DEVELOPMENT OF A CREDIT RISK SCORING MODEL FOR FINANCING BUSINESS UNITS OF SHARIA BUSINESS UNITS IN INDONESIA

***Misbahul Munir, Darwis Hude, Patria Yunita, Imron Natsir, Ahmad Zain Sarnoto**
Universitas PTIQ Jakarta, Indonesia
*Correspondence: Tel. + (62) 812-8854-6446, E-mail: mohamad.misbahul.munir@mhs.ptiq.ac.id, misbahulmunir1969@gmail.com

ABSTRACT: This study developed a Credit Risk Scoring model based on binary logistic regression to enhance the objectivity and effectiveness of credit risk management in the Sharia Business Unit. The model, involving 10 independent variables, is designed to assist Islamic financial institutions in better identifying, measuring, and managing credit risk while ensuring compliance with Sharia principles. The model's reliability was tested using ROC (Receiver Operating Characteristic) analysis, demonstrating high predictive ability with an AUC (Area Under Curve) value of 0.79 and a KS (Kolmogorov-Smirnov) value of over 0.42. Key statistical tests showed significant results: the Omnibus test had a value of 0.00 (<0.05), Nagelkerke R Square was 0.336, specificity was 66.9% (> 0.5), sensitivity was 74.3% (> 0.5), and the Hosmer & Lemeshow test had a value of 0.271 (> 0.05), indicating a well-fitting model. Univariate and multivariate tests confirmed that all independent variables significantly influence the probability of default, with the binary logistic regression model demonstrating strong and relevant predictive power. Implementing this model allows the bank to more accurately predict the probability of default, thereby reducing potential losses from non-performing financing. The model provides a standardized framework, reduces reliance on subjective judgment, and strengthens credit risk management through a scientific and data-driven approach. This research contributes significantly to the academic literature on credit risk management in Islamic banking and offers practical solutions to improve financing decision quality.

Keywords: Credit Risk Scoring, Islamic Finance, Binary Logistic Regression.

INTRODUCTION

In carrying out its business operations, Sharia Banks must be careful in safeguarding and preserving the interests of public funds entrusted to them and maintaining public trust in bank operations. Financing activities, as the main activities of banks, contain risks that can affect the health and continuity of the bank's business. Therefore, in practice, banks must operate based on sound financing principles. Providing consistent financing by sound principles requires strong, systematic and effective credit risk management. The main objective of risk management, especially credit risk, is to ensure that financing activities are not exposed to credit risks that could cause losses to the bank. Like conventional banking, in Sharia Banking there is also credit risk, namely the risk that arises due to the failure of customers or other parties to fulfill their obligations according to the agreement. For this reason, banks are required to have adequate capabilities in identifying, measuring, monitoring and controlling these risks, as well as providing sufficient capital. In studies, Islamic economists use the words khatar and mukhatarah for business risks as "situations involving the possibility of deviation and the possibility of loss. This is in line with Ibn Manzur in the book Lisan ul-Arab which explains the concept of risk in Arabic, namely mukhatir or mukhatarah or khatr.In the banking and financial sector, credit risk management is very important in determining the stability and sustainability of financial institutions. In Islamic financial institutions, risk management must be effective and by sharia principles which prohibit usury, gharar (uncertainty) and maisir (speculation). The development of credit risk assessment models that are effective and in line with sharia principles, such as credit risk scoring tools, is very crucial. The development of credit risk scoring as an alternative credit risk assessment model for sharia financial institutions is expected to help sharia financial institutions make better decisions regarding providing financing, measuring and responding explicitly to risks. This model will support in-depth analysis ranging from capacity assessments to borrowers' tendencies to meet loan repayment obligations. With this tool, banks can determine whether a financing application will be accepted or rejected, depending on the probability of default resulting from credit risk scoring. This tool allows Islamic financial institutions to have a strong basis for managing credit risk and anticipating potential losses from non-performing financing. This research will also adopt statistical tests and model validity using a binary logistic regression analysis method approach. This method uses variations of independent variables that are relevant for predicting the probability of default of financing. This research is expected to make a significant contribution to the development and understanding of managing credit risk in Islamic financial institutions, as well as providing better decisions in providing further loans to customers. In terms of regulations, the implementation of credit risk management in Commercial Banks and Sharia Business Units has been regulated by the Financial Services Authority through the Circular Letter of the Financial Services Authority of the Republic of Indonesia Number 25/SEOJK.03/2023. Risk management for credit risk is implemented both for individual banks and for Sharia Business Units (BUS) in consolidation with Subsidiary Companies, referring to Financial Services Authority Regulation Number 65/POJK.03/2016 and Number 38/POJK.03/2017 concerning Implementation Consolidated Risk Management for Banks that Control Subsidiaries.

