CHAPTER 6

Credit Risk Assessment for an Islamic Bank in Bosnia and Herzegovina

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1 Introduction

Credit risk management is the subject of many worldwide researches, for both conventional and Islamic financial institutions. Credit risk research is valuable for banking management, investors, business partners, and state regulatory agencies, but also globally, especially after major financial crises that negatively impacted the economic growth of developed and developing countries. After the growth of the Islamic banking market and the Great Depression of 2008, the Islamic banking sector has increased its interest in the analysis of credit risk, which resulted in scientific studies analyzing the factors affecting the creditworthiness of clients. Taking into account the specificity of Islamic financing, as well as compliance with the Sharia Law, the number of scientific studies on this topic is relatively

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small. Different regulatory rules in countries with developed Islamic banking have limited research to individual countries, and these are mainly the result of analysis of individual Islamic banking markets, mainly related to the probability of default (PD) or non-performing loans (NPL) of Islamic banks, but not their clients.

The reason for a very small number of studies is the difficulties in accessing financial and other data from Islamic bank clients. The lack of access to data is particularly present for small- and medium-sized enterprises which are not required to publicly publish their financial results and other business-related information.

With the credit risk assessment methods in Islamic banks being insufficiently researched, in the literature we can frequently find studies analyzing the models for the most accurate corporate predictions of failure in conventional banks using different modeling techniques. Statistical methods are most frequently used.

Classical statistical methods are discriminant analysis, regression analysis, neural network, and decision trees. Below is an overview of the most common models or methods, the authors of some of the researches and the countries where the models or methods on selected databases were used (Table 1).

Islamic Financial Service Board (IFSB) defines credit risk as “the potential that a counterparty fails to meet its obligations in accordance with agreed terms. This definition is applicable to Institutions Offering Islamic Financial Services (IIFS) managing the financing exposures of receivables and leases (e.g., *Murābahah, Diminishing Mushārakah, and Ijārah*) and working capital financing transactions/projects (e.g., *Salam*, *Istisnā’,* or *Muḍārabah*)” (2005, p. 6).

One of the first works (Abdou et al. 2014) on tools for predicting the creditworthiness in Islamic finance was made on the basis of 487 applications of natural persons in an Islamic Finance House in the UK. Three methods were used to create a scoring model of discriminant analysis (DA), logistic regression (LR), and multi-layer perceptron (MP) neural network.

The results showed that the LR model has the highest rate of correct classification applications, while MP has an advantage over other techniques in the prediction of rejected requests for loans, as well as the lowest cost incorrect classification. The MP model identifies monthly costs, age, and marital status as key elements that are significant in the decision-making process.

Table 1 The overview of some of the authors, statistical methods, models, and countries

Model	*Country*	*Authors*
Z score model	USA	Altman (1968)
	Greece	Gerantonis and Christopoulos (2009)
	Kenya	Odipo and Sitati (2010)
	Ghana	Appiah (2011)
	Turkey	Ali (2007)
	International	Altman (1984)
ZETA model		Altman et al. (1977)
Logit and probit model	Taiwan	Shen and Huang (2010)
	Korea	Nam and Jinn (2000)
Logistic regression	Croatia	Šarlija et al. (2009)
	Spain	Andreev (2005)
	Bosnia and Herzegovina	Memić (2015)
Discriminant analysis	Italy	Ciampi and Gordini (2008)
	Czech Republic	Dvoracek et al. (2008)
Decision trees	USA	Galindo and Tamayo (2000)
Neural network	Croatia	Zekic-Susac et al. (2004)
	USA (Credit Union)	Desai et al. (1997)

Source Authors' work

In their work on analyzing financial ratios in discriminating between healthy and distressed companies (Saracevic and Sarlija 2017), compared to previous researches, profitability ratios and activity ratios are the most important indicators in distinguishing healthy and distressed companies. The methods used are the statistical methods of Mann–Whitney test for years 2009 and 2010 and a t-test for years 2011–2013. Mann–Whitney method was used because of a relatively small number of clients and t-test from 2011 due to changes in accounting standards for the creation of balance sheet positions of clients. In order to obtain comparable results, different methodologies were used. This analysis is a step forward in the development of a scoring model based on SME clients of an Islamic bank financed by diminishing Musharakah.

Fuzzy logic methods for credit scoring model compliant with Sharia were used by Sidik et al. (2013). Their score is obtained by using an IT2FS algorithm based on two variables (sum of late day) and (installment amount) for each customer. They proposed two scenarios and concluded that they are fairer than the conventional method. Based on their proposed business model, "*the fines will be imposed if and only if the customer cannot prove that the delay was due to inadvertence*" (Sidik et al. 2013).

