IZVIRNI ZNANSTVENI ČLANEK – ORIGINAL SCIENTIFIC PAPER

ON THE MAIN FINANCIAL PREDICTORS OF CREDIT DEFAULT: EVIDENCE FROM THE FEDERATION OF BOSNIA AND HERZEGOVINA

O glavnih finančnih dejavnikih napovedovanja plačilne nesposobnosti – primer Federacije Bosne in Hercegovine

Deni Memić

Hypo-Alpe-Adria Bank
Deni.Memic@hypo-alpe-adria.com

Adnan Rovčanin

University of Sarajevo, Faculty of Economics
adnan.rovcanin@efsa.unsa.ba

1

Prejeto/Received:
Julij 2011
Popravljeno/Revised:
Oktober 2011
Sprejeto/Accepted:
November 2011

Abstract

The purpose of this paper is to investigate if any significant relationship exists between a wide set of financial ratios and the probability of credit default among the companies in the Federation of Bosnia and Herzegovina. Most existing literature in the field of credit default probability focuses on bond markets. Very few studies focus on credit default using bank loan data. To our knowledge, no such studies have been conducted and published covering data from Bosnia and Herzegovina. We found a significant relationship between the financial ratios and credit default probability. Return on assets (ROA) seems to be the most influential financial ratio on the probability of the credit default. We also found that other financial ratios have a significant influence on credit default, such as EBIDA-Replacement Capex and average account payable days. A broader study using similar data sets from companies in the Republic of Srpska as well as regional countries can be beneficial in assessing broader conclusions and possible similarities in credit default occurrence as well as the main variables affecting it. The similar data from the Republic of Srpska was unavailable for this study. The research results imply that banks may use the assessed model as an additional tool in risk management procedures when deciding whether to provide a new loan facility or not as well as in assessing the credit risk within the existing portfolio.

Keywords: Banks, credit default, logistic regression, financial ratios, Federation of Bosnia and Herzegovina

Izvleček

Namen članka je raziskati, ali obstaja kakršna koli pomembna povezava med širokim naborom finančnih kazalnikov in verjetnostjo plačilne nesposobnosti na primeru podjetij iz Federacije Bosne in Hercegovine. Večina literature s področja verjetnosti plačilne nesposobnosti se osredotoča na trg obveznic, zelo malo študij pa se nanaša na plačilno nesposobnost z uporabo podatkov o bančnih posojilih. Po našem védenju študije, ki bi upoštevale podatke za Bosno in Hercegovino, niso bile izvedene in objavljene. Ugotovili smo pomembno povezavo med finančnimi kazalniki in verjetnostjo plačilne nesposobnosti. Donos na sredstva (ROA) je finančni kazalnik, ki najbolje predvideva verjetnost plačilne nesposobnosti. Prav tako smo ugotovili, da tudi drugi finančni kazalniki, na primer za razdolževanje razpoložljivi denarni tok (EBIDA-Replacement Capex), in povprečni dnevi vezave obveznosti do dobavitelje močno nakazujejo na plačilno nesposobnost. Podrobnejša študija, ki bi vključevala podoben nabor podatkov o podjetjih iz Republike Srbske in iz držav v regiji, bi bila dobrodošla za sprejemanje širših sklepov in ugotavljaje potencialnih podobnosti in razlik pri pojavu plačilne nesposobnosti in glavnih finančnih kazalnikih, ki nakazujejo na plačilno nesposobnost. Podatki iz Republike Srbske za to študijo niso bili na

Naše gospodarstvo / Our Economy
Vol. 58, No. 1 – 2, 2012
pp. 3 – 15

UDK: 336.71/.77(497.6)
JEL: G17, G20, G21, G33

voljo. Rezultati raziskave kažejo, da bi banke lahko uporabile oblikovani model kot dodatno orodje v vsakodnevnem upravljanju kreditnega tveganja, ko se odločajo o odobritvi oziroma neodobritvi novih kreditov, pa tudi pri ocenjevanju kreditnega tveganja znotraj obstoječega portfelja.

Ključne besede: banke, plačilna nesposobnost, logistična regresija, finančni kazalniki, Federacija Bosne in Hercegovine

1 Introduction

Many economists consider the latest global financial crisis to be the worst crisis since the Great Depression. It is believed that the main cause of the crisis lays in the collapse of large financial institutions, generally banks, around the world. The banking failures were caused by a heavy increase of loan loss provisions, booked due to a heavy increase of non-performing loans (NPL). The failures were followed by the bailout plans by the national governments and severe shocks in stock markets, collapses in real estate markets, liquidity problems, declines in consumer wealth as well as declines in the overall economic activity.

Financial institutions, especially banks, have always focused on credit risk and different approaches in its mitigation or minimization, but the question remains if the risk measurement procedures and instruments are efficient enough. This function in represented through banks' risk departments lead by chief risk officers (CROs). However, banks tend to give the same analysis attention to all of the financial figures when measuring credit risk.

The purpose of this study is to determine the main factors affecting the probability of credit default within the indebted companies and consequently the increase of the loan loss provisions in the income statement of the bank. The aim is to investigate which of the key financial ratios has the highest impact on the credit default probability occurrence.

An effective and serious approach to credit risk management is essential for long-term banking success. Since loans represent the largest risk exposure for any bank in the world, bank managers need to focus most of their credit risk management attention on this segment of its operations. Traditionally, bank CROs tend to believe that the main determinant of credit default occurrence or its absence is the amount of free cash flow obtained by the company in one year. Therefore, commercial banking needs to give special stress to this part of successful management of its everyday operations.

The last few years have brought many challenges to financial institutions throughout the world, with the main problems directly caused by inappropriate credit standards and poor risk management, especially within the banking sector. The main cause of such frequently occurring scenarios lies in the way in which banks account for their defaulted loans. Banks are obliged to account for all of the loans within their portfolios through Loan Loss Provisions (LLP) in their income statements. LLP directly affects the profitability of each bank; loans with more delinquency or the higher default probability have higher LLPs. The correlation is obvious: the higher the LLPs, the lower the profitability of the bank.

