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FACTORS AFFECTING REPAYMENT PERFORMANCE IN MICROFINANCE BANKS IN YEMEN: THE CASE OF ALKURAIMI ISLAMIC MICROFINANCE BANK

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Abstract

Credit risk is one of the problems that banks are faced while doing their tasks. There is high competition among the financial institutions in Yemen, leading to the default of most finances. In this study, by using historical data on payments, demographic characteristics and a binary logistic regression model, we undertake to examine the factors that affect default among to the borrowers to calculate the probability of default. The results showed that the borrowers of large amounts default over the borrowers of small amounts. Older borrowers are more defaulted; the private sector employee borrowers are defaulted more than the public sector employees. Default rate increases with an increasing number of a dependent. Least educated borrowers are defaulted. Borrowers who have taken out finance from a previous borrower are defaulted as well as borrowers who are collateralized by commercial guarantee with personal and mortgaging are also defaulted. The predicting power of the model, as well as accuracy *rate of distinguishing defaulters from non-defaulters, is 79.6%. If one is identified as a defaulter, he/she had 79% chance of actual defaulting, where for identified non-defaulter, the chance of not actual defaulting is 80%.*

Keywords: Default, credit decision, credit scoring, logistic regression, AlKuraimi Islamic Microfinance Bank, Yemen

INTRODUCTION

The banking system plays an important role in the economic life of any country. The banking system has a strong relationship with all branches of economic activity and the various services it provides, which promote economic life with many developments and critical changes in the banking industry. The banks are vital to the prosperity of a country economy where the money the bank collects from the community are given back to the community in the form of finances to buy assets, to start and expand businesses, and for other various purposes, which necessitates conducting studies and researchers in The fields of this sector and its branches.

Bank credit also forms an important, if not the main, part of the work of microfinance banks. They represent not only a large part of the assets of microfinance banks but are also an important source of bank returns. However, the bank's ability to grant funding is limited as it is determined by the difference between the total (deposit numbers and the portion held by the bank in the form of liquid funds to meet customers' demands with taking into consideration the possibility of some customers withdrawing all or part of their deposits.

Focus on global credit analysis began to learn about customer risk and default signals since the early 1970s when two of the most important banks in the West had gone to stop continuing the first Franklin National Bank in the United States of America in 1972, it lost $ 40 million, almost a quarter of its capital the second bank is the Hasset Bank in West Germany, which suffered a major loss in the same year, forcing it to liquidate particularly(Mohammed, 2003). In Yemen, the bankruptcy of the National Bank at (2005) is a case in point which resulted making random decisions in granting finances without proper credit analysis and portfolio risk management(Settlements, 2017).

As a result, the decision by a bank to grant credit is very important. Therefore, banks must be aware of the potential risks which may be faced if the customer fails to repay. Credit decisions made by banks and financial institutions include many factors. For this reason, when an application is submitted to a bank for finance, it may not be easy for the bank to make the decision to extend credit. There are other decisions to make and other factors to take into consideration, including any guarantees, profitability, liquidity, the value of the finance, demographic and behavioral characteristics of customers when granting credit banks must follow a sound credit policy. For this policy to be realized, the bank examines the distribution of each item of the assets and liabilities in the bank budget to see whether the bank is able to provide liquid funds for the finance. The credit policy of microfinance banks is guided by the following considerations: (1) preservation and good use of depositors 'funds, (2) compliance with the state's general policy, that is, the decisions of the central bank, and (3) promotion of credit economic sectors and meeting the needs of the credit society as well as the policies of the Basel Committee.

The subject of credit analysis and the prediction of customers risks becomes a major objective for many microfinance banks; as a result, there is high competition among the financial institutions in Yemen leading to the default of most financing. In order to raise the quality of giving financing and reduce the risk involved in giving financing, credit scoring models have been developed by banks and researchers to improve the process of assessing creditworthiness during the credit evaluation process as an important tool to reach the accuracy of credit decisions and thus reduce the losses that may be uncovered to microfinance banks. Predictive signals have come to be regarded as extremely important and help to reduce occurrences of non-performing finances (Lu et al., 2013).