2 Basel Rules Review and Summary

Basel II represents the concept of calculating the capital adequacy of a bank, thereby defining the rules in the measurement and management of the risks the bank is exposed during its business. As the capital represents protection from unexpected losses and it is the basis of the bank growth, Basel II rules define how much the value of a bank's own capital is sufficient to cover unexpected losses.

Since the primary function of own capital is to protect the bank from the risk of insolvency, the banks are obliged to adjust this value to the risk assets of the bank. Capital adequacy is the basis for growth, development, and stability of the bank. If the bank's own capital is too low, there is a danger of the inability to absorb losses, the likelihood of bankruptcy increases, but the client deposits are also jeopardized. In the event that capital is too high, it is impossible to achieve a sufficiently high rate of return on sources of funds, thus leading to a business profitability problem (Šarlija and Gereč 2008).

As can be seen from Table 2, Basel II (Basel Committee on Banking Supervision 2003) is based on three pillars:

Table 2 3 Pillars of Basel II

Pillar 1	*Pillar 2*	*Pillar 3*
Minimum capital requirements: – Risk management incentives – New operational risk capital charge – Risk-weighted assets (RWA) for credit more risk-sensitive – Market risk largely uncharged	**Supervisory review**: – Solvency reports – Regulatory review – Capital determination – Regulatory intervention – Addresses risks that are not captured in Pillar 1 like concentration and liquidity risks	**Market discipline**: – Minimum disclosure requirements – Scope – Capital transparency – Capital adequacy – Risk measurement and management – Risk profiling

Source Bakiciol et al. (2013)

– Minimum capital requirement (Pillar 1),
– Supervisory review (Pillar 2),
– Market discipline (Pillar 3).

The minimum capital requirements consist of basic capital increased by retained earnings, after-tax reserves, and additional capital. The calculation of the capital adequacy ratio is made by dividing the regulatory capital by the amount of the total exposure to risk.

Unlike the previous rules, the operational risk is added to the credit and market risks. For banks operating in Bosnia and Herzegovina, the minimum capital adequacy ratio is 16%.

Even though the other risks are covered by these standards (2003), the credit risk, being the most important, is measured by the methods set in accordance with Basel II:

1. Standardized approach (SA),
2. Foundation internal rating-based (IRB) approach,
3. Advanced internal rating-based (IRB) approach.

The SA is similar to the Basel I standard based on the formation of fixed risk weights that are arranged in accordance with the type of a claim. Supervisors are responsible for determining the weights, and the banks are bound to adopt and implement them. Risk-weighted claims are categorized by the SA into claims from government institutions, banks, companies, households, and claims secured by mortgages on real estate. It is allowed to determine the risk weight in accordance with the rating determined by an external credit rating agency, verified by the national regulator. In addition to this, the Basel II standards define more weights for companies, and risky household claims are secured in the form of mortgages on residential property of a certain risk-weight level from 35 to 75%. Treatment of small and medium enterprises can be included in the framework of the retail segment and may be subject to various other criteria (Basel Committee on Banking Supervision 2003).

Internal rating-based (IRB) approach differs from the SA in terms of the responsibility for customer risk assessment. Namely, the sole responsibility for customer risk assessment, according to the IRB approach, lies with the bank, while the SA approach puts the exclusive responsibility at the regulator (Basel Committee on Banking Supervision 2003).

The bank classifies the claims in 5 risk groups:

1. Companies,
2. State institutions,
3. Banks,
4. Retail,
5. Equity securities.

For each group of the claims, the bank sets: elements of risk, the calculation of risk-weighted assets that are transformed in capital requirements, and minimum requirements relating to the adoption of standards that banks must have in order to apply the IRB approach.

According to Basel II standards, the basic risk elements are:

1. Probability of default—the probability that the borrower will not pay contractual obligations,
2. Loss given default (LGD)—the percentage loss rate exposure if the company happens default event,
3. Exposure at default (EAD)—the outstanding debt at the time of default,
4. Maturity—"the maximum remaining time (in years) that the obligor is permitted to take to fully discharge its contractual obligation, including principal, interest, and fees, under the terms of loan agreement" (Train 2018).

Foundation IRB approach and advanced IRB approach differ in responsibility for determination of risk elements, i.e., whether the bank or the regulator sets the basic elements as shown in Table 3.