Past experience regarding the main causes of banking failures provide an important guide for banking managers regarding future credit risk management decisions. One of the definitions given by the International Bank of Settlements (2011) defines credit risk as "the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms. The goal of credit risk management is to maximize a bank's risk-adjusted rate of return by maintaining credit risk exposure within acceptable parameters." The Bank of International Settlements—through its banking guides known as Basel I, II and III (named after the Basel Committee)—suggests that banks should be aware of the growing need to identify, measure, monitor and control credit risk. The second recommendation focuses on keeping an adequate capital structure compared to risk-weighted assets (RWA). Based on these facts, the main goal of every commercial bank should be early credit default prevention and its early prediction.

Banks registered in Bosnia and Herzegovina have been significantly affected by the global economic crisis and the increased percentage of Non-Performing Loans (NPL) in their portfolios due to the worsened liquidity situation in the real sector. Loans with unsettled overdue debt for 90 days or more are regarded as NPL loans or defaulted loans. In order to achieve the best results, banks need to conducted detailed financial analyses of current and potential clients in order to assess their financial health. A set of financial ratios has been established to help analysts assess the financial situation of the analyzed legal entity.

The main aim of this study is to recognize the main financial ratios predicting credit default of companies in the Federation of Bosnia and Herzegovina as well as to build an efficient credit default prediction model. According to the data from the Central Bank of Bosnia and Herzegovina (Centralna Banka BiH, 2011), by the end of the year of 2009, commercial banks in Bosnia and Herzegovina had loan portfolios of around 14 billion BAM (9.8 billion BAM were loans used in the Federation of Bosnia and Herzegovina) given to different sectors on the market. Of these 14 billion BAM, around 7 billion BAM were approved in favour of companies of different size operating in Bosnia and Herzegovina. The percentage of NPL loans in Bosnia and Herzegovina has been rising since the end of 2008, when their share in total loans was 3,00%. This percentage had risen by the end of 2009 to 5,90% and further to 9,20% by the end of 2010, with a high likelihood of further escalation in the future. This scenario would mean that some of the banks would go bankrupt, causing more spill-over effects of the real economy. All of these data show the importance of assessing the main factors influencing the credit defaults in Bosnia and Herzegovina. A total of 20 banks were operating in Federation of Bosnia and Herzegovina in the year of 2009.

Having in mind the presented data from the banking sector in Bosnia and Herzegovina, with more than 14 billion BAM (or around 7.2 billion EUR) in loans approved and disbursed to the corporate and retail sector, the importance of the study is evident. The importance and relevance of the banking market in Bosnia and Herzegovina can be seen through a comparison with the Croatian and Serbian banking markets, which are considered to be a few of the largest banking markets in the SEE region. By the end of 2009, Croatia's banking market had a total loan portfolio of around 33.7 billion EUR (Hrvatska Narodna Banka, 2009) while Serbia had a total loan portfolio of around 1,117 billion Serbian dinars around 10,7 billion EUR (Narodna banka Srbije, 2009).

If we assume that the financial results recorded by a company in the observed period represent a realistic financial and market situation in the company, it can be concluded that financial statements provide the best base from which to investigate the reasons for deviations in everyday business operations. Since credit default represents a situation in which a company fails to pay its interest-bearing debts within the period of 90 days, the reason for such a situation should be investigated within the figures recorded in financial statements of the analyzed company. Experience also shows that some companies often chose not to pay their banking debts regularly despite the fact that they have the means to do so.

According to the definition given by the Basel Committee on Banking Supervision (2001c), credit default occurs when one or more of the following takes place:

– "It is determined that the obligor is unlikely to pay its debt obligations (principal, interest, or fees) in full;
– A credit loss event associated with any obligation of the obligor, such as charge-off, specific provision, or distressed restructuring involving the forgiveness or postponement of principal, interest, or fees;
– The obligor is past due more than 90 days on any credit obligation; or
– The obligor has filed for bankruptcy or similar protection from creditors."

Van Horne and Wachowich (2009) suggested that five main groups of financial ratios represent the real "health" of the company:

– Profitability ratios
– Liquidity ratios
– Activity ratios
– Leverage ratios
– Coverage ratios

The structure of the paper is as follows. The introduction is followed by section two, which offers a brief literature review relevant for our analysis. Data used for the analysis are presented in section three. The methodology and the model-building procedure are presented in section four. Section five gives a brief results interpretation while section six gives concluding remarks and research limitations.

2 Literature review

The first credit default risk models were published around 1932. Many studies have since been published regarding credit default. Moody's RiskCalc for Private Companies is one of the most detailed studies on this topic, using a data set from some 25.000 companies (Falkenstein and Carty 2000). One of the studies (Sy, 2007) reports that credit default is jointly determined by two main variables: liquidity failure and negative equity or insolvency. Meanwhile, the probability of default is given by the joint probability of these two variables. The key hypothesis in this study is that a credit default is caused by both delinquency and insolvency. This study also demonstrates that this approach is only one of the many possible theories. The representative model for liquidity and delinquency can be obtained through the data provided on profit and loss statements, while the representative model for equity or solvency can be obtained through the data on the balance sheet.

Yau, Kenneth and Francis (2002) measured the probability of default, the credit risk premium and their impact on net interest cost for the Commonwealth of Virginia using 1995 data. Their results indicate that the probability of default as measured by ordinal probit is determined by several variables, such as population size, population change, ratio of long-term debt to total debt, real estate taxes, per capita income, and the organizational form of the government.

An investigation of borrowers of bank loans was conducted in 2000 (Gupton, Gates and Carty, 2000). The research looked at secondary market price quotes of bank loans one month after the time of default. Their intention was to allow markets to process the default news and revalue the debt. They analyzed a population of 181 bank loans involving 121 separate defaults for large public companies from 1989 to the date of publishing. The results showed that 69,5% of a recovery rate for Senior Secured loans was nearly the same as for the previous 1996 report's finding of 71%. Gupton, Gates and Carty's (2000) findings include the following:

– The presence of multiple loans within a borrower's debt structure has a strong (and negative) influence on the recovery of Senior Unsecured loans, but has no appreciable influence on Senior Secured loans.
– Defaults with "average" loss given default levels are among the longest to resolve.
– Loss-given default is 17,4% better for secured than for bank loans.

An interesting study regarding the current practices of credit risk management among the largest financial institutions in the US (Fatemi and Fooladi, 2006) found that the identification of a credit default risk of a client seems to be the most important factor for bank managers. As many as 50% of the respondents confirmed utilizing models that are also capable of dealing with counterparty migration risk. It was also found that very few banks use either a proprietary or a vendor-marketed model for the management of their credit risk.