The OJK regulations support the implementation of credit risk scoring tools by establishing policies for Commercial Banks or Sharia Business Units to:

- Considering the potential for default in the risk measurement system, both based on standard approach assessments and internal ratings;
- Having written systems and procedures for carrying out risk measurements that enable assessing differences in credit risk levels between customers or transaction counterparties;
- Using a quantitative and/or qualitative approach that is tailored to the objectives and complexity of the business and the bank's capabilities;
- Using statistical or probabilistic methodologies to measure the risk associated with certain types of credit risk transactions.

This research will not only focus on the application of existing risk management theories and practices, but also on innovations in risk assessment methodologies that can be integrated into Islamic banking practices. Thus, this research is expected to support the sustainability and growth of Islamic financial institutions, showing how effective risk management can provide concrete benefits in maintaining the financial and operational health of banks.

IDENTIFICATION OF PROBLEMS

From the background of the problem above, several identification problems related to the theme can be described ***as a Credit Risk Scoring Model for Financing in Sharia Financial Institutions as follows:***

- Lack of standardization in credit risk assessment when making financing decisions.
- The problem currently faced is that there is no standard framework for assessing credit risk in the Islamic financial institutions where the research is conducted, which causes inconsistencies and potential bias in the assessment process. The impact of this inconsistency can increase credit risk and affect the financial stability of the institution.
- Remember that credit assessments are still carried out using a qualitative approach and expert judgment can result in subjective assessments, resulting in subjective decisions that can reduce the effectiveness of risk management and increase the frequency of defaults.
- With a qualitative financing analysis approach, there is no integration with the Predictive Model for the Possibility of Default. This has the impact that financial institutions may not be able to accurately identify high-risk debtors, which has the potential to increase credit costs and financial losses.
- There is a need for a risk assessment model that is effective but also by Sharia Principles, so the development of a model like this will help ensure that the operations of Islamic financial institutions remain within the Sharia framework while improving risk management.

RESEARCH PURPOSES

Developing Credit Risk Scoring Based on Binary Logistic Regression to Increase the Objectivity and Effectiveness of Credit Risk Management in Sharia Financial Institutions. (Bank Jatim Sharia Business Unit)

LITERATURE REVIEW

Credit scoring is a method for assessing financing risk. Credit Scoring determines a value based on loan characteristics, borrower characteristics, historical default, and loss experience as an indication of the debtor's risk level. With a score, a separation can be made between customers with acceptable risk and unacceptable risk according to the predetermined cut-off value.

Credit scoring itself is generally defined as a mathematical tool used to predict the quality of a loan in the future based on statistical analysis of good and bad debtor data in the past.

RESEARCH OBJECTIVE

Research that has been carried out regarding Credit Risk Scoring is mostly carried out in conventional banking, research on credit risk scoring is as follows:

Researcher	Research Title	Research methods	Research Contribution
Hussein A. Abdou, Shaair T. Alam, James Mulkeen	Would Credit Scoring Work for Islamic Finance? A Neural Network Approach	Logistic regression, multilayer perceptron (MP) neural network, discriminant analysis	Comparison between Logistic Regression models, MP Neural network. The MP neural network model shows the best performance in predicting rejected financing applications
Antonio Manuel Sarmento Batista 2009	Credit Scoring - A Management Methodology for the Prevention and Reduction of Bad Credit	**Statistical Methodology**: Logistic regression, scoring table.	Using logistic regression models and scoring tables, significant factors can be identified in predicting the possibility of a debtor being a good or bad payer. This research also shows that the scoring method applied can increase the effectiveness of credit risk management
Broto Susanto Ajar (2009)	Application of Credit Risk Scoring in Micro Credit Analysis at Bank Bukopin	Logistic Regression	application of the credit risk scoring model which is used to assess the feasibility of microcredit and in applying credit scoring, scoring parameters are determined that meet statistical rules using the logistic regression method,

Researcher	Research Title	Research methods	Research Contribution
Safitri Dayu, Novianti Tanti, Sartono Good	*Analysis of Financing Risk Using Credit Scoring on Microfinance: A Case Study in X Islamic Bank.*	*Logistic regression analysis to evaluate the credit scoring model implemented by X Islamic Bank*	Provide insight to banks regarding variables that are significant in influencing financing risk, so that banks can improve the credit scoring model used
Nikita Kozodoi, Johannes, Jacob Stefan Lessmann	Fairness in Credit Scoring: Assessment, implementation and profit implications	application of fairness in credit scoring using machine learning (ML)	*using empirical analysis methods with several fairness processor approaches in developing ML model pipelines. This research examines fairness and processor criteria in the context of credit scoring by considering profitability implications.*