The objective of this paper lies in addressing the determinants relevant to the microfinance default rates objectively. In this regard, we undertake to examine the factors that affect decisions on personal grant finances in the AlKuraimi Islamic Microfinance Bank.

This paper is organized as follows: after a brief review of the empirical literature (Section 2), Section 3 is devoted to discussing the hypotheses related to the determinants of the microcredits' repayment rate. Section 4 deals with the relevant data and provides details regarding the methodology to be applied in this study. The achieved results pertaining to the logistic regression model are discussed in Section 5, with some concluding remarks provided in Section 6.

LITERATURE REVIEW

We showed a set of new and essential studies which addressed the factors affecting decisions on personal grant loans. (Puri et al., 2017) studied many of customer–bank relationships on loan default rates and its importance before making lending decisions in Germany. The results are that banks should use historical data on borrowers to establish a baseline that can assess new information for relevant clients, build good relationships with customers and need to improve future lending decisions.

(Mintah et al., 2014) tried to reveal how microfinance credits are managed and utilized by small businesses and what challenges available in both the microfinance institutions and small businesses. They have studied 200 customers from 20 Microfinance Institutions in Ghana also they used Excel program to analyze data. The study revealed that: The microfinance institutions provide credit creating an enabling environment for small businesses. Small Businesses pay the greater part of their profit to pay back the loan due to short repayment period and high-interest rate. The study recommends MFIs to be flexible in terms of repayment in order to enable small businesses to raise their capital to the level needed. Small businesses have to keep financial records to enable them measuring the growth of their businesses using profitability ratios also should Small Businesses fully implement the advice that the MFIs offer to them in order to promote their business growth.).

(Yap et al., 2011) used data mining to improve assessment of creditworthiness using credit scoring models. Due to privacy concerns and unavailability of real financial data from banks they used data of payment history of members from a recreational club for the credit scoring model. The club has been facing a problem of rising number of defaulters in their monthly club subscription payments. The management would like to have a model which they can deploy to identify potential defaulters. The classification performance of credit scorecard model, logistic regression model, and decision tree model was compared. The classification error rates for credit scorecard model, logistic regression, and decision tree were 27.9%, 28.8%,and 28.1%, respectively. They came to a conclusion that although no model outperforms the other, scorecards are relatively much easier to deploy in practical applications.

(Feroze et al., 2011) conducted a study dealing with a sample of 120 credit groups based in Haryana (India) for the sake of identifying the main factors influencing repayment performance. They used Excel program for data analysis with the dependent variables loan repayment, loan default, and the dependent variables group size, dependency ratio, female percentage, loan amount, Peer support, peer pressure, peer monitoring. Results of Tobit-regression analysis show that peer monitoring measured by the frequency of meetings per month, group size, and female percentage have a positive influence, whereas homogeneity and loan amount has a negative influence on the repayment performance.

(Khandani et al., 2010) applied machine-learning techniques to construct nonlinear nonparametric forecasting models of consumer credit risk. By combining customer transactions and credit bureau data from January 2005 to April 2009 for a sample of a major commercial bank's customers, they were able to construct out-of-sample forecasts that significantly improve the classification rates of credit card-holder delinquencies and defaults, with linear regression R2's of forecasted/realized delinquencies of 85%. Using conservative assumptions for the costs and benefits of cutting credit lines based on machine-learning forecasts, they estimated the cost savings to range from 6% to 25% of total losses. Moreover, the time-series patterns of estimated delinquency rates from this model over the course of the recent financial crisis suggests that aggregated consumer credit risk analytics may have important applications in forecasting systemic risk.

(Nawai and Shariff, 2010)Have made an attempt to review the literature dealing with the factors influencing the loan-repayment performance within the relevant microcredit programmers. They have argued that the factors affecting repayment performance can be divided into four major items, namely, the borrower characteristics, firm aspects, loan features along with the lender characteristics.