The mortality rate framework study, in the period between 1991 and 1996 for the actual credit default in the corporate bank loan market, was published. All of the previous studies were focused on the bond market and underlying defaults. The results show that the mortality rates on bank loans are remarkably similar to those of corporate bonds when measured cumulatively over the five-year period after issuance, but loan default rates appear to be considerably higher than bonds for the first two years after issuance (Altman and Suggitt, 2000).

Košak and Poljšak's (2010) study focused on the loss-given default (LGD) determinants in typical loan portfolios consisting of SME loans in a commercial bank in Slovenia. LGD was estimated by applying the discounted cash flow. Their findings suggest that reliable LGD can be explained by discounting expected future cash flows, type of collateral available, type of industrial sector, last available loan rating, size of the debt and loan maturity.

Oni, Oladele and Oyewole (2005) conducted a similar study on the main factors influencing credit default using a data set from poultry farmers in one region of Nigeria. A relatively small data set of 100 farmers was taken into consideration. The results showed that variables such as flock size, age, education level and income level of the farmers have a significant impact on the credit default. Meanwhile, variables such as household size, home distance form credit source, interest rate, loan size, marital status, occupation, financial outlet, preference and sex have do not have a significant impact on credit default within the studied data set.

Another study analyzed the credit-scoring model among 200 small business loans of one Croatian savings and loan association. The results demonstrated that variables such as entrepreneurial idea, growth plan, marketing plan, small business characteristics, personal entrepreneurs' characteristics and credit program characteristics have a significant effect on their small business credit scoring model (Bohaček, Šarlija and Benšić, 2003).

Very few studies focusing on credit default use loan data. Most of the relevant literature use bond market data due to the unavailability of relevant loan data. To our knowledge, no such studies have been conducted and published covering data from Bosnia and Herzegovina.

3 Data

The data for this study were obtained through an AFIP[1] database consisting of financial statements from all of the companies registered in Federation of Bosnia and Herzegovina in 2009. The total number of legal entities registered in the Federation of Bosnia and Herzegovina throughout 2009 exceeds 20.000. The chosen random sample consisted of 599 companies and their financial statements, which were later randomly divided into an original sample consisting of 300 companies and a holdout sample consisting of 299 companies. No data were missing in either the original or holdout samples. Since similar data for companies from Republic of Srpska were unavailable, this study focused exclusively on data from the Federation of Bosnia and Herzegovina.

Based on the previous theoretical background, a list of 11 financial ratios (chosen to represent the previously stated five groups of financial ratio groups) and four balance sheet and P&L positions were calculated for each of the companies in the original and holdout samples. Table 1 gives an overview of the financial ratios and balance sheet positions used in the study.

Each of the presented ratios, balance sheet, and income statement positions were calculated for the main sample (300 companies) and holdout sample (299 companies). Table 2 shows the descriptive statistics of the main sample used in the study, including all 15 variables.

Each of the companies in the sample was assigned a binominal variable representing credit default.

4 Methodology and model building

The first step of the study is to reduce the originally posed sample consisting of 15 different variables. SPPS software 19.0 version was used for the subsequent analysis. A principal component analysis (PCA) was used to assess the correlations among the chosen 15 variables and to group the highly correlated variables into factors. PCA provided the variable-by-variable correlations matrix to extract new variables, which are a linear combination of the original variables. The coefficients in each linear combination are known as factor loadings. The aim of the PCA is to achieve a data (variables) reduction, creating a new set of variables, which would replace the original set of 15 variables. Varimax rotation was conducted in order to redistribute the variance from earlier factors to later ones to achieve simpler, theoretically more meaningful factor patterns, as Hair, Black, Babin and Andersen (2010) suggested. The required sample size recommended in theory for the factor analysis was obtained as the sample used included 300 observations, or 20 per variable.

[1] State agency for financial, information and intermediation services (Agencija za finansijske, informatičke i posredničke usluge FBiH)

Table 1: *Overview of financial ratios*

Profitability ratios	
Gross_Profit _Margin	$\frac{\text{Gross profit}}{\text{Income}}$
Return on Assets (ROA)	$\frac{\text{Net profit (Loss)}}{\text{Assets}}$
Return on Equity (ROE)	$\frac{\text{Net profit (Loss)}}{\text{Equity}}$
Liquidity ratios	
Current_Ratio	$\frac{\text{Current assets}}{\text{Current liabilities}}$
Quick_Ratio	$\frac{\text{Current assets-Inventories}}{\text{Current liabilities}}$
Activity ratios	
Accounts receivables turnover in days (AR_days)	$\frac{\text{Accounts receivables}}{\text{Income}} \times 365$
Accounts payables turnover in days (AP_days)	$\frac{\text{Accounts payables}}{\text{Income}} \times 365$
Inventories turnover in days (Inventory_days)	$\frac{\text{Inventories}}{\text{Cost of goods sold}} \times 365$
Leverage ratios	
Debt_Ratio	$\frac{\text{Total liabilities}}{\text{Total assets}}$
Debt_to_Equity	$\frac{\text{Total liabilities}}{\text{Equity}}$
Coverage ratios	
Debt_to_Equity	$\frac{\text{EBIT}}{\text{Interest expense}}$
Balance sheet and Income statement positions	
Total_Revenues	
Equity	
EBIDA-Replacement Capex (EBIDA-RC)	
Profit (Net profit / Loss)	

Source: Van Horne and Wachowich, 2009

Table 2: *Descriptive Statistics*

	Mean	Std. Deviation	Analysis N
Equity	4922409,596	13132488,315	300
Total_Revenues	10872468,045	28098974,394	300
Profit	356102,147	2406365,172	300
Gross_Profit_Margin	,212	,285	300
ROA	,031	,091	300
ROE	,183	2,642	300
Current_Ratio	26,719	419,990	300
Quick_Ratio	26,038	420,027	300
Days_AP	1775,820	24239,204	300
Days_AR	162,065	826,224	300
Days_Inventory	614,380	5794,506	300
Debt_Ratio	,582	,255	300
Debt_To_Equity	15,339	89,305	300
Interest_Coverage	53,514	1829,191	300
EBIDA_RC	427880,112	2179850,788	300

Source: Authors' calculations

Appropriateness indicators of the conducted factor analysis were calculated. KMO measured is 0,480, while Bartlett's Test of Sphericity is 5717,110 and is a statistically significant at the 0,000 level.

