assets
KOP	Receivables turnover	Sales (revenue)	Receivables
KOPK	Accounts Receivable turnover	Sales (revenue)	Accounts Receivable
KOZ	Inventory turnover	Expenses from Operations	Inventory
KOD	Accounts	Expenses from Operations	Accounts Payable

Abbreviation	Financial ratio	Numerator	Denominator
	Payable turnover		
EUO	Total Economy Ratio	Total revenues	Total expenses
EPA	Operations Economy Ratio	Sales (revenue)	Expenses from Operations
EF	Economy of Financing Ratio	Financial Revenues	Financial Expenses
NMP	Net Profit Margin	Net income + Financial Expenses	Total revenues
BMP	Gross Profit Margin	Gross income + Financial Expenses	Total revenues
NROA	Net Return on Assets	Net income + Financial Expenses	Total Assets
BROA	Gross Return on Assets	Gross income + Financial Expenses	Total Assets
ROE	Return on Equity	Net income	Shareholders' Equity

Source: Žager et al., 2009.

To achieve larger representativeness of the sample, removal of outliers was performed, separately for the sub-sample of stable and for the sub-sample of unstable companies by using method of normal two-sided distribution which detects outliers as values lower than four standard deviations related to mean value, and those values which are higher than four standard deviation related to mean value. Those values were excluded from further research. The analysis includes only companies with all chosen financial ratios calculated. Companies that were with missing one or more ratios were excluded from further research.

As there were not enough unstable companies in the first stage of obtaining data and, in addition to that, companies with missing financial ratios were excluded, sub-samples of stable and unstable companies were unequal, i.e. the sub-sample of stable companies was twice the size of the sub-sample of unstable companies. According to Hair et al. (2010, p. 353): *"If the group sizes do vary markedly, the researcher may wish to randomly sample from the larger group(s), thereby reducing their size to a level comparable to the smaller group(s)"*. Considering the stated limitations, the sub-sample of stable companies needed to be reduced to be equal to the other two sub-samples. The number of stable companies in double stratified sub-sample is reduced by using the method of random double stratified sample where the number of companies was reduced by 42%. Finally, the analysis included a total of 343 companies,

from which 164 of them were considered stable, and 179 were considered unstable.

3.2. Model design methodology

Multivariate discriminant analysis was chosen as the most applicable method for designing the described model (Hair et al, 2010, pp. 335-413). In addition to discriminant analysis, logistic regression is often used. The main difference between those two methods is that categorical variable in discriminant analysis can include more than two modalities, while logistic regression is limited to only two modalities of the categorical variable. In business finance and accounting, classification problem is usually based on two extreme groups, for example default vs. non-default for commercial loans, conversion/non-conversion for convertible bonds, public vs. private companies, failure vs. non-failure companies (Fryman et al., 1985, p. 269).

The discriminant analysis has purpose to find linear combination of predictors with the best discriminant power between determined classifying groups (Laitinen & Kankaanpää, 1999, p. 69). The discriminant analysis is a form of regression analysis used for identification of variables with the best discriminant power, which classifies population or sample elements in accordance with chosen characteristics (Zenzerović, 2008, p. 130). By using discriminant analysis a researcher develops equation that results with value of a dependent variable based on values of independent variables, where dependent variable is qualitative (Aczel & Sounderpandian, 2008, p. 771).

The discriminant analysis includes designing discriminant function which should maximize differences between centroids around predictor variables (Pinches et al., 1977, p. 290). Characteristic of that method is ability to reduce multidimensional problem to one number with relatively high accuracy (Aljinović-Barać, 2011, p. 45). The quality of the designed discriminant function is shown in the accuracy of classification in one of the modalities of the categorical variable.

Logistic regression is a form of regression analysis developed to explain two-group categorical variable (Hair et al., 2010, p. 341). Function value is the score obtained by weighting the independent variables, resulting with the likelihood of affiliation to one of two groups (Laitinen & Kankaanpää, 1999, p. 69). Researchers in the field of financial statements analysis often in their studies use both methods to validate the reliability of conducted research, e.g. Zenzerović (2008). The robustness of logistic regression makes it an appropriate

method for designing the function for evaluating financial quality of business operations. Taking into account all the specified characteristics of both methods, multivariate discriminant analysis will be used to design the model and logistic regression will be used to validate it.