(Roslan and Karim, 2009) Investigate the determinants of loan repayment of loan issued by a commercial bank on a non-group lending basis. They believe that investigating the determinants for non-group based lending is important since the mechanism of group dynamics or peer pressure for ensuring loan repayment is almost non-existent. For this purpose, they undertake to examine the effect of borrowers' characteristics, project characteristics and loan characteristics on loan repayment relevant to the Eurobank Micro-Credit Scheme in Malaysia where studied 2630 borrowers at 2007 also they used Probit and logistic regression models to analyze data with these variables. The dependent variables are loan repayment, loan default. The independent variables are characteristics of borrowers (gender, level of education, age, other jobs, experience), characteristics of project (distance of project to nearest Agrobank office, ownership structure of project, types of projects) and characteristics of loan (amount of loan, repayment period). The results reveal that the probability for default is influenced by the borrower's gender, type of business activity, amount of loan, training and the repayment period.

(Abdou et al., 2008)Used information pertaining to 581 personal loans based in Egypt. They used discriminant analysis, probit analysis, and logistic regression for analysis data with the dependent variables loan repayment, loan default and they are used twenty independent variables some of which were loan amount, loan duration, sex, marital status, age, monthly salary, additional income, house owned or rent, and education level for building credit scoring models to evaluate credit risk. They find the neural models gave a better average correct classification rate than the other techniques for building credit scoring models to evaluate credit risk (paid or default) for personal loan.

(Salazar, 2008) They examines the determinants setting the repayment rate in Esperanza International, a microfinance institution in the Dominican Republic. They used information related to 15,104 loans divided amongst 8,991 individuals along with eight independent variables including gender, marital status, number of dependents, educational level, age, loan amount, type of microenterprise and regional office. The linear probability model (LPM) results indicate that the regional-office variable has the greatest effect on the repayment procedure, followed by educational level, gender and marital status.

(Dinh and Kleimeier, 2007)Used information pertaining to 56,000 loans personal in Vietnam from 1992 to 2005 year. They used Logistic regression for analysis data with the variables Income, Education ,Occupation, Employer type, Time with employer ,Age, Gender ,Region, Time at present address, Residential status, Marital status, Number of dependents, Home phone, Mobile phone, Loan purpose, Collateral type, Collateral value, Loan duration, Time with bank, Number of loans ,Current account, Savings account also propose a more specific credit scoring model allows banks to define those loans that are accepted or rejected as well as those which are further examined by the credit officer, also calibrated the credit scoring model to achieve the strategic objectives of the bank.

HYPOTHESES DEVELOPMENT

After collecting the variables advanced in the literature hypotheses as being the most prominent in the factors affecting decisions on personal grant finances relevant to the microfinance area, the hypotheses that are the subject of our study can, therefore, be specified as follows.

The finance amounts

It is usually defined as a finance feature resulting from the negotiation between borrower and bank. In this regard, we undertake to measure the credit amount as requested by the applicant. This variable reflects the borrower's intention, risk aversion, or self-assessment of the repayment ability. As stated by (Van Gool et al., 2012) customers who have requested the lowest credit amount tend to default more. The higher the amount of finance the higher the probability of default(Jonathan, 2012). The borrowers requesting substantial amounts do not have the tendency to divert and are more likely to apply the funds to acquire new technology and other necessary inputs useful for gaining a greater efficiency, competitive advantage or added value(Baklouti, 2013), the amount of finance have most important effect in identifying classification criteria of good customers and bad (Nazari & Alidadi, 2013), the incentive to deviate increases for bigger finances, so we expect that the bigger finance amount requested has a higher default.

The borrower's age

Different studies have actually found that the probability of finance default decreases with the increase in borrowers' age(Arminger et al., 1997, Dunn and Kim, 1999). It is often assumed that older borrowers are usually wiser, more risk averse, more knowledgeable and more responsible than younger borrowers and will, therefore, be less likely to default. Similarly, it can be assumed that younger borrowers are more independent and will, therefore, be less likely to default. 30-39-year-olds have the highest rate of default(Jonathan, 2012), older borrowers are more risk averse and will therefore be less likely to default (Dinh and Kleimeier-Ros, 2006) Thus, age might have a non-monotone effect on repayment rates. We expect the oldest borrowers have a high rate of default.

The borrower's occupation

We expect that employees in the public sector are more stable than private sector employees, especially in light of the political and economic fluctuations and the economic recession, which in some sectors leads to the dismissal of some of its employees. People who are self-employed have the highest rate of default than salary earners(Jonathan, 2012), the self-employed frequently receive a lower score in the evaluation of finance applications than do employed persons because of lack of stability of employment(Vojtek and Koèenda, 2006), the more stable employment, the higher the ability to repay a finance(Dinh and Kleimeier-Ros, 2006), so we expect that the borrower's employees in the private sector have a high rate of default.