Table 3 The difference between FIRB and AIRB

	PD	*LGD*	*EAD*	*M*
Foundation IRB	Bank	Regulator	Regulator	Regulator
Advanced IRB	Bank	Bank	Bank	Bank

Source Consultative Document; Overview of the New Basel Capital Accord (2003)

Basel III emerged as a response to the global economic crisis; also as a purpose of the Basel Committee to strengthen the banking regulatory framework with a group of reform measures which would make the banking sector resistant to the stresses caused by the financial and economic shocks. This regulatory framework implies improving risk management in banks and increasing their transparency in work. The first version of Basel III framework was issued in December 2010, revised version in June 2011, and the latest version, "Final post-crisis reforms," in December 2017. From the period of the first version of Basel III until the current version, several documents were adopted, completing the regulatory framework in order to protect banks against unexpected losses.

The basic elements of Basel III are:

- Increase of minimum capital requirements,
- Better management of bank liquidity,
- Banking protection against the likelihood of bank deposit withdrawal by a large number of clients (Bank Run).

Consequently, Basel III defines the regulatory capital, consisted of,

- Common Equity Tier 1—common shares, retained earnings, and other reserves,
- Additional Tier 1—capital instruments with no fixed maturity,
- Tier 2—subordinated debt and general loan-loss reserves.

The capital ratio is calculated as the amount of regulatory capital divided by the amount of risk assets. The higher the amount of risk assets, the greater the capital is needed and vice versa.

$$\text{Risk-based capital ratios} = \frac{\text{Regulatory capital}}{\text{Risk-weighted assets}}$$

In terms of capital requirements, Table 4 presents the difference between the Basel II and Basel III.

Table 4 Capital adequacy assessment—Basel II and Basel III

	Basel II (%)	*Base III (%)*
Common equity (risk-weighted assets after deduction)	2	4.5
Total common equity	4	7
Countercyclical buffer	–	0–2.5

Source Basel Committee on Banking Supervision (2017)

In order to strengthen the profitability position and control of debt of the banks, Basel III introduces a minimum leverage ratio which is calculated by dividing the Tier 1 capital to average total consolidated assets of the bank. Banks should maintain a leverage ratio up 3%.

$$\text{Leverage ratio} = \frac{\text{Tier1}}{\begin{array}{c}\text{On- and off-balance sheet exposures} \\ \text{(including derivates, repos, and other secururities} \\ \text{financing transaction)}\end{array}} \geq 3\%$$

“A leverage ratio constrains the build-up of debt to fund banks’ investment and activities (bank leverage), reducing the risk of a deleveraging spiral during downturns” (Basel Committee on Banking Supervision 2017).

Regarding to short-time liquidity position, liquidity risk management of the banks, among the other things, imposes the obligation of the banks to provide minimum coverage ratio of liquidity (Liquidity Coverage Ratio—LCR), which represents the ratio between the levels of the protective layer of liquidity and total net liquidity outflows during the period of stress for a period of 30 calendar days.

In terms of view, the long-term liquidity position Basel III introduces the net stable ratio of funding establishes a management standard of structural or long-term liquidity. It requires that the available amount of stable funding exceeds the required amount of stable funding in a period of 1 year of crisis.

Available stable sources (capital, long-term loans, stable deposits) must be larger than the required stable sources that are assessed on the basis of the maturity and quality of the approved loans.

3 Banking Legislation in Bosnia and Herzegovina

Banks in B&H, due to more rigorous requirements from Regulator, have more favorable indicators of capitalization. Indicators which measure the ratio of the amount of capital and assets are significantly higher than in Western European countries. In B&H this ratio is about 16%, while in Western European countries it is commonly found to be around 11% or 12%. It is a consequence of more stringent capital requirements, which were introduced precisely in order to provide additional resistance to the banking system in the "younger" markets.

The share of B&H banks within foreign banking groups is very small and ranges between 3 and 5%. Banks in B&H are dealing with traditional banking, and their assets did not include potentially dangerous assets, but almost exclusively loans for domestic economy. Therefore, their assets are not jeopardized by a significant decrease in the value of shares or real estate in countries with overpriced real estate prices.

Due to the very harsh demands regarding maturity compliance for B&H banks, fortunately, they did not have the flexibility to borrow for a short time and to provide long-term loans. Banks are heavily funded on the basis of domestic deposits, and this is a model that has survived in the USA where investment banks bought such banks (Centralna Banka Bosne i Hercegovine 2018).

Given the legislation applied in the banking sector, the only Islamic bank has found its place in this market and it is developing with very stable steps.