Intercorrelations among 15 variables used in the study were computed (see Appendix 1). Intercorrelations of coefficients were computed and found to be significant at the 5% level in all cases. Based on the obtained results from the intercorrelation table, the principal components technique was applied to the correlation matrix. Examining the eigenvalues of factors, six different factors were recognized, accounting for 71,198 % of the total variance (see Table 3). Each of the six chosen factors had eigenvalues greater than 1.

We used PCA to achieve data reduction as well as recognize one representative variable from each factor. For further analysis, we used the six variables with the highest factor loadings (correlation between the original variables and the factors). All other variables showing high factor loadings within one factor were removed as they showed high intercorrelations (see Appendix 1). If we had used all 15 variables in the subsequent logistic regression, most variables omitted by the PCA would not be included in the final logistic regression. This is also suggested in the relevant literature: "factor analysis can also be used to achieve data reduction by (1) identifying representative variable from a much larger set of variables for use in subsequent multivariate analysis, or (2) creating an entirely new set of variables, much smaller in number, to partially or completely replace the original set of variables. In both instances, the purpose is to retain the nature and character of the original variables, but reduce their number to simplify the subsequent multivariate analysis" (Hair, Black, Babin and Andersen, 2010).

Hair, Black, Babin and Andersen (2010) also suggest that "highly correlated variables, such as those within a single factor, affect the stepwise procedure of multiple regression and discriminant analysis that subsequently enter variables based on their incremental predictive power over variables already in the model as one variable from a factor is entered, it becomes less likely that additional variables from that same factor would also be included due to their high correlations with variable(s) already in the model, meaning they have little incremental predictive power." Thus, only one variable from each factor was used in logistic regression (e.g., EBIDA_RC has high correlations with Profit, Equity and Total_revenues; as it has the highest factor loading, it was chosen for further analysis).

Comparing the factor weights among the variables and corresponding factors, variables with the highest weights were picked for further analysis. As expected, the first factor consists of all four balance sheet and income statement positions: profit, total revenues, EBIDA-Replacement Capex and equity. The second factor consists of current ratio and quick ratio, representing the liquidity ratios used in the research. Debt to equity and return on equity (ROE) were recognized as the third factor members. Accounts receivables turnover in days (AR_days) and inventories turnover in days (Inventory_days) are the fourth factor members. The fifth factor consists of return on assets (ROA) and interest coverage. The two remaining members are the sixth factor: accounts payables turnover in days (AP_days) and gross profit margin. Thus:

Table 3: *Rotated (Varimax) Component Matrix*

	Component						
	First factor	Second factor	Third factor	Fourth factor	Fifth factor	Sixth factor	Communalities
EBIDA_RC	**,929**	-,004	,025	-,033	,116	,012	,760
Profit	**,912**	,001	,016	-,014	,154	-,070	,750
Equity	**,866**	,009	-,069	,073	-,017	-,012	,861
Total_Revenues	**,863**	-,026	-,011	-,042	-,049	,023	,513
Current_Ratio	-,011	**,989**	-,004	-,012	-,025	,018	,676
Quick_Ratio	-,011	**,989**	-,004	-,012	-,026	,019	,852
Debt_To_Equity	-,024	,003	**,943**	-,007	-,062	,022	,980
ROE	,013	,013	**,909**	,040	,150	-,050	,980
Days_AR	-,014	-,006	,024	**,968**	-,023	-,063	,839
Days_Inventory	-,010	-,024	-,012	**,868**	-,036	,462	,942
ROA	,159	-,101	,046	-,043	**,794**	-,082	,969
Interest_Coverage	-,014	-,034	,022	-,046	**,604**	,061	,450
Debt_Ratio	-,118	-,227	,328	-,226	-,402	,255	,895
Days_AP	,007	-,028	-,048	,137	-,046	**,903**	,373
Gross_Profit_Margin	-,047	,240	,091	,070	,468	**,471**	,879
Eigenvalues	3,233	2,080	1,843	1,779	1,447	1,340	
% variance explained	21,553	13,869	12,284	11,859	9,647	8,930	

Source: Authors' calculations

Factor 1: Profit, Total revenues, EBIDA-Replacement Capex and Equity

Factor 2: Current ratio and Quick ratio

Factor 3: Debt to equity and return on equity (ROE)

Factor 4: Accounts receivables turnover in days (AR_days) and inventories turnover in days (Inventory_days)

Factor 5: Return on assets (ROA) and interest coverage

Factor 6: Accounts payables turnover in days (AP_days) and gross profit margin

The next step involved selecting one variable from each of the six factors to use in the logistic regression analysis. A variable with the highest weight from each factor was chosen for the following logistic regression analysis. The variable chosen for the first factor was EBIDA-Repalcement Capex (EBIDA_RC), representing the free cash flow available for principal and interest repayment to the bank. The second factor was represented by Current ratio, which is a liquidity ratio. In the case of this factor, two different variables had the same factor loading, which is an expected outcome since Current_Ratio and Quick_Ratio are highly correlated. To further analyze the two, we chose Current_Ratio as a variable more often used in practice. Debt_to_equity was chosen as a variable for the third factor as a leverage ratio. Accounts payables turnover in days (AR_days), Return on assets (ROA) and Accounts payables turnover in days (AP_days) were chosen as variables for the fourth, fifth, and sixth factors, respectively.

A factor analysis was run on the holdout sample as well in order to validate the results from the original sample. Similar results were obtained with the exception of profit and inventory days chosen as the representatives for their respective factors instead of EBIDA-Replacement Capex and debt to equity ratio, respectfully. For the chosen variables, a logistic regression analysis was run in order to determine the set of variables influencing the probability of credit default occurrence among companies in Bosnia and Herzegovina.

The main objective of the study is to determine the main financial figures or ratios affecting the companies in Federation of Bosnia and Herzegovina to default their credit lines provided by the banks. Therefore, a null hypothesis and alternative hypothesis were developed:

H0i: $\beta i=0 \; i=1,2,\ldots,6$

The null hypothesis states that no statistically significant relationship exists between theoretically determined financial ratios and credit default probability.