3.3. Empirical results

The conducted research is based on multivariate discriminant analysis applying *forward stepwise* method which progressively includes into the model an additional independent variable with the highest ability to discriminate companies respecting categorical variable. *Tolerance level* used in the research was 0.010 and the defined critical *F value* for variables included (individual financial ratios) into the model was 1.00.

Table 7. An overview of the correlations between independent variables with the highest strength

Financial ratios	Correlation Coefficient
BMP vs. NMP	0.999
NROA vs. BROA	0.998
BMP vs. EPA	0.964
NMP vs. EPA	0.962
KOP vs. KOPK	0.820
BMP vs. EUP	0.750
NMP vs. EUP	0.740
SPII vs. SPI	0.705
RK/UI vs. SPI	0.702
EUP vs. EPA	0.685

Source: Author's calculations.

A preliminary analysis of input independent variables includes an assessment of the existence of a correlation between variables. A review of financial ratios with the strongest correlation is provided in Table 7. The greatest correlation strength exists between profitability ratios which differ substantially by income tax. Almost a perfect correlation exists between those ratios. In addition to those, a high correlation exists between profit margin to operations economy ratio, and to total economy ratio. Generally, it is possible to notice the existence of significant correlation between ratios that are based on

the same data from financial statements. The greatest correlation of the independent variables included into the model exists between total economy ratio and current ratio and it is of moderate strength (0.4477) (Table 8).

Table 8. Correlation between independent variables included into the model

Variable	AS	SD	KTL	FZ	PTK	EUP	ROE
KTL	1.102	1.020	1.000	0.152	0.390	0.448	-0.101
FZ	0.520	10.344	0.152	1.000	0.275	0.328	-0.003
PTK	-0.389	8.642	0.390	0.275	1.000	0.386	-0.056
EUP	0.851	0.295	0.448	0.328	0.386	1.000	-0.123
ROE	0.144	0.397	-0.101	-0.003	-0.056	-0.123	1.000

Source: Author's calculations.

Note: Marked correlations are statistically significant at level $p < 0.05$ (N=343).

Multivariate discriminant analysis is conducted up to the fifth step resulting with a model of five independent variables, i.e. individual financial ratios.

Table 9. A summary of the discriminant function for independent variables included into the model

	WILKS' LAMBDA	PARTIAL LAMBDA	F-REMOVE -1,157	P-VALUE	TOLER.	1-TOLER. (R-SQR.)
EUP	0.37605	0.781442	43.91062	0	0.887432	0.112568
FZ	0.398848	0.736774	56.09111	0	0.939637	0.060364
PTK	0.321491	0.914055	14.76202	0.000177	0.931877	0.068123
ROE	0.315852	0.930375	11.7491	0.000777	0.926291	0.073709
KTL	0.305153	0.962996	6.03281	0.015132	0.836514	0.163486

Source: Author's calculations.

Note: Wilks' Lambda: 0.29386, approx. $F(5,157)=75.453$, $p < 0.00$ (N=163).

According to research results, five individual financial ratios with the highest discriminant power are *total economy ratio*, *indebtedness factor*, *interest coverage ratio*, *return on equity* and *current ratio* (Table 9). For those ratios *Wilks' lambda* ranges between 0.305 and 0.399. *Tolerance level* is used to calculate the coefficient of determination, and should be as close as possible to

one. Low tolerance level represents a problem of approximate linear dependence. Tolerance levels for variables included into the model ranges between 0.837 and 0.940. Based on those results it can be concluded that that variables are linearly independent. All variables included into the model have empirical *p-value* less than the theoretical significance level of 5%, and due to that redundancy problem between variables in the model does not exist. In the process of designing the model, there was an option of adding additional variable into the model (*accounts payable turnover*), but that would result with lower classification power of the model (Table 10).