The borrower's marital status

The marital status is a very common variable in the default-repayment relevant literature. It is often considered as a sign of responsibility, reliability or maturity on the part of borrowers. (Dinh and Kleimeier, 2007) assume that the probability of default is higher for the married than single borrowers as married borrowers are generally related to a number of dependents (such as children), which in turn reflects a financial pressure on the borrower's ability to repay finance. However, we can also expect that the probability of default payment is higher for the single than the married borrower. For, more often than not, single borrowers tend to be less responsible(Dunn and Kim, 1999). Married customers defaulted more than the customers who are not married (single)(Jonathan, 2012). Therefore, we expect the borrowers married to have a high rate of default.

The number of dependents of borrowers

We expect borrowers with multiple dependents to be more vulnerable to underdevelopment. The higher the number of dependents, the more likely they will be, especially if their age is small and under study, the higher the number of dependents, the higher the default rate(Jonathan, 2012), Therefore, we expect the greater the number of dependents has increased the probability of default.

The borrower's educational level

Regarding the educational level, we expect better educated borrowers to be more able to manage and spend their salaries, to have higher social efficiency and to make appropriate decisions decisions (Bhatt and Tang, 2002) borrowers enjoying a vocational education and training level exhibit the highest repayment rate(Baklouti, 2013), the more educated borrowers consider the most income and salaries and can work in more than one job. Therefore, we expect the borrowers with a graduate degree and higher educational level have the greatest success and non-default.

The number of previous finances

The 'Number of previous finances concluded during the whole relationship with the bank is a behavioral variable that can indicate the relationship between the customer and the bank. (Kocenda and Vojtek, 2009) document that the number of previously concluded finances is the most important behavioral characteristic indicating that the longer the history between the customers and the bank is, the less the possibility for default risk will be. In this sense, (Dinh and Kleimeier, 2007) the defaulted borrower would face difficulties in receiving new finance. Hence, the number of previous finances concluded can be a proxy for the borrower' default risk, so we expect the borrowers for only one finance are more borrowers default.

The borrower's type of guarantee

We expect customers to have Commercial guarantee are more customers default and mortgaging guarantees the repayment rate is large where owners are afraid to sell or confiscated by the bank and personal, commercial guarantees, are important especially in areas where the tribal side is prevalent. Therefore, we expect the borrowers whose have guarantees commercial have a high rate of default.

To sum up, there are eight hypotheses, specified as follows:

H1: A larger finance amount requested has a higher default.

H2: The oldest borrowers have a high rate of default.

H3: The borrower's employees in the private sector have a high rate of default.

H4: The borrowers married have a high rate of default.

H5: The greater the number of dependents has increased the probability of default.

H6: The borrowers with a graduate degree and higher educational level have the greatest success and non-default.

H7: The borrowers for only one finance are more borrowers default.

H8: The borrowers whose have guarantees commercial have a high rate of default.

RESEARCH METHODOLOGY

For the purpose of implementing the investigation of our hypotheses related to the factors affecting decisions on personal grant finances, a sample made up of historical finances provided by the AlKuraimi Islamic Microfinance Bank. The sample consists of 650 applications deposited and granted between 2013 and 2017. 50 percent of them have turned out to be default finances, and 50 percent have performed well. The dependent variable is represented by the customer's credit status, with value 1 denoting finances default, and 0 stands for finances non-default with eight independent variables are the finance amount; the borrower's age; the borrower's marital status; the borrower's educational level; the borrower's occupation; the number of dependents of borrower's; the number of previous finances of borrower's; the borrower's type of guarantee.

We tested the hypotheses relevant to identifying the microfinance banks factors affecting decisions using a binary logistic regression model based on dummy coded variables given by:

$$\text{logit}\ (p_i) = \text{In}(\frac{p_i}{(1-p_i)}) = \beta_0 + \beta_1 \text{X}_1 + \beta_2 \text{X}_2 + \beta_n \text{X}_\text{n}$$

Where; $\text{X}_1 \ldots \text{X}_\text{n}$ represent independent variables and $\beta_1 \ldots\ldots \beta_n$ indicate logistic regression coefficients for n variables. The probability p obtained by Equation (1) is a bound of classification. The customer is considered non-defaulter if it is larger than 0.5 or defaulter on the contrary.