H1i: $\beta i\neq 0 \; i=1,2,\ldots,6$

The alternative hypothesis states that at least one financial ratio has a significant influence on the probability of credit default.

$$\text{Logit}(Prob_{credit\_default}) = \ln\left(\frac{Prob_{credit\_default}}{1\text{-}Prob_{credit\_default}}\right) = \\ = \alpha + \beta_1 X_1 + \ldots + \beta_6 X_6$$

$$\text{Odds}(Prob_{credit\_default}) = \left(\frac{Prob_{credit\_default}}{1\text{-}Prob_{credit\_default}}\right) = \\ = e^{\alpha + \beta_1 X_1 + \ldots + \beta_6 X_6}$$

Therefore, $Prob_{credit\_default}$ = Probability (Y = outcome of interest | X1 = X1…X6 = X6= $\frac{e^{\alpha + \beta_1 X_1 + \ldots + \beta_6 X_6}}{1+e^{\alpha + \beta_1 X_1 + \ldots + \beta_6 X_6}}$

We will also test overall regression model with the null hypothesis that the subsequently constructed prediction logit model is not statistically significant. The corresponding alternative hypothesis states that the prediction logit model is statistically significant.

$Prob_{credit\_default}$ is the probability of the event of credit default, α is the Y intercept, β-s are regression coefficients, and X-s are a set of predictors (financial ratios). The final number of logistic regression coefficients determined by factor analysis is six. α and β-s are typically estimated using the maximum likelihood (ML) method. The null hypothesis underlying the overall model states that all βs are equal to zero, meaning that no relationship exists between the probability of credit default and financial figures obtained in the year of its occurrence. A rejection of this null hypothesis implies that at least one β (chosen financial ratio) does not equal zero in the population, indicating that the proposed logistic regression equation predicts the probability of the credit default better than the mean of the dependent variable Y (Peng, Lee, and Ingersoll, 2002). As stated by Peng, Lee and Ingersoll (2002), the value of the coefficient β determines the direction of the relationship between X and the logit of Y, which can be positive or negative.

The alternative hypothesis can be defined as follows: the likelihood of credit default is significantly related to financial figures obtained by the company in a certain year.

The original sample used for logistic regression analysis, reduced by the factor analysis, consists of 300 companies and their six corresponding variables extracted by principal component analysis (financial ratios). The holdout sample consisting of 299 companies was also used to ensure the validation of the results obtained from the original sample. The original sample has a ratio of observations per estimated parameter of 50:1. Of all 300 companies in the original sample 228 (76%) recorded no credit default in the observed period, and the remaining 72 (24%) were defaulted companies (see Table 4).

Table 4: *Classification table*

Credit Default	No Credit Default (coded as 0)	Credit Default (coded as 1)	Total
Companies in Federation of Bosnia and Herzegovina	228 (76%)	72 (24%)	300 (100%)

The dependent variable (probability of credit default) is a binary dummy variable used for credit default occurrence probability, where 1 = credit default occurrence and 0 = no credit default occurrence. We can state that the probability that the firm defaulted is 24%. The odds that the company defaulted are 72 to 228 or 0,316 to 1. Thus, for every 10 companies from the sample, on average 3 companies defaulted.

Table 5: *Base model*

	B	S.E.	Wald	df	Sig.	Exp(B)
Constant	-1,153***	,135	72,705	1	,000	,316

Variables not in the Equation

Variables	Score	df	Sig,
EBIDA_RC	13,538***	1	,000
Current_Ratio	,323	1	,570
Debt_To_Equity	,049	1	,826
Days_AP	,323	1	,570
Days_AR	6,406**	1	,011
ROA	28,277***	1	,000

*p<0,10, **p<0,05; ***p<0,01

Source: Authors' calculations

Table 6: *Final logistic model*

Variable	B	S.E.	Wald (χ2)	df	Sig.	Exp(B)
EBIDA_RC	,000***	,000	15,278	1	,000	1,000
Days_AR	,002*	,001	3,294	1	,070	1,002
ROA	-3,908**	1,860	4,414	1	,036	,020
Constant	-1,368***	,192	50,529	1	,000	,255

*p<0,10, **p<0,05; ***p<0,01

Goodness-of-fit statistics – overall model evaluation

No. of steps	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square	Chi-square	df	Sig.
3	257,550	,216	,324	17,696	8	,024

Source: Authors' calculations

Table 7: *Final logistic model classification table*

	Predicted		Percentage Correct
	No default	Default	
No default	218	10	95,6
Default	46	26	36,1
Overall Percentage			81,3

Step 3:

Sensitivity = 218/(218+10)% = 95,6%.

Specificity = 26/(46+26)% = 36,1%.

False positive = 46/(46+218)% = 17,4%.

False negative = 10/(10+26)% = 27,8%.

Source: Authors' calculations

The intercept-only model was used as a baseline model in order to assess its improvement by the proposed model (Table 5). Table 5 also includes the data for all variables used that were potential model candidates.

The base model is statistically significant at the 0,00 level. The Wald test was used as a measure of the model improvement. A forward stepwise procedure was used to determine variables with a significant impact on the dependent variable. In the first step, ROA was entered in the model as the variable with the highest score, which is statistically significant at the ,05 level (p =,036). EBIDA_RC was entered into the model in the second step and it was statistically significant at the ,01 level (p = ,000). The final variable entered in the model was Days_AR; it was statistically significant at the ,10 level (p = ,070) (see also Appendix 2.).

Goodness-of-fit tests measured by -2 Log likelihood (-2LL) show improvement in all of the three steps. The final model (consisting of three variables) shows goodness-of-fit improvement in all of the three indicators: -2LL shows a value of 257,550, Nagelkerke R^2 of ,324 and Hosmer and Lemeshow test (Chi-square) of 17,696. All were statistically significant (p < ,05), which suggests that the model was well fit to the data. This also proves that the total logistic model is statistically significant, which means that we can reject the null hypothesis that the prediction logit model is not statistically significant.

A classification table showing the hit-ratios for all of the three conducted steps is given in Table 7 (see also Appendix 3.). Hit-ratio improvements are recorded in all of the three conducted steps assessing the final model. The final overall hit-ratio calculated was 81,3%, meaning that, when using the predicted model (three variables model), 81,3% of the credit default outcomes were correctly predicted.