RESEARCH METHODS

POPULATION AND SAMPLE

According to Scheaffer, et al (1990), determining the number of samples for statistical inference purposes must pay attention to the interval of estimation error, namely the difference between the value of an observed parameter/variable and the estimate of that value (O - Ō), which must be smaller than a specified value. specified, for example, B. Mathematically: estimation error = | O – Ō | <B; Usually this error has a probability of less than 95%, namely when B = 2□Ō or B = 5%. The number of samples to estimate credit performance (good or bad) can be calculated using the formula (Scheaffer, et al, 1990):

$$n = \frac{Npq}{(N-1)D + pq}$$

where: p = q = probability of credit being good or bad = 50%,

$$D = (B^2/4) = (0.052/4) = 0.000625$$

Calculation of Estimated Sample Size Required

Segmen Produk	Sample Window	Jumlah Debiur	Minimal Jumlah Sample
KPR Griya Barakah IB	18 bulan	5.314	372

The Credit Risk Scoring model was developed using 50% Bad data and 50% Good data with a total of 372 Bad data and 372 good data.

Model Performance Test Results

Several statistical tests used to test the performance of a model are the Kolmogorov-Smirnov test and the Receiver Operating Characteristic Test.

Kolmogorov Smirnov Test (KS-Test)

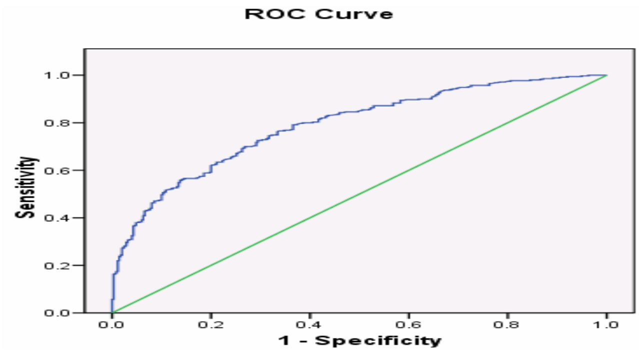
KS-test is one type of model validation

used to see whether the scores from the BAD and GOOD groups can be separated. Separate in the sense of having different score sizes. The high overlap between BAD and GOOD scores indicates that the model is unable to produce scores that can separate the Bad and Good groups. Testing using the KS-test is carried out based on the empirical cumulative distribution function for each group. The empirical cumulative distribution function is obtained from the cumulative sum of each range of values/scores. This means that before that, a procedure for creating a class/category/band/range for the score is carried out. Next, from each band score, the cumulative frequency is calculated. The cumulative distribution function is obtained by dividing the frequency by n (the amount of data). The KS test is to compare two empirical cumulative distribution functions, namely from the Bad and Good groups. The greater the difference, the greater the difference between the scores of the two groups. In modeling, it can be interpreted that a larger difference indicates a better model.

*Credit Risk Scoring*The KPR IB BARAKAH mentioned above was developed based on empirical data currently owned by the Sharia Business Unit. However, taking into account the limited data available when developing the scorecard model. Based on the results of research and testing, 10 variables meet the goodness of fit criteria, which include Weight of Evidence (WOE), Information Value, and p-value, so they can be predictors of default probability. Based on ROC curve testing, the model with 10 variables even though it has a value of 0.79 is considered adequate to be used as a model. ROC is a model testing method by measuring the area of the arena under the curve. The y-axis depicts sensitivity or true positives, namely the number of individuals in the Good (1) category who are correctly predicted to be Good (1) divided by the amount of Good data. If the cutoff value of the probability prediction used is small, then the individual tends to be predicted to have category 1 (Good). So when the cutoff value is small, the sensitivity will be large (close to 100%). In general, this sensitivity value will decrease if the cutoff value is increased. Meanwhile, the x-axis depicts 1- SPECIFICITY. Specificity itself is True Negative, namely the number of individuals in the Bad (0) category who are correctly predicted to be Bad (0) divided by the number of Bad data. 1

- Specificity is 1 minus the specificity value, or obtained from false positives divided by actual Bad data.

If the cutoff value of the probability prediction used is small, then individuals tend to be predicted to have a category 1 (Good). So when the cutoff value is reduced, this (1 – specificity) will be large (close to 100%). In general, this value (1 – specificity) will decrease if the cutoff value is increased.