It is worth highlighting that the forward stepwise method 4 is used to automate the variable selection process based on chi-square and its associated p-values. It selects the strongest variables and, therefore, eliminates the weakest variables for the ultimate model.

ANALYSIS AND RESULTS

Univariate Data Analysis

Table 1: Descriptive statistics

Variable	Value	Y=0 (%)	Y=1 (%)	Total (%)
Finance Amount	100,000-200,000	41.6	58.4	30.8
	200,001-400,000	60.8	39.2	30.6
	400,001-600,000	65.5	34.5	23.2
	Above 600,000	22.1	77.9	15.4
Borrower's age	Under 26	40.7	59.3	5.4
	26-30	44.6	55.4	18.4
	31-40	62.8	37.2	43.6
	41-50	29.9	70.1	21.4
	Above 50	51.8	48.2	11.2
occupation	Private sector	38.2	61.8	58.6
	Public sector	66.7	33.3	41.4
Borrower's marital status	Married	49.3	50.7	90.8
	Single	56.5	43.5	9.2

Number of dependents	Under 2	47.3	52.7	41.0	Table 1...
	2-4	52.4	47.6	33.2	
	5-7	60.8	39.2	20.4	
	Above 7	14.8	85.2	5.4	
Educational level	Under high school	50.0	50.0	6.8	
	High school	39.5	60.5	67.8	
	Postgraduate	78.0	22.0	25.4	
Number of previous finances	One	44.9	55.1	29.4	
	Two	28.0	72.0	10.0	
	Above two	64.7	35.3	3.4	
	New customer	55.6	44.4	57.2	
guarantee	Commercial	41.5	58.5	74.2	
	Commercial and personal	77.3	22.7	19.4	
	Mortgaging	65.6	34.4	6.4	

As can be deduced from Table 1, Most of the amounts that have been granted range from 100,000 to 400,000 (by 30.8, 30.6 percent respectively) This result is realistic because most of the borrowers with limited income and salaries are poor and also with the instability of the economic and political situation in the country, banks are working to increase the ability to pay to reduce default, the majority of the finances are granted to employees between 31 and 40 (43.6 percent) and repayment rate seems to be high. Regarding age, it has had a non-monotonous relationship with repayment rates. For the sake of confirming the statement that the relationship is statistically significant, the p-value should be administered and has to be as small as possible5 (i.e., less than 0.05), corresponding to a confidence level of 95 percent. The p-value is discovered to equal 0.000, which means that the difference in repayment rates by age classes is statistically significant. As noted in the table, private sector employees represent a larger proportion (58.6) of public sector employees and have a higher default rate. This is true, as most of the private sectors have gone bankrupt and their employees have terminated as a result of the situation in the country. It is noted that the default rate seems to be higher for the 'Married' (50.7 percent) than for the Single borrowers (43.5 percent) This difference between 'Married' and Single is statistically significant (p-value=0.353). In terms of a number of dependents, the results show that dependents Above 7 have default rate higher (85.2 percent) Indeed, this result is realistic as the number of dependents increases as family spending and school requirements and holidays of the money. High school, most customers, have finances (67.8 percent). In addition, borrowers with the highest default rate are those having High school (60.5 percent), followed by borrowers with an Under high school level (50 percent) and then come to the borrowers with Postgraduate level (22.0 percent). The p-value is very low (p=0.000), confirming that the difference is statistically significant. According to the variable number of previously finances, Table 1 illustrates that default rats (72.0 percent) of borrowers with the two previous finances as should study and applied procedures to old borrowers such as new borrowers without any indulgence or trust. In terms of guarantee, the results show that the commercial guarantee have default rate higher (58.5 percent).