The final outcome of the logistic regression analysis is the following model:

$$\mathrm{Logit}(Prob_{credit\_default}) = \ln\left(\frac{Prob_{credit\_default}}{1\text{-}Prob_{credit\_default}}\right) =$$

$$= -1.368 + .000 * \mathrm{EBIDA\_RC} + .002 * \mathrm{Days\_AR} - 3.908 * \mathrm{ROA}$$

$$\mathrm{Odds}(Prob_{credit\_default}) = \left(\frac{Prob_{credit\_default}}{1\text{-}Prob_{credit\_default}}\right) =$$

$$= e^{-1.368 + .000 * \mathrm{EBIDA\_RC} + .002 * \mathrm{Days\_AR} - 3.908 * \mathrm{ROA}}$$

$$Prob_{credit\_default} =$$

$$= \left(\frac{e^{-1.368 + .000 * \mathrm{EBIDA\_RC} + .002 * \mathrm{Days\_AR} - 3.908 * \mathrm{ROA}}}{1 + e^{-1.368 + .000 * \mathrm{EBIDA\_RC} + .002 * \mathrm{Days\_AR} - 3.908 * \mathrm{ROA}}}\right)$$

In order to validate the results from the original sample, a holdout sample consisting of 299 companies with the same characteristics (more than 800.000 BAM of revenues in 2009) was used. Table 8 shows the results obtained from the holdout sample (see also Appendix 4.). We can state that the holdout sample consists of two statistically significant variables—namely, ROA and Days_AR, which were also included in the original sample. The logistic regression coefficient signs are the same as in the original sample, confirming the direction of the effect of independent variables on the default probability and thus validating the original sample results (see Table 8). In other words, ROA has a negative relationship with the dependent variable while Days_AR has a positive relationship with the dependent variable

Table 8: *Final logistic model (holdout sample)*

	B	S.E.	Wald (χ^2)	df	Sig.	Exp(B)
ROA	-13,978***	2,642	27,998	1	,000	,000
Days_AR	,001**	,001	2,729	1	,099	1,001
Constant	-1,635***	,203	65,051	1	,000	,195

*p<0,10, **p<0,05; ***p<0,01

Source: Authors' calculations

Since a data set consisting of 300 companies was used in the study, where N=300, p1=0,208 and p2=0,792, we can conclude that the odds of a company having a credit default is 0,069. If we assume that the β/α ratio is 1, we can calculate the statistical power as 0,999, meaning that—given all the predefined parameters—the probability of correctly rejecting the null hypothesis is 99,9 %. The probability of not rejecting the null hypothesis when it is actually wrong (Type II error) is 0,01 or 0,1 %.

Given the sample size of 600 companies, it can be concluded that this sample can be used as a good representative of the analyzed population.

5 Interpretation of the results

The three-step procedure showed that three variables were statistically significant: ROA, Days_AR and EBIDA_RC. Since the sign of the B coefficient shows the direction of the relationship between the dependent and independent variables, we can state that Days_AR has a positive relationship, while ROA has a negative relationship with the dependent variable. Since the log effect of EBIDA_RC is ,000 (B coefficient), the anti-log (Exp B) is 1,000 and the probability is ,50, indicating that EBIDA_RC affects the probability of credit default occurrence without direction, although it is significant (p<0,01).

The B coefficient of ROA is negative and amounts to -3,908, which means that the anti-log and Exp(B) is ,020 (p<0,05). The negative B logistic coefficient means that an increased ROA is associated with a decreased probability of credit default occurrence. In other words, companies with higher returns on assets are less likely to experience credit default. Moreover, any positive change in ROA will cause a decrease in credit default odds. In order to assess the effect of ROA change on the probability of credit default change, we used the exponentiated logistic coefficients. We used the following formula to obtain the information of percentage change in odds:

Percentage change in odds =

*= (Exponentiated coefficient$_i$ – 1.00) * 100*

Since the exponentiated logistic coefficient for ROA is ,020, a one-unit positive change in ROA will decrease the odds of credit default by 98% and vice versa.

The B coefficient of Days_AR is positive (,002), meaning that the anti-log or Exp(B) is 1,002 (p<0,01). The positive B logistic coefficient means that an increase in Days_AR is associated with an increase in the probability of credit default occurrence; thus, companies with higher accounts receivables turnover in days are more likely to experience credit default. Any positive change in Days_AR will cause an increase of credit default odds. In order to assess the effect of Days_AR change on the probability of credit default change, we used the exponentiated logistic coefficients. We used the same formula for obtaining the information of percentage change in odds:

Since the exponentiated logistic coefficient for Days_AR is 1,002, a one-unit positive change in Days_AR will increase the odds of credit default by 0,2% and vice versa.

6 Conclusions and limitations

Given the nature of the problem studies, factor analysis and logistic regression appear to be the most appropriate techniques for addressing it. The analyzed data set contained no outliers or missing values. The study results demonstrated that at least one financial ratio has a significant influence on the probability of credit default. Therefore, we can reject the null hypothesis H0: $\beta i=0,\ i=1,2,\ldots,6$ and confirm the alternative hypothesis H1: $\beta i\neq 0,\ i=1,2,\ldots,6$. In other words, at least one financial ratio has a significant influence on the probability of credit default for the sample used from the banking market of Federation of Bosnia and Herzegovina, since β coefficients for ROA, Days_AR and EBIDA_RC are *≠0.*

A general conclusion can be drawn that three variables were determined to be statistically significant in the given model of credit default prediction. Out of the three chosen variables, one had a statistically significant impact but without direction (EBIDA_RC), one had a modest positive effect (Days_AR) and one had a very dominant effect on the probability of credit default (ROA). Contrary to previous expectations and the financial logic—namely, that free cash flow indicators for debt service (where EBIDA-RC is believed to be the best representative) would be the best predictor of the credit default occurrence—this study has shown different results. ROA seems to be the best predictor of credit default among the companies in the Federation of Bosnia and Herzegovina. This could imply the fact that managers may not be using their free cash flows efficiently. Being liquid enough and not paying banking debts on time may lead to many negative effects for a company, such as decreased profitability or declining credit ratings.

Given the amount of the credit exposure of the banks operating in the Federation of Bosnia and Herzegovina and the expanding share of NPL loans in their portfolios, the assessed model can represent an additional risk management tool in their everyday operations. The research results imply that banks may use the assessed model as an additional tool in risk management procedures when deciding whether to provide a new loan facility or not as well as in assessing the credit risk within the existing portfolio.

A broader study using similar data sets from the Republic of Srpska as well as from regional countries across different time spans would be beneficial in assessing broader conclusions and possible similarities or differences across different countries or cultures in credit default occurrence probability as well as the main variables affecting it. The authors propose further studies to determine the main causes and possible effects of an inefficient use of free cash flows by managers on a company's profitability and credit rating.