In terms of strengthening stability and resistance of B&H banks to possible capital risks, liquidity risks, market risks, and other significant risks related to the specificities of each bank's operation individually at the beginning of 2019, the Banking Agency of B&H adopted a decision on the Internal Capital Adequacy Assessment Process and Internal Liquidity Adequacy Assessment Process which will be implemented from January 2020 (Agencija za Bankarstvo Federacije Bosne i Hercegovine 2019).

4 Islamic Banking Data

The data used in this paper are the basis of financial statements—the balance sheets of an Islamic bank's client in B&H. Based on the available data, the authors calculated financial ratios that indicate the difference between healthy companies and those that show signs of instability. In

Table 5 Overview of financial ratios

Liquidity ratios	
CR—Current ratio	QR—Quick ratio
CshR—Cash ratio	CA/TA—Current assets/total assets
FA/NCp—Fixed assets/net capital	FSR—Financial stability ratios long-term assets/capital+long-term liabilities
Leverage ratios	
Csh/CA—Cash/current assets	WC/TA—Working capital/total assets
ShtFD/TD—Short-term financial debt/total debt	ShtD/TD—Short-term debt/total debt
DR—Debt ratio	Gearing—Liabilities(debt)/equity
LofCI—Level of coverage I	LofCII—Level of coverage II
LofCIII—Level of coverage III	
Activity ratios	
TATR—Total assets turnover ratio	STATR—ST assets turnover ratio
LTATR—LT assets turnover ratio	TrofRcvb—Turnover ratio of receivables
CollDay—Collection period in days	DaySlsInv—Days' sales in inventory
OpCy—Operating cycle	TrofInv—Turnover ratio of investment
Efficiency ratios	
Inv/CoGS—Inventories/cost of goods sold	EofTAc—Efficiency of total activity
EofBAc—Efficiency of business activity (sales activity)	EofFinOp—Efficiency of financial operations
EofOpAc—Efficiency of operating activity	GrMg—Gross margin
Profitability ratios	
GrMg—Gross margin	OpMg—Operating margin
NproMg—Net profit margin	ROA—Return on assets
ROA1—Gross ROA	ROE—Return on equity
CoIncR—Cost income ratio	Prof ExSrc—Profitability of external sources of financing
RE/TA—Retained earnings/total assets	

Source Authors' work

the calculation, 419 companies' data were used ranging from 2009 to 2013. Each individual financial ratio was analyzed. The financial ratios are divided into five groups as shown in Table 5:

- Liquidity ratios,
- Leverage ratios,

– Activity ratios,
– Efficiency ratios,
– Profitability ratios.

4.1 Research Methodology and Model Building

During the research of which companies are distressed or healthy and formation of the model, the following statistical methods were used:

– the Mann–Whitney test for years 2009 and 2010,
– *t*-test for years 2011–2013,
– LR for building the model.

The Mann–Whitney test is a non-parametric test for the difference in distribution (Sheskin 2004); the *t*-test is a parametric test for testing the difference in means (ibid., p. 375). The Mann–Whitney statistical method was used because of the relatively small number of customers and *t*-test due to changes in accounting standards since 2011 year to create balance sheet positions for clients. In order to obtain comparable results, different methodologies were used.

Logistic regression is defined usually as statistical method which is an integral part of any data analysis that deals with the linkage between dependent and independent variables. Its aim is to find a model that is best adapted to the data, which contain only those independent variables that affect the outcome of the dependent variable and which describes the relationship between dependent and independent variables. U izradi ovog modela LR ima za cilj izračunati koje varijable mogu ukazati na moguće kašnjenje u otplati ugovornih obaveza klijenta. In developing this model, LR aims at determining which variables may indicate a possible delay in repayment of client's contractual obligations.

5 Credit Risk Assessment Model

The model should predict the PD of the clients of an Islamic bank, based on an available database, which was formed in the time period of five years. The classification of clients to distressed or healthy is based on the delay in repayment of contractual obligations, for a period of time longer than 90 days. Dependent variables are 0 and 1, where 0 indicates a healthy company and 1 a distressed company.

Available data for this study consisted of 419 clients of an Islamic bank in B&H. As indicated in Table 6, through the total number of companies, the financial statements (balance sheet, income statement) of the companies were available during the period from 2009 to 2013, but not for all companies over the entire period.

The LR model classification results using the 9 predictor variables and the area under curve (AUC) was used from the standpoint of measuring the accuracy of the model.

"The area under curve (AUC), referred to as index of accuracy (A) or concordance index, is a perfect performance metric for ROC curve. Higher the area under curve, better the prediction power of the model" (Analytics Vidhya Content Team 2015).