Table 2: Values of Pearson chi-square statistic on cross-classifying explanatory variables with repayment performance (cross tabulation)

Explanatory variable	X^2value	Df	p-value
Finance Amount	46.693	3	0.000
Borrower's age	33.750	4	0.000
Occupation	39.249	1	0.000
Borrower's marital status	0.862	1	0.353
Number of dependents	19.091	3	0.000
Educational level	54.563	2	0.000
Number of previous finance	16.262	3	0.001
Guarantee	42.782	2	0.000

This result is realistic as the borrower default and his guarantee mortgaging maybe the bank will sell it If his guarantee commercial with personal has been made to the personal guarantor he is putting pressure on the client and this custom is very prevalent in Yemen It is practiced by most banks and microfinance institutions.

Model Estimation

The logistic-estimation results related to the repayment behavior are reported in Table 3 which reveals that seven out of the eight predicted influencing factors turn out to be statistically significant. Indeed, the applied backward-stepwise method has made borrower's marital status redundant, either due to their high correlation with some of the independent variables or due to their insignificant coefficients. With regard to the Wald statistic, it is useful in performing the chi-square distribution which helps to indicate whether the coefficient (b) is significantly different from zero or not. It highlights the importance of contribution of each variable to the model. Thus, a high value indicates the significant of variable contribution towards non-default. In this way, occupation proves to be the most important predictor than the other indicators.

Table 3. Estimated coefficients, standard errors and significance levels relevant to the final logistic regression model

Variable		Coeff. (B)	S. E	p-value	Exp(B)
Intercept		-1.693	0.978	0.083*	0.184
Finance Amount	100,000-200,000	-.733	0.393	0.062*	0.480
	200,001-400,000	-1.813	0.404	0.000***	0.163
	400,001-600,000	-2.138	0.410	0.000***	0.118
	Above 600,000	0.0000	N/A	N/A	N/A
Borrower's age	Under 26	0.607	0.621	0.328	1.834
	26-30	0.490	0.467	0.295	1.632
	31-40	-.407	0.407	0.318	0.666
	41-50	1.485	0.441	0.001***	4.413
	Above 50	0.0000	N/A	N/A	N/A
Occupation	Private sector	1.088	0.267	0.000***	2.968
	Public sector	0.0000	N/A	N/A	N/A
Borrower's marital status	Married	1.040	0.422	0.014**	2.829
	Single	0.0000	N/A	N/A	N/A
Number of dependents	Under 2	-1.568	0.661	0.018*	0.209
	2-4	-1.447	0.648	0.026*	0.235
	5-7	-1.735	0.654	0.008***	0.176
	Above 7	0.0000	N/A	N/A	N/A
Educational level	Under high school	1.040	0.507	0.040**	2.829
	High school	1.450	0.304	0.000***	4.261
	Postgraduate	0.0000	N/A	N/A	N/A
Number of previous finances	One	0.788	0.283	0.005***	2.198
	Two	1.552	0.440	0.000***	4.723
	Above two	-.352	0.659	0.593	0.703
	New customer	0.0000	N/A	N/A	N/A
guarantee	Commercial	1.663	0.505	0.001***	5.275
	Commercial and personal	-.380	0.557	0.495	0.684
	Mortgaging	0.0000	N/A	N/A	N/A

Notes: Coeff. (B) is the coefficient. S.E is standard error of the sample distribution. A small SE means that most sample pairs have similar means while a large SE signifies that sample means can deviate from the population mean and so, sample pairs difference can be quite large only by chance. P-value refers to the predictor significance. Exp(B) shows the odds ratios (OR) for each predictor. The number of stars (*) denote significant level: ***p-value < 0.01, **p-value < 0.05 and *p-value < 0.10.

Based on the results in Table 3, the finance amount variable gives a reliable indication of default borrowers who have requested the highest finance amount class tends to default a more constantly frequent basis. This result is consistent with the H1 hypothesis Which states, "A larger finance amount requested has a higher default", also consistent with the study conducted by (Bassem and Borhen, 2008) and (Jonathan, 2012) in addition to this result contradictory to the findings of (Van Gool et al., 2012).

As we see also that the salaries of employees are limited and sometimes disbursement of finances in times are not commensurate with the payment of salaries of employees. Political and economic conditions also play an active role in the default of customers.