Appendix 1: *Correlation Matrix*

	Equity	Total_ Revenues	Profit	Gross_Profit_ Margin	ROA	ROE	Current_Ratio	Quick_Ratio	Days_AP	Days_AR	Days_Inventory	Debt_Ratio	Debt_To_Equity	Interest_ Coverage	EBIDA_RC
Equity	1,000	,689***	,725***	-,054	,054	-,016	-,017	-,017	,043	,025	,025	-,241***	-,060	,020	,685***
Total_Revenues		1,000	,651***	-,071	,121	-,007	-,023	-,023	-,002	-,036	-,022	-,034	-,042	,019	,744***
Profit			1,000	,018	,274***	,022	-,011	-,011	-,084	-,010	-,055	-,118**	-,023	,050	,914***
Gross_Profit_ Margin				1,000	,178***	,066	,164***	,164******	,189***	,092*	,172***	-,071	,072	,089*	,050
ROA					1,000	,152***	-,080*	-,080*	-,067	-,056	-,057	-,188***	-,041	,243***	,231***
ROE						1,000	-,006	-,006	-,006	,006	-,007	,067	,772***	,053	,017
Current_Ratio							1,000	1,000***	-,005	-,008	-,006	-,139***	-,011	-,002	-,015
Quick_Ratio								1,000	-,004	-,008	-,006	-,138***	-,010	-,002	-,015
Days_AP									1,000	,001	,555***	,019	-,008	-,002	-,031
Days_AR										1,000	,803***	-,064	,000	-,008	-,022
Days_Inventory											1,000	-,022	-,013	-,003	-,033
Debt_Ratio												1,000	,257***	-,023	-,072
Debt_To_Equity													1,000	-,005	-,016
Interest_Coverage														1,000	,053
EBIDA_RC															1,000

*p<0,10, **p<0,05; ***p<0,01

Source: Authors' calculations.

Appendix 2: *Stepwise model building procedure*

		B	S.E.	Wald (χ2)	df	Sig.	Exp(B)
Step 1	ROA	-8,215***	1,963	17,522	1	,000	,000
	Constant	-1,125***	,144	60,778	1	,000	,325
Step 2	EBIDA_RC	,000***	,000	16,773	1	,000	1,000
	ROA	-4,061**	1,923	4,460	1	,035	,017
	Constant	-1,136***	,154	54,408	1	,000	,321
Step 3	EBIDA_RC	,000***	,000	15,278	1	,000	1,000
	Days_AR	,002*	,001	3,294	1	,070	1,002
	ROA	-3,908**	1,860	4,414	1	,036	,020
	Constant	-1,368***	,192	50,529	1	,000	,255

*p<0,10, **p<0,05; ***p<0,01

Goodness-of-fit statistics – overall model fit

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square	Chi-square	df	Sig.
1	295,864	,109	,164	26,737	8	,001
2	265,159	,196	,294	24,270	8	,002
3	257,550	,216	,324	17,696	8	,024

Source: Authors' calculations.

Appendix 3: *Classification Table – stepwise procedure*

			Predicted		Percentage Correct
			No default	Default	
Step 1	No default	0	224	4	98,2
	Default	1	62	10	13,9
	Overall Percentage				78.0
Step 2	No default	0	218	10	95,6
	Default	1	52	20	27,8
	Overall Percentage				79.3
Step 3	No default	0	218	10	95,6
	Default	1	46	26	36,1
	Overall Percentage				81.3

Step 3: Sensitivity = 218/(218+10)% = 95,6%. Specificity = 26/(46+26)% = 36,1%. False positive = 46/(46+218)% = 17,4%. False negative = 10/(10+26)% = 27,8%.

Source: Authors' calculations.

Appendix 4: *Stepwise model building (holdout sample)*

		B	S.E.	Wald (χ^2)	df	Sig.	Exp(B)
Step 1a	ROA	-14,395***	2,632	29,919	1	,000	,000
	Constant	-1,452***	,169	73,820	1	,000	,234
Step 2b	ROA	-13,978***	2,642	27,998	1	,000	,000
	Days_AR	,001**	,001	2,729	1	,099	1,001
	Constant	-1,635***	,203	65,051	1	,000	,195