Table 10. A summary of the discriminant function for independent variables not included into the model

	WILKS' LAMBDA	PARTIAL LAMBDA	F TO ENTER	P-VALUE	TOLER.	1-TOLER. (R-SQR.)
KTrL	0.293298	0.998085	0.299394	0.585045	0.830318	0.169682
KUL	0.293281	0.998027	0.308402	0.579458	0.378454	0.621546
KFS	0.29386	0.999996	0.000669	0.979391	0.721721	0.278279
RK/UI	0.293552	0.998948	0.164316	0.685769	0.475436	0.524564
KZ	0.292093	0.993983	0.944405	0.332652	0.630826	0.369174
KVF	0.292093	0.993983	0.944405	0.332652	0.630826	0.369174
KF	0.289987	0.986816	2.084145	0.150841	0.668697	0.331303
SPI	0.287822	0.979451	3.272899	0.072358	0.802034	0.197966
SPII	0.292871	0.996632	0.527168	0.468888	0.962466	0.037534
KOUI	0.293859	0.999993	0.001069	0.973955	0.821213	0.178787
KOKI	0.293556	0.998964	0.161828	0.688029	0.846794	0.153206
KOP	0.292558	0.995567	0.694624	0.405871	0.914558	0.085442
KOPK	0.293275	0.998007	0.311585	0.57751	0.929364	0.070636
KOZ	0.29158	0.992239	1.220233	0.271016	0.892874	0.107126
KOD	0.283096	0.963368	5.931959	0.015995	0.855912	0.144088
EPA	0.291759	0.992848	1.123818	0.290736	0.742472	0.257528
EF	0.293511	0.998808	0.186123	0.666759	0.856498	0.143502
BMP	0.293811	0.999832	0.026272	0.871447	0.623692	0.376308
NMP	0.293849	0.999959	0.006416	0.93626	0.631431	0.368569
BROA	0.290297	0.987871	1.915338	0.168348	0.703006	0.296994
NROA	0.290383	0.988166	1.868274	0.17364	0.711233	0.288767

Source: Author's calculations.

Note: Df for all F-tests: 1.156 (N = 163).

Canonical analysis is used in order to determine the *real* discriminant function, i.e. to determine the way of variables discrimination (Table 11). A comprehensive assessment of the designed model is conducted by using

Eigenvalue, *Canonical R*, *Wilks' Lambda* and *Chi-square*. *Eigenvalue* represents a characteristic root of the categorical variable and preferably it should be as high as possible, but at least one. *Canonical R* is the measure of multiple correlation between each predictor and the discriminant function. Its value of 0.8403 shows that the model explains 84.03% of the deviation of the dependent variable.

Table 11. Evaluation of the designed model applying appropriate statistical tests.

Roots removed	Eigenvalue	Canonical R	Wilks' Lambda	Chi-square	Df	P-value
0	2,402971	0,840321	0,293861	194,1068	5	0

Source: Author's calculations

Wilks' lambda is used for assessing the quality of discriminant power and significance of the function for the designed model. It is used to test equality of mean of the ratio vectors for each group. Converted to an F value indicates the likelihood of a significant separation between scores (Deakin, 1972, p. 174). *Wilks' lambda* reaches values between zero and one. In situations when its value is zero, a perfect discriminant power of the model exists, and opposite, when its value is one, there is no discriminant power. At the fifth step of the conducted discriminant analysis *Wilks' lambda* has the value of 0.29386.

Table 12. Unstandardized and standardized coefficients of the design discriminant function

Variable	Raw coefficients for canonical variables	Standardized coefficients for canonical variables	Rank	Factor structure matrix - correlations variables - canonical roots (pooled-within-groups correlations)
EUP	-4.92959	-0.590569	2	-0.640171
FZ	-0.08157	-0.629853	1	-0.476616
PTK	-0.08001	-0.361397	3	-0.493109
ROE	-0.88672	-0.326259	4	-0.152322
KTL	-0.35955	-0.250289	5	-0.374896
Constant	5.40821	2.402971		
Eigenvalue	2.40297	1		
Cum.Prop	1			

Source: Author's calculations.

The obtained coefficients of the discriminant analysis represent linear combinations of independent variables included into the model and the standardized coefficients represent comparative scales (Table 12). It is possible to rank the importance of financial ratios included into the model. Although the *indebtedness factor* has almost the lowest weight within the discriminant function, according to the results of standardized coefficients its contribution to power of discriminant function is the highest. *Current ratio* has the lowest contribution to the discriminant power. Unstandardized coefficients represent weights for every independent variable included into the model for evaluating the financial quality of business operations [1]. The obtained value is compared with the *cut-off point* which represents decision point referring to the financial quality of business operations. The coefficients of the *factor structure matrix* represent correlation between independent variables and discriminant values (Zenzerović, 2008, p. 149). Those can be defined as correlations of every independent variable with a discriminant function. The designed discriminant function is:

$$Z = 5.41 - 4.93EUP - 0.08FZ - 0.80PTK - 0.89ROE - 0.36KT \quad [1]$$

After designing the model, the next step of the research includes determining the value of the *cut-off point* which indicates the value for classifying companies into one of the two modalities, i.e. determining companies as *stable* or *unstable*. Marginal value is used for designing classification matrix, and its optimal value depends on groups' sizes (Ramayah et al., 2010, p. 1,655). In case when two groups are not exactly of the same size, *cut-off point* is obtained as weighed value related to group size. According to Hair et al. (2010) optimal *cut-off point* is calculated by using the following equation [2]:

$$Z_{CS} = \frac{N_A Z_B + N_B Z_A}{N_A + N_B}, \quad [2]$$

where Z_{CS} represents *optimal cutting score* and N is the sample size of the first and second modalities of the categorical variable (Hair et al., 2010, p. 362).

Table 13. Centroids of canonical variables

	Root 1
Stable companies (S)	-1,30342
Unstable companies (N)	1,82096

Source: Author's calculations.

Centroids obtained used for calculating optimal *cut-off point* by applying equation for unequal modality sizes, considering the fact that the number of *stable* companies included into the sub-sample is 164, and of *unstable* ones is 179. The analysis included a total of 343 companies (Table 13).

$$Z_{CS} = \frac{-1.30343 * 179 + 1.82096 * 164}{164 + 179} = 0,190447 \quad [3]$$

If the value of the discriminant function is below 0.190447, then the company is considered as *stable* [3]. In the opposite case, if the value of the function for a particular company is higher than 0.190447 then it is classified as *unstable*. Resulting centroids represent lower and upper boundaries of the model. Considering that if the value of the function is below -1.30342, the financial quality of business operations can be characterized as *very stable* and when the function value is above 1.82096, the financial quality of business operations can be characterized as *very unstable*.

Classification matrix is used to analyse the classification accuracy of companies into one modality of a categorical variable (*stable* or *unstable*). According to the obtained results, all the companies included into the analysis that were determined as *stable*, were correctly classified into the group of *stable* companies. From a total number of 179 companies initially determined as *unstable*, 165 companies were correctly classified into the group of *unstable* companies, and remaining 14 *unstable* companies were classified as *stable*. Consequently, the probability of wrong classification of *unstable* companies into the group of *stable* ones (*error type I*) is 7.82%, and the probability of wrong classification of *stable* companies into the group of *unstable* ones (*error type II*) is 0.00%. According to the overall results, the probability of wrong classification of any group of companies is 4.08% (Table 14).

Table 14. Classification matrix of design discriminant function

Group	Percentage of classification accuracy	S p=.58282	N p=.41718
Stable companies (S)	100	164	0
Unstable companies (N)	92.1788	14	165
Total	95.9184	178	165

Source: Author's calculations.

Note: Observed classifications in rows, predicted classifications in columns.

Hair et al. (2010) highlight the fact that is possible to evaluate the efficiency of the model by calculating theoretical probability by using following equation [4]:

$$C_{PRO} = p^2 + (1 - p)^2, \quad [4]$$

where p marks the share of group elements (Hair et al., 2010, p. 366). Considering the fact that the conducted research included 164 (0.4781) *stable* and 179 (0.5180) *unstable* companies, the theoretical marginal probability of classification accuracy is 45.72%. Also, it is important to emphasise that "the classification accuracy should be at least one-fourth greater than achieved by chance" (Hair et al, 2010, p. 367). In accordance with that, to obtain that minimal preferred level of probability it is necessary to multiply theoretical value with 1.25 which results with marginal probability of 57.15%. By comparing conducted theoretical and empirical probabilities of classification accuracy it can be concluded that the designed model for evaluating the financial quality of business operations is efficient.

To assess the designed model by using multivariate discriminant analysis, logistic regression is used. In that context, logistic regression includes only those independent variables (individual financial ratios) that, according to the results of the conducted multivariate discriminant analysis, have the best discriminant power from the aspect of determining companies' stability. The objective of using logistic regression is to confirm the results obtained by using multivariate discriminant analysis. The sample used in logistic regression is the same as in discriminant analysis, and includes a total of 343 companies out of which 164 are characterized as *stable* and 179 as *unstable*. *Unstable* companies from the sample are marked with "0" and *stable* ones with "1" (Table 15).