The result in Table 3 shows, one can conclude that age has a non-monotonic effect on default rates. The youngest and middle-age borrowers appear to have the lowest default risk while the oldest borrowers seem to have the highest default rate. The age variable is important in determining the most vulnerable customers and the result that is consistent with H2 hypothesis which states, “The oldest borrowers have a high rate of default”, it is also consistent with the results obtained by (Dinh and Kleimeier-Ros, 2006)that older borrowers are more riskier about averse and will, therefore, by (Jonathan, 2012) 30-39-year-olds have the highest rate of default.

According to the results in Table 3, one can figure out that occupation has an effect on default rates. The employees in the private sector have a high rate of default while the employees in the public sector seem to have the lowest default rate. This result is consistent with the H3 hypothesis which states, "The borrower employees in the private sector have a high rate of default." also consistent with the study conducted by (Jonathan, 2012) and(Vojtek and Koèenda, 2006).

As noted in table 3 the marital status X41 variable is not important with a significance level of 0.05. However, the p-value for remaining independent variables are greater than 0.05 level of significance. Hence, we fail to reject the null hypothesis as their coefficients of regression are equal to zero. Therefore, they are not statistically significant. This independent variable is excluded from the model.

Considering the results in Table 3, one can assume that the number of dependents has an effect on default rates. Borrowers who own a large number of dependents have the highest default rate while borrowers who own few dependents have the lowest default rate. This result is consistent with the H5 hypothesis which states, "The greater the number of dependents has increased the probability of default", also consistent with the study conducted by(Jonathan, 2012).

As noted in table 3, with regard to the variable of education level, borrowers with a high school seem to be high default than those having an under high school and Postgraduate level. This result is consistent with the H6 hypothesis which states, "The borrowers with a graduate degree and higher educational level have the greatest success and non-default", also consistent with the study conducted by(Baklouti, 2013).

Focusing on the results in Table 3, one can conclude that the number of previous finances has an effect on default rates. Where customers who have been granted two finances are more default. This result is not consistent with the H7 hypothesis which states, "The borrowers for only one finance are more default", also consistent with the study conducted by(Dinh and Kleimeier, 2007).

Based on the results in Table 3, one can find out that type of guarantee has an effect on default rates, and the commercial guarantees have the highest default rate. This result is consistent with the H8 hypothesis which states, "The borrowers who have guarantees of commercial have a high rate of default."

Classification of the model

Classification of the model, that is, how well the model distinguishes default and non-default of finance can be assessed using the classification table. The model is able to predict default and non-default adequately (78.8% and 80.4% respectively). Overall, the model has 79.6% accuracy rate of distinguishing defaulters from non-defaulters.

Validation of the credit-scoring model

Table 4 reports predictive accuracy with 23% of the sample. As reported in Table 4, the model correctly predicts 82% of the observations in the validation sample. A separate examination of the finances as Bad versus Good reveals that the correctly classified percentage is mainly driven by the Good finances, as the PCCgood (80.2%) proves to be much higher than the PCCbad (84.4%). The SPEC measure indicates that among the rejected finances, 76% would have defaulted whereas 24% would have been repaid. 24% of the finances that have been incorrectly rejected should be interpreted as the cost of foregone business opportunities (Type II error). Note that SPEC is an abstract measure because a bank cannot check whether its rejected finance applicants would have defaulted; 13% of the finances are incorrectly accepted which leads to losses due to missed interest and principal payments (Type I error). Both sensitivity and specificity rely on a single cutoff point to perform classification. A complete description of classification accuracy is captured by the AUC. The AUC value is equal to 0.832.

This confirms the statement that the model exhibits good discerning power to separate default and non-default borrowers.

Table 4: Predictive accuracy

Observed	Predicted		
	Non-Default	Default	PCC
Non-Default	69	17	$\mathrm{PCC}_{\mathrm{good}} = 80.2\%$
Default	10	54	$\mathrm{PCC}_{\mathrm{bad}} = 84.4\%$
Overall Percentage			$\mathrm{PCC}_{\mathrm{total}} = 82.0\%$
SENS	87%		
SPEC		76%	

We compare our model's performance with the results reported in previous credit-scoring studies for microfinance this finding is consistent with the results of others.