*p<0,10, **p<0,05; ***p<0,01

Source: Authors' calculations

References

1. Altman E. I., Resti A. and Sironi A. (2005), *Recovery Risk: The next challenge in credit risk management*, London: Risk Books.
2. Altman E. I. and Suggitt H. J. (2000), "Default rates in the syndicated bank loan market: A mortality analysis", *Journal of Banking and Finance*, Volume 24, Issues 1-2.
3. Araten M., Jackobs M. and V Arshney P. (2004), "Measuring LGD on commercial loans: An 18-Year Internal Study", *The RMA Journal*, May, pp. 28-35.
4. Badu Y. A., Daniels K. N., and Amaghoh F. (2002), "An Empirical Analysis of Net Interest Cost, the Probability of Default and the Credit Risk Premium: A Case Study Using the Commonwealth of Virginia", *Managerial Finance*, Volume 28, Number 4.
5. Basel Committee on Banking Supervision (2003, April), "Third Consultative Paper," Available at: http://www.bis.org/bcbs/bcbscp3.htm.
6. Basel Committee on Banking Supervision (2001a), "The New Basel Capital Accord", January. Available at: http://www.bis.org/publ/bcbsca03.pdf.
7. Bank of International Settlements (2011), Principles for the Management of Credit Risk, Available at: http://www.bis.org/publ/bcbs54.htm
8. Basel Committee on Banking Supervision (2001b), "Overview of the New Basel Capital Accord", May. Available at: http://www.bis.org/publ/bcbsca02.pdf.
9. Basel Committee on Banking Supervision (2001c), "The Internal Ratings Based Approach", January. Available at: http://www.bis.org/publ/bcbsca05.pdf.
10. Bohaček Z., Šarlija N. and Benišić M. (2003), "The usage of credit scoring model for evaluation of credit worthiness of small entrepreneurs", *Ekonomski pregled*, Volume 54, Issue 7-8.
11. Centralna Banka BiH (2009), "Bilten 2009", *Sarajevo Bosna i Hercegovina*. Available at: http://www.cbbh.ba/index.php?id=29&lang=bs.
12. Centralna Banka BiH (2011), "Finansijski sektor BiH". Available at: http://www.cbbh.ba/index.php?id=33&lang=bs&table=ukupni_depoziti_i_krediti_komercijalnih_banaka_bih.
13. Costello A. B. and Osborne J. W. (2005), "Best practices in exploratory factor analysis: four recommendations for getting the most from your analysis", *Practical Assessment, Research & Evaluation*, Volume 10, Issue 7.
14. Crouhy M., Galai D. and Mark R. (2000), "A comparative analysis of current credit risk models", *Journal of Banking and Finance*, Volume 24, pp. 59-117.
15. Dermine J. and Cavalho C. (2006), "Bank loan losses-given default. A case study", *Journal of Banking and Finance*, Volume 30, pp. 1219-1243.
16. Falkenstein E., Boral A. and Carty L. V. (2000), RiskCalc™ for private companies: Moody's default model, Moody's Investor Service.
17. Fatemi A and Fooladi I. (2006), "Credit risk management: a survey of practices", *Managerial Finance*, Volume 32, Issue 3.
18. Falu F., Erdfelder E., Buchner A. and Lang A. G. (2011), "Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses", *Behavior Research Method*, Volume 1 / 1968 - Volume 43.
19. Field A. (2006), "Discovering statistics using SPPS and sex, drugs and rock n roll", Second Edition, *Sage Publications*.
20. Frecka T. J. and Hopwood W. S. (1983), "The effects of outliers on the cross-sectional distributional properties of financial ratios", *The Accounting Review*, Volume 58, Issue 1, pp. 115-128.
21. Gupton G. M., Gates D. and Carty V. L. (2000), "Bank-loan loss given default", Moody's Investor Service.
22. Guptno G. M. and Stein R. M. (2002), "Losscal: Model for predicting loss given default (LGD)", Moody's KMV.
23. Hair Jr. J., Black W. C., Babin B. J. and Andersen R. E. (2010), *Multivariate data analysis*, 7th Edition, Prentice Hall.
24. Hui T. K. (2005), "Portfolio Diversification: a Factor Analysis Approach", *Applied Financial Economics*, Volume 15.
25. Hrvatska Narodna Banka (2009), "Bilten o bankama", Available at: http://www.hnb.hr/publikac/godisnje/2009/h-god-2009.pdf
26. Kamakura W. A. and Wedela M. (2000), "Factor analysis and missing data", *Journal of Marketing Research*, Volume 37, Issue 4, pp. 490-498.
27. Košak M. and Poljšak J. (2010), "Loss given default determinants in a commercial bank lending: an emerging market case study", *Zbornik radova Ekonomskog fakulteta Rijeka*, Volume 28.
28. Miller J. E. and Rodgers Y. van der M. (2008), "Economic importance and statistical significance: guidelines for communicating empirical research", *Feminist Economics*, Volume 14, Issue 2, pp. 117-149.
29. Narodna Banka Srbije (2009), *Statistika-bilans banaka*, Available at: http://www.nbs.rs/export/sites/default/internet/latinica/80/monetarni_sektor/SBMS03.xls
30. Oni O.A., Oledele O.I. and Oyewole, I. K. (2005), "Analysis of factors influencing loan default among poultry farmers in Ogun state Nigeria", *Journal of Central European Agriculture*, Volume 6, Issue 4.
31. Peng C-Y J., Lee K. L. and Ingersoll G. M. (2002), "An introduction to logistic regression analysis and reporting", *The Journal of Educational Research*.

32. Shugan S. M. (2002), "In search of data: an editorial", *Marketing Science*, Volume 21, Issue 4, pp. 369-377.

33. Simova J. (2009), "Concept models of customer value implication for clothing retailing", *E+M Ekonomie a Management*, Volume I.

34. Sy W. (2007), "A Causal Framework for Credit Default Theory", *Quantitative Finance Research Centre: University of Technology*, Number 204.

35. Van Horne J. C. and Wachowich Jr. J. M. (2009), *Fundamentals of financial management*,13th edition, Prentice Hall.

36. Walster G. W., and Cleary T. A. (1970), "Statistical significance as a decision rule, *Sociological Methodology*, Volume 2, pp. 246-254,

37. Yaw A. B., Kenneth N. D. and Francis A. (2002), "An Empirical Analysis of Net Interest Cost, the Probability of Default and the Credit Risk Premium: A Case Study Using the Commonwealth of Virginia", *Managerial Finance*, Volume 28, Issue 4, pp. 31-47.

Deni Memić, MSc, is a PhD candidate in business at the Faculty of Economics in Sarajevo, the University of Vienna, and the University of Ljubljana. He is a licensed investment advisor, a stockbroker and dealer. He is currently employed as the head of the Monitoring and Provisioning Department in Hypo-Alpe-Adria Bank. He is also engaged as an expert consultant at Memić Consulting d.o.o. Sarajevo. His fields of expertise include banking, financial management, risk management and technical and fundamental analysis.

Mag. Deni Memić je doktorski študent na Ekonomski fakulteti v Sarajevu ter na univerzah na Dunaju in v Ljubljani. Je licencirani svetovalec za investicije in borzni posrednik. Trenutno je zaposlen kot vodja oddelka za nadzor in odobritve v Hypo-Alpe-Adria Bank, deluje pa tudi kot strokovni svetovalec v podjetju Memić Consulting d.o.o. v Sarajevu. Njegova strokovna področja so bančništvo, finančni menedžment, upravljanje tveganj, tehnična in temeljna analiza itd.

Adnan Rovčanin, PhD, is a full professor at the Faculty of Economics, University of Sarajevo. He has also lectured as visiting professor at the University of Greenwich in London and the Belgrade Banking Academy, among others. His fields of expertise include financial management and engineering and corporate finance. Professor Rovčanin has published several books and a number of important research papers; he has also participated in many international conferences. He has contributed to the process of evaluating a great number of projects.

Prof. dr. Adnan Rovčanin je redni profesor na Ekonomski fakulteti v Sarajevu. Kot gostujoči profesor je med drugim predaval na univerzah v Greenwichu in Londonu ter na Beograjski bančni akademiji. Njegovo strokovno področje obsega finančni menedžment in inženiring, podjetniške finance itd. Profesor Rovčanin je objavil več monografij in pomembno število znanstvenih člankov ter sodeloval na številnih mednarodnih konferencah in pri ocenjevanju velikega števila projektov.