Table 15. Results of logistical regression

	Const.B0	KTL	PTK	FZ	EUP	ROE
Estimate	-1,53506	0,41178	1,503354	0,2	-0,54892	0,61405
Odds ratio (unit ch)	0,21544	1,50951	4,496746	1,2	0,577573	1,8479
Odds ratio (range)		15,38489		288506,3	0,499025	7,140065

Source: Author's calculations.

Note: N of 0's: 179, 1's: 164; Final loss: 28,388693294 Chi2(5) = 418,07 p = 0,00 (N=343).

The conducted logistic regression resulted with the following equation [5]:

$$P(z) = \frac{1}{1 + (\exp[-(-1.535 + 0.412KTL + 1.503PTK + 0.200FZ - 0.549EUP + 0.614ROE)])} \quad [5]$$

The designed function results with values in range between 0 and 1, and represents the conditional probability of uncertainty of business operations. If the value of the function is zero or close to zero then a company can be considered as *unstable* and a company is considered as *stable* if the function value is one or close to one. The probability of 0.5 is set as a *cut-off point* for classifying companies into the two defined groups.

Table 16. Classification matrix of the model design using logit analysis

Observed	Predicted 0's	Predicted 1's	Percent Correct
0	174	5	97.2067
1	0	164	100

Source: Author's calculations.

According to the results of the classification test, all 164 *stable* companies are correctly classified, and error type II, i.e. the error that *stable* companies will be mistakenly classified as *unstable* ones is 0% (Table 16). On the other hand, out of the 179 *unstable* companies, 174 of them are correctly classified and five are classified as *stable*. According to that error type I, i.e. the error that *unstable* companies will be classified as *stable* is 2.79%. All together, classification accuracy of the logistic regression model is 98.54%, i.e. the total error of classification is 1.46%. The obtained results by using logistic regression confirm the results obtained by using multivariate discriminant analysis.

3.4. Model evaluation

After designing models and determining their classification accuracy, it is necessary to test them using an independent sample. For that purpose, a new triple stratified random sample is formed. Gathered data refers to 2012 and includes 828 companies divided into four groups of business activity and three groups according to size. The formed sample includes 299 *stable* and 211 *unstable* companies.

For companies from the independent sample, individual financial ratios from previous research stage are calculated, including *total economy ratio*,

indebtedness factor, interest coverage ratio, return on equity and current ratio. In the following research phase, those companies with missing data were excluded from the sample. Finally, independent sample includes 279 *stable* and 177 *unstable* companies. In order to have two sub-samples of an equal size, the sub-sample of *stable* companies was reduced to 178 using double stratified random sample.

Table 17. Classification matrix for the discriminant function using the independent sample

	Stable companies (S)	Unstable companies (N)	Total
Stable companies (S)	178	0	178
Unstable companies (N)	14	163	177
Total	192	163	355

Source: Author's calculations.

For the given sample, values for the designed functions were calculated. The obtained value for discriminant function was compared to *cut-off point* of 0.190447 and to the designation of the categorical variable. If the value of discriminant function for the company was below *cut-off point* and it was classified as *stable*, it was considered correctly classified. In the opposite case, if the value of discriminant function was above 0.190447, and initially the company was categorized as *unstable*, it was considered that the company was correctly classified. All 178 companies classified as *stable* had the value of the discriminant function of less than 0.190447. Out of 177 *unstable* companies, 163 of them had the value of discriminant function above 0.190447 and they were correctly classified as *unstable* (Table 17). The remaining 14 companies, which were initially classified as *unstable*, had the function value less than 0.190447, and by that they were wrongly classified as *stable*. The probability of incorrect classification of *unstable* companies into the group of *stable* ones (error type I) was 7.91%, and the probability of incorrect classification of *stable* companies into the group of *unstable* ones (error type II) was 0%. Overall probability that a company from any of two groups was incorrectly classified is 3.94%. The designed model for evaluating the financial quality of business operations has the classification accuracy of 96.06% based on companies included into independent testing sample. It is important to emphasize that the sample included companies from the *non-financial business economy* sector, as well as all sizes of companies in Croatia.

Finally, testing the logistic regression model was also conducted by using the same independent sample. The obtained values of logistic regression function were compared with *cut-off point* of 0.5. If the value of the function was above 0.5, then the company was considered as *stable*, and on the other hand, if the value of the function was less than 0.5, the company was classified as *unstable*.