Area Under the Curve

Test Result Variable(s): PD

Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
			Lower Bound	Upper Bound
,790	,017	,000	,757	,823

*Based on*validation with C statistics which produces a Receiver Operating Characteristic (ROC) curve, showing an area of 0.790. The area is above the standard average set. Standard Field Area under ROC curve:

1. $\leq$0.5 = not good to use (random selection)
2. > 0.5 – < 0.7 = usable
3. $\geq$0.7 = good for use (adequate)

Determination of Score Scales, Ratings, PD and Definitions

Method for determining the score/Grade scale

By what is mandated by Basel, the ranking system must be able to distribute exposure to avoid excessive concentration on customer rankings and certain facility rankings. (Consultative Document BIS-IRBA, 2001; Max. concentration limit = 30% for each rank). Apart from this, the rating system must have a minimum of 7 (seven) ratings for non-default customers and 1 (one) rating for default customers. The grade is determined by grouping the score scale in the same range using visual binning techniques. This process produces 10 rating levels, each of which has an average probability of default (PD) level based on sample data. The number of rating levels of 10 is designed to meet the recommendations of Basel II paragraph 404, namely a minimum of 8 levels consisting of 7 levels for current loans and 1 level for problem loans. Of the 10 levels, 8 are allocated to current loans (L and DPK), while the last 3 ratings (ratings 8,9,10) are allocated to loans with KL, D and M collectibility.

Determination of Probability of Default

From binary logistic regression, a predicted default or non-default can be produced depending on the PY(1) used for the Good (non-default) or Bad (default) group. Considering that the dependent variable (PY (1) is Good, the resulting predicted is the probability of non-default. To find the probability of default, you can use equation 1 - predicted non-default. Mathematically, the prediction is obtained from the following formulation (Elizabeth Mays) :

Probability = 1/[1 + e B0 - (B1 X1 + . . . + Bn Xn)

From the above process, a PD sample or posterior PD is obtained. Because the number of Good and Bad samples is the same, compared with the actual conditions in the population, compositionally there has been oversampling for the Bad samples. In this regard, a transformation from posterior PD to an adjusted PD estimate is required which is carried out using the following formula (Naeem Siddiqi) With this sample size, the proportion between Bad and Good is not comparable to the non-performance level of IB BARAKAH KPR Loan (account) which is only 7.87%. It can be said that the bad data used is oversampling, so to determine the probability an offset method is used through transformation. Transformation of posterior PD into adjusted PD estimates is carried out using the following formula:

$$PDadjusted = \frac{(PDsampel * \rho_0 * \pi_1)}{[(1 - PDsampel) * \rho_1 * \pi_0 + PDsampel * \rho_0 * \pi_1)]}$$

Where, ρ_1 And ρ_0 is the proportion of bad and good in the sample, whereas π_0 And π_1 is the proportion of bad and good in the population (portfolio). The customer grade starts from Grade 1 to 10. Grade 1 is the highest, while grade 10 is the lowest. The lower the risk level, the customer is given a higher score. The PD for each rating is the average PD for the one-year determination period (Basel II paragraph 414). It should be noted that the PD determined in developing this scorecard does not take into account data from abnormal (adverse) economic periods.

Cut Off Determination

Cut Off is a value or grade that is used as a limit for acceptance or rejection of applications submitted by prospective customers. Applicants who have a score above the cut-off. Meanwhile, applicants who have a score below the cut-off will have their credit application rejected. The development of a cut-off score is a trade-off between risk and acceptance rate. There are two cut-off approaches, the first is to determine the cut-off so that the estimated projected acceptance is the same as before the application of the scorecard, or the second is to determine what level of acceptance rate and bad rate can be accepted or is a function of the probability of default (risk predict) of each grade of scoring. For the first approach, the cut-off is carried out based on a comparison between the results of the scoring calculation and the manual decision:

Decision Score	Decision Manuals	Meaning	Actions
Agree	Agree	Correct	Approved
Agree	Reject	Potential Risk	Reviews
Reject	Agree	Market Losses	Reviews
Reject	Reject	Correct	Rejected

Even though the scorecard can mathematically determine the cut-off for accepted/rejected applications, in practice there is still a gap called the grey area where the scorecard cannot show the ability to differentiate between bad customers and good customers. To overcome this, it is necessary to implement an override policy. For example, applicants with a score above 700 are automatically accepted, while applicants with a score below 500 are immediately rejected. For applicants with a score of 500 – 700, an override can be applied. Considering that the development of the CRS model has used a statistical approach, the determination of the cut-off is based on an acceptable probability of default. If the acceptable PD is 8.99% then the cut-off is made at Grade 6. For customers who get a grade up to grade 6, they will automatically be accepted, while for customers who get grades 7.8, 9 and 10 they will automatically be rejected.

CONCLUSION

1. Considering that there is still limited data available when developing the scorecard model, the Sharia Business Unit must develop a database and develop a Data Warehouse.
2. CRS KPR IB BARAKAH must always enrich the data that is taken into consideration in determining the internal rating. Periodically, reviews and measurements must be carried out on the stability of the CRS in measuring risk. Every customer characteristic that might influence the probability of default must be disciplinedly recorded in the database. In this case, the Loan Origination System and Data Warehouse systems play an important role in providing valid, reliable, consistent and objective data.

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