The best accuracy of the calculated model is in the case when the AUC is

$$0.5 < \text{AUC} < 1.0. \text{ In this model, AUC} = 0.71.$$

Kolmogorov–Smirnov (K–S) statistic is one of the most widely used measures for the predictive strength of credit risk models. The K–S statistic is usually calculated for LR results in order to obtain the model quality indication. "*K-S or Kolmogorov-Smirnov chart measures performance of classification models. More accurately, K-S is a measure of the degree of separation between the positive and negative distributions. The K-S is 100 if the scores partition the population into two separate groups in which one group contains all the positives and the other all the negatives. On the other hand, if the model cannot differentiate between positives and negatives, then it is as if the model selects cases randomly from the population. The K-S would be 0. In most classification models the K-S will fall between 0 and 100, and that the higher the value the better the model is at separating the positive from negative cases*" (Model Evaluation—Classification 2018).

In our case, K–S = −0.46 which shows good quality model's prediction.

Table 7 shows the percentage of accuracy of the tested model for the prediction of healthy and distressed companies on the basis dataset from an Islamic bank in B&H. The results showed 71.4% accuracy of the company health forecasting model in the analizyed periods, which is a good

Table 6 Descriptive analysis

Year	*2009*		*2010*		*2011*		*2012*		*2013*	
	%	*N*	%	*N*	%	*N*	%	*N*	*N*	%
Healthy	89.69	174	89.59	241	83.59	219	82.62	328	75.86	176
Distressed	10.31	20	16.41	28	16.41	43	17.38	69	24.14	56
Total	100	194	100	269	100	262	100	397	100	232

Source Saracevic and Sarlija (2017)

Table 7 The rate of accuracy of tested model

Total rate of hits	71.4%
Rate of hits for variable 0	83.3%
Rate of hits for variable 1	62.5%

Source Authors' work

Table 8 List of predictor variables and their importance used in building the scoring model

Variable	*Code*	*Ratio-type*	*Importance*
Financial stability ratios	FSR_1	Liquidity	0.253
Level of coverage I	LofCI_1	Leverage	0.644
Total assets turnover ratio	TATR_1	Activity	0.122
LT assets turnover ratio	LTATR_1	Activity	0.531
Turnover ratio of receivables	TRofRcvb_1	Activity	0.413
TrofInv—Turnover ratio of investment	TRofInv_1	Activity	0.314
Inventories/cost of goods sold	Inv_CoGS_1	Efficiency	0.221
Gross margin	GrMg_1	Profitability	0.039
Return on assets	ROA_1	Profitability	0.092

Source Authors' work

level of prediction. Table 8 summarizes 9 predictors and their importance for the accuracy of the model.

As Table 8 shows, the most important variables for the model are LofCI, LTATR, TRofRcvb TRofInv, FSR, Inv_CoGS, and TATR with contribution weightings of 0.644, 0.531, 0.431, 0.314, 0.253, and 0.221, respectively. On the other hand, the least influential variables are ROA and GrMg with contribution weightings of 0.092 and 0.039. The most influential variables are from the group of leverage and activity ratios, as well as a bit less importance carries the variables from the group of liquidity and efficiency ratios.

6 Future Work

One of the areas of future research related to Islamic banking credit risk prediction is incorporation, in a precise mathematical way, of so-called soft (subjective expert opinions) data. In practice, soft data are used in credit risk assessment in all banks, but in an ad hoc way, based on credit expert personal opinion or with soft coding as hard and then plugging into statistical methods. In our other work in progress (Brkić et al. 2018), we presented a soft–hard data fusion approach for default probability prediction improvement for general banking environment. This approach can be readily extended to Islamic banking area with the proper soft data modeling. The database was from a B&H commercial bank with 300+ commercial customer data used. In this context, we are looking to obtain a larger database of Islamic credit risk-related customers, so our approach can be validated further.

7 Conclusion

The aim of this research is to form a model that would serve as a tool for better credit risk management, based on existing clients of an Islamic bank from B&H. Prediction of PD based on financial indicators, and a 5-year time series, is based on statistical methods, and the final model is formed on the basis of LR results.

Comparing the previous works with the results obtained in this research, it became evident that financially troubled businesses have a lower level of liquidity ratios, higher leverage ratios, and lower ratio of activity compared to financially healthy companies. In the resulting credit risk assessment model, we have leverage and activity ratios with higher contribution weightings than other from groups of efficiency, liquidity, and profitability ratios. As in the previous study (Saracevic and Sarlija 2017), it has been shown that the ratio of activity is very important for the analysis of Islamic bank companies in our results, although it can be very effective for commercial banks as well.

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