Table 18. Classification matrix for logistical regression function using the independent sample

	Stable companies (S)	Unstable companies (N)	Total
Stable companies (S)	178	0	178
Unstable companies (N)	12	154	166
Total	190	154	344

Source: Author's calculations.

According to company results obtained by classification testing using independent sample it is possible to notice that all 178 *stable* companies are correctly classified, i.e. classification accuracy is 100% (Table 18). For 11, out of total 177 *unstable* companies, it was not possible to calculate function value, so they were excluded from further testing. For the remaining 166 companies, company value of function was calculated and 154 companies were correctly classified as *unstable* companies, i.e. classification accuracy of *unstable* companies is 92.77%.

From the total of 166 companies, 12 of them were incorrectly classified as *stable* companies, and by that it can be concluded that error type I is 7.23%. The probability of wrongly classifying *stable* companies into the group of *unstable* ones (error type II) is 0%. Overall classification accuracy for logistic regression by using independent sample is 96.51%, i.e. the overall probability that a company will be incorrectly classified is 3.49%.

Designing a model for evaluating the financial quality of business operations by using multivariate discriminant analysis, which includes five individual financial ratios with the best discriminant power, and respecting results obtained in the classification matrix with a classification accuracy of 95.92% for the original sample, or accuracy of 96.06% for the independent sample, it can be concluded that is possible to evaluate the financial quality of

business operations of companies in Croatia using the model consisting of individual financial ratios.

The logistic regression confirms the results obtained by using discriminant analysis. It is interesting to notice that both models incorrectly classified the same companies within all variations of testing. Conclusions reached confirm the findings of the analysis. Taking into account all the results, **the initial hypothesis can be accepted.**

4. CONCLUSION

The model for evaluating the financial quality of business operations is designed by using data for all business activities of the *non-financial business economy* sector. Considering the fact that the model is design by using sample of *non-financial business economy sector* in Croatia makes it applicable to the wide scope of companies. In 2012, in Croatia, this sector included 84,421 companies.

The main objective of the model is to evaluate the financial quality of business operations, i.e. to characterize business operations of companies as *stable* or *unstable* at any time for which necessary input data exists. For the simplicity of calculating used financial ratios, necessary data are available within the accounting system of the company in every moment, and accordingly it is possible to continually keep track of the financial quality of business operations which leads to improving the business decision-making process.

Besides internal users such as management, internal auditors and other organizational units in the company, the model can also be simply applied by external stakeholders, including investors, banks, government, shareholders, and employees. Its usefulness and its practical application is highlighted by the simplicity of operations and its comprehensiveness, as the majority of business sectors in Croatia can be included. Future research regarding the studied area should be oriented to include trend analysis into the design model by testing it during more accounting periods. Also, future research can be focused on including additional qualitative information into the model to reach more comprehensive conclusions about the comprehensive business quality.

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DIZAJNIRANJE MODELA ZA PROCJENU FINACIJSKE KVALITETE POSLOVANJA – DOKAZI IZ HRVATSKE

Sažetak

Cilj ovog rada je dizajniranje modela za procjenu financijske kvalitete poslovanja. Pritom se financijska kvaliteta poslovanja definira kao sposobnost za dosizanje odgovarajuće vrijednosti pojedinih pokazatelja financijske pozicije i procjene (financijskih) učinaka. Cilj modela je dobivanje sveobuhvatnog zaključka o poslovanju na temelju vrijednosti (jedne) funkcije. Podaci korišteni prilikom dizajniranja modela su ograničeni na financijske pokazatelje iz godišnje bilance te računa dobiti i gubitka. Ova ograničenja, pak, omogućavaju korištenje dizajniranog modela poduzećima iz nefinancijskog sektora, bez obzira na veličinu, u svrhu procjene rezultata poslovanja. Prilikom izrade modela korištene su multivarijantne statističke metode diskriminacijske analize i logističke regresije. Diskriminacijska je analiza dovela do funkcije, koja uključuje pet financijskih pokazatelja, koji imaju najveću diskriminacijsku snagu. Na temelju rezultata točnosti klasifikacije od 95,92% za korišteni uzorak, odnosno 96,06% za drugi, neovisni uzorak, može se zaključiti da je model, utemeljen na izabranim financijskim pokazateljima, moguće koristiti za procjenu financijske kvalitete poslovanja u Hrvatskoj. Logistička regresija potvrđuje rezultate dobivene diskriminacijskom analizom.