DISCUSSION

It is worth noting that our results turn out to have some major implications, generally related to the managerial decision-making area. Indeed, by highlighting the determinants of finance re-payment, finance officers will be able to improve the selection accuracy regarding the potential borrowers. Based on the findings from this study, it is recommended that the bank can combine statistical and best practices of human to determining the creditworthiness of the customer. The results suggest that borrowers of big amount are the most default and we recommend that the finance specialist should study the client and calculate the ability to pay accurately and must take into account the client's personal and family expenses and verify any other revenue provided by the client. The results suggest that borrowers who are aged between 41-50 years old have more customers stumbled and this is what (Jonathan, 2012) found out that older customers are more default and we recommend that the rate of repayment capacity be increased to borrowers who are in this category. A number of dependents represent the number of people that the borrower has to support. As the number of dependent increases so does the pressure on the borrower's income due to higher expenses such as food and daycare fees. The results suggest that the employees in the private sector are more default. Because of economic and political problems in Yemen, the bankruptcy of some companies and institutions of the private sector or the dismissal of some of its employees happen. The results suggest that borrowers with two previous finances are more defaulted and we recommend that the finance specialist examine the customer who took out previous finance as he is a customer for the first time and not to tolerate the procedures. As we can see that borrowers with commercial guarantee are more defaulted, and we recommend that the finance specialist should take more guarantee to reduce risk. It is necessary for the bank to hire qualified personnel to analyze credit risk. The personnel can periodically analyze and adjust the weight of every risk factor and control the rate of overdue payment finance at the right moment, develop a database of all personal finance cases to adapt the future policy of personal consumer finances and also take into consideration the society and political environment and also the state of the economy. Central Bank of Yemen has to enact policies and place plans to improve the microcredit service.

CONCLUSION

Understanding the process of making financial decisions is crucial for academics, banks, consumers, and regulators. Especially for increasing competition among banks and microfinance institutions in Yemen, it is needed to estimate the risk of default of microfinance borrowers.

The study has attempted to address the factors objectively which affect the decision making of personal finances in the Al-Kirimi Islamic Microfinance Bank as a dependent variable and eight independent variables as finance amount, borrowers age, occupation, marital status, number of dependents, educational level, number of previous finances and type of guarantee.

The researcher prepared a questionnaire for this purpose, which was distributed to 650 personal finance customers and a finance specialist Also, a sample of customers who were granted finances during the period from 2013 to 2017, the logistic regression model was developed to determine the factors that affect customers' default on repayment of finances. After the analysis of the data, we get the results regarding the subject of the study.

Results of this study show that such factors like the finance amount, borrowers age, occupation, number of dependents, educational level, number of previous finances and type of guarantee have a noticeable effect on the finance default where borrowers of large amounts are more defaulted over borrowers of small amounts, older borrowers are more defaulted than younger, the borrower of private sector employees are more defaulted than the public sector employees, default rate increases with an increasing number of dependent, least educated borrowers are defaulted as well as borrowers who have taken out a finance from a previous borrower are also defaulted, borrowers who are collateralized by commercial have also defaulted.

This means that the decision makers should focus on these factors when making a decision to lend, etc. However, the discriminatory power of our model is still weak in the process of granting finances. In fact, it is not reliable enough to replace finance staff, but through this, we can combine statistical and best practices of a human. This paper has been designed to provide some valuable contributions in improving the repayment performance due to the microfinance banks through a better understanding of its pertinent determinants. This gives some guidelines to decrease the probability of default, which ensures more sustainability, reliability and further outreach for the microfinance banks.

We recommend more research regarding the effect of repayment performance in the microfinance banking with regards to capturing all factors which influence the repayment performance. Furthermore, in the following studies, it will be interesting to study how Variables like negative political environment and economic recession have effects on customers' loan default tendency. The study is subjected to limitations in that the respondents were limited to only one microfinance bank. Therefore, it is proposed to select respondents from multiple microfinance banks. This study used the logistic regression model for estimating the credit scoring model. It is suggested to use alternative models such as discriminant analysis, neural networks, survival analysis and decision trees to check if the present findings holds ground. Eight variables were studied in this study. There are other independent variables that can determine the creditworthiness of the borrower, for example, gender, household income, employee salary, etc.

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